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by

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Abstract

Farmers can be encouraged to voluntarily adopt environmentally sound management practices through the use of incentive payments. This paper uses both a bivariate probit with sample selection model and a double hurdle model on data from a survey of farmers to predict farmer adoption of the practices as a function of the payment offer. The five management practices addressed here are integrated pest management, legume crediting, manure testing, split applications of nitrogen, and soil moisture testing. Also estimated are models that predict the acreage on which these practices would be applied given the decision to accept the incentive payments estimated.

Key words: bivariate probit, double hurdle, incentive payments, sample selection, water quality

In response to increasing public concern over the contribution of agricultural pollutants to the degradation of surface and ground water supplies, the 1990 Food, Agriculture, Conservation and Trade Act (FACTA) authorized the USDA to initiate the Water Quality Incentive Program (WQIP). WQIP is administered by the Natural Resources Conservation Service (NRCS) through the Agricultural Conservation Program (ACP). Its goal is to mitigate the negative impacts of agricultural activities on ground and surface water supplies through the use of stewardship payments and technical assistance to farmers who agree to implement approved practices. With these incentives, farmers are encouraged to experiment with more environmentally benign production practices than they otherwise would use. In 1992 and 1993, the funding levels for WQIP were $6.75 million and $15 million, respectively. Currently, farmers in only a small number of watersheds are eligible to enter the program. However, the issue has been raised (e.g., Sinner) of making this type of incentive payment program more widely available.

WQIP incentive payments are not determined through market interaction. Instead, the payments are essentially a fixed offer amount. As a result, a function modeling the probability of adoption of a practice as a function of the incentive payment cannot be estimated from current market data. Using the results of a survey of farmers, our goal is to model the probability of adopting a preferred farming practice as a function of the incentive payments. This response function would be useful in comparing the benefits and costs of encouraging farmers to try the various preferred management practices. In conjunction with this goal, our secondary goal is to model how many acres the farmer will devote to the new practice, given the decision to adopt.

The USDA believes that the five agri-chemical management and production strategies to protect groundwater that we will examine in this paper are generally profitable for the farmer. Yet, even though their implementation should theoretically boost profitability, not all farmers who could adopt these practices have done so. One reason may be that the farmer is risk averse: even if the alternative practice might appear profitable on paper, the farmer may be unwilling to adopt the practice unless the farmer sees neighboring farmers adopting it. Another reason for not adopting the practice might be that the farmer either has no information, or lacks sufficient information, on the alternative practice. Hence, an empirical comparison of profits or costs under the old and the new practices will not provide enough information to determine the necessary incentive payment to encourage adoption. To avoid these problems associated with estimating minimum willingness to accept (WTA) to change practices as the difference in cost or profit between the two states, one can use a direct revelation technique for assessing the probability of farmer adoption at various incentive payment levels.

Economic Model for WTA in the Case of No Market Transactions

While the researcher could directly elicit from the current nonadopting farmer his or her minimum WTA necessary to adopt the practice, a dichotomous choice (DC) approach is likely to be preferable. Under this approach, the respondent is prompted to provide a "Yes" or "No" response to a dollar bid amount contained in the valuation question, where the bid amount is varied across the respondents. This method is particularly likely to reveal accurate statements of value as the format provides reasonable incentives for value formulation and reliable value statement (Hoehn and Randall).[1] In fact, the National Oceanic and Atmospheric Administration Blue Ribbon Panel's (co-chaired by Kenneth Arrow and Richard Solow) proposed guidelines for conducting natural resource damage assessment using the contingent valuation method (CVM) suggesting that all CVM studies should use the DC format (U.S. Department of Commerce). With the DC approach, instead of trying to identify the farmer's profit function (which would not include any profit-independent reasons to accept the program), we simply need to determine whether or not the farmer's minimum WTA is less than or equal to the offered payment incentive.

The farmer's decision process is modeled using the random utility model approach. From the utility theoretic standpoint, a farmer is willing to accept \$C to switch to a new production practice if the farmer's utility with the new practice and incentive payment is at least as great as at the initial state; i.e., if $U(0,y;x) \leq U(1,y + C;x)$, where 0 is the base state, 1 is the state with the WQIP practice, y is farmer *i*'s income, and **x** is a vector of other attributes of the farmer that may affect the WTA decision. C can be written as $C^* + \delta$, where δ is state 0 pecuniary costs less state 1 pecuniary costs, and where C^* is the government's incentive payment. Hence, C can be considered a 'net' incentive payment. Note that δ can be positive; due to some nonpecuniary costs, a farmer may not have switched to the preferred practice even if δ is positive. The farmer's utility function U(i,y;s) is unknown because some components are unobservable to the researcher, and thus, can be considered a random variable from the researcher's standpoint. The observable portion is V(i,y;x), the mean of the random variable U. With the addition of an error ε^i, where ε^i is an independently and identically distributed random variable with zero mean, the farmer's decision to accept \$C can be re-expressed as

(1) $$V(0,y;x) + \varepsilon^0 \leq V(1,y + C;x) + \varepsilon^1.$$

If $V(i,y;x) = \gamma^i + \alpha y$, where $\alpha > 0$, for i = 0,1, then the farmer is willing to accept \$C for the change if $\gamma^0 + \alpha y + \varepsilon^0 \leq \gamma^1 + \alpha(y+C) + \varepsilon^1$.

The decision to accept \$C can be expressed in a probability framework as $\Pr\{WTA \leq \$C\} = \Pr\{V^0 + \varepsilon^0 \leq V^1 + \varepsilon^1\} = \Pr\{\varepsilon^0 - \varepsilon^1 \leq V^1 - V^0\}$, where $V^1 - V^0 = \gamma + \alpha C$, and where

$\gamma = \gamma^1 - \gamma^0$. Because $V^1 - V^0 = \gamma + \alpha C$ is generated directly from the utility model given above, it is compatible with the theory of utility maximization. The probabilities of participation in the program for a schedule of incentive payments simply can be obtained through $P_i = F_\varepsilon(\Delta_i)$.[2] Because rates of adoption at a particular incentive payment value may vary among the practices, the optimal rate of adoption may not be the same across the practices from a cost effectiveness standpoint.

Estimation of Minimum WTA and Level of WQIP Enrollment.

Traditionally, univariate probit or logit is used to analyze qualitative dependent variable data. However, in this case the DC data may be nonrandomly selected from the survey respondents as only those respondents who do not currently use the preferred practices were asked the DC questions. Regressing the DC data without accounting for the nonrandom selection of this data from the survey data set can produce biased and inefficient coefficient estimates (Boyes, Hoffman, and Low). For the survey, a sample selection question was used to identify respondents who do not currently (in 1992) use the practice. Next, respondents who said that they did not currently use the practice were asked the WTA question. Formally, denoting the 0/1 response to the sample selection question as y_{2i} and denoting the 0/1 response to the adoption question as y_{1i}, y_{1i} is observed only when $y_{2i} = 0$. In other words, the disturbances are correlated between the two questions. The system of equations is presented in utility difference form as:

(2) $\Delta V_{1i} = \mathbf{x}_{1i}'\boldsymbol{\gamma}_1 + \alpha C_i = \varepsilon_{1i}$ where $y_{1i} = 1$ if $\Delta V_{1i} \leq \varepsilon_{1i}$, $y_{1i} = 0$, otherwise,

(3) $\Delta V_{2i} = \mathbf{x}_{2i}'\boldsymbol{\gamma}_2 = \varepsilon_{2i}$ where $y_{2i} = 1$ if $\Delta V_{2i} \leq \varepsilon_{2i}$, $y_{2i} = 0$, otherwise

$(\varepsilon_{1i}, \varepsilon_{2i}) \sim$ bivariate normal $(0,0,1,1,\rho)$,

where equation (2) is the adoption equation discussed in the previous section, $y_{1i} = 1$ if farmer i's true WTA is greater than the bid offer, $\Delta V_{1i} = V^0_i - V^1_i$, $\mathbf{x}_i^{1\prime}\boldsymbol{\gamma} = \mathbf{x}^0_{1i}{}'\boldsymbol{\gamma}_0 - \mathbf{x}^1_{1i}{}'\boldsymbol{\gamma}_1$, $\varepsilon_{1i} = \varepsilon^1_{1i} - \varepsilon^0_{1i}$, and C is the incentive payment offer. Using the same format as (2), equation (3) is the sample selection equation. Assuming a bivariate normal relationship for ε_{1i} and ε_{2i}, bivariate probit is used to estimate the two sets of coefficients. The bivariate probit with sample selection log-likelihood function for the situation where y_{1i} is observed only when $y_{i2} = 0$ is:

(4) $$\ln L(\boldsymbol{\gamma}_1,\boldsymbol{\gamma}_2,\rho_{12}) = \sum_{y_{2i}=0,y_{1i}=1} \ln\Phi_a[\mathbf{x}_{1i}'\boldsymbol{\gamma}_1,-\mathbf{x}_{2i}'\boldsymbol{\gamma}_2,-\rho_{12}] + \sum_{y_{2i}=0,y_{1i}=0} \ln\Phi_a[-\mathbf{x}_{1i}'\boldsymbol{\gamma}_1,-\mathbf{x}_{2i}'\boldsymbol{\gamma}_2,\rho_{12}] + \sum_{y_{2i}=1} \ln\Phi[\mathbf{x}_{2i}'\boldsymbol{\gamma}_2],$$

where **C** is included in $\mathbf{X}_1$ for notational simplicity, Φ is the normal CDF, Φ_a is the bivariate CDF, and ρ_{12} is the correlation coefficient between the two equations. Because the likelihood function in equation (4) contains more information than would a univariate probit likelihood function for equation (2), maximization of equation (4) offers efficiency gains over univariate probit. Furthermore, equation (4) accounts for potential correlation between (2) and (3) and therefore corrects for the sample selection bias that could occur if (2) were to be estimated singly (Boyes, Hoffman, and Low). The disadvantages of the bivariate log-likelihood function in equation (4) are that convergence of the estimates is not always easily achieved and estimated covariance matrices are frequently singular. Note that if estimated $\rho_{12} = 0$, then the farmers who answer the WTA question can be assumed to be randomly drawn from the sample and equation (3) can be ignored. Equation (2) can then be estimated using probit.

Applying the definition of conditional probability, the farmer response function for the bivariate probit case is as follows:

(5) $\text{Prob}(\text{WTA}_i \geq \text{bid}_i \mid y_{2i} = 0) = \Phi_a(\mathbf{x}_{1i}'\boldsymbol{\gamma}_1, -\mathbf{x}_{2i}'\boldsymbol{\gamma}_2, \rho)/\Phi(-\mathbf{x}_{2i}'\boldsymbol{\gamma}_2)$,

where Φ_a is the bivariate normal probability density function and Φ is the normal probability density function. Potential explanatory variables for $\mathbf{x}_{1i}$ and $\mathbf{x}_{2i}$ include whether or not the farmer believes the practice will affect farm profitability, soil type, type of crop(s) planted, farm size, amount of training needed to implement the practice, and level of environmental awareness and concern. Except for the bid offer, there is no a priori reason why both equations should not use the same explanatory variables. However, even if the variables in the two equations are the same, the estimated coefficients are not necessarily similar. Because observations for those farmers who currently use the practice are analyzed in the regression, additional information is added to the estimation of equation 2 if it is estimated simultaneously with equation 3.

As stated earlier, estimating the probit or bivariate probit with the sample selection model is the first step of our research agenda. In addition to developing the farmer participation equation as a function of the offer amount, we would also like to know how many acres the farmer will enroll given, the decision to participate.[3] The number of acres enrolled in the preferred practice by farmer *i* can be stated as:

(6) $PACRES_i = \mathbf{z_i}'\boldsymbol{\theta} + u_i$,

where $PACRES_i$ is the amount of acres in the preferred practice, $\mathbf{z_i}$ is a vector of explanatory variables, and u_i is a random disturbance with mean zero. Explanatory variables can include the payment offer, length of participation in the program, total acreage, erosion potential, farm income, and amount of off-farm work.

Unfortunately, ordinary least squares (OLS) estimates of equation (6) on farmers who do not currently use the preferred practice, but agree to do so with the incentive payment, have the potential for serious bias. Because these hypothetical acreage enrollments are only observed for the farmers who answered "Yes" to the WTA question, the sample for equation (6) is not drawn randomly from the population who answered the survey, implying omitted variable bias. Furthermore, additional bias may be added as only those answering "No" to the sample selection question were asked the WTA question. In addition to being potentially biased, OLS estimation of equation (6) is inefficient (Greene, 1990). Equation (6) can be corrected by considering the responses to the two qualitative dependent variable questions in the analysis of equation (6).

In this paper, an extension of the Heckman procedure to three equations is used for estimation (Tunali; Greene, 1992) when ρ is statistically different from zero. Since $PACRES_i$ is observed only when $y_{1i} = 1$ and $y_{2i} = 0$, the revised version of equation (6) is:

(7) $E[PACRES_i \mid z_i, \text{in sample}] =$

$$= E[PACRES_i \mid z_i, y_{1i} = 1, y_{2i} = 0]$$

$$= E[PACRES_i \mid z_i, \varepsilon_{1i} \geq \Delta V_{1i}, \varepsilon_{2i} < \Delta V_{2i}]$$

$$= \mathbf{z_i}'\boldsymbol{\theta} + E[u_i \mid \varepsilon_{1i} \geq \mathbf{x}_{1i}'\boldsymbol{\gamma}_1 + \alpha C_i, \varepsilon_{2i} < \mathbf{x}_{2i}'\boldsymbol{\gamma}_2]$$

Tunali shows that equation (7) reduces to:

(8) $PACRES_i = \mathbf{z_i}'\boldsymbol{\theta} + \lambda_{1i}\tau_1 + \lambda_{2i}\tau_2 + \eta_i,$

where η_i is a disturbance term. λ_{1i} and λ_{2i} are defined as:

(9)
$$\lambda_{1i} = \varphi(-\mathbf{x}_{1i}'\boldsymbol{\gamma}_1)\Phi[(-\mathbf{x}_{2i}'\boldsymbol{\gamma}_2 - \rho_{12}\mathbf{y}_{1i})/(1 - \rho_{12}^2)^{1/2}]/\Phi_a$$

$$\lambda_{2i} = \varphi(-\mathbf{x}_{2i}'\boldsymbol{\gamma}_2)\Phi[(-\mathbf{x}_{1i}'\boldsymbol{\gamma}_1 - \rho_{12}y_{2i})/(1 - \rho_{12}^2)^{1/2}]/\Phi_a,$$

where $\mathbf{x}_1 = [\mathbf{x}_1, C]$ and $\boldsymbol{\beta}_1 = [\boldsymbol{\gamma}, \alpha]$ and where Φ_a = bivariate normal CDF $\Phi(\mathbf{x}_1'\boldsymbol{\beta}_1, -\mathbf{x}_2'\boldsymbol{\beta}_2, -\rho_{12})$. The derivatives $\partial\lambda_{1i}/\partial Bid$ and $\partial\lambda_{2i}/\partial Bid$ are less than zero.[4] Consistency of the coefficient estimates from the regression of $PACRES_i$ on $\mathbf{z_i}$, λ_1, and λ_2 follows from the consistency of the estimates of λ_1 and λ_2 (Tunali).

A potential drawback of this selectivity model with bivariate probit sample selection is that it does not address the censored nature of PACRES, which cannot be less than zero. Tobit regression is commonly applied to models where the dependent variable is censored. The tobit application in a sample selection framework is the double hurdle, or Cragg, model (Cragg; Lee and Maddala; Blaylock and Blisard; Gould; Yen). To respecify the selectivity model with bivariate probit sample selection with a tobit structure for the continuous portion would require a trivariate normal distribution to tie together the three equations; i.e., the joint probability $P_i(y_{2i} = 0, y_{1i} = 1, pacres_i > 0)$ would have to be calculated. Because trivariate models are extremely difficult to estimate, for practical purposes, the sample selection equation (3) needs to be dropped in order to use the double hurdle specification. As a result, some of the gains in consistency associated with using the tobit model with the censored data over OLS must be traded-off against some possible loss consistency in giving up the first sample selection stage. In the double hurdle model, equations (2) and (6) are estimated jointly. Assuming that u_i is distributed $N(0,\sigma^2)$ and $corr(u_i, \varepsilon_{1i}) = \rho$, the double hurdle log-likelihood function for the situation where $PACRES_i$ is observed only when $y_{i1} = 0$ is (Greene, 1992):

$$(10) \quad \ln L(\boldsymbol{\gamma}_1,\boldsymbol{\theta},\rho) = \sum_{y_{1i}=0} \ln\Phi[-\mathbf{x}_{1i}'\boldsymbol{\gamma}_1] + \sum_{y_{1i}=1,pacres_i=0} \ln\Phi_a[-\mathbf{z}_i'\boldsymbol{\theta},\mathbf{x}_{1i}'\boldsymbol{\gamma}_1,-\rho]$$
$$+ \sum_{y_{1i}=1,pacres_i>0} \{-0.5[\ln 2\pi + \ln\sigma + (u_i/\sigma)^2] + \ln P_i\}$$

where $u_i = PACRES_i - \mathbf{z}_i'\boldsymbol{\theta}$, $\tau_i = \mathbf{x}_{1i}'\boldsymbol{\gamma}_1 + \rho u_i/\sigma$, and $P_i = \Phi[\tau_i/(1 - \rho^2)^{1/2}]$. As with the bivariate model, interaction between the two equations is carried on through ρ. Note that since the data set does not contain cases where $y_{i1} = 1$ and $PACRES_i = 0$, the middle term of the log-likelihood function drops out and the log-likelihood model reduces to the standard tobit model.[5]

Because the survey sampled some regions at higher rates than others (e.g., noncropland areas were sampled at lower rates than cropland areas), the data were scaled by sampling weights. Not accounting for this exogenous stratified sampling presents the potential for serious bias in the coefficient estimates. Multiplying the data by the weights gives greater weight to observations that have a lower probability of being selected and less weight to observations with a higher probability of being selected. For estimation, the weights are multiplied by the sample size and divided by the sum of the weights so that the sum of the weights across the observations is the sample size (Greene, 1992). Performing weighted estimation without scaling the weight variable in this manner can result in very low standard errors, and thus, very high t-statistics for the estimated coefficients (Greene, 1992).

Data Description

The 1992 Area Studies project is a data collection and modeling effort undertaken jointly by NRCS (formerly SCS), the Economic Research Service (ERS), the U.S. Geological Survey (USGS), and the National Agricultural Statistical Service (NASS). For 1992, data on cropping and tillage practices and input management were obtained from comprehensive field and farm level surveys of about 1,000 farmers apiece for 1992 cropping practices in each of four critical watershed regions: the Eastern Iowa and Illinois Basin areas, the Albermarle-Pamlico Drainage Area covering Virginia and North Carolina, the Georgia-Florida Coastal Plain and the Upper Snake River Basin Area. These study areas were selected from within the set of U.S. Geological Survey's National Water Quality Assessment (NAWQA) sites, and sample sites were chosen to correspond to NRCS's National Resource Inventory (NRI) so that information on the physical characteristics corresponding to farming activities would be available. For example, slope and erosion potential of the soil are likely factors influencing the decision to adopt conservation tillage.

Information about the extent of the farmers' current use of the preferred practices as well as their willingness to adopt these practices if they do not currently use the practice were provided by a supplemental questionnaire. Respondents to the comprehensive questionnaire were asked to complete and mail in this additional section. For the final analysis, 1,261 observations were available. No participants in existing WQIP programs were found among the survey respondents. The practices analyzed here, a short description (as provided in the survey, excluding the sentences on the incentive payment levels) of each, and the current incentive payment levels are presented in table 1.

All of these practices are currently being supported by WQIP. For the willingness to adopt question for all of the practices, the bids offered are $2, $4, $7, $10, $15, and $20. The bid ranges were chosen to cover what we perceived to be the likely range of WTA. The bids were randomly assigned with equal probability to the surveys.[6] The specific DC CVM question asked to the farmer is, "If you don't use this practice [listed in the question] currently, would you adopt the practice if you were given a $[X] payment per acre?" (answer "Yes" or "No"). The sample selection equation is "Is this practice [listed in the survey] currently in use on your farm?" (answer 'Yes' or 'No'). A copy of the survey is available from the authors.

Explanatory variables are defined in table 2. The decision on which variables to include in the regressions for each of the practices was based on whether or not the variables appear justified from a farm management standpoint. For instance, SNT is not included in the regressions for IPM as the former should have little to do with the latter. Table 2 also presents sample statistics for these variables for current nonusers of the practice.[7]

Estimation Results

Tables 3 and 4 present the weighted bivariate probit results for the willingness to adopt question and the sample selection question (i.e., the question of whether or not the farmer currently uses the practice), respectively.[8] For bivariate normal densities (though not necessarily for other densities), a value for ρ_{12} of zero would imply that the two equations are independent. If significant, a negative correlation is expected as y_1 can equal 1 only if $y_2 = 0$. Of the five practices, the correlation coefficient between the two equations (ρ) is significantly different from 0 at the 1% level for three of the practices.

With regards to the other coefficients, in table 3, the key variable, BID, is of the correct sign and is significant to at least the 1% level for four of the practices and is significant at the 5% level for one of the other practices. In general, explanatory power among the other variables was lower, as would be expected. For several practices, BPWORK was significant and had a negative sign, suggesting that the greater the amount of off-farm work the primary operator performs, the less likely the farmer is to adopt the practices. Some variables that were significant for current users of the practices were not significant for current non-users, and vice versa.

Incorporating the information from the regression results presented in tables 3 and 4, table 5 presents the final, continuous stage of the selectivity model with bivariate probit sample selection regression results. Using the coefficient results from tables 3 and 4, the $\boldsymbol{\lambda}_1$ and $\boldsymbol{\lambda}_2$ variables were calculated as defined in equation (9) in the Gauss programming language. Then, for farmers who do not currently use the practices but say they will at the posted offer amounts, **PACRES** was regressed on $\boldsymbol{\lambda}_1$, $\boldsymbol{\lambda}_2$, and the rest of the explanatory variables. As table 5 shows, the coefficients on $\boldsymbol{\lambda}_1$ and $\boldsymbol{\lambda}_2$ are significant for all the applicable practices. Generally, the R^2's are quite good for cross-sectional regressions. The coefficient on the BIDVAL is significant and has a correct sign for four of the five practices. It is negative and insignificant for SMTST. However, the net impact of

BIDVAL on acres enrolled for SMTST is positive when the impact of BIDVAL through λ_1 and λ_2 is included. Among the other regressors, TACRE, BPWORK, and NETINC were significant to at least the 5% level for the all the continuous portions of the bivariate probit sample selection regressions.

Tables 6 and 7 present the tobit double hurdle results, with the former presenting the probit portion (see "Obs" in tables 3 and 4 for sample sizes) and the latter the continuous portion. Presented at the bottom of table 7 is the bias of the predicted value of the dependent variable with respect to the actual value, as well as the mean square error (MSE) of the predicted value. Noting that the equations in table 7 and in table 5 are nested, the MSE values can be compared between the two models. The results show that, except for LEGCR, the MSE for the continuous portion of the double hurdle model is lower than that for the bivariate probit sample selection model. However, for all double hurdle regressions, the bias is unacceptably high when compared to those from the bivariate model.[9] Hence, if the researcher's goal is to predict enrollment, the selectivity model with bivariate probit sample selection approach appears to be preferable to the double hurdle approach.[10]

Model Applications

Applying the bivariate probit coefficients results to the conditional probability equation in equation (5), figure 1 presents graphs of the relationship between the offer amount and the probability of acceptance for those farmers who do not currently use the practices. The positive adoption rates ranging from 12-20% at $0 suggests that some current non-users may be willing to adopt the practice without an incentive payment (as do current users), provided that they are given sufficient information on the practice. However, the figure also shows that only around an additional 10 % of current nonusers will adopt the practices if they are offered the current WQIP payments of around $10/acre. Hence, it is expensive to get current nonadopters of the practices described earlier to adopt the practice. Current use rates of the practices at $0 incentive payment for farmers in the survey range from a low of 7.9% for MANTST to a high of 45% for SPLTN.[11]

As figure 1 shows, the payments needed to encourage 50% of current non-users to adopt are much higher than the current payments levels. Increasing payments to promote 100% adoption by current non-users would be costly. Given this, a cost-efficiency or cost-benefit analysis could be used to determine what participation rates, and hence, what offer amounts would be desirable for each practice.

Conclusion

Farmers can be encouraged to voluntarily adopt environmentally sound management practices through the use of incentive payments. Current USDA practice is to offer a fixed "take it or leave it" payment per acre to those not currently using the desired practices. Hence, there is insufficient observed data to model the probability of farmer adoption of the environmentally sound management practices as a function of the payment offer. Without this function, one does not know at what level to set incentive payments to achieve desired levels of participation. This paper uses a direct revelation technique based on a random utility model to develop and estimate models predicting farmer adoption of the practices as a function of the payment offer. Models that predict the acreage enrolled given the decision to accept the incentive payments are also estimated. These results can be used in a cost-benefit analysis to best decide how to allocate the program budget among the preferred production practices.

References

Adamowicz, W.L., J. Louviere, and M. Williams. "Combining Stated and Revealed Preference Methods for Valuing Environmental Amenities." Journal of Environmental Economics and Management 26(May, 1994):271-292.

Boyes, W., D. Hoffman, and S. Low. "An Econometric Analysis of the Bank Credit Scoring Problem." Journal of Econometrics 40(January, 1989):3-14.

Blaylock, J.R. and W.N. Blisard. "U.S. Cigarette Consumption: The Case of Low-Income Women." American Journal of Agricultural Economics 74(August, 1992):698-705.

Cooper, J. "Optimal Bid Selection for Dichotomous Choice Contingent Valuation Surveys," Journal of Environmental Economics and Management Vol. 24(January, 1993):25-40.

Cragg, J.E. "Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods." Econometrica 39(September, 1971):829-844.

Gould, B.W. "At Home Consumption of Cheese: A Purchase Infrequency Model." American Journal of Agricultural Economics 74(May, 1992):453-59.

Greene, W. 1992. Limdep: User's Manual and Reference Guide, Version 6.0. Econometric Software, Inc., Bellport, New York.

Greene, W. 1990. Econometric Analysis. MacMillan Publishing Company, New York, NY.

Hanemann, M., J. Loomis, and B. Kanninen. "Statistical Efficiency of Double-Bound Dichotomous Choice Contingent Valuation." *American Journal of Agricultural Economics* 73(November, 1991):1255-1263.

Hanemann, M. "Welfare Evaluations in Contingent Valuation Experiments with Discrete Response Data: Reply." American Journal of Agricultural Economics

71(November, 1989):1057-1061.

Hanemann, M. "Welfare Evaluations in Contingent Valuation Experiments with Discrete Response Data." American Journal of Agricultural Economics, 66(August, 1984):332-341.

Hoehn, J. and A. Randall. "A Satisfactory Benefit Cost Indicator From Contingent Valuation." Journal of Environmental Economics and Management 12(September, 1987):226-247.

Kanninen, B. "Optimal Experimental Design for Double-Bounded Dichotomous Choice Contingent Valuation." Land Economics 69(May, 1993):138-46.

Maddala, G.S. 1983. Limited Dependent and Qualitative Dependent Variables in Econometrics, Cambridge University Press.

Lee, L. and G. Maddala. "The Common Structure of Tests for Selectivity Bias, Serial Correlation, Heteroscedasticity and Non-Normality in the Tobit Model." International Economic Review 26(February, 1985):1-20.

Osborn, T., F. Llacuna, and M. Linsenbigler. 1992. "The Conservation Reserve Program: Enrollment Statistics for Signup Periods 1-11 and Fiscal Years 1990-92." USDA/ERS, Statistical Bulletin No. 843.

Sinner, J. "We Can Get More for Our Tax Dollars." Choices 5(September, 1990):10-13.

Tunali, I. "A General Structure for Models of Double-Selection and an Application to a Joint Migration/Earnings Process with Remigration." Research in Labor Economics 8(Part B, 1986):235-282.

U.S. Department of Commerce, National Oceanic and Atmospheric Administration. "Proposed Rules: Natural Resource Damage Assessment." Federal Register 58(January 15, 1993): 4601-4614.

Yen, S.T. "Working Wives and Food Away From Home: The Box-Cox Double Hurdle Model." American Journal of Agricultural Economics 75(November, 1994):884-895.

Endnotes

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1. While willingness to pay (WTP) questions are considered to be incentive compatible in the referendum format, some capacity for strategic response bias (in both the upper and lower directions) may still exist with WTA questions. However, the referendum format most likely diminishes this bias over the open-ended question format.

2. Hanemann (1984; 1989) provides formulas for estimating mean WTA.

3. As any government program would reserve the right (as the WQIP program does) to admit only the acreage it deems most critical for controlling water quality, the modeling of this supply response function does not imply that the farmer will be able to enroll all the acreage he desires into the program. However, the acreage supply response functions are important to the agency by giving some indication of the upper bound on the total cash payments the agency would have to make at each incentive level.

4. For estimation, it was found that convergence of the bivariate model was more easily achieved if the selection equation (equation 3) was set up such that y_{2i} is reversed, i.e. such that $y_{2i} = 0$ if the farmer current uses the practice and $y_{2i} = 1$, otherwise. In this case, the bivariate probit CDF is $\Phi_a(-\mathbf{x}_1'\boldsymbol{\beta}_1,-\mathbf{x}_2'\boldsymbol{\beta}_2,\rho_{12})$ and $\partial\lambda_{1i}/\partial \text{Bid} > 0$ and $\partial\lambda_{2i}/\partial \text{Bid} < 0$.

5. Conditional mean prediction of PACRES_i (Maddala; Greene, 1992) of a bivariate standard normal distribution is:

$E[\text{ pacres}_i \mid \text{pacres}_i > 0, y_{1i} = 1] = \Phi_a[(\mathbf{z}_i'\boldsymbol{\theta})/\sigma, \mathbf{x}_{1i}'\boldsymbol{\gamma}, \rho]\mathbf{z}_i'\boldsymbol{\theta} + \sigma\{\varphi(-\mathbf{z}_i'\boldsymbol{\theta})\Phi[\delta(-\mathbf{x}_{1i}'\boldsymbol{\gamma} - \rho(-\mathbf{z}_i'\boldsymbol{\theta}) + \rho\varphi(\mathbf{x}_{1i}'\boldsymbol{\gamma})\Phi[\delta(\mathbf{z}_i'\boldsymbol{\theta} - \rho(x_{1i}'\boldsymbol{\gamma}))]\}$, where $\delta = -1/(1 - \rho^2)^{1/2}$.

6. The survey procedures in place did not allow a more complex allocation of bids. See Cooper and Kanninen for other possible surveys designs.

7. Sample statistics for all farmers and by practice are available from the authors.

8. As stated in note 4, the sample selection portion (equation 3) was estimated with $y_{2i} = 0$ if the farmer currently uses the practice. Hence, one can reverse the coefficient signs in table 4 to make them comparable to those in table 3. In deference to tradition, the convention that y_{2i} equals 1 for users is maintained in the text.

9. By practice, in the order presented in the tables, the mean stated level of acres enrolled per farm are 415, 616, 326, 284, and 583, respectively.

10. In this paper, we used sample selection approaches to select out the non-users of the practices for the purpose of estimating minimum WTA. However, even though we did not ask current users of the practice a valuation question, we know that they are willing to accept a $0 incentive payment per acre to use the practice. Hence, as an anonymous reviewer noted, if users and non-users have the same preference structure, then they can be combined together in the qualitative variable regression for determining minimum WTA, thereby adding more information to the model than if only hypothetical users are elicited for their minimum WTA. We tried this approach with a multiple bound model along the lines of than in Hanemann, Loomis, and Kanninen. The qualitative dependent variable model results showed that for all cases except for LEGCR, the coefficients on BIDVAL are larger for the pooled data results than those from the probit adoption regressions with the current users excluded (table 3). Additional information on the methods used and the results are available from the authors.

11. These rates are 1 minus "Table 3 Observations"/"Table 4 Observations."

Table 1. Descriptions of the Farm Management Practices.

Integrated Pest Management (IPM) - Pest control strategy based on the determination of an economic threshold that indicates when a pest population is approaching the level at which control measures are necessary to prevent a decline in net returns. This can include scouting, biological controls and cultural controls. Current WQIP incentive payment does not exceed $12 per acre for this practice.

Legume Crediting (LEGSR) - Nutrient management practice involving the estimation of the amount of nitrogen available for crops from previous legumes (e.g., alfalfa, clover, cover crops, etc.) and reducing the application rate of commercial fertilizers accordingly. WQIP incentive payment does not exceed $10 per acre.

Manure Testing (MANTST) - Nutrient management practice which accounts for the amount of nutrients available for crops from applying livestock or poultry manure and reducing the application rate of commercial fertilizer accordingly. Current WQIP incentive payment does not exceed $10 per acre for this practice.

Split Applications of Nitrogen (SPHN) - Nutrient management practice whereby one-half or less of the required amount of nitrogen for crop production is applied at or before planting, with the remainder applied after emergence, in order to supply nutrients more evenly and at times when the crop can most efficiently use them. Current WQIP incentive payment does not exceed $10 per acre for this practice.

Soil Moisture Testing (SMTST) - Irrigation water management practice in which tensiometers or water table monitoring wells are used to estimate the amount of water available from subsurface sources. WQIP payment does not exceed $10 per acre.

Table 2. Definitions of the Explanatory Variables (Mean/Standard Deviation).

BIDVAL - Bid Offer ($) in the WTA question (9.44/6.16).

TACRE - Total acres operated (1053/1457).

EDUC - Formal education of operator, by category (3.11/1.40).

FLVALUE - Estimated market value per acre of land ($1321/$742).

EXPER - Farm operator's years of experience (25.0/13.2).

BPWORK - Number of days annually operator worked off the farm (45.3/88.3).

NETINC - Operation's Net farm income in 1991 ($27426/$20840).

SNT - Soil nitrogen test performed in 1992 (dummy)(0.16/0.37).

TISTST - Tissue test performed in 1992 (dummy)(0.04/0.18).

PESTM - Destroy crop residues for host free zones (dummy)(0.189/0.39).

ANIMAL - Farm type-beef,hogs,sheep (dummy)(0.20/0.40).

ROTATE - Grasses and legumes in rotation (dummy)(0.05/0.22).

MANURE - Manure applied to field (dummy)(0.13/0.33).

IA - Sample located in the Eastern Iowa or Illinois Basin Area (dummy)(0.56/0.48).

ALBR - Sample located in the Albermarle-Pamlico Drainage Area (dummy)(0.20/0.39).

IDAHO - Sample located in the Upper Snake River Basin Area (dummy)(0.15/0.36).