RESPONDENT EXPERIENCE AND CONTINGENT VALUATION OF ENVIRONMENTAL GOODS

by

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ABSTRACT

Respondent experience (i.e. a respondent's information set) has long been suspected to influence contingent valuation estimates of environmental values. We assess the influence of experience by explicitly modelling the relationship between respondent experience and both fitted individual resource values and the conditional variance of these estimated values. Using three different joint specifications for experience and WTP--normal/censored-normal, Poisson/censored-normal, and Zero-Inflated Poisson/censored-normal--we find discrete jumps in resource values as experience increases from zero and that more-experienced respondents have smaller conditional variances. Simulation of arbitrary levels of experience allows standardization of the amount of information for the sample when developing welfare estimates.

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I. INTRODUCTION

Contingent valuation (CV) methods--wherein survey respondents are posed questions regarding their willingness to pay for environmental goods in hypothetical market scenarios--are now widely used. An important issue is the degree of information about, familiarity or experience with the environmental resource that respondents possess. Many surveys provide explicit background information about the resource to respondents prior to asking the contingent valuation questions. In this paper we focus on the respondent's own experience with the good, above and beyond the information provided in the survey.

Since CV methods have been applied to value a variety of environmental goods it is not surprising that some prior related work exists in the literature. Cummings, Brookshire, and Schulze (1986) address the issue of respondent experience. Kealy, Dovidio and Rockel (1988) examine experimental discrepancies between contingent values and actual purchase values. They find that the discrepancy tends to decline with increases in experience. Kealy, Montgomery and Dovidio (1990) also explore the skepticism about the reliability and validity of contingent values due to peoples' lack of familiarity or experience.[1] Bergstrom, Stoll and Randall (1990) argue that information affects willingness-to-pay for environmental commodities and that information is important for accurate environmental commodity consumer valuations. Davis and O'Neill (1992) divide their contingent valuation survey data for recreational anglers into subgroups with and without experience purchasing game-permits or licenses and find systematic differences in median willingness to pay across these two groups. Teisl et al. (1995) examine samples with and without success in a moose hunting permit lottery, and therefore with or without actual experience with a hunt. Other earlier research on the subject (such as Irwin et al, 1990, McClelland et al., 1992, and Lazo et al., 1992) has addressed respondent familiarity or experience in the form of information provided by the survey instrument. Alternately, the respondent's familiarity or experience with the resource is limited to physical conditions on the day the survey is administered (Boyle, Welsh, and Bishop, 1993).

More recently, Whitehead et al. (1995) partition a contingent valuation sample by observed user status (on-site users, off-site users, and non-users) and estimate separate Tobit willingness-to-pay regression equations for each group. Validity of WTP is assessed through the theoretical plausibility of the regression coefficients. Reliability is assessed through comparing WTP estimates responses to a separate question about the "worth" of the resource to the respondent. They conclude that "information acquired by respondents before the survey information is presented can be a key determinant of validity and reliability. In general, validity and reliability increase with familiarity."

Ajzen et al. (1996) use a laboratory experiment and concentrate upon information provided by the survey instrument, concluding that "the nature of the information provided in CV surveys can profoundly affect WTP estimates, and that subtle contextual cues can seriously bias these estimates under conditions of low personal relevance." Personal relevance in this context may reflect prior experience with the good in question.

In this paper, we interpret valuation accuracy to encompass two statistical concepts: the *expected value* of willingness to pay for an environmental resource and the *variance* or *standard error* of the conditional distribution of resource values. It is straightforward in most existing single-equation CV models to allow the expected value of WTP to depend upon experience or familiarity with the good (provided that some exogenous measure of individual experience is available). A variance or standard error for the conditional distribution of the expected value of willingness to pay that varies according to the respondents previous experience with the good is a form of heteroscedasticity. Allowing the variance of WTP to depend upon experience or familiarity requires models that allow for this heteroscedasticity.

The modelling exercise is further complicated by the fact that experience or familiarity with environmental goods may be obtained in two ways. A respondent may have experience that is *exogenously provided* by a survey instrument, or *endogenously determined* by the respondent's past behavior. The exogeneity of experience has been a maintained hypothesis in most previous research. Abstraction from endogenously obtained prior experience may be appropriate with very obscure commodities, but for most environmental commodities, respondents themselves will have acquired varying levels of experience with the commodity in question, or at least with closely related commodities. The incremental information provided on a survey questionnaire will not be perfectly correlated with the totality of their experience with the good. Thus it may not be an adequate proxy for total experience. In most settings, two basic relationships must be modelled simultaneously: one that predicts willingness-to-pay (WTP) as in a traditional single-equation CV setting, and one that predicts the varying amounts of prior information or experience that each respondent possesses and may utilize when answering the CV questions.

This paper develops an econometric framework to assess the impact of experience on both the expected value of estimated WTP and the variance around that value. We apply our framework to a question about the willingness to pay for a doubling of the abundance of trout in the northeastern United States. First, we examine simple single-equation models for WTP that treat the respondent's experience as exogenously given. We then extend the analysis to a two-equation framework that models explicitly the joint determination of cumulative experience or information (INF) and respondents' nonmarket values. Finally, we develop and implement two-equation models to avoid simultaneity bias and further generalize by allowing our submodel for WTP to display heteroskedasticity with respect to experience.

Why are the effects of respondent experience an important consideration in empirical CV analyses? In the aftermath of the Exxon Valdez oil spill in Prince William Sound in Alaska, considerable academic, policy and legal interest focussed upon the use of contingent valuation methods (see Hausman, 1993, and Arrow et al., 1993). One important controversy concerns the use of CV to assess the value of a resource to non-users, also called "passive use" value. Much of the discussion hinges upon the notion that everyone can be readily classified as either a user or a nonuser of the resource in question. In reality, there is a multi-dimensional continuum of usage intensity. Usage status is not a simple binary variable.

In one interpretation, strictly passive users could be argued to be those individuals with zero personal experience with the resource in question. One methodology for estimating passive use value consistent with this definition might be to calibrate a model wherein value depends upon use, and then to simulate the economic values to each individual if positive levels of use were reduced counterfactually to zero. Since usage histories are likely to depend upon many of the same unobservable variables as resource values, self-selected users would form an inappropriate sample upon which to calibrate a model to use in such counterfactual simulations. Our illustrative empirical example has the benefit of a random sample of both users and non-users.

While reliable measures of passive use value are one current objective in CV research, one troubling aspect of non-use valuation is that non-users may not have experience with good in question and, as a result, their contingent values are often deemed "unreliable." As a remedy for the potential distortions in value that arise from inexperience, models such as those described in this paper could be used to calibrate the effects of experience on both the mean and the variance of the conditional distribution of resource values. These models could then be used to simulate, counterfactually, individuals' value distributions if they possessed some standardized minimum level of experience with the resource.

The second section of this paper outlines alternative econometric specifications for experience-heteroscedastic referendum CV data with endogenous experience levels. Section 3 describes a sample of data we use to illustrate this model. Section 4 assesses the empirical results and section 5 highlights the major findings and the policy implications of this study.

II. A MODEL OF INFORMATION IN CONTINGENT VALUATION

Our theoretical model closely follows the development of the conventional referendum contingent valuation model. We begin with a utility function that is defined over an environmental good, G, and the respondent's degree of familiarity with (or information about) this good, INF:

$$U = F(G, INF) \tag{1}$$

The compensated willingness-to-pay (C^* or WTP) for the good is defined as

$$U(0, INF, Y) = U(G, INF, Y-C^*) \tag{2}$$

Solving for the compensated WTP yields

$$WTP = C(G, INF, Y) \tag{3}$$

Following from equation (3), our empirical implementation begins with the assumption that the respondent's true but unobservable WTP for the environmental improvement varies systematically with a vector of individual attributes, X_i. It also varies systematically with the respondent's information about (experience with) this environmental resource, INF_i. The simplest specification we examine is single-equation and linear:

$$(4) \qquad WTP_i = X_i'\beta + (INF_i R_i)'\delta + \epsilon_i.$$

R_i, the vector of variables interacted with INF_i, may include some or all of the variables in X_i, or it may be as simple as a constant term. Our contention, however, is that information or experience may be endogenously determined, so we also specify an equation for information:

$$(5) \qquad INF_i = Z_i'\gamma + \eta_i.$$

Since common unobservable factors may simultaneously influence the magnitudes of WTP_i and INF_i, we must assume that their error terms, ϵ_i and η_i, are correlated.

Empirical researchers in this area are well-accustomed to the use of probit- or logit-based algorithms for fitting WTP functions using the valuation data produced by discrete-choice (or "referendum") contingent valuation surveys. In this particular survey format, each survey instrument merely offers a certain randomly assigned dollar amount and asks whether the respondent would or would not be willing to pay this amount under the scenario in question. Their discrete yes/no responses lead to the use of the probit or logit framework. (See Bishop and Heberlein, 1979, Hanemann, 1984, and Cameron and James, 1987)

Standard maximum likelihood probit or logit coefficients produced by packaged computer algorithms can be transformed to produce estimates of the underlying WTP function (Cameron (1987,1989), and Patterson and Duffield (1991)). For this application, however, we must specify and estimate a model for WTP with an endogenous explanatory variable (INF). The more-familiar single-equation algorithms will be inappropriate. Furthermore, we wish to allow for systematic variation in the estimated error variance in the WTP model (i.e. heteroscedasticity). Standard applications which rely upon transformations of the estimates produced by a packaged probit maximum likelihood algorithm are inappropriate because they typically assume a constant conditional error variance in the underlying stochastic willingness-to-pay function. We must develop new econometric models to accommodate this framework.

A Joint Normal/Censored-Normal Model for Experience and WTP

One common approach to modelling referendum CV questions is to assume that the WTP is distributed normally.[2] The assumption of normally distributed errors suggests using a probit-type model for the referendum WTP responses. In this application, however, we also simultaneously model the information set or degree of experience (INF) of each respondent. One natural approach would be to assume that information is normally distributed also. In this framework the errors in equations (1) and (2) are bivariate normally distributed with correlation ρ:

$$(6) \qquad (\epsilon_i,\eta_i) \sim BVN(0,0,\sigma^2,\nu^2,\rho)$$

This error specification might suffice except for our prior belief that respondents with more information (greater experience) may be able to answer the CV question more precisely. This increased precision will manifest itself as heteroscedasticity in the conditional standard error of the WTP equation, σ. It would be inappropriate to allow σ to vary systematically with the level of *observed* INF_i, because this variable has η_i as one of its components.[3] Thus we will convert the conditional standard error of the WTP function, σ, to a systematic varying parameter by modelling it as a function of the fitted value of INF_i, namely $Z_i'\gamma$, as well as a vector of other sociodemographic attributes of the respondent, $Y_i'\sigma^*$. Since σ must be constrained to be non-negative, we will estimate the joint model in terms of $\sigma = \exp(Y_i'\sigma^* + \sigma_1 Z_i'\gamma)$.

A statistical inconvenience of the referendum format is that we do not observe the point value of the WTP_i variable, but only a discrete response, I_i, to the question of whether this WTP is greater than a specified randomly assigned threshold, t_i. If $WTP_i \geq t_i$, then $I_i = 1$; if $WTP_i < t_i$, then $I_i = 0$. This means that the joint density for the two observable quantities involves one binary discrete variable, I_i, and one continuous (or, later, integer) variable, INF_i. In constructing the log-likelihood function for the model, it is convenient to represent this joint probability as the product of a conditional probability and a marginal probability density function. Suppressing the i subscripts, the log-likelihood can be written as:

(7) $$\log \mathcal{L} = -(n/2)\log(2\pi) - n \log \nu - .5\, \Sigma_i \{ (INF_i - Z_i'\gamma)/\nu \}^2 + \Sigma_i \{ I_i \log[1 - \Phi (W_i)] + (1 - I_i) \log [\Phi (W_i)] \}$$

where

$$W_i = [(t_i - X_i'\beta)/\sigma - \rho((INF_i - Z_i'\gamma)/\nu)] / (1-\rho^2)^{.5}$$

and

$$\sigma = exp[Y_i'\sigma^* + \sigma_1 (Z_i'\gamma)].$$

The likelihood function in (4) must be maximized with respect to the vectors of coefficients (β,γ,σ^*) and the scalar coefficients (σ_1,ν,ρ) using a general nonlinear function-optimizing program.[4,5]

A Joint Poisson/Censored-Normal Model for INF and WTP

The stochastic properties of the joint normal distribution underlying the model in the previous subsection are not entirely compatible with the properties of the data. While WTP could conceivably be negative, it is not possible to have negative amounts of information or experience as measured by our particular proxy variable. The experience variable, number of years of fishing, takes on only non-negative integer values in our illustrative data. Experience in this case can be modelled more naturally as a discrete random variable that is distributed Poisson. Models based on jointly distributed Poisson and normal random variables, with non-zero correlation, appear not to have been employed in the literature. Consequently, the log-likelihood function for this model must be explicitly derived. The complete derivation of a joint Poisson/censored-normal model (without regressors) is contained in the Appendix.

To use this Poisson/censored normal model with our application, we must generalize the log-likelihood derived in the Appendix to a bivariate *regression* model. This is accomplished by letting the Poisson parameter λ (i.e. the expected value of the experience variable, INF) depend upon a vector of explanatory variables according to $\lambda = exp(Z_i'\gamma)$. The mean of the normal variable (i.e. willingness to pay, WTP) is likewise generalized to depend on covariates according to $\mu = X_i'\beta$. The joint regression log-likelihood function becomes:[6]

(8) $$\log \mathcal{L} = -\sum_i exp(Z_i'\gamma) + \sum_i INF_i(Z_i'\gamma) - \sum_i \log(INF_i!) + \sum_i \{ I_i \log[1 - \Phi(W_i)] + (1 - I_i) \log[\Phi(W_i)] \}$$

where

$$W_i = [(t_i - X_i'\beta - \rho\sigma(INF_i - exp(Z_i'\gamma))/(exp(Z_i'\gamma)^{.5}) / \sigma(1-\rho^2)^{.5}$$

If we introduce heteroscedasticity by allowing the conditional variance of the valuation distribution to depend systematically upon expected experience, $\exp(Z_i'\gamma)$ and other control factors, the σ term in the expression for W_i in (10) generalizes to

(9) $$\sigma = exp[Y_i'\sigma^* + \sigma_1 \log(exp(Z_i'\gamma))].$$

Above, we mentioned the potential usefulness of these models for counterfactual simulation of WTP values if experience was zero for all respondents. In this formulation, simulating zero experience would mean setting $\exp(Z_i'\gamma)$ to zero. Since the log of zero is negative infinity, the predicted conditional standard deviation, σ, will go either to infinity or to zero according to the sign of the coefficient σ_1. This artifact of functional form prevents us from offering simulated distributions for WTP under the assumption that all users are passive users--an exercise that may be sensible in other, future analyses using different distributional assumptions.

A Joint Zero-inflated Poisson/Censored-Normal Model for Experience and WTP

In situations where there are more zeros than expected under any distribution in the Poisson family, it is possible to generalize the Poisson distribution to accommodate these excess zeroes with a zero-inflated Poisson (ZIP) model (see Greene, 1994). The simplest of these models allows extra probability, in the amount q, to be associated with the zero outcome, while the Poisson portion of the distribution is scaled by a factor (1 - q). It is straightforward to make this modification to the model described in the section above.

Since the Poisson probability at zero can be expressed as exp(-λ), the ZIP univariate density function can be described most easily by distinguishing between the probability at zero and the probability at positive integer values:

$$\Pr(INF=0) = q + (1-q)\,exp(-\lambda)$$

$$\Pr(INF=INF_i) = (1-q)\,exp(-\lambda)\,\lambda^{INF_i} / INF_i!\ .$$

Recall that $\lambda = exp(Z_i'\gamma)$ generalizes these models to a regression context.

The log-likelihood function can be simplified by defining an indicator variable, POS_i, such that $POS_i = 1$ if $INF_i > 0$ and $POS_i = 0$ if $INF_i = 0$. The "Poisson" terms in the first portion of the log-likelihood function differ, as does the definition of W_i, but the "probit" terms in the second portion of the log-likelihood are similar (except for the term W_i):

$$(10)\qquad \log \mathcal{L} = \Sigma_i\,(1 - POS_i)\log[(1-q)exp(-Z_i'\gamma) + q]$$
$$+ POS_i\,[\,\log(1-q) - exp(Z_i'\gamma) + INF_i(Z_i'\gamma) - \log(INF!)\,]$$
$$+ \Sigma_i\,\{\,I_i \log[1 - \Phi(W_i)] + (1 - I_i)\log[\Phi(W_i)]\,\}$$

where

$$W_i = \{\,(t_i - X_i'\beta)/\sigma - \rho[\,(INF_i - (1-q)exp(Z_i'\gamma)) / (\,(1-q)exp(Z_i'\gamma)[1+q(exp(Z_i'\gamma)]\,)^{.5}\,]\,\} / (1-\rho^2)^{.5}$$

and now,

$$\sigma = exp[\ Y_i'\sigma^* + \sigma_1 \log(\ (1\text{-}q)exp(Z_i'\gamma)\ )\ ].$$

The modifications to W_i and σ stem from the fact that for a ZIP distribution, $E[INF] = (1 - q)\lambda$ and $Var[INF] = (1 - q)\lambda[1 + \lambda q]$.

Note that this simplest ZIP/censored-normal model involves only one more parameter, q, than our Poisson/censored-normal model. In more general specifications, it would be possible to let q depend upon observable data as well, but we do not pursue such models here.

III. DATA

In this application we employ a subset of the data from the National Acid Precipitation Assessment Program (NAPAP). Interested readers are referred to the documentation for that extensive study (Shankle, et al. (1990)) for further information about the survey questionnaire, the sampling strategy, response rates, and other pertinent information concerning the full data set.

Much of the data used in this study was collected as part of the NAPAP "screening questionnaire", which was designed to be a stratified random sample of all residents of 40 counties in New York, Vermont, Maine and New Hampshire. The particular referendum CV question upon which we will focus was worded:

"If the abundance of trout could be doubled in lakes and streams in the Northeast, would you be willing to pay ____ per year for this benefit?"

Dollar amounts between $5 and $100 were randomly inserted on each questionnaire prior to each interview. Each respondent's yes or no answer was recorded. Several socioeconomic variables were also collected.[7]

Following Hanemann (1984), we treat the annual offered payment amount, t, as a subtraction from annual income. Our underlying indirect utility function is assumed to be linear in income, and thus the level of income itself drops out of the utility-difference function, $X_i'\beta$, that is presumed to dictate each respondent's yes or no responses to the referendum WTP question. We specify willingness-to-pay to double trout abundance as a function of the X-vector consisting of AGE (and AGE^2), gender (FEMALE), and three state dummy variables (ME, NH, and VT for Maine, New Hampshire, and Vermont, relative to the base category, New York). Descriptive statistics for all of the variables employed in our analysis are given in Table 1.

There are a number of alternative types of information about the nature of each respondent's experience with trout fishing. We know whether the respondent has ever gone fishing either in the current year or in the past, whether they are experienced enough to list their target species, and the number of past years in which they have fished. While it seems attractive to develop more elaborate models which allow multi-dimensional indicators for experience, current computational limitations require that we select a single variable to measure experience. One manageable candidate seems to be the number of past years in which they have fished plus whether they have fished yet in the current year. This variable will be INF_i in our models.

As explanatory variables for INF, we will employ the same set of variables as are used to explain systematic variation in WTP, so $Z_i = X_i$. Excluded exogenous variables are usually employed to identify the coefficient on an endogenous regressor in fundamentally linear models. However, the intrinsic nonlinearity of our specification does make it possible to identify successfully the coefficients δ on the terms involving INF despite the fact that the other regressors in the two sub-models are identical.[8]

IV. RESULTS

The results consist of a selection of estimated models that explore our sample of contingent valuation data for evidence of dependence of both the expected value and the conditional variance of WTP upon respondents' cumulative experience with the resource. We first present the findings when

Table 1. Descriptive Statistics
(n = 4328)

VARIABLE	DESCRIPTION	MEAN (Std. Dev.)
t	Offered threshold in referendum CV question	\$ 28.84 (29.98)
I	WTP offered threshold? 1=yes, 0=no	0.4198
INCOME	Midpoint of income bracket	\$ 36,257. (27,642.)
AGE	Age of respondent in years	42.25 (15.97)
FEMALE	Dummy variable = 1 if female, = 0 if male	0.5303
ME	Dummy variable = 1 for state of Maine (New York State is omitted category)	0.1446
NH	Dummy variable = 1 for New Hampshire (New York State is omitted category)	0.0975
VT	Dummy variable = 1 for Vermont (New York State is omitted category)	0.1409
TRIPS	Number of Trips	7.98 (13.39)
INF	Number of years in which respondent has gone fishing	7.662 (13.10)

we restrict our specification to the naive assumption that experience is exogenous, the standard censored normal WTP specification. We then present the results when experience is recognized to be potentially endogenous under three alternative distributional assumptions for INF. These include the joint normal/censored normal specification for INF and WTP, the joint Poisson/censored normal specification, and finally the joint zero-inflated Poisson/censored normal specification.

Conventional Single-equation Censored Normal Models for WTP

The first column in Table 2 gives point estimates and associated asymptotic t-test statistics for a the conventional single equation censored normal model of WTP. This model uses the *level* of WTP as the implicit dependent variable. Recall that to restrict σ to be non-negative, we are estimating the logarithm of the conditional regression standard error. Relaxing the assumption of homoscedasticity only marginally improves the log likelihood, from -2579.82 to -2577.48 (using three covariates to explain σ). Thus, we report only the homoscedastic results.

The estimated regression parameters for the expected value of WTP have intuitively plausible signs. The slope coefficients should be considered in light of the average fitted WTP in the sample being roughly \$11. While the coefficients on the AGE variables are not statistically significant, AGE provides an upper bound on experience, so intuition suggests AGE variables ought to be present in the specification so that low values for experience are not simply proxying for lower ages. Female respondents appear willing to pay about \$6 less to double the abundance of trout. Compared to New York residents, residents of Maine, New Hampshire, and Vermont are willing to pay, on average, about \$23, \$10, and \$19 more, respectively, to double the abundance of trout. Actual experience sharply increases WTP; incremental years of experience have an insignificant, although apparently positive effect on WTP.

Table 2. Parameter Estimates for Single- and Two-Equation Models, Without and With Heteroscedasticity (asymptotic t-ratios)

	Normal WTP σ constant	Normal Experience Joint Model, σ constant		Poisson Experience Joint Model, heteroscedastic			Zero Inflated Poisson Experience, Joint Model, heteroscedastic		
	WTP	WTP	INF Experience	WTP	σ	INF Experience	WTP	σ	INF Experience
Constant	-13.05	-16.56	-1.436	-7.045	4.148	0.6841	-9.232	4.374	1.435
	(-1.110)	(-0.906)	(-0.946)	(-0.567)	(13.583)	(13.583)	(-0.731)	(12.915)	(28.543)
Age	0.1565	1.347	0.4869	0.2536	0.03116	0.06680	0.2216	0.03394	0.05194
	(0.299)	(0.299)	(7.010)	(0.438)	(1.820)	(29.741)	(0.383)	(1.724)	(23.049)
$Age^2/100$	-0.3556	-1.443	-0.4446	-0.4322	-0.02855	-0.06131	-0.3334	-0.02036	-0.02845
	(-0.651)	(-0.350)	(-6.111)	(-0.703)	(-1.565)	(-26.438)	(-0.546)	(-1.170)	(-12.144)
Female	-5.768	-19.12	-5.460	-13.79		-0.6932	-9.774		-0.3102
	(-1.899)	(-0.382)	(-13.802)	(-3.168)		(-61.737)	(-2.890)		(-27.588)
Maine	23.13	30.04	2.823	27.51		0.3258	25.22		0.06810
	(5.161)	(1.144)	(4.903)	(5.860)		(22.482)	(5.571)		(4.691)
New Hampshire	10.24	13.55	1.353	13.08		0.1711	11.98		0.06813
	(2.009)	(1.004)	(1.992)	(2.506)		(9.409)	(2.326)		(3.732)
Vermont	19.05	23.79	1.937	22.17		0.2419	20.68		0.1213
	(4.235)	(1.298)	(3.325)	(4.793)		(15.812)	(4.620)		(7.939)
Any INF?	47.78	47.78		45.89			43.35		
	(9.464)	(9.460)		(9.051)			(8.303)		
Years Fished	0.1717	-2.274		-0.6128			-0.3932		
	(1.053)	(-0.248)		(-1.407)			(-1.449)		
Ln(Fitted INF)					**-0.2938**			**-0.5362**	
					(-2.474)			**(-2.086)**	
q									0.5846
									(-2.086)
σ_{WTP}	4.288	4.375							
	(79.47)	(7.326)							
σ_{INF}			12.96						
			(93.04)						
ρ		-0.3991			0.03395			0.1086	
		(-0.3175)			(1.917			(2.609)	
Log Likelihood	-2579.82	-19808.09			-43944.46			-16399.53	

Jointly Estimated Normal/Censored-Normal Models for INF and WTP

The second block of results in Table 2 illustrate the consequences of allowing for endogeneity in the normally distributed experience variable, while retaining homoscedasticity. Since the environmental good in question is not particularly "exotic", individual respondents have self-selected their personal levels of experience with the good. The model uses the likelihood function in equation (7). Further allowing for heteroscedasticity with respect to experience (controlling for AGE and AGE^2) increases the log likelihood only to -19803.49, so we again report just the homoscedastic model.

While none of the regressors except Any INF? in the WTP portion of the model are significant, all of the slope parameters in experience (INF) submodel are statistically significant. The experience submodel contains ssome interesting results. On average, females have gone fishing in five and a half fewer years than have males, and residents of Maine, New Hampshire, and Vermont have fished 1.3 to 3 years more than residents of New York. The linear and quadratic AGE coefficients are both statistically significant and suggest that lifetime fishing experience is greatest for respondents currently about 55 years old. (This may be a cohort effect or an age effect; it is impossible to distinguish between cohort and age effects in a cross-sectional sample such as this one.)

Jointly Estimated Poisson/Censored-Normal Models for Experience and WTP

Troubled by the probably inappropriate normality assumption for the experience variable, we have considered the implications of alternative specifications. The third block of results in Table 2 summarize the consequences of employing the Poisson distribution to model experience. The Poisson submodel captures both the non-negativity of the years-of-experience variable and its integer character. Note that the fitted value of a Poisson-distributed random variable will never be zero or negative because of its inherent log-linear functional form. This has implications for the logical specification of the WTP standard error submodel. Since the submodel for experience specifies fitted INF as *exp*($Z_i'\gamma$), we are implicitly assuming log(INF) = $Z_i'\gamma$. Therefore, instead of using simply the level of Fitted INF in the WTP standard error submodel, we employ log(fitted INF).

The most important aspect of this model, however, is its results for heteroscedasticity: neither of the AGE variables has, individually, a strong statistically significant effect upon the magnitude of the WTP standard error, σ. (Nevertheless, the point estimates on the coefficients suggest that maximum WTP standard error is attained in the 55-year-old cohort.) The key result is that this model suggests that log(fitted INF) has a statistically significant effect upon the magnitude of this standard error; WTP is heteroscedastic, with the error dispersion decreasing with increasing experience. The "elasticity" of the WTP error standard deviation with respect to fitted experience is -0.2938 (t = 2.474).

Jointly Estimated ZIP/Censored-Normal Models for INF and WTP

The preponderance of zeros in the data for number of years fished (INF_i) prompts exploration of zero-inflated Poisson (ZIP) generalizations. This generalization allows for the possibility that some of the observed zeros are not part of the Poisson process, but rather, respondents face a separate "hurdle" that keeps them from having any experience. The experience submodel for the joint ZIP/censored-normal model in the last block of Table 2 reveals that the parameter capturing the additional probability at zero, q, is 0.5846, with a t-ratio of over 78, so the ZIP generalization is clearly warranted. This parameter suggests that 58.46% of the population will not ever go fishing, indicating that they are not "in the market" to be anglers.

The effect of the ZIP generalization is to decrease somewhat the slope coefficients in the WTP expected value submodel and to decrease more substantially the slopes in the experience submodel. The E[WTP] continues to be on the order of $43 higher for respondents who have had any years of fishing experience at all. The point estimate of the incremental effects of additional years of fishing experience on WTP remains negative, as in all models with endogenous experience, but is statistically insignificantly different from zero.

In the WTP standard error submodel, the coefficients on the age variables are again not individually statistically significant. The key result, again, concerns the coefficient on the log(FITTED INF) variable. The ZIP specification roughly doubles the elasticity of the estimated WTP error standard deviation with respect to fitted experience, from -0.29 to -0.54, and the coefficient remains statistically significant (t = -2.086).

Implications of Alternative Specifications for Estimated WTP (Fitted Values)

In models where the conditional density function for WTP is assumed to be normal, it is possible for the conditional expectation of WTP for individual observations to be negative. Sometimes negative WTP values are intuitively acceptable (interpreted as the amount the respondent would have to be paid to accept the scenario, rather than the amount the respondent would be willing to pay to obtain the scenario). In other contexts negative values are not acceptable. The desire by researchers to avoid negative fitted WTP values frequently leads to specifications involving logarithmic transformations, so that fitted WTP cannot be less than zero. This transformation can impose a too-highly skewed distribution for the implicit WTP variable, however, leading to implausibly large expected values for the *level* of WTP (especially after the customary $\exp(\sigma^2/2)$ factor is applied).[9]

An alternative approach is to adapt the intuition behind a conventional maximum likelihood Tobit regression model. We can interpret the latent dependent variable in the WTP portion of the model as a "propensity-to-pay." If the fitted propensity is positive, it is interpreted as a fitted WTP. If the fitted propensity is negative, it is interpreted as a zero value for WTP. We can thus admit for positive probability associated with negative values of the latent propensity variable, fitting a specification with conditional normal errors.

At the stage of calculating fitted WTP, though, each respondent can be treated as representative of some large number of identical potential respondents in the population. The fitted conditional probability density function for WTP for that respondent with a particular set of characteristics is interpreted as the distribution of WTP values in that subset of the population. If negative WTP values are to be disallowed, the appropriate strategy is to treat all respondents with negative WTP as having simply zero WTP. The "average" value of WTP for this subset of the population is then inferred from the expected value of WTP conditional on WTP being positive, times the fraction of this subset of the population having positive WTP. The appropriate formulas employ the expectation of a censored normal random variable (see Maddala, 1983, p. 365, or Greene's (1993) econometrics textbook). It can be shown that expected WTP under this interpretation is given by:

$$(11) \qquad \Phi(X_i'\beta/\sigma) \, [\, X_i'\beta + \sigma \, \{ \, \phi(X_i'\beta/\sigma) \, / \, \Phi(X_i'\beta/\sigma) \, \} \,].$$

Where $X_i'\beta$ is the fitted value of the normally distributed WTP variable. Depending upon the particular specification in question, the parameter σ may be either a scalar or some function of the fitted value of the INF variable ($Z_i'\gamma$ in the case of the Normal model (or $exp(Z_i'\gamma)$ for the Poisson model, and $(1-q)exp(Z_i\gamma)$ in the case of the ZIP model).

Table 3 reports the implications for sample average fitted WTP for each model of allowing or dis-allowing negative WTP. The first two rows allow negative fitted values of WTP to be included as legitimate values. The second two rows use the representative individual interpretation outlined above and impute zero fitted WTP to the proportion of the conditional distribution of WTP lying below zero for each observation. The entries in the body of Table 3 give the sample average of

Table 3. Simulations of Expected Willingness-to-pay Under Two Experience Baselines

	Normal WTP σ constant	Normal Experience Joint model, σ constant	Poisson Experience Joint model, heteroscedastic	Zero Inflated Poisson Experience, Joint model, heteroscedastic
NEGATIVE WTP ADMISSIBLE				
Sample Average	$11.49	$11.49	$10.09	$10.74
Experience $\geq$ 1 year	$39.52	$38.09	$36.56	$35.85
NEGATIVE WTP INADMISSIBLE				
Sample average	$37.31	$39.26	$36.42	$36.54
Experience $\geq$ 1 year	$53.26	$56.44	$52.06	$42.20

individual fitted values of E[WTP].

If negative WTP values are admitted, all of the specifications examined in Table 2 imply roughly the same overall average fitted WTP (an amount varying from \$10.09 to \$11.49). If the negative portions of each WTP distribution are treated as zero values the models have similar findings as well, but with larger overall averages between \$36 and \$39.

There has been some suggestion in the literature that CV estimates of WTP for some environmental goods are only reliable if respondents have had some degree of experience with the commodity being valued. Our models are also well-suited to simulation of the results for E[WTP] of imposing a minimum of one year of fishing experience for all respondents. Table 3 also reports the results of these simulations. When we allow negative fitted values of E[WTP], the second row of Table 3 gives the results for each specification. For all specifications, the simulated sample average E[WTP] is in the neighborhood of \$35 to \$49. This implies that the estimated value of the resource would be between three and four times greater if all respondents had a minimum of one year angling experience. Recall that we have estimated experience and WTP jointly in so we have controlled to a considerable extent for the self-selection of active users in the WTP specifications in those models.

Alternatively, we may disallow the negative portion of the fitted conditional WTP distributions and treat all negative values as zero WTP values. Simulated average E[WTP] values when all respondents are assigned a minimum of one year of experience are around \$52 or \$53 when we do accept negative fitted WTP. The normal/censored-normal models exhibit fitted average E[WTP] values on the order of \$56, whereas the Poisson/censored-normal model implies \$52 and the ZIP/censored-normal model implies \$42. These results suggest that the value of the environmental enhancement in the scenario (a doubling of the abundance of trout) would be roughly five times higher if all respondents had some minimal level of experience with the environmental good in question and negative WTP values were disallowed.

V. SUMMARY

This research has addressed the issue of whether the level and precision of willingness to pay for environmental resources is systematically related to respondents' own experience with the good in question. Earlier research on the subject (such as Irwin et al, 1990, McClelland et al., 1992, and Lazo et al., 1992, Ajzen et al., 1996) concentrated on "experience" in the form of information provided by the survey instrument. Others have treated respondents' own experience as exogenous (Whitehead et al., 1995). Others have limited the respondent's "experience" with the resource to their physical experiences on the day the survey is administered (Boyle, Welsh, and Bishop, 1993). In this paper, we interpret experience as the number of years in which an individual has been a user of the resource in question--the amount of time the respondent has had to allow their value to "crystallize." We believe that this definition of experience is particularly relevant to the issue of use versus non-use (or active- versus passive-use) values for an environmental good. In general both definitions can be handled in the framework presented here.

What have been the innovations in this research? One innovation is the explicit recognition that experience of this variety cannot be considered to be exogenous. We first demonstrate this by implementing a bivariate normal/censored-normal model for experience and WTP. A further innovation is our modification of this joint model to employ a Poisson or a ZIP distribution for the non-negative integer-valued experience variable. A third innovation is the use of our calibrated models to simulate the consequences for expected WTP of endowing all respondents with a minimum level of experience (one fishing year). These counterfactuals explore the implications of requiring that all respondents have some minimum common experience with the good in question before their referendum contingent valuation WTP responses are considered credible.

What are our results concerning the effect of experience with the resource on the conditional distribution of willingness-to-pay for this particular environmental enhancement? In all of our specifications, the expected value of WTP jumps markedly and significantly with any positive amount of experience (by an amount in the order of $45). If the endogeneity of experience is ignored, the expected value of WTP may appear to *increase* for each additional year of fishing experience. In models with endogenous experience, however, additional years of experience seem to be associated with expected WTP that is slightly *lower*, although this effect is not generally significant.

We do uncover a *robust* tendency for additional experience to decrease systematically the conditional standard deviation of our fitted WTP function. Our Poisson/censored-normal and ZIP/censored-normal specifications with endogenous experience are consistent with the prevailing intuition that more experienced respondents provide more precise WTP information.

Where should future research proceed from here? First, our empirical results demonstrate what *can* happen, and are not necessarily generalizable to all other applications. It is also true that "experience" is a multi-faceted concept. It would be informative to conduct a study wherein a wide variety of different experience variables were collected and evaluated. For example, in the current context, years of experience could be expanded into an entire distribution of past and present fishing habits, with geographical resolution, species resolution, and life-cycle resolution. Any information regarding the resource that is provided by the survey instrument could also be varied systematically across respondents in an effort to distinguish between the independent and interaction effects of personally acquired "natural experience" and of researcher-provided "survey instrument experience".

Econometrically (and preferably with a richer data set) it would be helpful to explore models that allowed skewed, strictly non-negative distributions for the latent variable underlying the discrete referendum WTP variable. These distributions would have to be specified jointly with an appropriate more-general distributional assumption for quantity of endogenous experience. In addition to the dominant ZIP model above, one could consider even further generalizations. For example, the excess probability at zero, q, could easily be rendered a systematic varying parameter.

What about using samples of active resource users to infer the passive use value of a resource to non-users? Extrapolation from active-user samples, loosely speaking, is the underlying assumption in much current theoretical research pertaining to passive use values. For example, Larson (1992) addresses the measurement of nonuse (passive use) values by holding the consumption of weakly complementary market goods to zero. Our empirical findings suggest, however, that the equivalent variation associated with our proposed environmental enhancement scenario does not change smoothly as active use goes to zero. If possible, then, current non-users of the resource should always be included among the survey sample so that continuity in expected WTP and the variance of WTP as experience goes to zero can be assessed. Only if the valuation problem pertains to a resource for which a sufficient number of studies with this breadth have concluded that there is a smooth transition--with no jumps in either mean or variance of WTP with the transition from active to passive user status--can researchers safely contemplate extrapolating passive use value from convenience samples of current resource users. All of the models estimated in this paper reveal a pronounced discrete drop in resource value as our measure of experience (use) changes from some positive amount to zero. The evidence in this study suggests that the simple strategy of extrapolating from a sample of users can greatly over-estimate the passive value of environmental resources.

VI. ENDNOTES

1. The survey research literature tends to use the terms "validity"--whether a measure indeed measures what it is supposed to be measuring, and "reliability"--whether a measure will give approximately the same result when applied to another, similar population. These concepts are related to mean and variance and are subsumed by the less technical term "accuracy."

2. While the normal distribution has very useful econometric properties, it does associate positive probability density with negative WTP values. Depending on the context of the analysis, negative values for WTP may be more or less plausible.

3. Specifically, it would be undesirable to have the dispersion parameter of one of the random variables in a joint distribution such as (6) depend upon the observed value of the other random variable.

4. We use GQOPT, written by S. Goldfeld and R. Quandt at Princeton University. All models are estimated beginning with the DFP algorithm, and then continuing to convergence using the GRADX algorithm with an accuracy level of 10^{-10}.

5. In order to constrain the denominator of W_i to be non-negative and real, it is sometimes helpful to define ρ as $[1-exp(-\rho^*)]/[1+exp(-\rho^*)]$ and estimate the model initially in terms of the unconstrained parameter ρ^* instead of ρ. The invariance property of maximum likelihood ensures that the identical underlying value of ρ can be recovered by employing ρ^* during estimation and then inverting the transformation. One can then solve for ρ and use this starting value for final iterations that produce the desired parameter variance-covariance matrix.

6. The complete derivation is provided in the Appendix.

7. Since the time of this survey, there have been many enhancements to contingent valuation survey techniques. We make no claim that the convenience sample for this illustration represents the state-of-the-art in contingent valuation methodology.

8. With newer and more detailed data sets, richer specifications should certainly be entertained.

9. Other WTP distributional assumptions, such as the Weibull, are not amenable to being generalized for joint distributions.

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APPENDIX

Derivation of a Joint Poisson/Censored-Normal Model

We begin with two independently distributed random variables, Z_1 and Z_2, where Z_1 is distributed Poisson with parameter λ and Z_2 is distributed standard normal. This implies that:

(A1)
$$E[Z_1] = \lambda;\ Var[Z_1] = \lambda$$
$$E[Z_2] = 0;\ Var[Z_2] = 1$$

Now generate two new random variables as follows:

(A2)
$$INF = Z_1$$
$$WTP = \sigma\ [\ \rho(Z_1-\lambda)/\lambda^{.5} + (1-\rho^2)^{.5}\ Z_2\ ] + \mu$$

With these transformations, it can be shown that:

(A3)
$$E[INF] = \lambda;\quad Var[INF] = \lambda$$
$$E[WTP] = \mu;\quad Var[WTP] = \sigma^2$$

The covariance between INF and WTP can be calculated as follows:

(A4)
$$E[(INF-\lambda)(WTP-\mu)] = E\{\ (Z_1-\lambda)\ (\sigma\ [\rho(Z_1-\lambda) + (1-\rho^2)^{.5}\ Z_2])\ \}$$
$$= \rho\sigma\lambda^{.5}$$

Given the variances in equation (A3), the correlation between INF and WTP can be shown to be:

(A5)
$$\rho_{INF,WTP} = \rho$$

The joint density of Z_1 and Z_2, given that they are independent, is

(A6)
$$g(Z_1,Z_2) = [\ exp(-\lambda)\ \lambda^{Z_1}\ /\ Z_1!\ ]\ [\ (2\pi)^{-.5}\ exp(-Z_2^{\ 2}/2)\ ]$$

The transformation from (Z_1,Z_2) to (INF,WTP) is linear, with a Jacobian of:

(A7)
$$J = [\sigma(1-\rho^2)^{.5}]^{-1}$$

The joint density for INF and WTP can be derived by solving the equations in (A2) for Z_1 and Z_2 in terms INF and WTP, substituting these expressions into the joint density in (A6) and scaling by the Jacobian in (A7). This yields:

(A8)
$$f(INF_i,WTP_i) = [2\pi\sigma^2(1-\rho^2)]^{-.5}\ exp(-\lambda)\ \lambda^{INF_i}/INF_i!\ .$$
$$exp\{\ -.5\ (\ [WTP_i - \mu - \rho\sigma(INF_i-\lambda)/\lambda^{.5}]\ /\ [\sigma(1-\rho^2)^{.5}]\ )^2\ \}.$$

Due to the referendum nature of the valuation variable ($I = 1$ if $WTP > t$; $I = 0$ if $WTP \leq t$), it is far more convenient to work with the joint distribution in (A8) decomposed into (i.) the conditional distribution for WTP given INF, multiplied by (ii.) the marginal distribution for INF. Fortunately, INF is distributed Poisson with parameter λ (by construction). Its marginal density is simply:

(A9) $$f(INF) = exp(-\lambda)\, \lambda^{INF_i}/INF_i!$$

Dividing the joint density in (A8) by the marginal density for INF_i given in (A9) yields the conditional density function desired:

(A10) $f(WTP_i \mid INF_i) =$

$$[2\pi\sigma^2(1-\rho^2)]^{-.5}\, exp\{\, -.5\ (\ [WTP_i - \mu - \rho\sigma(INF_i-\lambda)/\lambda^{.5}]\ /\ [\sigma(1-\rho^2)^{.5}]\ )^2\ \}.$$

Note that this conditional density is simply normal, with mean and variance:

(A11) $$E[WTP \mid INF] = \mu + \rho\sigma(INF-\lambda)/\lambda^{.5}$$
$$Var[WTP \mid INF] = \sigma^2(1-\rho^2) \quad \text{(constant)}$$

Since there are discrete outcomes for the valuation question, a probit-like component to the log-likelihood function can be expected. For a sample of n independent observations on the pair of variables (INF,WTP), the joint density can be written in terms of the conditional density times the marginal density and converted to the log-likelihood function as:

(A12) $$\log \mathcal{L} = -n\lambda + \log(\lambda) \textstyle\sum_i INF_i - \sum_i \log(INF_i!)$$
$$+ \textstyle\sum_i \{\ I_i \log[1 - \Phi\ (W_i)] + (1 - I_i) \log\ [\Phi\ (W_i)]\ \}$$

where

$$W_i = [\ (t_i - \mu - \rho\sigma(INF_i - \lambda)/\lambda^{.5})\ /\ \sigma(1-\rho^2)^{.5}$$

To implement this log-likelihood function in a regression context, it is necessary to generalize λ and μ each to be some function of a vector of explanatory variables.