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

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ABSTRACT

In this paper we develop an econometric model of willingness to pay that integrates data on respondent uncertainty regarding their own willingness to pay. The integration is utility consistent and does not involve calibrating the contingent responses to actual payment data, and 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 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, contingent valuation decisions can simulate actual payment decisions. This method allows for more reliable estimates of WTP that incorporates respondent uncertainty without the need for collecting comparable actual payment data.

1. 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[1] such studies have found that responses to CV questions generate higher willingness to pay (WTP) estimates than more or less comparable cash commitments, a phenomenon that has come to be 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), Champ and Bishop (2001), and Champ et al. (2002), who have now 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 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.

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[1] See, for example, Johnston (2006).

Champ et al. reasoned that hypothetical bias might stem, at least in part, from respondents' uncertainty about whether they would actually pay. Champ et al. 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 et al. 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 willingness to pay 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 then applies this 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 is available, it is unclear why the analyst would need contingent valuation 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 *et al*. 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 (CV model), the recoded CV model (CV/recoded model) and an actual donation model (AD model) using donation data for a whooping crane reintroduction project, the same data used in the third of the Champ et al. studies (2002). The results support the hypothesis that respondent uncertainty leads to hypothetical bias and that utility-consistent treatment of uncertainty can reduce this bias substantially.

2. Respondent Uncertainty in Contingent Valuation

There are many reasons why an individual might be uncertain about her response to a CV question (Jorgensen et al 2006), and methods for measuring and eliciting respondent uncertainty have been developed and compared in several recent studies. 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.

The first paper to attempt to provide an empirical model of 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 reflects the likelihood of such an error. One major limitation of the Li and Mattsson paper, as well as many of the more recent studies of uncertainty and hypothetical bias, is the lack of data from actual market transactions to compare to the CV results. Without such a comparison, the authors are unable to empirically judge the extent to which their alternative model reduces this bias.

Berrens et al (2002) identify two general methods of identifying respondent uncertainty in CV studies: directly, through the CV response, or indirectly, with 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 (Alberini et al 2003; Evans et al 2003; Welsh and Poe 1998). However, instead of directly incorporating this uncertainty into the estimation of WTP, previous studies using this approach recoded the categories into "Yes/No" responses.

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 Champ et al. studies. 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, 2002; Champ and Bishop 2001; Loomis and Ekstrand 1998), or probabilities (Li and Mattsson 1995). All of these methods have shown that at least some respondents who respond “Yes” to the CV express uncertainty about their response. In some cases, the reported uncertainty is quite significant. All three of the Champ et al. studies 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) found that dichotomous choice questions generated higher WTP values than polychotomous responses, and that with the polychotomous choice format respondents were more certain of their answers. Samnaliev et al (2006) compared the effects of a 10-point follow up certainty question with the inclusion of a “Not Sure” option within the CV question and found the two methods produced different WTP estimates possibly due to the differences in type of uncertainty captured with each approach. Using two different CV data sets, Shaik et al (2007) compared five empirical methods for incorporating uncertainty into the estimation of WTP. They, too, found that different empirical methods had different impacts on estimated WTP. For example, methods similar to those used in Li and

Mattson and Champ et al. decreased WTP estimates, whereas a method similar to that used by Loomis and Ekstrand (1998) increased estimated WTP. Vossler et al (2003) compared direct elicitation of uncertainty in the CV question to elicitation with a follow-up question in an analysis of participation in a green electricity program. They found that while both approaches result in program participation rates that resembled actual participation rates, the approaches generated very different estimates of how quickly the probability of a "yes" response decreased as the offer amount increased. In summary, previous studies provide substantial empirical evidence that respondents can be, and frequently are, uncertain about their responses to CV questions. In addition, they suggest that how this uncertainty is measured and used in the estimation can have a significant impact on WTP estimates. The majority of existing studies rely on ad hoc methods of recoding the data to fit into the standard RUM model and many of the studies that do compare different empirical approaches for addressing respondent uncertainty do not benchmark the comparison with actual cash transactions data. On the other hand, very few studies compare actual payments/donations to CV responses supplemented by uncertainty responses, and those that do, such as Champ et al. (2002) 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.

3. 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,

$$u_i = \alpha_i + \beta y + \varepsilon_i \qquad , \qquad (1)$$

where α_i denotes the choice-specific contribution to utility, *y* is the individual's income and ε_j 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. Because 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), her individual decision is completely deterministic. If we denote the unsubscripted *u* as the difference in utility resulting from "Yes" and "No" responses, she will answer "Yes" if

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

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 i.i.d. logistic with mean μ and scale parameter $\sigma = 1$. From the analyst's perspective, the probability of observing a "Yes" response for offer amount *D* is then,

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

$$\Pr(CV = "Yes" \mid D) = \Pr(\alpha - \beta D + \varepsilon \geq 0) \\ = 1 - \frac{1}{1 + e^{\alpha - \beta D + \mu}} \quad . \tag{3}$$

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

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

Modeling respondent uncertainty

The empirical analysis of section 5 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 Champ et al. studies. In practice it takes the following form in a survey:

Question 1. Would you be willing to pay \$*D* in order to have…?

1 No
2 Yes

Question 2. <u>If you answered YES to question 1</u>, 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. When the respondent is uncertain of her CV response, the conventional modeling approach 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, $\overline{c}$, so that only a "Yes" respondent with $c_j > \overline{c}$ would be considered a "true 'Yes'" respondent. When properly implemented, $\overline{c}$ is determined by comparing contingent valuation 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 $\overline{c}$ chosen by the analyst is completely arbitrary.

We submit that rather that 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—that is, that she knows ε_j . Instead, she knows the *distribution* of ε_j. Put another way, she knows the *probability* that she would actually pay \$*D* were the opportunity to arise, and uses this information to answer both the CV question and the uncertainty question. Assuming ε_j is distributed logistically with mean μ_j and scale $\sigma=1$, the probability that individual *j* will make an actual payment of *D* dollars, is given by

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

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 this formulation looks like that in (3) except that, unlike in(3), 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 problem giving rise to (3), the value of ε_j is known by the respondent, but not by the analyst, implying that, were the hypothesized situation to actually 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 (5) the respondent is not sure how she would behave were the actual payment scenario 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_j's, and so from his perspective 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 .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,

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

The last line of equation (6) clarifies the relationship between the respondent's decision and her underlying utility. In the case where *pmin* is .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 last line of (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 (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* one would expect that on the follow-up certainty scale, respondent *k* would choose a higher value than respondent *j*. Moreover, as *D* increases, the probability of an actual payment 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 their response on the 10-point certainty scale presented above. 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* = .5, it could be that the probability range .5 to .55 is mapped into the value "1" on the certainty scale, the probability range .55 to .6 is mapped into the value "2", and so on, terminating with the probability range .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

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

where λ and *pmin* are estimable parameters, and k is a scaling term that ensures that $p^h(10)$ equals one. Setting λ equal to zero generates the linear mapping presented above. 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 (-∞, *pmin*).

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,

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

Given the distribution of μ_j, equations (6)-(8) provide the components of the likelihood function for survey responses. Assuming that μ_j is iid logistic with mean zero (the mean is otherwise embedded in the estimate of α) and scale parameter η, from (6) we know that the likelihood that respondent *j* responds "No" to the CV question is,

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

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

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

where the functions $p^h(c)$ and $p^l(c)$ are defined in (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 expected 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 expected WTP of an individual, which is the expectation of WTP *conditional* on μ_j, E{WTP|μ_j}, and the (unconditional) expected WTP for the population, E(WTP). The conditional expectation can be calculated using a modified version of equation (4).

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

Recall that μ is distributed logistically with mean 0 and scale parameter η. Letting g(μ) denote the pdf of μ, the unconditional expected WTP –the expected WTP taken across the population –is

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

4. Use of Donation Vehicles in CV Research

The next section of this paper presents an empirical application of the uncertainty model developed above and compares 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 (Carson and Machina 1999; Hoehn and Randall 1987), 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 (Byrnes et al 1999; Spencer et al 1998) 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 questions would have seemed implausible to Wisconsinites, while a donation opportunity seems 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 et al 2003; Vossler and Kerkvliet 2003), and even then the natural experiments can be hard to interpret with confidence as responses to a referendum vote are only reported in aggregate and cannot 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 actual donation for an improvement in a particular environmental good is a *lower bound* on the true value of the improvement.[3] One can further offer for empirical evaluation the hypothesis that in the right setting—one where a donation mechanism is a "natural" elicitation format—the hypothetical bias associated with contingent donation surveys arises mostly—perhaps entirely—because survey respondents do not account for their free-riding behavior in an actual donation situation. That is, in situations where the donation scenario is realistic and familiar, sources of hypothetical bias are minimized except for that arising because people tend to understate their own tendency to free-ride. It follows that the "conventional" estimate of the value of the improvement 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 actual donation 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 actual donation data, then we might fairly judge such contingent donation surveys to generally provide a lower bound on true WTP. This

[3] For a discussion of true values see Bishop (2003). To us, 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 (1998) argue that actual donations 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.

lower bound is often sufficient information for many management decisions and policy analyses.

5. 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. Whooping cranes are the most endangered crane species in the world. They are threatened primarily by the conversion of their wetland habitat into agricultural and residential lands. Though once widespread, since the 1950's 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 intervene and rescue the bird. The first class of cranes, 18 birds, 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 the 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.

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 actual **donation** responses from others[4]. 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 and a follow up certainty question similar to the example given in section 4. 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 actual donation, and 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. A total of $1510 in donations was collected from this treatment group. Table I 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.

[4] There were actually three treatment groups in this survey. The third group was given a contingent donation question preceded by a "cheap talk" script and is not discussed here. Details of this aspect of the survey can be found in Champ et al (2002).

We analyze the survey data with both the conventional CV model (CV) and our model incorporating respondent uncertainty (CV/uncertainty). 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 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 actual donations (Champ et al 2002). The final column of Table I 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 actual donation scenario, and highlighting the need for a modeling approach that incorporates this uncertainty. The mean certainty was 7.72.

Estimating the CV and CV/Uncertainty Models

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

At this juncture it is important to remember that the recoding model is ad hoc unless there exists actual donations data to provide a calibration reference. The CV/uncertainty model, on the other hand, is estimated independently of the actual donation data. Results for the CV/uncertainty model are presented in the final column of Table II. 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 III. The point estimate *pmin*=.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 actual donation scenario.

Comparing the Estimation Results

Several interesting conclusions can be drawn from the results in Table II. 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 .5, and indicates that many respondents answer "Yes" to the dichotomous choice question even though they do not expect to donate the specified amount. This idea is illustrated in Figure 4. Individual j is presented with a hypothetical donation question with bid amount D_j. Because their value of p_j is .17, which is greater than $pmin$, this individual will answer "Yes" to the CV question. The conventional CV model interprets a "Yes" response as an indication that ε_j is greater than $-(\alpha - \beta D)$; see the first line of equation (3). With the CV/uncertainty model, individual j's expected value of ε is significantly less than $-(\alpha - \beta D)$ and yet the individual will still give a "Yes" response to the CV question. In fact, all respondents whose value of μ lies between μ_j and $-(\alpha - \beta D)$ have a conditional E{WTP|μ} less than the offer amount, D, but will respond "Yes" to the CV question. Our results imply that explicitly allowing for this type of "inconsistent" response will produce an E{WTP} estimate closer to that implied by the actual donation data, reducing the hypothetical bias.

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{WTP|μ} 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{WTP|μ} < D, but who still answer "Yes" to the CV question. Table III 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 specifically ("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.

6. Conclusion

This study makes two basic contributions to the contingent valuation literature. First, it provides the theoretical foundation for directly incorporating information on respondent choice uncertainty—as expressed on a Likert 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 willingness to pay. For many goods, donation scenarios are the most "natural" way to elicit payment for an environmental good. Due to free-riding, actual donation 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 actual donation data. The results of the empirical 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 actual donation 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 two 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. One could avoid the mapping altogether by directly asking respondents for their payment probability: "What is the probability that you would say 'Yes' to a request for a donation of the amount $D?" Though some researchers have pushed for a version of this response format, there appears to be a general concern about the ability (or willingness) of respondents to explicitly state their choice probabilities.

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 post-estimation 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.

In summary, this paper describes an approach to modeling the decision of the uncertain respondent in a contingent valuation 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.

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

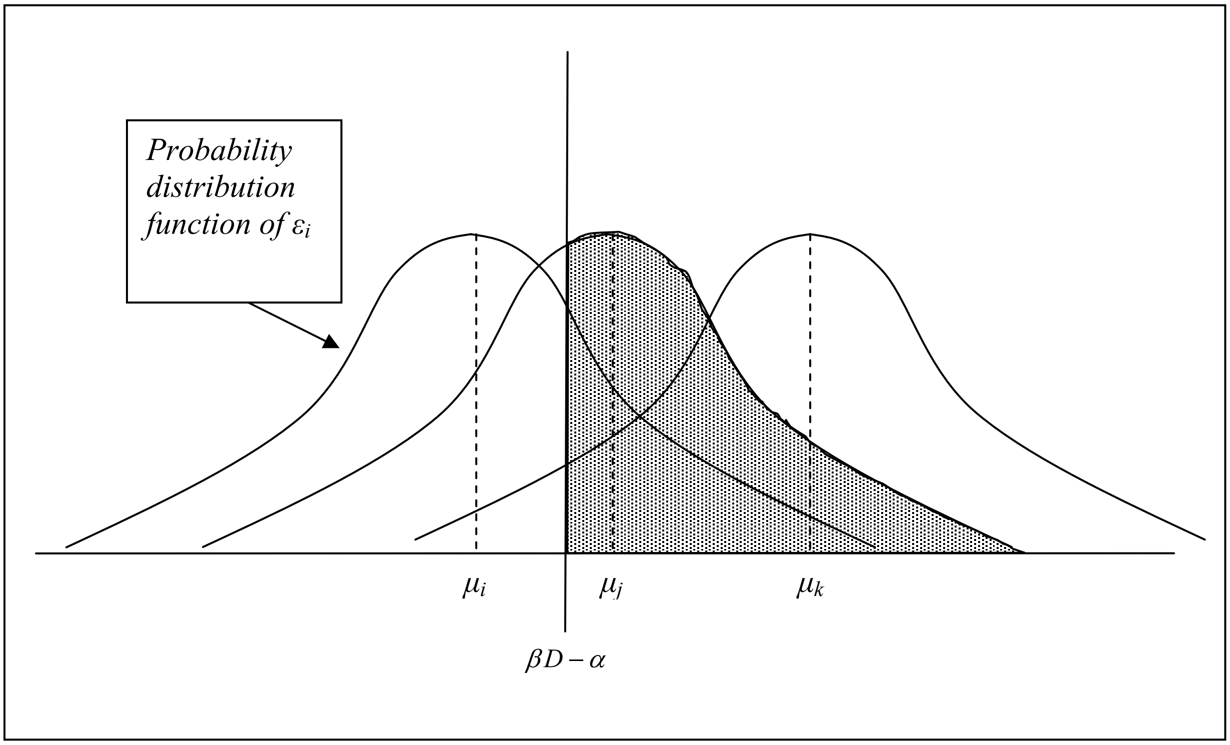

Figure 2. Frequency of certainty responses

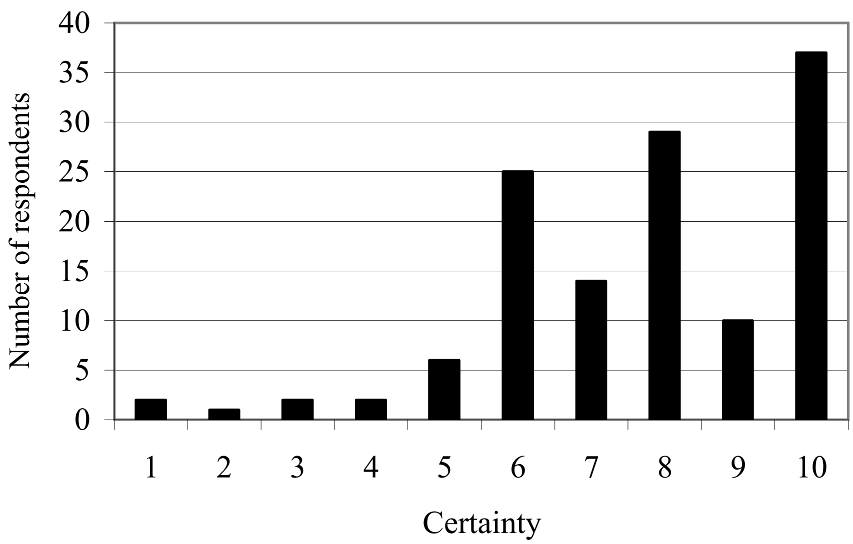

Figure 3. CV responses and E{WTP}

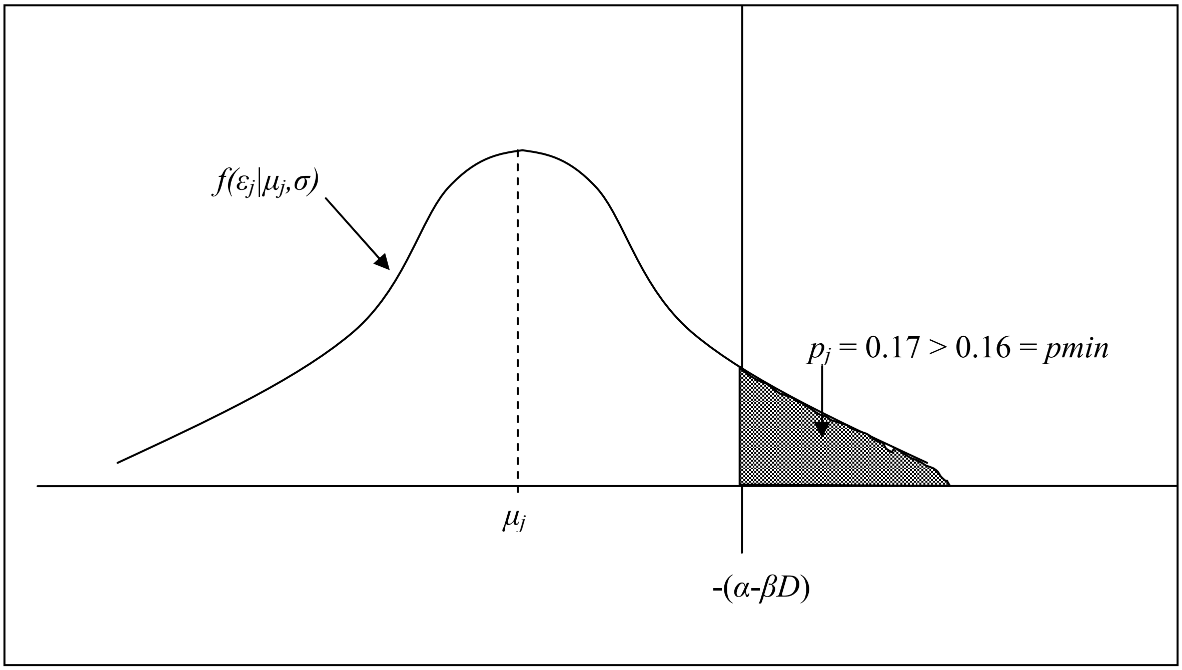

Table I. Response rates and percentage of "Yes" responses, by treatment and offer amount.

	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/calibrated
$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%

Table II. Parameter estimates and expected willingness to pay.

	Actual Donation (AD)	Conventional Contingent Donation Model (CV)	Calibrated Contingent Donation Model (CV/calibrated)	Uncertain Respondent Model (CV/uncertainty)
α (std. error)	-0.082 (0.261)	0.953^{**} (0.226)	0.051 (0.233)	-0.403 (0.636)
β (std. error)	0.030^{**} (0.008)	0.018^{**} (0.005)	$.021^{**}$ (0.006)	$.024^{**}$ (.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]

[1] Calculated using the Krinsky and Robb Procedure [**Error! Reference source not found.**] with 10,000 draws of β.

**Significant at 5% level *Significant at 10% level

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

Certainty, c	Actual Donation Probability	
	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

Table IV. 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]

[a] Significant difference at 5% level
[b] Significant difference at 10% level