Accounting for Respondent Uncertainty to Improve Willingness-to-Pay Estimates

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In this paper, we develop an econometric model of willingness to pay (WTP) that integrates data on respondent uncertainty regarding their own WTP. The integration is utility consistent, there is no recoding of variables, and no need to calibrate the contingent responses to actual payment data, so the approach can "stand alone." In an application to a valuation study related to whooping crane restoration, we find that this model generates a statistically lower expected WTP than the standard contingent valuation (CV) model. Moreover, the WTP function estimated with this model is not statistically different from that estimated using actual payment data suggesting that, when properly analyzed using data on respondent uncertainty, CV decisions can simulate actual payment decisions. This method allows for more reliable estimates of WTP that incorporate respondent uncertainty without the need for collecting comparable actual payment data.

Dans le présent article, nous avons élaboré un modèle économétrique d'estimation qui internalise l'incertitude des répondants quant à leur propre consentement à payer. L'internalisation est fidèle à la notion «d'utilité»; il n'a pas été nécessaire de transformer les variables ni de calibrer les réponses des répondants avec des paiements réels. L'application de la méthode n'est donc pas dépendante d'autres données ou méthodes. Dans une étude d'évaluation sur le rétablissement de la grue blanche d'Amérique dans laquelle ce modèle a été utilisé, nous avons trouvé que le consentement à payer attendu était statistiquement plus faible que celui obtenu à l'aide de la méthode d'évaluation contingente standard. Par ailleurs, la fonction de consentement à payer estimée à l'aide de ce modèle n'est pas statistiquement différente de celle estimée à l'aide de paiements réels. Cette observation autorise à penser que, lorsque le modèle tient compte des données sur l'incertitude des répondants, les décisions obtenues à l'aide de la méthode d'évaluation contingente peuvent simuler les décisions obtenues à l'aide de paiements réels. Cette méthode permet d'obtenir des estimations du consentement à payer plus fiables, lesquelles intègrent l'incertitude des répondants sans la nécessité de collecter des données comparables de paiements réels.

Canadian Journal of Agricultural Economics 58 (2010) 381–401
DOI: 10.1111/j.1744-7976.2010.01190.x

INTRODUCTION

Despite sometimes intense controversy, contingent valuation (CV) remains the most commonly applied nonmarket valuation technique worldwide (Bishop 2003). At the same time, research on the validity of CV continues. Many studies have sought to compare value estimates from CV with values from actual cash transactions. Many, though not all such studies (see, e.g., Johnston 2006) have found that responses to CV questions generate higher willingness-to-pay (WTP) estimates than more or less comparable cash commitments, a phenomenon known as "hypothetical bias."

Several approaches to reduce or eliminate hypothetical bias have been proposed. In this paper, we build on the work of Champ et al (1997, 2009) and Champ and Bishop (2001), who conducted separate studies involving three environmental goods: road removal in Grand Canyon National Park, wind power in Wisconsin, and a whooping crane reintroduction project. In each case, they collected actual donations (ADs) toward the environmental good using a dichotomous choice question (referred to here as the AD treatments) to serve as a benchmark. With separate samples, they also conducted CV surveys using a hypothetical dichotomous choice donation question (the CV treatment). Results from all three studies were consistent with hypothetical bias: estimated mean donations from CV respondents were statistically larger than estimated mean donations from the AD treatments.

Champ et al (1997, 2009) and Champ and Bishop (2001) reasoned that hypothetical bias might stem, at least in part, from respondents' uncertainty about whether they would actually pay.[1] These authors attempted to capture the uncertainty of subjects who said "Yes" to the donation in the CV treatment by asking them to indicate on a 10-point scale how certain they were that they would actually donate. The authors then calibrated CV values to the AD values using a recoding scheme. That is, for the CV treatment, "Yes" responses for subjects whose level of certainty fell below some specified threshold were recoded to "No" and the analysis was repeated. Not surprisingly, this brought the CV values down; more "No" responses in the data mean lower values. More importantly, in all three studies the characteristics and attitudes of the recoded "Yes" CV respondents were quite similar to the characteristics and attitudes of those who sent in a donation in the AD treatment. These results are consistent with the hypothesis that hypothetical bias stems in part from respondent uncertainty about their behavior in an analogous actual cash transaction.

The recoding method used by Champ and colleagues (1997, 2001, 2009) has been incorporated in many other CV studies, including studies that do not include actual payment data with which to calibrate the recoding. In such cases an arbitrary certainty level, such as 7 or 10 on a scale of 10, is imposed by the analyst as the cutoff for recoding. While the recoding method will obviously produce smaller WTP estimates, as some "Yes" responses are turned into "No" responses, it is problematic on both theoretical and empirical grounds. It presents a theoretical contradiction because, while the recoding explicitly accounts for respondent uncertainty, it employs the recoded data in a traditional random utility model in which respondents are presumed to be certain of their behavior. Perhaps most importantly from the practitioner's perspective, in the absence of actual payment data for calibration, the choice of the recoding cutoff value is completely arbitrary. In fact, when actual payment data are available, it is unclear why the analyst would need CV data in the first place.

We argue that, when the analyst has data expressing respondent uncertainty, the appropriate analytical response is to incorporate the uncertainty data in the econometric model in a utility-consistent fashion. We do this using the uncertainty scale of Champ and colleagues (1997, 2001, 2009). The advantage of our approach is that it addresses hypothetical bias *without the need for actual payment data.* We compare this model (the CV/uncertainty model) to the conventional CV model, the recoded CV model (CV/recoded model), and an AD model using donation data for a whooping crane reintroduction project, the same data used in the third of the Champ et al studies (2009). The results support the hypothesis that respondent uncertainty leads to hypothetical bias and that utility-consistent treatment of uncertainty can reduce this bias substantially.

RESPONDENT UNCERTAINTY AND HYPOTHETICAL BIAS

We use the terms "certainty" and "uncertainty" in their general sense, reflecting the sense of confidence a respondent has regarding how well they predicted their response to an actual valuation decision. This is a holistic approach, in which we acknowledge several possible sources of uncertainty, or hesitation, but do not try to distinguish among these sources. This use of "uncertainty" is common in CV experiments with follow-up certainty as discussed below, and similar to the concept of decision making under ambivalence (e.g., Ready et al 1995) and the notion of fuzzy preferences (e.g., van Kooten et al 2001). An important element of our formulation is that the uncertainty respondents express is due to uncertainty over their own preference relation, and is therefore expressed within the utility function itself.

This is different but complementary to how the term is often used in the literature on risk, uncertainty, and ambiguity, where the future outcomes are unknown and probabilities associated with those outcomes may or may not be known. For example, the potential success of a program to protect endangered species includes scientific uncertainty, but it also includes, in a referendum scenario, the case where voters do not have complete information regarding the outcome of the vote at the time their decision is made. The approach in this case typically uses the expected utility or nonexpected utility framework (see for example Cameron 2005; Riddel and Shaw 2006). With the exception of Harrison (2006) and Champ et al (2009), little attention has been paid to hypothetical bias in the literature on risk and uncertainty.

Measuring Preference Uncertainty

There are a variety of methods for measuring uncertainty (as we use the term) suggested in the CV literature. While many of these studies do not include the data necessary to investigate hypothetical bias, they provide the motivation for developing a utility-based theoretical model of an uncertain respondent's decision. Berrens et al (2002) identify two general methods of identifying respondent uncertainty in CV studies: directly through the CV response, or indirectly using a post-CV follow-up question. The direct approach typically presents the respondent with a polychotomous response format. Instead of a simple "Yes" or "No," response options might be "Definitely No," "Probably No," "Not Sure," "Probably Yes," or "Definitely Yes," where the two extreme responses indicate complete certainty. Typically, many respondents express uncertainty over at least some of their responses (Welsh and Poe 1998; Alberini et al 2003; Evans et al 2003). Some studies recode these responses into one or more binary variables, estimating separate logit models for each recoding (e.g., Ready et al 1995; Welsh and Poe 1998). Other studies more directly integrate the expressed uncertainty into the estimation, such as with random valuation models (Wang 1997; Alberini et al 2003), or a loss function approach (Evans et al 2003).

The other general method for identifying respondent uncertainty is to use a follow-up question to a standard dichotomous choice CV question, as done in the studies by Champ and colleagues (1997, 2001, 2009). The follow-up question asks respondents how certain they are of the answers they provided to the CV question. The possible responses could be verbal categories as in "Probably Sure" or "Definitely Sure" (Blumenschein et al 1998), numerical categories, such as the common 10-point scale (Champ et al 1997, 2009; Loomis and Ekstrand 1998; Champ and Bishop 2001), or probabilities (Li and Mattsson 1995). All of these methods have shown that at least some respondents who respond "Yes" to the CV question express uncertainty about their response. In some cases, the reported uncertainty is quite significant. All three of the studies by Champ and colleagues (1997, 2001, 2009) found that less than 50% of the respondents who responded "Yes" to the hypothetical dichotomous choice donation question were certain of their answer (10 out of 10 on the certainty scale). Li and Mattsson (1995) found that almost 14% of the "Yes" respondents indicated a confidence level of less than 50%.

A few studies have attempted to compare the different approaches for incorporating respondent uncertainty into CV studies (Ready et al 2001; van Kooten et al 2001; Vossler et al 2003; Samnaliev et al 2006; Shaikh et al 2007). Most such studies report differences in how the two different approaches work to impact WTP.

Modeling Uncertain Preferences

As noted above, one common approach to analyzing uncertain responses in CV studies is to recode the uncertain responses into one or more binary variables and apply standard logit models to each new variable. While easy to implement, this recoding approach does not take full advantage of the uncertain responses and, more importantly from a practical perspective, *recoding methods either use ad hoc recoding schemes or require comparable actual valuation decisions to provide a benchmark*. One of the first attempts to provide an empirical model of preference uncertainty based on a conventional CV model was Li and Mattsson (1995), which treats respondent uncertainty as one source of measurement error. In their model, respondents' uncertainty of their own valuation for a good might lead them to give a "wrong" answer to the CV question and the magnitude of their uncertainty (interpreted as a subjective probability) reflects the likelihood of such an error. The uncertainty is incorporated into the variance of the error term in the individual's WTP function. A similar approach using a random utility framework would be to allow the scale parameter of the utility function to vary for different groups depending on the respondent's certainty level (see Adamowicz et al 1998; Cameron et al 2002).

The Li and Mattsson (1995) approach assumes the respondent has a true WTP, but does not know what that value is. An alternative approach is to apply fuzzy CV methods, as suggested in van Kooten et al (2001) and Sun and van Kooten (2009). Rather than assuming the respondent does not know his own true WTP, van Kooten et al (2001) posit that the respondent might never know their WTP with certainty because their preferences are not defined. They assume only that the respondent knows the bounds of what that bid might be, and model how the CV choice is made under these circumstances. Sun and van Kooten (2009) use the fuzzy set theory to develop a fuzzy random utility model where separate utility functions are assumed for different clusters of respondents based on certainty, but an individual's WTP is a type of weighted average of the degree to which the individual belongs in each cluster.

Relating Hypothetical Bias and the Preference Uncertainty

The notion of uncertainty most relevant to this paper has been explored and modeled in a variety of ways, including ambivalence (Ready et al 1995), random variance in the WTP function (Li and Mattsson 1995), and fuzzy preferences (van Kooten et al 2001). However, a major limitation of this literature is the lack of data from actual market transactions to compare to the CV results. Without such a comparison, the authors are unable to judge empirically the extent to which their alternative model reduces this bias. On the other hand, relatively few studies that do compare actual payments/donations to CV responses are supplemented by uncertainty responses, and those that are, such as Champ et al (2009) and the recent study by Blumenschein et al (2008), do not integrate the uncertainty responses in a manner that is theoretically defensible in applications without such data. This gap in the literature motivates the analysis presented below.

THE UNCERTAIN RESPONDENT MODEL

The Conventional Random Utility Approach (CV Model)

The conventional random utility model of choice behavior first applied to CV data by Hanemann (1984) typically assumes a linear functional form, with the utility associated with choice i stated as

$$u_i = \alpha_i + \beta y + \varepsilon_i \tag{1}$$

where α_i denotes the choice-specific contribution to utility, y is the individual's income, and ε_i is known by the individual but unobserved and treated as stochastic by the analyst.[2] An individual faced with a dichotomous choice CV question, such as, "Would you be willing to pay \$$D$ in order to have…?," will answer "Yes" if the utility of doing so is greater than the utility resulting from a "No" response. With the traditional economics interpretation of the random utility model, it is assumed the individual knows with certainty the utility she would receive from both answers (i.e., she knows the value of all elements of her utility function) and so her individual decision is deterministic. If we denote the unsubscripted u as the difference in utility resulting from "Yes" and "No" responses, she will answer "Yes" if

$$\begin{aligned} u = u_{yes} - u_{no} &= (\alpha_{yes} + \beta(y - D) + \varepsilon_{yes}) - (\alpha_{no} + \beta y + \varepsilon_{no}) \\ &= (\alpha_{yes} - \alpha_{no}) - \beta D + (\varepsilon_{yes} - \varepsilon_{no}) \\ &= \alpha - \beta D + \varepsilon > 0 \end{aligned} \tag{2}$$

The respondent knows the value of ε, but the analyst does not. Instead, the analyst knows the distribution of ε across the population, usually assumed to be independent and identically distributed (i.i.d.) logistic with mean μ and scale parameter $\sigma = 1$.[3] From the analyst's perspective, the probability of observing a "Yes" response for offer amount D is then

$$\begin{aligned}\Pr(CV = Yes \mid D) &= \Pr(\alpha - \beta D + \varepsilon \geq 0)\\ &= 1 - \frac{1}{1 + e^{\alpha - \beta D + \mu}}\end{aligned} \tag{3}$$

As an empirical matter, α and μ can not be separately identified, so μ is assumed to be equal to zero. Hanemann (1984) shows that if WTP is restricted to be nonnegative (as is reasonable for our application to whooping crane protection), expected WTP (E$\{WTP\}$) can be calculated as

$$E\{WTP\} = \int_{D=0}^{\infty} \Pr(WTP > D)dD = \int_{0}^{\infty} \left(1 - \frac{1}{1 + e^{\alpha - \beta D}}\right) dD \tag{4}$$

Modeling Respondent Uncertainty

The empirical analysis in a later section is based on a survey framework in which respondents answering "Yes" to a dichotomous choice CV question are queried about how certain they are that, in an actual payment/donation setting, they would make the indicated payment/donation. This is the framework used in the studies by Champ and colleagues (1997, 2001, 2009). In practice it takes the following form in a survey:

Question 1. Would you be willing to pay \$$D$ in order to have . . .? No Yes

Question 2. If you answered Yes to question 1, on a scale of 1 to 10, where 1 means "very uncertain" and 10 means "very certain," how certain are you that you would pay \$$D$ if you had an opportunity to actually do so?

1	2	3	4	5	6	7	8	9	10
Very uncertain									very certain

Let c_j denote the number from 1 to 10 circled in the follow-up certainty question by individual j. When the respondent is uncertain of her CV response, the conventional modeling approach as typically interpreted by economists is *not* appropriate. Typically, some respondents admit uncertainty ($c_j < 10$) about what their behavior would be in an actual payment scenario, which directly contradicts the assumption of the conventional model that, from the perspective of the respondent, utility is deterministic. The recoding technique uses responses on the certainty scale to recode the "Yes" and "No" responses according to a Yes/No cutoff value on the certainty scale, $\bar{c}$, so that only a "Yes" respondent with $c_j > \bar{c}$ would be considered a "true 'Yes'" respondent. When properly implemented, $\bar{c}$ is determined by comparing CV data to actual payment data in a calibration exercise. Previous studies have found this cutoff value to range from 7 to 10. In the absence of actual data for comparison, the value of $\bar{c}$ chosen by the analyst is completely arbitrary.

We submit that, rather than using the uncertainty scale to "fix" the data, the analyst should use the scale to alter the econometric model to reflect respondent uncertainty. One way to do this in the context of a random utility model is to relax the assumption that the respondent knows with certainty her actual payment decision. Instead, we assume only that she knows the *probability* that she would actually pay $\$D$ if the opportunity were to arise, and uses this information to answer both the CV question and the uncertainty questions. Put another way, the respondent does not know ε_j; instead, she knows the *distribution* of ε_j. Assuming ε_j is distributed as a logistic with mean μ_j and scale $\sigma = 1$, the probability that individual j will make an actual payment of D dollars, is given by

$$p_j(D_j, \mu_j, \sigma) = 1 - \frac{1}{1 + e^{\alpha - \beta D_j + \mu_j}} \tag{5}$$

A respondent faces the dichotomous choice CV question with this payment probability in mind. She will answer "Yes" if her payment probability is sufficiently large, and "No" otherwise.

The right-hand side of Equation (5) looks like that in Equation (3) except that the expected value of ε_j, μ_j, is now indexed by the respondent. This seemingly small notational change embodies a substantial conceptual change with significant econometric implications. In the decision framework giving rise to Equation (3), the value of ε_j is known by the respondent, but not by the analyst, implying that, if the hypothesized situation were to arise, the respondent knows exactly what she would do, but the analyst does not. From the perspective of the analyst the respondent's behavior is probabilistic, and this probability is known by the analyst. In the decision problem giving rise to Equation (5), the respondent is not sure how she would behave if the actual payment scenario were to arise, and so she treats her own behavior as probabilistic. She knows the *probability* of her choice behavior because she knows the distribution of ε_j, in particular the mean μ_j. In a sense, her information set is the same as that of the analyst in the conventional choice problem. By contrast, in this choice problem the analyst has far less information than in the conventional choice problem, because from his perspective there is no longer a single distribution with known mean $\mu = 0$, but rather a distribution of μ_js, and so that the respondent's choice probability is itself a random variable. In this light, the purpose of the uncertainty scale is to aid the analyst in identifying the distribution of μ_j by identifying the distribution of p_j; for instance, a "low" value on the certainty scale implies a low value of p_j, which in turn implies a low value of μ_j.

Formalizing the Relationship between Respondent Uncertainty and the CV Question

We now formalize the relationship between this new model of the respondent and the probability of a "Yes" response on the CV question. Let *pmin* represent the minimum actual payment probability needed to generate a "Yes" response. Conceptualized in this way, a "Yes" on the CV question does not guarantee the individual would actually pay if faced with an actual payment scenario, only that the probability of an actual payment is greater than *pmin*. It would seem sensible to assume that *pmin* equals 0.5, in which case a respondent answers "Yes" if she judges the probability of a "Yes" in an actual payment situation to be greater than one-half. Yet, this assumption is not necessary and it is better, we would argue, to let the data speak to the issue by treating *pmin* as a model parameter to be estimated.

If p_j represents individual *j*'s probability of an actual payment of D_j, the probability that individual *j* will answer "Yes" to the CV question is given by

$$\begin{aligned}
\Pr(CV_j = Yes \mid D_j) &= \Pr(p_j \geq pmin) \\
&= \Pr\left(1 - \frac{1}{1 + e^{\alpha - \beta D_j + \mu_j}} \geq pmin\right) \\
&= \Pr\left(\mu_j \geq \ln\left(\frac{pmin}{1 - pmin}\right) - (\alpha - \beta D_j)\right) \\
&= \Pr\left(\alpha - \beta D_j + \mu_j \geq \ln\left(\frac{pmin}{1 - pmin}\right)\right) \qquad (6)
\end{aligned}$$

The last line of Equation (6) clarifies the relationship between the respondent's decision and her underlying utility. In the case where *pmin* is 0.5, the respondent will answer "Yes" to the CV question if the expected (net) utility of doing so is greater than zero, which is analogous to the certain respondent model (see the bottom line of Equation (2)).

Figure 1 illustrates this response rule for three different individuals, *i, j,* and *k*. The functions graphed are the probability density functions of ε for each of the individuals, with expected values of μ_i, μ_j, and μ_k, respectively. For this illustration, *pmin* is specified to be 0.5, and so from Equation (6) it is clear that for an offer amount *D*, the respondent gives a "Yes" response if her value of μ_j is greater than $\beta D - \alpha$, the value indicated in Figure 1 by a solid vertical line. Individual *i* will answer "No" to the CV question because $\mu_i < \beta D - \alpha$. Both *j* and *k* will answer "Yes." The actual payment probability for *j* is shown by the shaded area in the figure. This is the area under the pdf of μ_j and to the right of $\beta D - \alpha$. Because $\mu_k > \mu_j$, the actual payment probability of person *k* is greater than that of person *j* and one would expect that on the follow-up certainty scale,

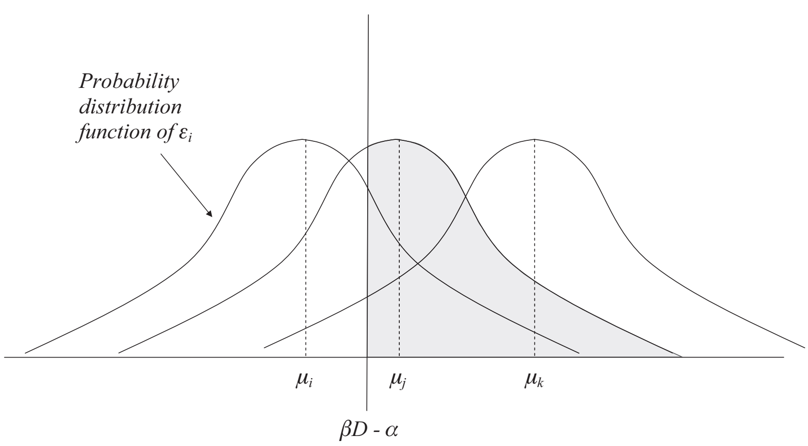

Figure 1. The individual's decision rule if *pmin* = 0.5

respondent k would choose a higher value than respondent j. Moreover, as D increases, the probability of an actual payment of \$$D$ decreases—graphically, the solid vertical line in Figure 1 shifts right, whereas the probability functions are fixed characteristics of the individuals, and so the probability mass to the right of the vertical line decreases—and we would expect the value chosen by respondents k and j on the follow-up certainty scale to decrease. This relationship is examined next.

Formalizing the Relationship between Respondent Uncertainty and the Certainty Scale

In the whooping crane restoration survey described below, only respondents answering "Yes" to the CV question were asked to indicate how certain they were of making an AD. Put another way, the certainty scale applies only to those respondents for whom the actual probability of payment exceeds *pmin*, $p_j \geq pmin$. Presumably, then, the certainty scale embodies a mapping of p_j into the integers 1–10, with a higher value on the scale indicating a higher probability of an actual payment, and *pmin* forming the lower bound of the mapping. For instance, if $pmin = 0.5$, it could be that the probability range 0.5 to 0.55 is mapped into the value "1" on the certainty scale, the probability range 0.55 to 0.6 is mapped into the value "2," and so on, terminating with the probability range 0.95 to 1.0 mapped into the value "10." This example is a linear mapping in which each certainty level captures a probability range of 0.05. This mapping is one of many possibilities, and to avoid unnecessary assumptions we specify a general functional form for the mapping, using the responses to the uncertainty question to estimate specific parameters. Let $p^l(c)$ and $p^h(c)$ represent the lower and upper bound on the actual payment probability associated with certainty level $c = 1, 2, \ldots, 10$. A parsimonious yet general mapping of the certainty scale into probabilities is

$$p^l(c) = \begin{cases} pmin & \text{if } c = 1 \\ p^h(c-1) & \text{if } c > 1 \end{cases}$$
$$p^h(c) = p^l(c) + k \cdot (c)^{\lambda}, \quad k = (1 - pmin)\left(\sum_{i=1}^{10} i^{\lambda}\right)^{-1} \tag{7}$$

where λ and *pmin* are estimable parameters, and k is a scaling term that ensures that $p^h(10)$ equals 1.[4]

Equation (7) does not assume that each value of c represents the same range of probability values; that is, the certainty scale is ordinal, but not necessarily cardinal. If lambda is zero, the scale would ordinal, and lead to the linear mapping we described above. However, lambda is estimated in the likelihood function, and our application finds lambda significantly different from zero, which means the range of probability values represented by a $c = 1$ is smaller than that represented by a $c = 10$, as shown in Table 1. Similarly, the value of *pmin* is estimated in the likelihood function and affects the bounds represented by all certainty levels because it defines the range of values that must be represented by the 10-point scale. For example, assuming a linear mapping, if $pmin = 0.5$, the 10-point certainty scale represents a range of probabilities from 0.5 to 1, with each value of c representing 1/10th of that range, or 0.05. But if $pmin = 0.1$, each value of c represents 0.09, which is still just 1/10th of the full range from *pmin* to 1. By including

Table 1. Actual donation probability indicated by certainty response, with $\lambda = 2.51$ and $pmin = 0.16$

	Actual donation probability	
Certainty, c	Lower bound, p_l	Upper bound, p_h
1	0.160	0.161
2	0.161	0.165
3	0.165	0.177
4	0.177	0.202
5	0.202	0.246
6	0.246	0.315
7	0.315	0.417
8	0.417	0.559
9	0.559	0.751
10	0.751	1

parameters lambda and *pmin*, we allow greater flexibility in the mapping. We assume that all individuals answering "Yes" to the CV question interpret the certainty scale in the same manner, though it is possible to depart from this assumption by, for instance, making *pmin* and λ functions of observable characteristics of respondents.

Answering "No" to the CV question indicates that the probability of an actual payment falls in the range [0, *pmin*). Note that our model does not imply that a No respondent necessarily has a zero probability of making an AD. In our application, we estimate $pmin = 0.16$, so a "No" respondent is indicating the probability he or she would make an AD is between 0 and 16%.[5]

The Likelihood Function

Given respondent j chooses "Yes" on the CV question and level c_j on the uncertainty question, the analyst can use Equations (6) and (7) to infer upper and lower bounds of μ_j, so that

$$\mu_j^s = \ln\left(\frac{p^s(c_j)}{1 - p^s(c_j)}\right) - \alpha + \beta D_j, \quad \text{for } s = l, h \tag{8}$$

Given the distribution of μ_j, Equations (6)–(8) provide the components of the likelihood function for survey responses. Assuming that, from the analyst's perspective, μ_j is i.i.d. logistic with mean zero (the mean is otherwise embedded in the estimate of α) and scale parameter η, from Equation (6) we know that the likelihood that respondent j responds "No" to the CV question is,

$$L_j(\mu, \beta, \eta, pmin; D_j \mid CV_j = No) = \frac{1}{1 + e^{(-\ln(pmin)+\ln(1-pmin)+\alpha-\beta D_j)/\eta}} \tag{9}$$

From Equation (8) the likelihood that respondent j says "Yes" on the CV question with level c_j on the uncertainty question is

$$L_j(\mu, \beta, \eta, \lambda, pmin; D_j \mid CV = Yes\ and\ \text{Certainty} = c_j) = \frac{1}{1 + e^{\left(-\ln(p^h(c_j)) + \ln(1-p^h(c_j)) + \alpha - \beta D_j\right)/\eta}} - \frac{1}{1 + e^{\left(-\ln(p^l(c_j)) + \ln(1-p^l(c_j)) + \alpha - \beta D_j\right)/\eta}} \quad (10)$$

where the functions $p^h(c)$ and $p^l(c)$ are defined in Equation (7). The likelihood value for the observed responses of all respondents is the product of all likelihood values. Maximum likelihood estimation can be used to obtain estimates of parameters α, β, η, λ, and *pmin*.

Calculating the Expected WTP

Respondent uncertainty complicates the calculation of E$\{WTP\}$. In the conventional model each agent knows his value of ε and thus his WTP, and the expectation operator refers to the distribution of ε across the population. When respondents indicate uncertainty about their CV response they implicitly indicate uncertainty about their actual WTP (Li and Mattsson 1995). This implies two levels of expectations over WTP: the E$\{WTP\}$ of an individual, which is the expectation of WTP *conditional* on μ_j, E$\{\text{WTP}|\mu_j\}$, and the (unconditional) E$\{WTP\}$ for the population, E(WTP). The conditional expectation can be calculated using a modified version of Equation (4)

$$E\{WTP \mid \mu_j\} = \int_{D=0}^{\infty} \Pr\{WTP > D \mid \mu_j\} dD = \int_{D=0}^{\infty} \left(1 - \frac{1}{1 + e^{\alpha - \beta D + \mu_j}}\right) dD \quad (11)$$

Recall that μ_j is distributed logistically with mean zero and scale parameter η. Letting g(μ) denote the pdf of μ, the E(WPT)—the E$\{WTP\}$ taken across the population—is

$$\begin{aligned} E\{WTP\} &= \int_{-\infty}^{\infty} g(\mu) E\{WTP \mid \mu_j\} d\mu \\ &= \int_{\mu=-\infty}^{\infty} \left(\frac{1}{\eta} \frac{e^{\mu/\eta}}{(1 + e^{\mu/\eta})^2} \int_{D=0}^{\infty} \left(1 - \frac{1}{1 + e^{a - \beta D + \mu}}\right) dD\right) d\mu \end{aligned} \quad (12)$$

USE OF DONATION VEHICLES IN CV RESEARCH

We present an empirical application of the uncertainty model developed above and compare the WTP estimates provided by this model to estimates resulting from the recoding technique that is frequently used in CV research. Our primary objective is to determine how to interpret contingent data to best reflect actual behavior. Our application uses a donation mechanism to elicit payment data, a design element of which many are skeptical (Hoehn and Randall 1987; Carson et al 1999), primarily on the grounds that a donation mechanism presents a classic free-rider problem. There are two practical advantages of using donation scenarios in CV research. First, many environmental public goods, such as open space, endangered species funds, and instream flows, are provided via donations. Therefore donation mechanisms are often appropriate and credible for provision of these types of goods (Spencer et al 1998; Byrnes et al 1999) and thus may be less vulnerable than alternative payments scenarios to biases associated with scenario rejection. For example, in the first of the Champ et al studies (1997), Wisconsin residents were asked about their values for removal of some old dirt roads on the north rim of the Grand Canyon so that a Wilderness Area could be established. A scenario involving a referendum on the question would have seemed implausible to Wisconsinites, while a donation opportunity seemed natural and plausible. Incentive compatible mechanisms, such as taxes, are subject to protest responses due to the unpopularity of taxes and the skepticism that associated governmental entities will spend the tax revenue wisely.

Second, compared to other payment scenarios, it is easier to find and fund opportunities for field experiments where actual and contingent donations for real public goods can be measured and compared. It is much more difficult, for example, to construct a field experiment involving a referendum on the provision of a real public good, unless a natural experiment presents itself (Carson et al 1986; Champ and Brown 1997; Vossler and Kerkvliet 2003; Vossler et al 2003), and even then natural experiments can be hard to interpret with confidence as responses to a referendum vote are only reported in aggregate and can not be combined with information about the voters as it is not known if a particular voter actually submitted a vote on a particular referendum.

Given these practical advantages, the next logical question is whether contingent donation data provide useful information. We argue that they could, and that together with the relative inexpensiveness of comparing actual and contingent donation data, this possibility compels research on the question. Our argument for the usefulness of contingent donation data begins with the understanding that due to free riding, the expected AD for an improvement in a particular environmental good is a *lower bound* on the true value of the improvement.[6] Substantial empirical evidence indicates that contingent donation data overestimate WTP as compared to AD data. One might hypothesize that in the right setting—one where a donation mechanism is a "natural" elicitation format—the hypothetical arises mostly or entirely because survey respondents do not account for their free-riding behavior in an AD situation. That is, in situations where the donation scenario is realistic and familiar, sources of hypothetical bias are minimized except for those arising because people tend to understate their own tendency to free ride. If so, it follows that the "conventional" estimate of WTP derived from contingent donation responses is an upper bound on the lower bound on the true WTP. This is not altogether helpful, and it indicates the need to frame the contingent donation question in a manner that encourages respondents to account for their free-riding behavior.

The certainty scale provides respondents with the opportunity for more nuanced evaluation of their own behavior, including the tendency to free ride. If research studies comparing contingent and AD data for environmental improvements consistently find that CV donation surveys that properly account for respondent uncertainty generate estimates of the value of improvements that are not significantly different from those obtained from AD data, then we might fairly judge such contingent donation surveys generally to provide a lower bound on true WTP. This lower bound is often sufficient information for many management decisions and policy analyses.

WILLINGNESS TO DONATE FOR WHOOPING CRANE REINTRODUCTION

To examine empirically the CV/uncertainty model, we use data from a mail survey designed to value a program to establish a wild flock of whooping cranes. The most endangered crane species in the world, whooping cranes are threatened primarily by the conversion of their wetland habitat into agricultural and residential lands. Though once widespread, since the 1950s only one migratory flock of whooping cranes has survived worldwide, spending its summers in Canada and winters in Texas. The International Whooping Crane Recovery Team—a group of crane biologists and U.S. and Canadian officials—has been orchestrating efforts to ensure the survival of the species. As part of these efforts, a second migrating flock of whooping cranes is being bred and introduced into the wild. Each year, whooping crane chicks are hatched in captivity and taught behaviors crucial to their survival in the wild. An important aspect of this program is teaching the young cranes how to make the annual 1,250 mile journey from central Wisconsin to Florida. After being led to Florida by an ultralight aircraft their first year, the cranes are able to make the return trip to Wisconsin unassisted the next spring. They continue the migration annually as a flock, without the assistance of an aircraft. However, to ensure the success of the program, radio transmitters are placed on the leg of each crane in the flock to monitor the birds during migration and throughout the year. If a bird is in danger or sick, project personnel might intervene and rescue the bird. The first class of 18 cranes was hatched in the spring of 2001. The project will continue until the flock has grown to 125 cranes (approximately 10–15 years). At the time of this study, funding was needed to purchase radio transmitters for whooping crane chicks who were to be hatched in the spring of 2004. The transmitters cost around $300 each, and while survey respondents were not told the cost of the transmitters, they were told that the transmitters could only be provided if there was sufficient support in the form of donations. "Sufficient" was not explicitly defined.

The survey was mailed to a sample of Madison, WI residents in January 2004 using a split sample design to elicit hypothetical donation responses from some and AD responses from others.[7] All respondents were presented with identical descriptions of the whooping crane reintroduction project. Following this description, one group was asked a dichotomous choice contingent donation question ("If you were asked to make a donation to purchase radio transmitters today, would you be willing to donate $___?") and a follow-up certainty question similar to the example given in the previous section. We will refer to the data from this group as CV data. The other group was asked a similar dichotomous choice question, but in the context of an AD ("Would you donate $___ to purchase radio transmitters for the whooping cranes in Wisconsin this summer?"). We refer to this data as the AD data. For this group, respondents answering "Yes" to the donation question were asked to include a check for the bid amount when they returned their survey.[8] A total of $1,510 in donations was collected from this treatment group.

Table 2 presents the sample size, response rate, and percentage of respondents answering "Yes" to the donation question for each offer amount in both treatments. Response rates are fairly consistent across offer amounts and overall response rates are 33% for the CV group and 24% for the AD group. We also examined differences in prior knowledge, environmental interest, and demographic characteristics. Other than a slight gender imbalance (the AD group was 42% female versus 32% for the CV group), we found no major

Table 2. Response rates and percentage of "Yes" responses, by treatment and offer amount

	Number of surveys mailed		Response rate		Percent of respondents with CV_j = "Yes"		
	Actual donation	Contingent donation	Actual donation	Contingent donation	Actual donation	Contingent donation	CV/ recoded
\$10	139	114	27%	34%	47%	77%	51%
\$15	220	160	24%	33%	31%	67%	46%
\$25	229	156	20%	34%	33%	57%	32%
\$50	188	167	30%	33%	14%	40%	15%
\$100	157	110	21%	33%	6%	36%	19%
Total	933	707	24%	33%	26%	55%	25%

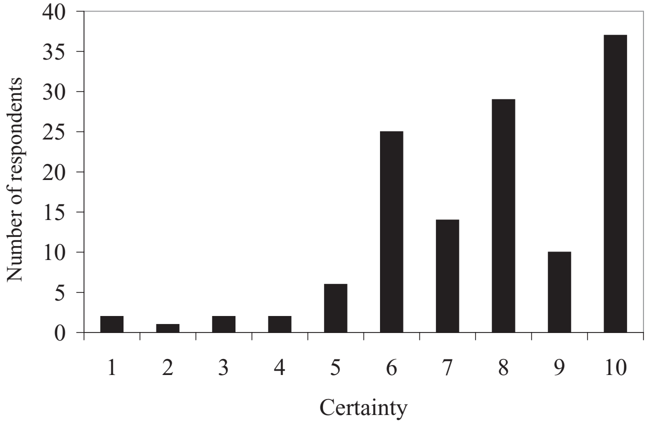

Figure 2. Frequency of certainty responses

differences between the treatment groups. We feel confident the two treatments represent the same population.

We analyze the survey data with both the conventional CV model and our model incorporating respondent uncertainty (CV/uncertainty model). As an additional point of comparison, we also present the results from estimating the conventional model with "recoded" CV data. This CV/recoded model is the same as the conventional CV model, but with "Yes" responses for which the respondent's certainty level was 7 or less recoded as "No." This particular recoding was previously identified as most closely calibrating the WTP to that of ADs (Champ et al 2009). The final column of Table 2 indicates the percentage of "Yes" respondents identified by this calibrated data. Figure 2 shows the frequency of responses to the follow-up certainty question. Though the most common certainty response was 10, the median response was 8, indicating that over half of the "Yes" respondents are at least somewhat uncertain of their behavior in an AD scenario, and highlighting the need for a modeling approach that incorporates this uncertainty. The mean certainty was 7.72.

Table 3. Parameter estimates and E{*WTP*}

	Actual donation (AD) ($n = 225$)	Conventional contingent donation model (CV) ($n = 235$)	Calibrated contingent donation model (CV/recoded) ($n = 233$)	Uncertain respondent model (CV/uncertainty) ($n = 233$)
α (std. error)	−0.082	0.953*	0.051	−0.403
	(0.261)	(0.226)	(0.233)	(0.636)
β (std. error)	0.030*	0.018*	0.021*	0.024*
	(0.008)	(0.005)	(0.006)	(.007)
η (std. error)	–	–	–	1.31*
				(0.260)
λ (std. error)	–	–	–	2.51*
				(0.708)
pmin (std. error)	–	–	–	0.160
				(0.109)
E{*WTP*}	\$21.21	\$69.38	\$33.86	\$39.71
90% CI for E{*WTP*}[1]	[16.84, 30.86]	[54.96, 103.33]	[26.39, 52.08]	[26.83, 70.36]

Notes: [1]Calculated using the Krinsky and Robb procedure (1986) with 10,000 draws of β.
*Significant at 5% level.

Estimating the Conventional CV and CV/Uncertainty Models

The first three columns of Table 3 report parameter estimates and standard errors of the utility parameters α and β and a point estimate of the E{*WTP*} for ADs, the conventional CV model and the CV/recoded model, as derived from Equation (4). Several techniques are available to estimate the distribution of E{*WTP*} (Kling 1991; Cooper 1994). For this study, we rely on the Krinsky and Robb (1986) procedure to estimate a 90% confidence interval for E{*WTP*}. These results clearly show a hypothetical bias in the data. The E{*WTP*} of the CV group (\$69.38) is over three times larger than that of the AD group (\$21.21). The recoding lowers the E{*WTP*} estimate to values not significantly different from the AD results.

At this juncture it is important to remember that the CV/recoding model is *ad hoc* unless there exists AD data to provide a calibration reference. The CV/uncertainty model, on the other hand, is estimated independently of the AD data. Results for the CV/uncertainty model are presented in the final column of Table 3. This model includes three additional parameters: η, λ, and *pmin*. Recalling that $\lambda = 0$ generates a linear mapping of probability mass into the certainty scale, the point estimate $\lambda = 2.51$ generates a highly nonlinear mapping with more mass in the upper end of the scale, as reported in Table 1. The point estimate $pmin = 0.16$ indicates that respondents are likely to say "Yes" to the CV question even when they are quite unlikely to make the requested donation in an AD scenario.

Comparing the Estimation Results

Several interesting conclusions can be drawn from the results in Table 3. First, the CV/recoded model produced a lower E{*WTP*} than the conventional CV model, and the confidence intervals of the CV/recoded and AD models overlap. These results are consistent with previous studies (Champ et al 1997; Champ and Bishop 2001). Second, the CV/uncertainty model generated an E{*WTP*} between that of the conventional CV and AD models. This is intuitive, considering that the estimated value of *pmin* is well below 0.5, and indicates that many respondents answer "Yes" to the dichotomous choice question even though they do not expect to donate the specified amount.

So far in the discussion we have not considered the impact of covariates in the decision model, which can significantly increase the predictive power of the model. The inclusion of additional explanatory variables is straightforward in both the CV and CV/uncertainty models; these variables enter as part of the deterministic portion of the utility function. E{*WTP*} estimates are then conditional on particular values of these additional variables. For this paper, we are not particularly concerned with the impact of these variables on E{*WTP*}, but it is still instructive to look at the additional information these variables provide. It is particularly enlightening to divide the respondents answering "Yes" to the CV question into two groups: those who likely would donate the amount requested if actually asked to do so, and those who likely would not. We label the first group the "Consistent" respondents, because their CV response is consistent with their expected AD response. This is the group of individuals whose conditional $E\{\mathrm{WTP}|\mu\}$ is greater than the bid amount. In other words, their values of μ are greater than $-(\alpha-\beta D)$. The other group contains the "Inconsistent" respondents for whom $E\{\mathrm{WTP}|\mu\} < D$, but who still answer "Yes" to the CV question. Table 4 compares the reported attitudes of the individuals in these two groups. As expected, the consistent respondents report a greater desire to support the whooping crane reintroduction project ("The *whooping crane program* would be worth that much to me"), while the inconsistent respondents are more likely to value broader environmental ideals ("*Animals* have a right to exist"). The consistent respondents are also more likely to have donated time or money to environmental causes in the past, providing them with additional experience on which to base their expectation.

CONCLUSION

This study makes two basic contributions to the CV literature. First, it provides the theoretical foundation for directly incorporating information on respondent choice uncertainty—as expressed on a certainty scale that survey respondents seem to be comfortable with—into an econometric model of choice behavior. Importantly, there is no recoding of data, and thus no need for actual payment data on which to calibrate a recoding.

Second, the results of the analysis provide evidence of the potential merit of the modeling approach when used in conjunction with a contingent donation scenario to elicit WTP. For many goods, donation scenarios are the most "natural" way to elicit payment for an environmental good. Due to free riding, AD data are likely to underestimate the true value of an environmental improvement, and yet CV studies find that in the conventional modeling approach a donation scenario produces WTP estimates that are significantly *higher* than derived from comparable AD data. The results of the empirical

Table 4. Attitudinal characteristics of consistent and inconsistent respondents to the CV question as identified with the CV/uncertainty model

	"Inconsistent" CV respondents $\mu_j^l < -(\alpha - \beta D_j)$	"Consistent" CV respondents $\mu_j^l > -(\alpha - \beta D_j)$
The whooping crane reintroduction program would be worth that much to me. (% agree)	44.4%[a]	78.7%[a]
I wanted to show my support for whooping crane reintroduction. (% agree)	53.1%[a]	72.3%[a]
I can't afford to make a donation to help pay for the transmitters. (% agree)	11.0%[a]	0%[a]
I think fitting the whooping cranes with the radio transmitters will have a positive impact on the ability of researchers to save the whooping cranes. (% agree)	77.8%[b]	91.3%[b]
Animals have a right to exist independent of human needs. (% agree)	88.9%[b]	76.6%[b]
I donate money to environmental causes. (% answering "Frequently")	58.0%[a]	80.4%[a]
I volunteer my time to environmental causes. (% answering "Frequently")	19.8%[b]	32.6%[b]

Notes: [a]Significant difference at 5% level.
[b]Significant difference at 10% level.

application in this paper suggest that properly accounting for respondent uncertainty when analyzing contingent donation data produces WTP estimates that are lower than those of the conventional model, and closer to those from AD model. If this result is consistently found in future analyses—analyses that perhaps refine the format and modeling to further close the gap between WTP for actual and contingent donation data—it would support the use of contingent donation data as a means of providing cheap estimates of the *lower bound* of the value of improvements for a wide variety of environmental goods. Such a lower bound is likely sufficient in many policy applications.

Refinements in the modeling can take many forms, including changes in three key assumptions of the model. The first is the parametric form for mapping choice probabilities into the certainty scale. Though our chosen functional form is quite flexible, we have not tested the robustness of our results to changes in this mapping. The second assumption worth further investigation is that μ is distributed logistically around zero. A truncated distribution of μ could be used to impose restrictions on the range of WTP. With a donation payment vehicle, it is reasonable to assume that WTP is bounded below by zero and above by income. Imposing this restriction postestimation is acceptable in certain cases, but it would be better to impose the restriction in the estimation itself. Methods of imposing bounds in the estimation of the conventional model have been suggested, but they are complex and not always well behaved (Haab and McConnel 2003). Our formulation of respondent uncertainty might be more amenable to imposing these bounds. Third, we assume constant a scale parameter in both the individual-specific error term and the distribution of mean error across the population. This is a reasonable assumption, but it is also possible that different subgroups, such as "Yes" and "No" respondents, have different error variances. Future research could allow for heteroskedasticity.

In summary, this paper describes an approach to modeling the decision of the uncertain respondent in a CV study. The practical advantage of this approach is that the resulting WTP estimates appear to resemble that from actual payment data, but the CV/uncertainty estimates themselves were derived without the need to collect actual payment data. Further applications of this and other theoretical models of respondent uncertainty are needed before larger conclusions can be drawn regarding the link between uncertainty and hypothetical bias. Particularly, applications with other types of goods, different elicitation methods, and different payment vehicles are needed. It is important to continue to improve the current methods of collecting and analyzing CV data due to their potentially large role in cost-benefit analysis, a decision-making tool used frequency by both public and private groups.

NOTES

[1]We use the terms "certainty" and "uncertainty" in a general sense throughout the paper to reflect the respondents' confidence, or strength of conviction, in their response to the valuation question. We compare this to studies addressing uncertainty and risk in its more technical definition in the next section.

[2]Importantly, α_i may be conditioned by observable variables.

[3]We present the most straightforward model in which the linear utility implies no income effect and scale parameter is assumed constant (and equal to 1) across the population. These assumptions have been discussed and relaxed in some valuation studies (e.g., Adamowicz et al 1998; Cameron et al 2002).

[4]Conceptually, our interpretation of the CV and follow-up certainty response is similar to a fuzzy logic approach in that the CV response is no longer treated as a (crisp) binary variable. The follow-up certainty response allows the respondent to indicate the degree of membership in the "Yes" category. See van Kooten et al (2001).

[5]It is relatively straightforward to extend this approach by incorporating additional certainty information from the "No" respondents and narrowing the probability range for these respondents as we have done with the "Yes" respondents. Our application does not include this data, and so we do not develop this extension here.

[6]For a discussion of true values see Bishop (2003). Arguments for free riding are compelling. For example, could one infer from the fact that if only 10% of the viewers of the public television programming are contributors, the other 90% are getting no value from what they are watching? The theoretical arguments that might counterbalance the notion that free riding leads to value underestimation are those associated with nonuse values and whether altruism is paternalistic (see Flores (2002) and McConnell (1997)). There is limited empirical evidence of this. Chilton and Hutchinson (1999) argue that ADs are not necessarily a lower bound on consumer surplus if the government is providing the good, but our application is not one of government provision.

[7]There were actually three treatment groups in this survey. The third group was given a contingent donation question preceded by a "cheap talk" script but is not discussed here. Details of this aspect of the survey can be found in Champ et al (2009).

[8]Respondents who sent checks for amounts greater than the offer amount were coded as saying "Yes" to the offer amount. Similarly, respondents who sent checks for less than the offer amount were coded as saying "No" to the offer amount.

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