Capturing Preferences Under Incomplete Scenarios Using Elicited Choice Probabilities.

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Abstract

Manski [13] proposed an approach for dealing with a particular form respondent uncertainty in discrete choice settings, particularly relevant in survey based research when the uncertainty stems from the incomplete description of the choice scenarios. Specifically, he suggests eliciting choice probabilities from respondents rather than their single choice of an alternative. A recent paper in *IER* by Blass *et al.* [1] further develops the approach and presents the first empirical application. This paper extends the literature in a number of directions, examining the linkage between elicited choice probabilities and the more common discrete choice elicitation format. We also provide the first convergent validity test of the elicited choice probability format vis-à-vis the standard discrete choice format in a split sample experiment. Finally, we discuss the differences between welfare measures that can be derived from elicited choice probabilities versus those that can obtained from discrete choice responses and illustrate these differences empirically.

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1 Introduction

The Random Utility Maximization (RUM) model (McFadden [15, 16]) provides the foundation of most discrete choice analyses in transportation, housing and a wide array of consumer goods. A fundamental premise of the standard RUM framework is that individuals, in making a choice among the available alternatives, know *exactly* what utility they will receive from each alternative.[2] The error terms in the model reflect, not the individual's uncertainty, but rather missing information on the part of the analyst. This missing information can take the form of unobserved factors affecting the choice, measurement error, or misspecification of the conditional indirect utility function itself. The analyst makes assumptions about the distribution of the error terms, allowing them to specify conditional choice probabilities for each individual, and then estimates the parameters associated with the assumed distributions. Yet, in many applications, the assumption that individuals have no uncertainty about the choices they face, while convenient, seems tenuous at best, particularly when individuals are asked to evaluate goods or scenarios with which they have little past experience.

Manski [13] proposed an innovative approach for dealing with a particular form of uncertainty in discrete choice settings, particularly relevant when the uncertainty stems from the incomplete description of the choice scenarios. In survey based research, space constraints and concerns regarding respondent fatigue often leads researchers to provide only a skeletal depiction of the choice alternatives, highlighting those attributes the researcher views as essential.[3] Yet these descriptions leave much to the imagination of the survey respondent, both in terms of the alternatives directly and in terms of their own situation at the time when a real choice might arise. For example, electric utilities have often used survey instruments to assess its customers' outage costs stemming from power interruptions (See [2]). Respondents are typically asked to choose from among outage scenarios that vary the maximum frequency and duration of outages, along with corresponding changes to their electricity bill. However, considerable uncertainty remains, not only in terms of what might be the realized frequency and duration of outages, but also in terms of their precise timing and coincidence with the customer's need for electricity. As Blass *et al.* [1] note, "...[w]hen scenarios are incomplete,

[2]One can use the standard RUM model to allow for preference uncertainty (or, perhaps more accurately, preference risk) by assuming that the individual's choice is made on the basis of expected utility and that the conditional utility function itself is quadratic. The choice between alternatives in this case becomes a function of the perceived mean and variance of each alternative's utility. To out knowledge, however, this approach has not been used, in part because of the difficulty in eliciting each individual's perceptions regarding the distribution of their own conditional utilities.

[3]Indeed, more detailed descriptions of the choice alternatives can be counter-productive, causing respondents to rely on only part of the overall information provided and employ simple heuristics to make their choices (See, e.g., [4], [5]).

stated choices cannot be more than point predictions of actual choices."

Manski [13] suggests capturing the respondent's uncertainty at the time of the choice by eliciting choice *probabilities* from respondents rather than their single choice of an alternative. Thus, respondents might be asked to report the probability that they would prefer one outage scenario versus another, rather than a single "all or nothing" decision, as in the standard discrete choice framework. The idea itself is simple, yet elegant. In essence, Manski suggests viewing the survey respondent much like the standard RUM model treats the analyst. The survey respondent *ex ante* (i.e., at the time they are asked to express a preference over, say, option A versus option B) has incomplete information. As such, they can only express the probability that they would *ex post* (i.e., once their information uncertainties are resolved) prefer option A over option B.[4] Blass, *et al.* [1] further develop the approach and present the first empirical estimation of a random utility model using elicited choice probabilities.

This paper extends the literature in a number of directions. First, Manski [12] suggests that, when faced with a discrete choice question, individuals will compute a subjective choice probability for each alternative and choose that alternative with the highest choice probability. We examine this conjecture in the context of an expected utility framework. We then provide the first convergent validity test of the elicited choice probability format vis-à-vis the standard discrete choice format using a split sample survey design drawn from the recreation demand literature. Specifically, in the 2009 Iowa Lakes Project, half of the individuals in the survey were asked to choose between two hypothetical lakes (Lake A and Lake B) with differing attributes, while the other half of the sample were asked to indicate the probability that they would prefer Lake A over Lake B.

Second, as the subjective choice probabilities are assumed to be driven by the incomplete nature of choice scenarios, we examine the impact that changes in the survey's information content have on both elicited choice probabilities and discrete choice responses. Both survey subsamples were split a second time, with half of each subsample receiving a high information treatment, while the other half received a low information treatment. Finally, survey responses are often used to derive estimates of willingness-to-pay (WTP) for use in policy analysis, whether it is to determine outage costs for commercial and industrial electricity

[4]The fact that the individual can express a probability associated with their preferences suggests that, strictly speaking, we are considering the situation of *choice under risk*, in which the probability distribution for the possible states of the world is known to the decision maker, versus *choice under uncertainty* in which the relevant probability distributions are unknown. Throughout this paper, we use the term *uncertainty* less formally, to refer to the fact that the individual, *ex ante* does not know what the future state of the world will be, but, as in Blass, *et al.* [1], it is assumed that they do have subjective beliefs regarding the probabilities associated with each state of the world.

customers or the WTP for a proposed environmental protection or remediation program. We discuss the differences between welfare measures derived from elicited choice probabilities and those obtained from discrete choice responses and illustrate these differences empirically.

2 Modeling Discrete Choices and Elicited Choice Probabilities

We begin by describing the underlying modeling framework for both the standard discrete choice problem and the elicited choice probability setting.

2.1 Discrete Choices

In the standard RUM model of a binary choice from among two options ($j = A, B$), it is assumed that the individual i knows the utility that they would receive from each option (U_{ij}) with certainty and simply chooses that option that maximizes their utility. The stochastic nature of the problem is in the eyes of the analyst alone, who observes only a subset of the factors influencing the individual's decision. For example, suppose that

$$U_{ij} = \alpha_j + \boldsymbol{\beta}_x \boldsymbol{x}_{ij} + \boldsymbol{\beta}_z \boldsymbol{z}_{ij} \tag{1}$$

where both $\boldsymbol{x}_{ij}$ and $\boldsymbol{z}_{ij}$ are known to the decision-maker, but only $\boldsymbol{x}_{ij}$ is observed by the analyst. The outcome that option A is chosen (denoted $y_i = 1$) is determined by the individual by comparing U_{iA} and U_{iB}, with

$$y_i = \begin{cases} 1 & U_{iA} \geq U_{iB} \\ 0 & U_{iA} < U_{iB}. \end{cases} \tag{2}$$

For the analyst, however, the outcome (y_i) is a random variable, since $\boldsymbol{z}_{ij}$ is unknown. The utility that individual i receives from alternative j takes the form:

$$\begin{aligned} U_{ij} &= \alpha_j + \boldsymbol{\beta}_x \boldsymbol{x}_{ij} + \tilde{\epsilon}_{ij} \\ &= \tilde{V}_{ij} + \tilde{\epsilon}_{ij} \end{aligned} \tag{3}$$

where $\tilde{V}_{ij} \equiv \alpha_j + \boldsymbol{\beta}_x \boldsymbol{x}_{ij}$ and $\tilde{\epsilon}_{ij} \equiv \boldsymbol{\beta}_z \boldsymbol{z}_{ij}$ captures the unobservable factors influencing U_{ij}. Without knowledge of $\boldsymbol{z}_{ij}$ (and hence $\tilde{\epsilon}_{ij}$), the analyst can only make probabilistic statements about the choice between options A and B. Specifically, the conditional probability that option A is chosen (denoted by P_{iA}) is given by

$$\begin{aligned} P_{iA} &= Pr(y_i = 1|\boldsymbol{x}_{ij}) \\ &= Pr(U_{iA} \geq U_{iB}|\boldsymbol{x}_{ij}) \\ &= Pr(\tilde{V}_{iA} + \tilde{\epsilon}_{iA} \geq \tilde{V}_{iB} + \tilde{\epsilon}_{iB}|\boldsymbol{x}_{ij}) \\ &= Pr(\tilde{\epsilon}_i \leq \tilde{V}_i|\boldsymbol{x}_{ij}), \end{aligned} \tag{4}$$

where

$$\begin{aligned} \tilde{V}_i &\equiv \tilde{V}_{iA} - \tilde{V}_{iB} \\ &= (\alpha_A - \alpha_B) + \boldsymbol{\beta}_x(\boldsymbol{x}_{iA} - \boldsymbol{x}_{iB}) \\ &= \alpha + \boldsymbol{\beta}_x\boldsymbol{x}_i, \end{aligned} \tag{5}$$

with $\alpha \equiv \alpha_A - \alpha_B$ and $\boldsymbol{x}_i \equiv \boldsymbol{x}_{iA} - \boldsymbol{x}_{iB}$, and

$$\tilde{\epsilon}_i \equiv \tilde{\epsilon}_{iB} - \tilde{\epsilon}_{iA}. \tag{6}$$

Different assumptions about the unobservables (i.e., the $\tilde{\epsilon}_{ij}$) yield different functional forms for the choice probabilities. For example, if the $\tilde{\epsilon}_{ij}$'s are assumed to be *iid* Type I extreme value random variables, then a logistic model results, with

$$P_{iA} = \frac{exp(\tilde{V}_i)}{1 + exp(\tilde{V}_i)} = \frac{exp(\alpha + \boldsymbol{\beta}_x\boldsymbol{x}_i)}{1 + exp(\alpha + \boldsymbol{\beta}_x\boldsymbol{x}_i)}. \tag{7}$$

More general RUM models result if we assume that there are unobserved individual attributes (say s_i) that interact with $\boldsymbol{x}_{ij}$ in determining U_{ij}.[5] In this case, we might have

$$\begin{aligned} U_{ij} &= \alpha_j + \boldsymbol{\beta}_x\boldsymbol{x}_{ij} + \boldsymbol{\beta}_z\boldsymbol{z}_{ij} + \boldsymbol{\gamma}_{xz}\boldsymbol{x}_{ij}s_i \\ &= \alpha_j + (\boldsymbol{\beta}_x + \boldsymbol{\gamma}_{xz}s_i)\boldsymbol{x}_{ij} + \boldsymbol{\beta}_z\boldsymbol{z}_{ij} \\ &= \alpha_j + \boldsymbol{\beta}_{xi}\boldsymbol{x}_{ij} + \tilde{\epsilon}_{ij} \end{aligned} \tag{8}$$

where $\boldsymbol{\beta}_{xi} \equiv \boldsymbol{\beta}_x + \boldsymbol{\gamma}_{xz}s_i$ is a random parameter from the analyst's perspective, capturing heterogeneity in consumer preferences induced by s_i. If the $\tilde{\epsilon}_{ij}$'s are again assumed to be *iid* Type I extreme value random variables, then the mixed logit model results (see, e.g., Train [18]), with

$$P_{iA} = \int \frac{exp(\alpha + \boldsymbol{\beta}_{xi}\boldsymbol{x}_i)}{1 + exp(\alpha + \boldsymbol{\beta}_{xi}\boldsymbol{x}_i)} f(\boldsymbol{\beta}_{xi})d\boldsymbol{\beta}_{xi}, \tag{9}$$

where $f(\boldsymbol{\beta}_{xi})$ is the assumed distribution of the random parameter $\boldsymbol{\beta}_{xi}$.[6]

[5]For ease of notation, we specify these unobserved attributes as a scalar, though this can easily be generalized.

[6]The mixing distribution can instead be discrete, generated by discrete unobserved individual attributes, leading instead to a latent class model.

2.2 Elicited Choice Probabilities

In Manski's [13] elicited choice probabilities setting, the problem is similar to the discrete choice problem, except that now we allow for uncertainty on the part of both the analyst and the decision-maker.[7] Specifically, it is assumed that there are aspects of the choice alternatives that are incompletely described in the survey and about which the decision-maker forms subjective probability distributions.[8] Suppose that $\boldsymbol{z}_{ij}$ is segmented into these *certain* and *uncertain* components, with $\boldsymbol{z}_{ij} = (\boldsymbol{z}_{ij}^{c\,\prime}, \boldsymbol{z}_{ij}^{u\,\prime})'$. The conditional utility that individual i *anticipates* receiving from choosing alternative j described in (1) now becomes:

$$\begin{aligned} U_{ij} &= \alpha_j + \boldsymbol{\beta}_x \boldsymbol{x}_{ij} + \boldsymbol{\beta}_c \boldsymbol{z}_{ij}^c + \boldsymbol{\beta}_u \boldsymbol{z}_{ij}^u \\ &= V_{ij} + \epsilon_{ij}, \end{aligned} \tag{10}$$

where $V_{ij} \equiv \alpha_j + \boldsymbol{\beta}_x \boldsymbol{x}_{ij} + \boldsymbol{\beta}_c \boldsymbol{z}_{ij}^c$ and $\epsilon_{ij} \equiv \boldsymbol{\beta}_u \boldsymbol{z}_{ij}^u$. To fix ideas, suppose we are considering a dichotomous choice question in which respondents are asked to evaluate two competing hypothetical lakes, described in terms of their water quality conditions (say, water clarity) and the cost of visiting each lake. In this case, $\boldsymbol{x}_{ij}$ would include the choice attributes as described in the survey, along with individual socio-demographic factors elicited via the survey instrument. The $\boldsymbol{z}_{ij}^c$ would include factors known to the decision-maker, but unknown to the analyst, such as their general interest in fishing, whether or not they own a boat, the age of their children, etc. Finally, $\boldsymbol{z}_{ij}^u$ would include those aspects of the alternatives and individual, unknown to both the decision-maker and the analyst, that arise because the survey paints only an incomplete picture of the choice alternatives or other factors that are uncertain but resolvable between the time the question is completed and the decision is made. For example, $\boldsymbol{z}_{ij}^u$ might include weather conditions at the respective sites on the day the individual would actually be choosing where to recreate, the health of their children on the day in question, etc. The assumption is that these factors, while unknown to the respondent *ex ante* when the survey is administered, would be resolved *ex post*, when actually making the site selection decision.

[7] In the nonmarket valuation literature, where survey participants are asked to choose from among alternative sets of environmental scenarios, some studies have attempted to allow for respondent uncertainty by adding "probably yes," "probably no," "uncertain", and similarly equivocating options to the list of possible responses (e.g., [20]; [17]) or by asking respondents to rate the *certainty* of their answers on a numerical scale (e.g., [8, 9], [10]). The problem with these approaches is it is no longer clear which response one should use in defining the choice probabilities and the associated welfare measures. While studies have sought to calibrate stated preference survey responses using parallel "real" experimental transactions data (e.g., [8, 9],[3],[11]), a consensus has yet to be reached on the form that such calibrations should take.

[8] Blass *et al.* [1] emphasize that the uncertainty in this setting is *resolvable uncertainty*; i.e., that the individual anticipates knowing the actual state of the world when eventually faced with choosing among the available alternatives.

Because $\boldsymbol{z}_{ij}^u$ is unknown to the decision-maker, they can no longer identify with certainty which alternative will yield the highest utility. Instead, at the time the analyst elicits choice probabilities, the individual can only reveal their subjective assessment as to which alternative will maximize their utility. With a choice between two alternatives (i.e., $j = A, B$), individual i's subjective choice probability that alternative A would be preferred is given by:

$$\begin{aligned} q_{iA} &= Pr\left[U_{iA} > U_{iB}\right] \\ &= Pr\left[V_{iA} + \epsilon_{iA} > V_{iB} + \epsilon_{iB}\right] \\ &= Pr\left[\epsilon_i < V_i\right] \end{aligned} \tag{11}$$

where

$$\begin{aligned} V_i &\equiv V_{iA} - V_{iB} \\ &= \alpha + \boldsymbol{\beta}_x \boldsymbol{x}_i + \boldsymbol{\beta}_c \boldsymbol{z}_i^c, \end{aligned} \tag{12}$$

with $\boldsymbol{z}_i^c \equiv \boldsymbol{z}_{iA}^c - \boldsymbol{z}_{iB}^c$, and

$$\epsilon_i \equiv \epsilon_{iB} - \epsilon_{iA}. \tag{13}$$

In developing a strategy for empirically modeling the elicited choice probabilities, Blass *et al.* [1] assume that $\epsilon_{ij} \overset{iid}{\sim}$ Type I extreme value, in which case the elicited choice probabilities take the familiar logistic form

$$q_{iA} = \frac{exp(V_i)}{1 + exp(V_i)} = \frac{exp(\alpha + \boldsymbol{\beta}_x \boldsymbol{x}_i + \boldsymbol{\beta}_c \boldsymbol{z}_i^c)}{1 + exp(\alpha + \boldsymbol{\beta}_x \boldsymbol{x}_i + \boldsymbol{\beta}_c \boldsymbol{z}_i^c)}. \tag{14}$$

They go on to suggest estimating the parameters associated with $\boldsymbol{x}_i$ by applying LAD estimation to the log-odds transformation of (14); i.e.,[9]

$$ln\left(\frac{q_{iA}}{q_{iB}}\right) = \alpha + \boldsymbol{\beta}_x \boldsymbol{x}_i + \eta_i, \tag{15}$$

where $\eta_i \equiv \boldsymbol{\beta}_c \boldsymbol{z}_i^c$.[10]

There are several comments that are worth making regarding these subjective choice probabilities. First, the underlying assumption that the ϵ_{ij} are *iid*, while convenient, is a relatively

[9] The LAD estimator is proposed to deal with a practical problem in elicited choice probability settings, namely the problem with the log-odds transformation in those cases in which $q_{iA} = 0$ or 1. The LAD estimator is not sensitive to outliers, allowing these extreme cases to be handled by replacing $q_{iA} = 0$ or 1 with δ and $1 - \delta$, respectively, where δ is a small number.

[10] Note that our model departs from [1] in that the error term in (15) is driven, not by heterogeneous preferences (i.e., variation in $\boldsymbol{\beta}_x$ across individuals), but rather by unobservable factors impacting the individual's preferences over the alternatives; i.e., the $\boldsymbol{z}_i^c$'s. This is important in that Blass *et al.* [1] use fitted error terms to infer the nature of preference heterogeneity in their sample, but it may instead be simply reflecting the incomplete information available to the analyst.

strong one, requiring that all individuals share the same subjective assessments regarding the uncertainty associated with the alternatives presented in the survey (i.e., the $\boldsymbol{z}_{ij}^u$).[11] Second, while the subjective choice probabilities in (14) are similar in structure to those for the discrete choice setting in (7), they differ in that the subjective choice probabilities are themselves random variables from the analyst's perspective, depending as they do on the attributes $\boldsymbol{z}_{ij}^c$, which are unobservable by analyst, but known to the decision-maker.

As was the case with the discrete choice setting, the elicited choice model can be generalized to allow for preference heterogeneity by introducing interaction terms associated with $\boldsymbol{s}_i$, individual specific factors observed by the decision-maker, but not the analyst. The conditional utility in equation (10) becomes

$$\begin{aligned} U_{ij} &= \alpha_j + \boldsymbol{\beta}_x \boldsymbol{x}_{ij} + \boldsymbol{\beta}_c \boldsymbol{z}_{ij}^c + \boldsymbol{\beta}_u \boldsymbol{z}_{ij}^u + \boldsymbol{\gamma}_x \boldsymbol{x}_{ij} \boldsymbol{s}_i + \boldsymbol{\gamma}_c \boldsymbol{z}_{ij}^c \boldsymbol{s}_i + \boldsymbol{\gamma}_u \boldsymbol{z}_{ij}^u \boldsymbol{s}_i \\ &= \alpha_j + (\boldsymbol{\beta}_x + \boldsymbol{\gamma}_x \boldsymbol{s}_i)\boldsymbol{x}_{ij} + (\boldsymbol{\beta}_c + \boldsymbol{\gamma}_c \boldsymbol{s}_i)\boldsymbol{z}_{ij}^c + (\boldsymbol{\beta}_u + \boldsymbol{\gamma}_u \boldsymbol{s}_i)\boldsymbol{z}_{ij}^u \\ &= \alpha_j + \boldsymbol{\beta}_{xi} \boldsymbol{x}_{ij} + \boldsymbol{\beta}_{ci} \boldsymbol{z}_{ij}^c + \boldsymbol{\beta}_{ui} \boldsymbol{z}_{ij}^u \\ &= V_{ij} + \epsilon_{ij}, \end{aligned} \tag{16}$$

where now $V_{ij} \equiv \alpha_j + \boldsymbol{\beta}_{xi} \boldsymbol{x}_{ij} + \boldsymbol{\beta}_{ci} \boldsymbol{z}_{ij}^c$ has parameters that vary over individuals and $\epsilon_{ij} \equiv \boldsymbol{\beta}_{ui} \boldsymbol{z}_{ij}^u$, where $\boldsymbol{\beta}_{ui} = \boldsymbol{\beta}_u + \boldsymbol{\gamma}_u \boldsymbol{s}_i$. Note that now, even if individuals share the same subjective beliefs about the uncertain site characteristics $\boldsymbol{z}_{ij}^u$, the error term ϵ_{ij} will be heteroskedastic due to differences in $\boldsymbol{\beta}_{ui}$. As an example of this, suppose that $\boldsymbol{z}_{ij}^u$ represents the fishing conditions at site j and s_i represents an index on the unit interval indicating an individual's general interest in fishing. For an individual who cares about fishing, s_i will be close to one and the corresponding $\boldsymbol{\beta}_{ui}$ will be relatively large. Because they like fishing, any uncertainty they have about fishing conditions at site j ($\boldsymbol{z}_{ij}^u$) induces substantial uncertainty in terms of the utility they anticipate receiving from visiting site j. In contrast, an individual who does not care about fishing will have an s_i will be close to zero and the corresponding $\boldsymbol{\beta}_{ui}$ will be relatively small. For this non-fisherman, even if they share exactly the same subjective beliefs about the fishing conditions at site j as the avid fisherman, the uncertainty does not translate into uncertainty about U_{ij} since they simply do not care about the fishing conditions.

The implication of this heteroskedasticity is that the identified parameters of the subjective choice probabilities will now vary by individual. To see this, consider the case in which $\boldsymbol{z}_{ij}^u$ is a scalar, with the z_{ij}^u's assumed to be *iid* Type I extreme value random variables. Then

[11] It should be noted that Blass *et al.* [1] acknowledge the strength of this assumption and explore a less restrictive set of assumptions; namely that each individual places a subjective median of zero on $\epsilon_{iB} - \epsilon_{iA}$ and that parameter distributions are symmetric. This is used to suggest an alternative maximum score approach to estimation.

$\epsilon_{ij} \equiv \beta_{ui} z^u_{ij}$ and the subjective choice probabilities become:

$$
\begin{aligned}
q_{iA} &= \frac{exp(V_i/\beta_{ui})}{1 + exp(V_i/\beta_{ui})} \\
&= \frac{exp\left(\frac{\alpha + \boldsymbol{\beta}_{xi}\boldsymbol{x}_i + \boldsymbol{\beta}_{ci}\boldsymbol{z}^c_i}{\beta_{ui}}\right)}{1 + exp\left(\frac{\alpha + \boldsymbol{\beta}_{xi}\boldsymbol{x}_i + \boldsymbol{\beta}_{ci}\boldsymbol{z}^c_i}{\beta_{ui}}\right)} \\
&= \frac{exp(\tilde{\alpha}_i + \tilde{\boldsymbol{\beta}}_{xi}\boldsymbol{x}_i + \tilde{\boldsymbol{\beta}}_{ci}\boldsymbol{z}^c_i)}{1 + exp(\tilde{\alpha}_i + \tilde{\boldsymbol{\beta}}_{xi}\boldsymbol{x}_i + \tilde{\boldsymbol{\beta}}_{ci}\boldsymbol{z}^c_i)}.
\end{aligned}
\tag{17}
$$

where

$$
\tilde{\alpha}_i \equiv \frac{\alpha}{\beta_{ui}}, \qquad \tilde{\boldsymbol{\beta}}_{xi} \equiv \frac{\boldsymbol{\beta}_{xi}}{\beta_{ui}}, \qquad \text{and} \qquad \tilde{\boldsymbol{\beta}}_{ci} \equiv \frac{\boldsymbol{\beta}_{ci}}{\beta_{ui}}. \tag{18}
$$

Note that both $\tilde{\boldsymbol{\beta}}_{xi}$ and $\tilde{\boldsymbol{\beta}}_{ci}$ will vary by individual, even if the corresponding $\boldsymbol{\beta}_{xi}$ and $\boldsymbol{\beta}_{ci}$ do not. The corresponding log-odds equation used for estimation becomes:

$$
\begin{aligned}
ln\left(\frac{q_{iA}}{q_{iB}}\right) &= \tilde{\alpha}_i + \tilde{\boldsymbol{\beta}}_{xi}\boldsymbol{x}_i + \tilde{\boldsymbol{\beta}}_{ci}\boldsymbol{z}^c_i \\
&= a + \boldsymbol{b}_x\boldsymbol{x}_i + \tilde{\eta}_i
\end{aligned}
\tag{19}
$$

where a and $\boldsymbol{b}_x$ denote the mean values of $\tilde{\alpha}_i$ and $\tilde{\boldsymbol{\beta}}_{xi}$, respectively, and

$$
\tilde{\eta}_i \equiv (\tilde{\alpha}_i - a) + (\tilde{\boldsymbol{\beta}}_{xi} - \boldsymbol{b})\boldsymbol{x}_i + \tilde{\boldsymbol{\beta}}_{ci}\boldsymbol{z}^c_i. \tag{20}
$$

2.3 Linking Elicited Choice Probabilities and Discrete Choices

While the elicited choice probabilities format allows respondents to reveal uncertainty regarding their preferred alternative, Manksi [12] suggests that there is a direct link between the two elicitation approaches. In particular, he argues that when faced with *resolvable uncertainty* in a stated-choice questionnaire, the respondent "...computes his subjective choice probability for each alternative and reports the one with the highest probability" [1, p. 423].[12] Specifically, it is assumed, in a binary choice setting, that:

$$
y_i = 1[q_{iA} \geq 0.5], \tag{21}
$$

where $1[\cdot]$ is the standard indicator function. Though the logic of (21) is intuitively appealing, there are a number of factors that might cause it not to hold, including risk aversion on the

[12] This same line of reasoning is used in [1] to suggest that the maximum score method can be used to estimate a subjective random utility model with stated choice data, since "...a person's statement that he would choose option j over option k means that $q_{ij} \geq 0.5$ [1, p. 426].

part of survey respondents and asymmetries in their subjective beliefs regarding the uncertain choice outcomes. In this section we examine the relationship between the two elicitation response formats using a relatively simple expected utility framework.[13] Understanding this linkage is important in understanding what can be learned from each and the potential biases that might stem from ignoring respondent uncertainty.

We start with a more general (nonlinear) version of equation (10), with the conditional utility that individual i receives from choosing alternative j given by:

$$U_{ij} = U(\boldsymbol{x}_{ij}, \boldsymbol{z}_{ij}^{c}, \boldsymbol{z}_{ij}^{u}). \tag{22}$$

Suppose that utility is separable in terms of the observed and unobserved factors; i.e.,

$$U_{ij} = U\left[V(\boldsymbol{x}_{ij}, \boldsymbol{z}_{ij}^{c}) + \epsilon(\boldsymbol{z}_{ij}^{u})\right] \tag{23}$$

and that $\epsilon_{ij} \equiv \epsilon(\boldsymbol{z}_{ij}^{u}) \sim N(0, \sigma_{ij}^{2})$, where σ_{ij} measures the degree of uncertainty for individual i regarding alternative j.[14] Furthermore, assume that utility takes the form $U(a) = -exp(-\theta_i a)$, with θ_i denoting the constant absolute risk aversion coefficient for individual i. Then expected utility takes the form[15]

$$E\left[U_{ij}\right] = -e^{-\theta_i (V_{ij} - \frac{\theta_i}{2}\sigma_{ij}^{2})}, \tag{24}$$

where $V_{ij} \equiv V(\boldsymbol{x}_{ij}, \boldsymbol{z}_{ij}^{c})$. With this structure in mind, the question is: What is the relationship between the elicited choice probabilities and the discrete choice response? The elicited choice probability for alternative A becomes:

$$\begin{aligned} q_{iA} &= Pr\left[U(V_{iA} + \epsilon_{iA}) \geq U(V_{iB} + \epsilon_{iB})\right] \\ &= Pr\left[V_{iA} + \epsilon_{iA} \geq V_{iB} + \epsilon_{iB}\right] \\ &= Pr\left[V_{iA} - V_{iB} \geq \epsilon_{iB} - \epsilon_{iA}\right] \\ &= \Phi\left[\frac{V_{iA} - V_{iB}}{\sigma_i^2}\right] \end{aligned} \tag{25}$$

[13] There are other forces that might drive a wedge between the preferences suggested by the two elicitation formats. For example, the discrete choice format is often advocated because, under certain assumptions, it is incentive compatible, inducing respondents to reveal their true preferences. It is not clear what the incentive properties are for elicited choice probabilities. Perhaps more fundamentally, it is not clear what decision rule is used by individuals in a discrete choice framework when the choice outcomes are risky, let alone when true uncertainty (or ambiguity) exists. See, e.g., dePalma *et al.* [6] and Wilcox [21, 22].

[14] The switch in this subsection to characterizing the individual's prior uncertainty using normal errors, rather than extreme value errors, is for the sake of convenience, as it facilitates deriving a closed-form expression for the individual's corresponding expected utility. Of course, Blass *et al.* [1] assume extreme value error terms in the first place because they yield a convenient linear log-odds model, as in (15). We note, however, that while normal errors yield a probit model in a standard RUM framework and extreme value errors yield a logit specification, the two models are known to yield very similar choice probabilities and marginal effects.

[15] See Varian [19] p. 189.

where $\sigma_i^2 \equiv Var(\epsilon_{iB} - \epsilon_{iA}) = \sigma_{iA}^2 + \sigma_{iB}^2 - 2Cov(\epsilon_{iB}, \epsilon_{iA})$. Clearly

$$q_{iA} \geq 0.5 \Leftrightarrow V_{iA} \geq V_{iB} \tag{26}$$

However, assuming that the individual maximizes expected utility, we have that

$$\begin{aligned} y_i &= 1\left[-e^{-\theta_i(V_{iA} - \frac{\theta_i}{2}\sigma_{iA}^2)} \geq -e^{-\theta_i(V_{iB} - \frac{\theta_i}{2}\sigma_{iB}^2)}\right] \\ &= 1\left[V_{iA} - \frac{\theta_i}{2}\sigma_{iA}^2 \geq V_{iB} - \frac{\theta_i}{2}\sigma_{iB}^2\right] \\ &= 1\left[V_{iA} - V_{iB} \geq \frac{\theta_i}{2}\left(\sigma_{iA}^2 - \sigma_{iB}^2\right)\right]. \end{aligned} \tag{27}$$

The term $\frac{\theta_i}{2}\left(\sigma_{iA}^2 - \sigma_{iB}^2\right)$ in the last line of (28) corresponds to the utility premium required to offset any *additional* uncertainty associated with alternative A versus alternative B. Combining these two results, we have

$$y_i = 1(q_{iA} \geq 0.5) \Leftrightarrow \frac{\theta_i}{2}\left(\sigma_{iA}^2 - \sigma_{iB}^2\right) = 0. \tag{28}$$

If individual i is risk averse (with $\theta_i > 0$) *and* alternative A is riskier (i.e., $\sigma_{iA} > \sigma_{iB}$), then one can have $q_{iA} > 0.5$ *and* $y_i = 0$ (i.e., $y_i \neq 1(q_{iA} \geq 0.5)$). In short, the desire to avoid a risky choice can lead a respondent to choose the least risky alternative even when there is a higher than fifty percent chance that their utility would be higher under the riskier choice.

It should be noted that distributional assumptions in Blass *et al.* [1], while not the same as those above, are consistent with the conditions required to yield $y_i = 1(q_{iA} \geq 0.5)$. Specifically, since they assume that the errors ϵ_{ij} are *iid* extreme value random variables, the risk is implicitly being assumed to be the same across alternatives. If expected utility takes a mean-variance form (i.e., $E(U) = \bar{V} + \theta\sigma_\epsilon^2$), then the variance component will cancel when comparing the two options and only the difference in mean outcomes will matter. This will, in turn, yield the result in their paper that $y_i = 1(q_{iA} \geq 0.5)$, but it is predicated on the assumption of equal degrees of uncertainty regarding the two choices and a mean-variance form for expected utility.

The above argument suggests that risk aversion *combined with* differential risk can lead to $y_i \neq 1(q_{iA} \geq 0.5)$. However, that is not the only case that can lead to this outcome. Consider a simple situation in which the uncertainty regarding outcomes under the two scenarios is discrete, with

$$\Delta_i \equiv U_{iA} - U_{iB} = \begin{cases} \delta & \text{with subjective probability } q_{iA} \\ -\tau & \text{otherwise,} \end{cases} \tag{29}$$

where $\tau > 0$ and $\delta > 0$. In this case,

$$\begin{aligned} E\left[U_{iA} - U_{iB}\right] &= q_{iA}\delta - (1 - q_{iA})\tau \\ &= q_{iA}(\delta + \tau) - \tau. \end{aligned} \tag{30}$$

Assuming that the individual maximizes expected utility, we then have

$$\begin{aligned} y_i = 1 &\Leftrightarrow E\left[U_{iA}\right] > E\left[U_{iB}\right] \\ &\Leftrightarrow q_{iA}(\delta + \tau) - \tau > 0 \\ &\Leftrightarrow q_{iA} > \frac{\tau}{\delta + \tau}. \end{aligned} \tag{31}$$

Essentially, in this simple setting there are two states of the world, one in which A is preferred and one in which B is preferred. As long as these effects are asymmetric, we will have $y_i \neq 1(q_{iA} \geq 0.5)$.

3 The Iowa Lakes Data

The data used in this paper are drawn from the 2009 Iowa Lakes Survey. The survey is part of an ongoing research effort (funded jointly by the Iowa Department of Natural Resources and the U.S. EPA) to understand lake usage in the state and the value residents place on the site and water quality attributes of Iowa's primary lakes. The project began in 2002 with a mail survey of 8000 Iowa households selected at random. The survey elicited the respondents' visitation rates to each of 132 primary lakes, as well as socio-demographic information for each household. Similar surveys were administered to the same households over the next three years.[16]

The most recent survey, administered in late 2009, was mailed to a total of 10,000 Iowa households, consisting of the respondents to the 2005 Lakes Survey (approximately 4500 households) and an additional random sample of households to augment the sample size. As with earlier surveys, respondents were asked to recall their numbers of day- and overnight-trips to each to the 132 primary lakes over the past year, along with providing socio-demographic information. In addition, Section 2 of the survey consisted of a contingent valuation (CV) exercise. It is this section that provides the basis for our analysis below.

[16]In 2003, the surveys were sent to respondents to the 2002 survey (approximately 4500 households) and to an additional random sample of households used to return the total sample size once again to 8000 households. In 2004 and 2005, the surveys were sent only to those household that responded in the previous year.

A total of four versions of the CV exercise were used. In all four versions, respondents were asked to compare two hypothetical lakes (A and B). The lakes differed in terms of their water quality attributes, with Lake B being substantially cleaner than Lake A, and in terms of each lake's distance from the respondent's home and the associated entrance fee. Figure 1 provides the illustration used in both Versions 1 and 3 of the survey. In addition to the illustration, a textual description of each lake was provided. Versions 2 and 4 of the survey also asked respondents to compare Lakes A and B, however less information was provided in both the text and the illustration (See Figure 2) regarding each lake's condition, especially in terms its fishing conditions. The purpose of these *low information* versions of the survey was induce greater uncertainty for the survey respondent, which should induce corresponding shifts in the estimated preference parameters.

The other distinguishing feature of the four CV versions was the evaluation format employed. Versions 1 and 2 elicited choice probabilities, as suggested by Manski [13], using the text:

> *Assume that you have to choose between visiting one of the two lakes described on the previous page. What are the chances in percentage terms that you would choose to visit Lake A rather than Lake B? The chance of each alternative should be a number between 0 and 100 and the chances given to the two alternatives should add up to 100. For example, if you give a 5% chance to one alternative it means that there is almost no possibility that you will choose that alternative. On the other hand, if you give an 80% or higher chance to an alternative it means that almost surely you would choose it.*

Versions 3 and 4 of the survey, on the other hand, asked respondents to simply choose their preferred alternative. Table 1 summarizes the four versions of the CV exercise in terms of the information and value elicitation formats. Each survey also included a second paired comparison (Lakes C and D), following the same format as the first paired comparison. The second two lakes were identical to the earlier lakes in terms of water quality and site attributes. The only changes were in terms of the distances and entrance fees associated with the two lakes.[17] The overall survey sample was split evenly between the four versions,

[17] The distances and entrance fees were varied across individual surveys. Distance were set at one of three levels (10, 30 and 60 miles), while the entrance fees were set at one of three levels (0, 10, and 20 dollars). A balanced design was used, including all possible combinations of the distance and entrance fees for Lakes A and B, excluding those combinations that would designate the cleaner lake (B) as both *as close or closer* and *as cheap or cheaper* when compared to the dirtier lake (A). The distance and entrance fee combinations were similarly assigned for Lakes C and D.

with 2500 observations assigned to each version.[18] The overall response rate to the survey was approximately sixty percent.

Figure 3 provides an overall summary of the survey responses for each of the paired comparisons (AB and CD) by version, indicating the percentage of households that prefer the dirtier of the two lakes presented in the two scenarios.[19] For the stated choice probability versions of the survey, an individual is counted as preferring the dirtier lake if they assign a choice probability greater than fifty percent to that alternative. While not consistent with the exceptions to the Blass *et al.* [1] model we discussed in the previous section, this assumption provides a useful baseline from which to compare the elicitations obtained from the two approach. In general, respondents prefer the cleaner of the two lakes in the paired comparison by margin of more than four to one. Curiously, this margin consistently shrinks for the second paired comparison (CD) relative to the first (AB), even though the quality attributes of the lake pairs do not change between the two paired comparisons.

The results in Figure 3 average over all of the survey responses, ignoring the variation in responses by the distance and cost differentials between the dirty and cleaner lake options. Figures 4 and 5 provide the distribution of responses for the AB and CD paired comparisons, respectively, broken down by the cost premium for the dirtier lake (ranging from -$20 to +$20). As expected, when the dirtier lake is cheaper (e.g., -$20), a larger portion (roughly 20%) of the survey respondents prefer the dirtier lake. Preferences for the dirtier lake generally diminish as its relative cost increases, with less than five percent of the respondents choosing the dirtier lake when it costs $20 more to visit. Figures 6 and 7 provide a similar breakdown in terms of the distance premium associated with the dirtier lake. In this case, the pattern is less clear, though in general respondents do appear to be more likely to choose the dirtier lake when it is closer than the cleaner lake.

Finally, one concern when eliciting choice probabilities is that respondents will exhibit little

[18] As noted above, the 2009 survey sample consisted two subsamples: (a) Subsample A: the roughly 4500 respondents to the 2002-2005 surveys and (b) Subsample B: an additional random sample of 5500 Iowa households. For reasons unrelated to the contingent valuation exercise, households receiving Version 4 of the survey were selected at random from the latter subsample, with Versions 1 through 3 randomly selected from the remaining 7500 households. This creates a potential bias in any treatment effects measured below involving Version 4 of the survey, driven by differences between the two subsamples. However, comparisons between the responses of households in Subsample A and Subsample B to Versions 1 through 3 indicate no significant differences between the two groups. Moreover, controlling for these sub-samples in the modeling below, we consistently found the differences to be statistically insignificant.

[19] Figures 3 through 9 use the abbreviations in Table 1 to distinguish the four versions of the survey. Thus, CP-High and CP-Low refer to the elicited choice probability versions with high and low information treatments, respectively, while DC-High and DC-Low denote the discrete choice versions for the high and low information treatments, respectively.

variation in their responses and mass around specific probability values, such as 0%, 50%, and 100%. Figures 8 and 9 depict the cumulative distribution for the stated choice probability for the dirtier of the two lakes in the AB and CD paired comparisons, respectively. In each case, we distinguish the high (CP-High) and low (CP-Low) information versions of the survey. The distributions indicate that, while most households reveal a low choice probability for the dirtier of the two lakes, the responses are not massed significantly at a few points and the empirical cdf varies relatively smoothly from 0% to 100%. For the AB paired comparison, for example, less than 15% of the sample assigns zero probability to preferring the dirtier of the two lakes. The other interesting feature of the empirical cdf's is that they suggest that the respondents prefer the cleaner lake more when more information is provided about it, with the cdf for the high information treatment virtually always lying above the cdf for the low information treatment.

4 Results

In our analysis of the CV data from the 2009 Lake Survey, we focus our attention on two modeling approaches. First, we provide a direct comparison and convergent validity test of the elicited choice and discrete choice survey responses by converting the former into a discrete choice outcome and estimating a simple logit for both data sources. We use the conversion described above; namely, if the respondent reports a choice probability greater than 0.5. Second, we employ the LAD estimator proposed by Blass *et al.* [1] to examine the impact of the information treatment on the elicited choice responses.

4.1 Logit Model Comparison

Separate models are estimated for the first (AB) and second (CD) paired comparisons, in each case pooling the data from the discrete choice and elicited choice probability samples. Three alternative model specifications are considered. The first model pools the data from the high and low information treatments. In this simple specification, it is assumed that $\tilde{V}_i$ in (7) takes the form:

$$\tilde{V}_i = \alpha + \gamma P_i + (\beta_{OD} + \delta_{OD} P_i) ODist_i + (\beta_{OC} + \delta_{OC} P_i) OCost_i \tag{32}$$

where $ODist_i$ and $OCost_i$ denote the additional distance and additional entrance cost associated with the dirtier lake. The dummy variable P_i distinguishes those individuals who were asked for their subjective choice probabilities (P_i=1) from those who were asked to simply choose one of the two options (P_i=0). Thus, the parameters γ, δ_{OD}, and δ_{OC} measure the *differences* in the intercept, distance and entrance fee coefficients, respectively, for the respondents who were asked for their subjective choice probabilities versus those who faced a discrete choice question. Convergent validity corresponds to the restriction $H_{0A} : \gamma = \delta_{OD} = \delta_{OC} = 0$. Since $y_i = 1$ denotes the choice of the dirtier lake in each paired comparison, we would anticipate that α would be negative (indicating the dirtier lake yields a lower level of utility given identical entrance fees and travel distances) and both β_{OD} and β_{OC} would be negative as well.

The second model controls for potential information effects, distinguishing the marginal impacts of the distance and cost variables for the low and high information treatments. In particular, (32) is generalized to

$$\begin{aligned}\tilde{V}_i &= \alpha + \gamma P_i + (\beta_{OD} + \delta_{OD} P_i) ODist_i + (\beta_{OC} + \delta_{OC} P_i) OCost_i \\ &+ \left[\tilde{\alpha} + \tilde{\gamma} P_i + (\tilde{\beta}_{OD} + \tilde{\delta}_{OD} P_i) ODist_i + (\tilde{\beta}_{OC} + \tilde{\delta}_{OC} P_i) OCost_i\right] \times L_i\end{aligned} \tag{33}$$

where L_i is a dummy variable indicating that individual i received the low information treatment. Thus, the parameters with tilde's denote the differential effect for the low information treatment. Constraining these parameters to zero (i.e., $H_{0B} = \tilde{\alpha} = \tilde{\beta}_{OD} = \tilde{\beta}_{OC} = \tilde{\gamma} = \tilde{\delta}_{OD} = \tilde{\delta}_{OC} = 0$) yields the simple model in (32).

Finally, one concern in asking multiple questions in a stated preference survey is that the respondents will react, not only to conditions of the current question, but will *anchor* their responses to the other questions in the survey (see, e.g., Herriges and Shogren [7]). The third specification allows for cross-question effects, generalizing the simple model (32) to allow an individual's choice to depend, not only on the distance and entrance fee comparisons presented in the paired comparison, but on the distance and entrance fee presented in the "other" paired comparison. Specifically, we set

$$\begin{aligned}\tilde{V}_i &= \alpha + \gamma P_i + (\beta_{OD} + \delta_{OD} P_i) ODist_i + (\beta_{OC} + \delta_{OC} P_i) OCost_i \\ &+ (\beta_{CD} + \delta_{CD} P_i) CDist_i + (\beta_{CC} + \delta_{CC} P_i) CCost_i\end{aligned} \tag{34}$$

where $CDist_i$ and $CCost_i$ denote the distance and cost differentials in the "other" paired comparison. Thus, when modeling the AB- paired comparison, $CDist_i$ and $CCost_i$ denote the distance and cost differentials in the CD-paired comparison. If there are no spillover (or "anchoring") effects, we would anticipate the restriction $H_{0C} : \beta_{CD} = \beta_{CC} = \delta_{CD} = \delta_{CC} = 0$ to hold. If this condition does not hold, then respondents are making their choices based, not only on the choice in front of them, but on the conditions outlined in the other paired comparison.

The results from estimating these three models are presented in Table 2. Starting with the simplest model, we see that the base coefficients (α, β_{OD}, and β_{OC}) have the anticipated negative signs and are each statistically significant at a 1% level for both the AB- and CD-paired comparison. The differential impacts of the elicitation format are measured by (γ, δ_{OD}, and δ_{OC}). In the case of the AB-paired comparison, both γ and δ_{OC} are positive and statistically significant. Moreover, a joint test of the format effects (i.e., $H_0 : \gamma = \delta_{OD} = \delta_{OC}$) is rejected at a 1% level, with $\chi^2_3 = 14.71$, suggesting that the converted stated choice probability and discrete choice formats do not yield the same estimated preference parameters.

One way to provide context for the interpretation of the parameters is to use them to infer the opportunity cost of time. Specifically, for the discrete choice respondents the implicit willingness-to-pay for a 1-mile reduction in travel distance would be given by

$$WTP_m = \frac{\beta_{OD}}{2\beta_{OC}}, \tag{35}$$

where the factor of two in the denominator accounts for the round-trip nature of travel to a site. A similar expression for the stated choice probabilities group is given by:

$$WTP_m = \frac{\beta_{OD} + \delta_{OD}}{2(\beta_{OC} + \delta_{OC})}. \tag{36}$$

Assuming an average speed of sixty miles per hour, the implicit value of time in both cases becomes $WTP_t = 60WTP_m$. For the AB-paired comparison, the point estimates in Table 2's simple model yields a value of time of \$5.53/hour for the discrete choice respondents and a value of time of \$10.25/hour for the elicited choice probability respondents. For the CD-paired comparisons, both formats yield a value of time between \$10 and \$11 per hour.

Turning to the model with information effects, we see relatively little evidence that the differing information treatments altered the choices made by survey respondents. In the case of the AB-paired comparisons, none of the information parameters (i.e., those with tilde's) are individually significant and a joint test restricting all of these parameters to zero is not rejected at a 5% level. For the CD-comparison, $\tilde{\beta}_{OC}$ is significant at a 5% level and $\tilde{\delta}_{OD}$ is significant at a 1% level, but the joint test that the information treatment does not alter individual responses is not rejected at a 5% level (with $\chi^2_6 = 11.22$). Interestingly, convergent validity of the converted stated choice and discrete choice formats is now rejected for both paired comparisons at a 5% level.

Finally, estimates of the third model in (34) suggests little evidence of cross-question effects. None of the individual coefficients estimates for β_{CD}, β_{CC}, δ_{CD}, and δ_{CC} differ significantly from zero at a 5% level. Moreover, the joint hypothesis that these coefficients are all zero (H_{0C}) is not rejected for either of the two paired comparisons.

4.2 Least Absolute Deviation Model

While the conversion of the elicited choice probabilities to a discrete choice outcome provides a direct comparison between the two elicitation formats, doing so censors much of the information contained in the choice probabilities. In this section, we focus our attention on the choice probabilities data, providing least absolute deviation estimates for the parameters of the log-odds model in (15). Table 3 provides estimates for the three models, analogous in structure to those used in the previous section. It should be kept in mind, however, that the parameters in Table 3 are not directly comparable to those in Table 2 in that different parameter scalings underly the identified parameters.

Starting with the simplest model, the LAD estimates reveal very similar results to those obtained using the logit transformation. In particular, we again find that distance and entrance fees have a negative and statistically significant impact on the respondents propensity to choose a given lake. As was the case in Table 2, the entrance fee parameters are two to three times those for the distance variables. This suggests a marginal implicit value of time between \$10 and \$15 per hour.

The information effects, as revealed in Table 3, are more clearly identified using the elicited choice probabilities than when using their censored discrete choice counterparts (in Table 2). For both paired-comparisons, all three information parameters are statistically significant at the 5% level, indicating in general that households are more responsive to the distance and entrance fee treatments when they have relatively little information regarding the alternatives than when they are given more detailed water quality and fishing information. It is interesting to note that, despite significant differences across the information treatments, there is relatively little variation in the implicit value of time. In the AB-paired comparison, the implicit value of time is \$8.57 and \$10.00 per hour for the high and low information treatments respectively. For the CD-paired comparison, the corresponding implicit values of time are \$11.79 and \$12.86 per hour, respectively.

Finally, the LAD log-odds model confirms the earlier results regarding cross-paired comparison effects. None of the cross-question terms are statistically significant at the 5% level.

4.3 Drawing Welfare Implications

While models presented in Tables 2 and 3 are useful in characterizing the factors that influence individual choices, stated preference surveys often have as their ultimate goal the estimation of welfare measures. Outage cost surveys are used to infer a price for reliability, which can in turn be used for capacity planning or the design and evaluation of interruptible/curtailable rates. Contingent valuation surveys are used to derive individual WTP for a proposed environmental program to be used in a cost-benefit analysis. The question is: what can we learn from the two elicitation formats regarding consumer welfare and which set of results is most appropriate for policy analysis? While a complete treatment of these issues is beyond the scope of the current paper, we use this final subsection to make some observations.

Perhaps the most important issue in terms of drawing welfare implications from the two elicitation formats is that the two approaches provide information on different aspects of consumer welfare. The essential difference lies in the fact that the discrete choice format requires respondents to weigh the risk associated with the various states of the world and come up with a single decision regarding which option is preferred *ex ante*. In contrast, the elicited choice format simply asks for the probability that one option will dominate the other *ex post*; no weighing of the different possible outcomes is required. To illustrate this, consider again the more general conditional utility specification in (23); i.e.,

$$U_{ij} = U\left[V(\boldsymbol{x}_{ij}, \boldsymbol{z}^c_{ij}) + \epsilon_{ij}\right] \tag{37}$$

In most applications, one of the factors impacting conditional utility is the individual's net income upon choosing alternative j; i.e., $\hat{y}_{ij} \equiv y_i - p_{ij}$, where y_i denotes income and p_{ij} denotes the cost of alternative j. As a practical matter, most analysts then go onto assume that $\hat{y}_{ij}$ enters as an additively separable term in $V(\cdot)$, so that

$$V(x_{ij}, z^c_{ij}) = \beta_y \hat{y}_{ij} + \hat{V}(\hat{x}_{ij}, z^c_{ij}), \tag{38}$$

where $\hat{x}_{ij}$ denotes those elements of x_{ij} other than $\hat{y}_{ij}$. Assuming, as we did in Section 2.3, that $\epsilon_{ij} \equiv \epsilon(\boldsymbol{z}^u_{ij}) \sim N(0, \sigma^2_{ij})$ and that $U(a) = -exp(-\theta_i a)$, then the expected utility used by the survey respondent in comparing two options (e.g., A and B) in a discrete choice elicitation format is given by

$$E\left[U_{ij}\right] = -e^{-\theta_i[\beta_y \hat{y}_{ij} + \hat{V}(\hat{x}_{ij}, z^c_{ij}) - \frac{\theta_i}{2}\sigma^2_{ij}]}. \tag{39}$$

The willingness-to-pay (WTP^d_B) for option B (the cleaner of the two lakes in our application) is given implicitly by:

$$-e^{-\theta_i[\beta_y(\hat{y}_{iB} - WTP^d_B) + \hat{V}(\hat{x}_{iB}, z^c_{iB}) - \frac{\theta_i}{2}\sigma^2_{iB}]} = -e^{-\theta_i[\beta_y \hat{y}_{iA} + \hat{V}(\hat{x}_{iA}, z^c_{iA}) - \frac{\theta_i}{2}\sigma^2_{iA}]}. \tag{40}$$

Solving for the WTP term, we have the explicit formula:

$$WTP_B^d = \frac{1}{\beta_y}\left[\hat{V}(\hat{x}_{iB}, z_{iB}^c) - \hat{V}(\hat{x}_{iA}, z_{iA}^c) + \beta_y(\hat{y}_{iB} - \hat{y}_{iA}) - \frac{\theta_i}{2}(\sigma_{iB}^2 - \sigma_{iA}^2)\right]. \tag{41}$$

Note that this WTP explicitly includes a weighing of the relative risk associated with the two alternatives through the last term within the square brackets.

In contrast, the elicited choice probabilities only provide information on the perceived distribution of utilities under alternative states of the world, and consequently can only provide information on the perceived distribution of WTP *conditional on* a given state of the world. Specifically, using equation (23), a WTP for alternative B conditional on $(\epsilon_{iA}, \epsilon_{iB})$, $WTP_B^e(\epsilon_{iA}, \epsilon_{iB})$, can be implicitly defined as

$$U\left(\beta_y[\hat{y}_{iB} - WTP_B^e(\epsilon_{iA}, \epsilon_{iB})] + \hat{V}(\hat{x}_{iB}, z_{iB}^c) + \epsilon_{iB}\right) = U\left(\beta_y\hat{y}_{iA} + \hat{V}(\hat{x}_{iA}, z_{iA}^c) + \epsilon_{iA}\right). \tag{42}$$

Solving for WTP_B^e, the conditional welfare measure obtained from the elicited choice probabilities is given by:

$$WTP_B^e(\epsilon_{iA}, \epsilon_{iB}) = \frac{1}{\beta_y}\left[\hat{V}(\hat{x}_{iB}, z_{iB}^c) - \hat{V}(\hat{x}_{iA}, z_{iA}^c) + \beta_y(\hat{y}_{iB} - \hat{y}_{iA}) + (\epsilon_{iB} - \epsilon_{iA})\right]. \tag{43}$$

The mean WTP under our assumptions regarding the error distributions is then given by:

$$\overline{WTP}_B^e = \frac{1}{\beta_y}\left[\hat{V}(\hat{x}_{iB}, z_{iB}^c) - \hat{V}(\hat{x}_{iA}, z_{iA}^c) + \beta_y(\hat{y}_{iB} - \hat{y}_{iA})\right]. \tag{44}$$

Clearly, if our modeling assumptions are correct and both models can be estimated, then the discrete choice elicitation format provides more information in that it reveals the individual's risk aversion parameter θ_i. However, from a practical point of view, this requires a large number of rather strong assumptions, including expected utility maximization, the form of the individual utility function being used, and the individual's subjective distribution regarding the information that is missing from the incomplete choice scenarios.

5 Conclusions

The goal of this paper has been to compare and contrast the information regarding consumer preferences that is learned from discrete choice versus elicited choice probabilities. While Blass, *et al.* [1] suggest that the two formats are linked in a rather simple fashion, with the discrete choice response indicating the alternative with the highest subjective choice probability, we find that this will not necessarily be the case. Instead, elicited choice probabilities reveal information regarding the distribution of relative returns to alternatives in the choice set, but do not require that the respondent weigh these states to define a single preferred choice *ex ante*. In particular, the elicited choice probabilities will not identify risk aversion or asymmetries in the subjective beliefs regarding choice uncertainties. We also provide empirical evidence regarding differences between the two elicitation formats. Using a split sample treatment for the 2009 Iowa Lakes Survey, we consistently find significant differences between the two formats in terms of implied preferences for two hypothetical lake scenarios.

Finally, the potential welfare measures that can be extracted from the two elicitation formats differ in fundamental ways. The elicited choice probabilities can only identify willingness-to-pay measures that are *conditional* on a specific state of the world, whereas, because the discrete choice format requires that the respondent aggregate the alternative states of the world into a single choice, the discrete choice format reveals aN overall measure of the *ex ante* welfare anticipated from the competing choices. The problem, of course, is that proper measurement of this overall welfare requires information on, or assumptions about, the subjective choice probabilities being used by the survey respondent in completing the survey. Additional research is needed to determine how analysts might extract such information effectively from survey participants.

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6 Tables and Figures

Table 1: CV Survey Treatment Options

	Information Treatment	
Elicitation Method	High Information	Low Information
Choice Probabilities	Version 1 (CP-High)	Version 2 (CP-Low)
Discrete Choice	Version 3 (DC-High)	Version 4 (DC-Low)

Table 2: Logit Models

Parameter	Models					
	Simple Model		Information Effects		Spillover Effects	
	AB	CD	AB	CD	AB	CD
α	-2.63**	-2.12**	-2.52**	-2.19**	-2.67**	-2.14**
	(0.11)	(0.08)	(0.15)	(0.12)	(0.12)	(0.10)
β_{OD}	-0.013**	-0.019**	-0.011**	-0.022**	-0.013**	-0.019**
	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
β_{OC}	-0.069**	-0.054**	-0.068**	-0.060**	-0.069**	-0.055**
	(0.008)	(0.006)	(0.010)	(0.008)	(0.007)	(0.006)
γ	0.33*	-0.11	0.15	0.011	0.36*	-0.16
	(0.14)	(0.12)	(0.20)	(0.17)	(0.16)	(0.14)
δ_{OD}	-0.013	-0.001	-0.003	0.008	-0.003	0.001
	(0.002)	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)
δ_{OC}	0.023*	0.001	0.016	0.013	0.023**	0.001
	(0.010)	(0.008)	(0.014)	(.012)	(0.009)	(0.008)
$\tilde{\alpha}$			-0.18	0.15		
			(0.22)	(0.16)		
$\tilde{\beta}_{OD}$			-0.004	0.008*		
			(0.004)	(0.004)		
$\tilde{\beta}_{OC}$			-0.004	0.013		
			(0.015)	(0.011)		
$\tilde{\gamma}$			0.35	-0.26		
			(0.29)	(0.25)		
$\tilde{\delta}_{OD}$			-0.0003	-0.018**		
			(0.0070)	(0.006)		
$\tilde{\delta}_{OC}$			0.013	-0.027		
			(0.019)	(0.017)		
β_{CD}					0.0014	0.0021
					(0.0030)	(0.0020)
β_{CC}					-0.005	-0.009
					(0.005)	(0.005)
δ_{CD}					0.0014	-0.004
					(0.0033)	(0.003)
δ_{CC}					0.002	-0.003
					(0.008)	(0.007)
H_{0A}: No format effects	$\chi^2_3 = 14.71^{**}$	$\chi^2_3 = 1.95$	$\chi^2_6 = 16.50^{*}$	$\chi^2_6 = 12.99^{*}$		
H_{0B}: No information effects			$\chi^2_6 = 6.20$	$\chi^2_6 = 11.22$		
H_{0C}: No spillover effects					$\chi^2_6 = 1.30$	$\chi^2_6 = 9.60$

Table 3: LAD Parameter Estimates for the Log-Odds Model

Parameter	Models					
	Simple Model		Information Effects		Spillover Effects	
	AB	CD	AB	CD	AB	CD
α	-1.48**	-1.52**	-1.44**	-1.59**	-1.45**	-1.51**
	(0.05)	(0.08)	(0.05)	(0.03)	(0.05)	(0.09)
β_{OD}	-0.0047**	-0.0135**	-0.0034**	-0.0099**	-0.0052**	-0.0135**
	(0.0014)	(0.0019)	(0.0015)	(0.0008)	(0.0011)	(0.0022)
β_{OC}	-0.0144**	-0.0269**	-0.0118**	-0.0251**	-0.0158**	-0.0279**
	(0.0037)	(0.0050)	(0.0040)	(0.0021)	(0.0029)	(0.0057)
$\tilde{\alpha}$			-0.14**	0.16**		
			(0.07)	(0.04)		
$\tilde{\beta}_{OD}$			-0.0056**	-0.0041**		
			(0.0022)	(0.0011)		
$\tilde{\beta}_{OC}$			-0.0151**	-0.0076**		
			(0.0056)	(0.0029)		
β_{CD}					0.0014	0.0000
					(0.0011)	(0.0022)
β_{CC}					0.0002	0.0009
					(0.0029)	(0.0057)
H_{0B}: No information effects			$F_{(3,2524)}$ = 3.17**	$F_{(3,2517)}$ = 31.59**		
H_{0C}: No spillover effects					$F_{(2,2525)}$ =0.99	$F_{(2,2518)}$ =0.02

	Lake A	Lake B
Water clarity	Objects distinguishable 3 to 10 feet under water	Objects distinguishable 8 to 10 feet under water
Algae blooms	1 to 3 per year	Rarely more than 1 per year
Water color	Bluish to greenish brown	Blue
Water odor	Mild to occasionally strong	Usually fresh
Bacteria	Possible short-term swim advisories	Rare swim advisories (most years none)
Fish	Good diversity	Excellent diversity and abundant populations
Distance from your home	<<DA>> miles	<<DB>> miles
Entrance fee	$<<CA>>	$<<CB>>

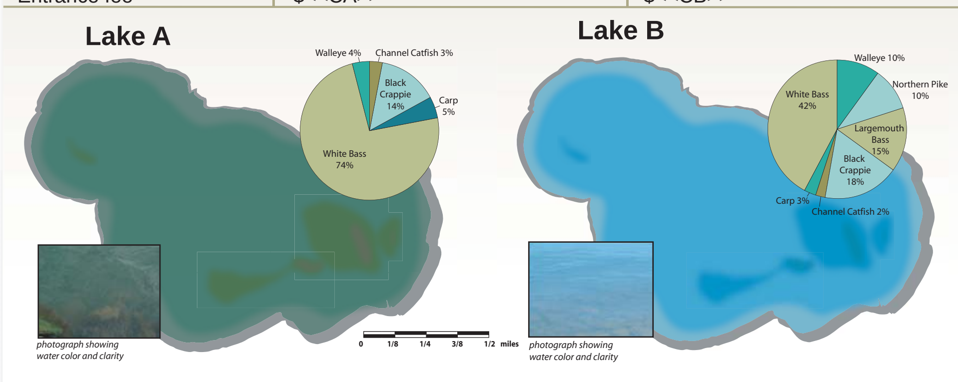

Figure 1: CV Illustration (High Information Treatment - Versions 1 and 3)

	Lake A	Lake B
Water clarity	Objects distinguishable 3 to 10 feet under water	Objects distinguishable 8 to 10 feet under water
Algae blooms	1 to 3 per year	Rarely more than 1 per year
Water color	Bluish to greenish brown	Blue
Water odor	Mild to occasionally strong	Usually fresh
Bacteria	Possible short-term swim advisories	Rare swim advisories (most years none)
Distance from your home	<<DA>> miles	<<DB>> miles
Entrance fee	$<<CA>>	$<<CB>>

Figure 2: CV Illustration (High Information Treatment - Versions 2 and 4)

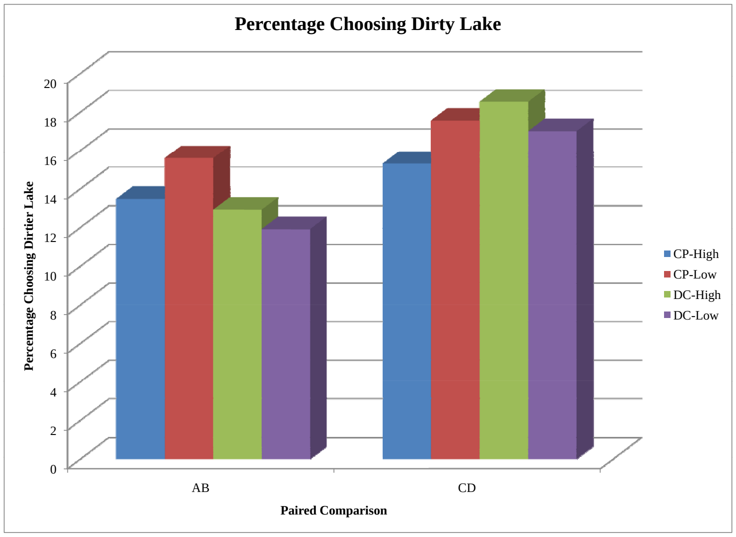

Figure 3: Overall Survey Response Comparison

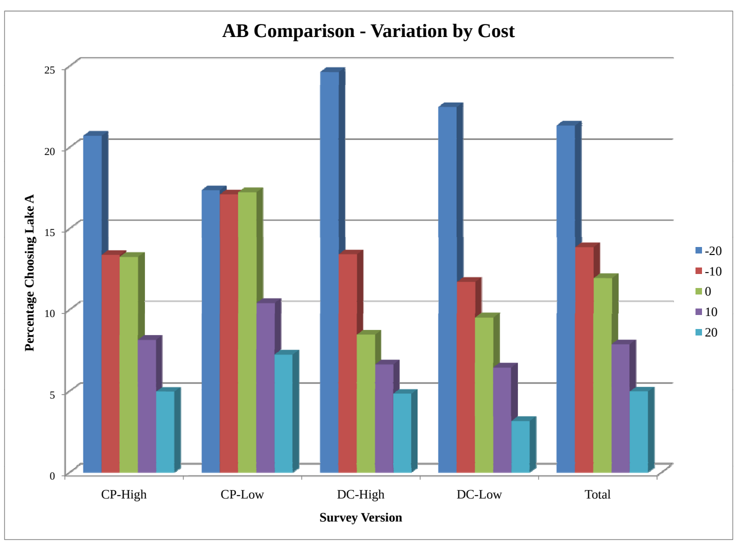

Figure 4: AB Paired Comparison by Cost Differential

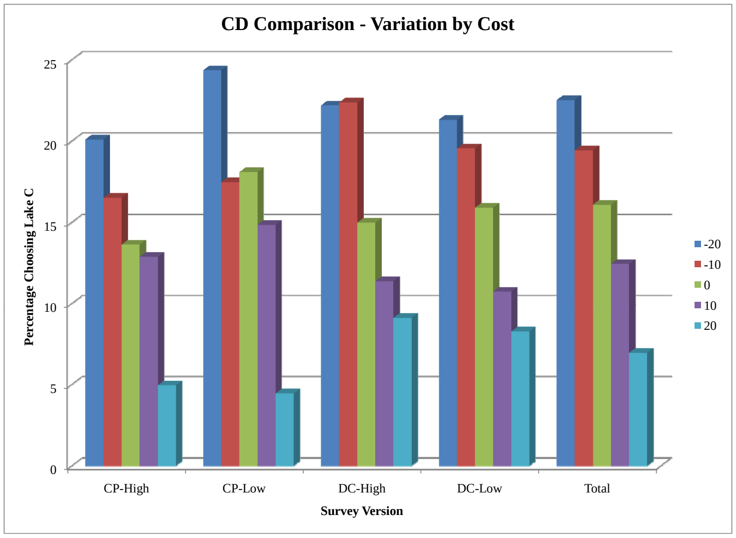

Figure 5: CD Paired Comparison by Cost Differential

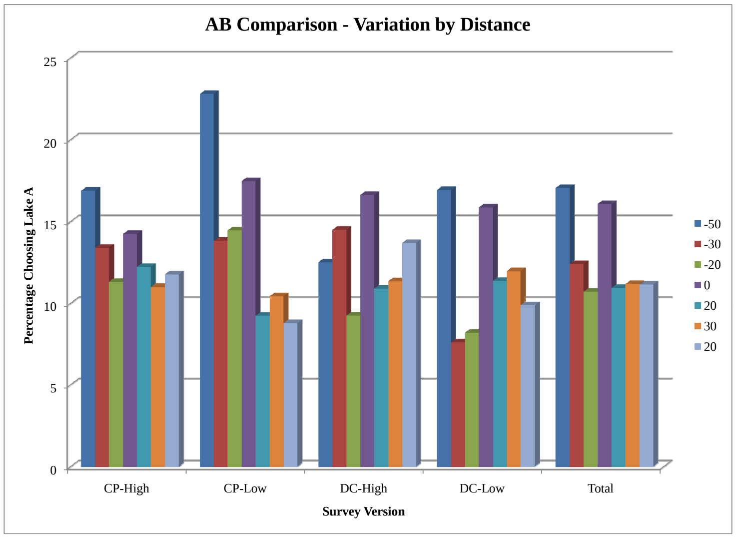

Figure 6: AB Paired Comparison by Distance Differential

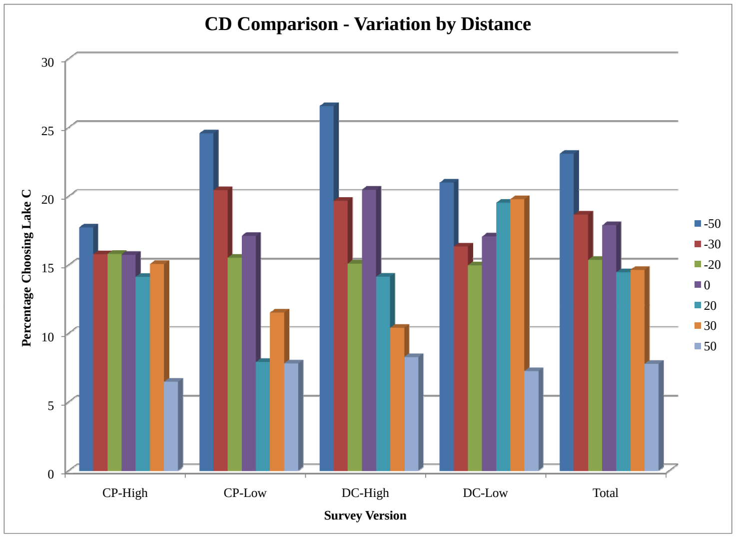

Figure 7: CD Paired Comparison by Distance Differential

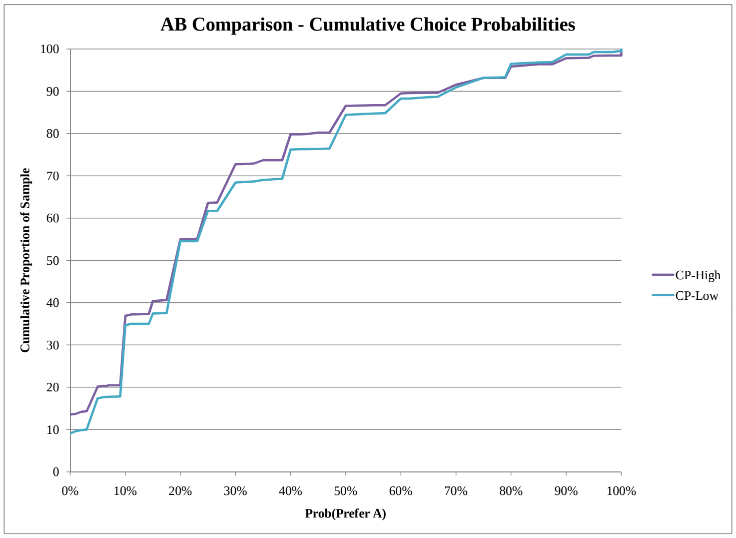

Figure 8: AB Paired Comparison Cumulative Choice Probability Distribution

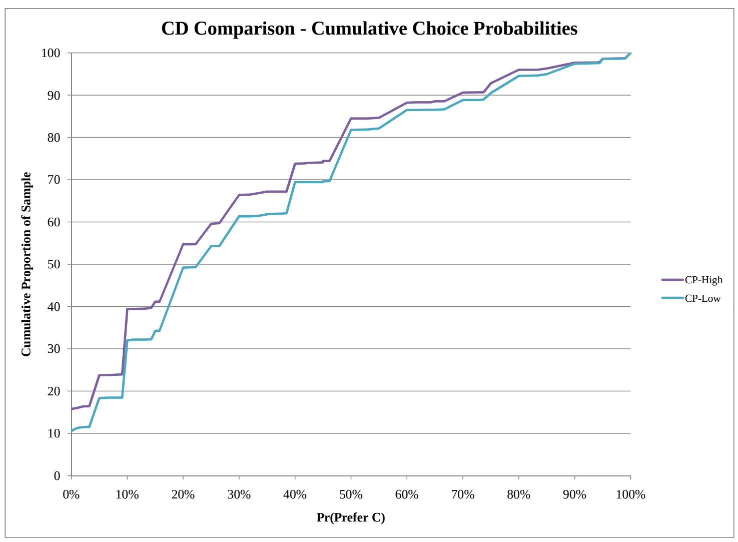

Figure 9: CD Paired Comparison Cumulative Choice Probability Distribution