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Combining Actual and Contingent Behavior Data to Model Farmer Adoption of Water Quality Protection Practices

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Using farmer responses to contingent valuation method (CVM) survey data in combination with actual market data from four watershed regions in the United States, this study estimates the minimum incentive payments a farmer would accept in order to adopt more environmentally friendly "best management practices" (BMPs). Combining actual market data with the CVM data adds information to the analysis, thereby most likely increasing the reliability of the results compared to analyzing the contingent behavior survey response data only. Given the decision to adopt, the article also presents a pooled model for the number of acres enrolled in the BMPs as a function of the incentive payments.

Adoption rates predicted with the combined data model are significantly higher over a wide range of offers than those predicted using the traditional discrete choice analysis with the hypothetical data only. Hence, using the traditional CVM analysis results to determine payments to attain a given level of adoption may result in overpayment.

Key words: best management practices, contingent valuation method, discrete choice, incentive payments, tobit, water quality

Introduction

In response to increasing public concern over agricultural pollutants degrading surface- and groundwater supplies, the 1990 Food, Agriculture, Conservation, and Trade Act (FACTA) authorized the U.S. Department of Agriculture (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 surface- and groundwater supplies by using stewardship payments and technical assistance to help farmers who agree to implement approved practices. With these incentives, farmers are encouraged to experiment with more environmentally benign production practices than they would otherwise. In 1992 and 1993 the funding levels for WQIP were $6.75 million and $15 million, respectively. Currently, farmers in a small number of watersheds are eligible to enter the program. However, Sinner has suggested making this type of incentive payment program more widely available.

WQIP incentive payments are not determined through market interaction. Instead, the

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payments are essentially fixed offer amounts. 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. Without this function, the government can only guess at the incentive payment levels necessary to achieve desired levels of adoption. Given the inability to estimate this function from market data, the USDA surveyed farmers currently not using the "best management practices" (BMPs) on whether or not they would adopt the practices given hypothetical bid values per acre. These questions were written in the contingent valuation method (CVM) format. Based on an analysis of these results, it is then possible to model the probability of adoption of a practice as a function of the incentive payments.

However, modeling this data using just the hypothetical data ignores some potentially useful information. Specifically, market data on the farmers' responses to no incentive payments, that is, the response to the $0 bid value are left out.[1] The vast majority of current users of the BMPs do not receive incentive payments for using the practices. Therefore, we know that by definition, the current (i.e., nonprogram) users are willing to accept a $0 incentive payment per acre to use the practices. If users and nonusers have the same utility function and associated coefficients—as they appear to for the data sets used in this study—then they can be combined together in a qualitative dependent variable regression for determining minimum willingness to accept (WTA), thereby adding more information to the model than using only hypothetical answers.[2] This study combines farmers' actual bid response data with CVM survey data in a qualitative dependent variable regression, thereby increasing the information content in the analysis.[3] While previous research has combined revealed and stated preference data for travel cost method modeling (Adamowicz, Louviere, and Williams; Craig, Boyce, Criddle), the author is not aware of any published work in the CVM literature on directly pooling hypothetical and actual market data in estimation.

Theoretical Basis for Estimating the Hypothetical Model

While the researcher could directly elicit from the current nonadopting farmer his or her minimum WTA necessary to adopt the practice, the referendum approach, in which the respondent is asked to vote yes or no on some action, is likely to be preferable (U.S. Department of Commerce). The dichotomous choice (DC) form of CVM is used to take this approach. Under DC-CVM, the respondent is prompted to provide a yes or no

[1] The WQIP program is small enough that none of the randomly sampled farmers in the data sets used here were enrolled in the program. Also note that insufficient information is available to determine the number of farmers in WQIP program areas who wanted to adopt the practices at the currently offered incentive levels of $10–$12 per acre.

[2] On the other hand, even if the two groups are somewhat different, combining the actual users and contingent users together in estimation should still be advantageous: the actual users give unbiased market responses to the $0 offer, while the responses to the hypothetical bids may be subject to the numerous potential biases associated with CVM, such as strategic bias. Hence, restricting the coefficients to be equal between the two groups can help smooth out biases in the contingent behavior responses. Of course, this restriction will increase bias in the estimated coefficients of the actual users, but since they already use the BMPs at $0, predicting their change in adoption rates in response to different bid levels is irrelevant.

[3] Alternatively, the hypothetical data can be modeled in a bivariate probit with a sample selection framework in which the hypothetical data are analyzed by taking into account the sample selection bias (i.e., CVM data are available only for those responding farmers who do not currently use the practice, and furthermore, hypothetical acreage data are available only for nonuser farmers who answer yes to the CVM question). As the bivariate probit model predicts WTA and acreage levels only for hypothetical users, its results are not directly comparable with those in this article and, hence, is left out for brevity. A working paper on this subject is available from the author.

response to a dollar bid amount contained in the valuation question, where the bid amount is varied across the respondents. Compared with eliciting the WTP in an open-ended fashion, this method is particularly likely to reveal accurate statements of value as the format reduces the ability of the respondent to purposely bias the study results (Hoehn and Randall).[4] Respondents should also be more comfortable with this take-it-or-leave-it approach, since this is the situation they usually face in the marketplace. 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, that is, 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 $U(\cdot)$. 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 reexpressed as

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

The most prevalent functional form for the indirect utility function in the dichotomous choice CVM literature is $V(i,y;x) = \gamma^i + \alpha y$, where $\alpha > 0$, for $i = 0,1$. Using this functional form, the farmer is willing to accept \$$C$ for the change if $\gamma^0 + \alpha y + \epsilon^0 \leq \gamma^1 + \alpha(y+C) + \epsilon^1$.

The decision to accept \$$C$ can be expressed in a probability framework as $\text{Prob}\{WTA \leq C\} = \text{Prob}\{V^0 + \epsilon^0 \leq V^1 + \epsilon^1\} = \text{Prob}\{\epsilon^0 - \epsilon^1 \leq V^1 - V^0\}$, where $V^1 - V^0 = \gamma + \alpha C$, and $\gamma = \gamma^1 - \gamma^0$. Because $\Delta_i = V^1 - V^0 = \gamma + \alpha C$ is generated directly from the utility model given above, it is compatible with utility maximization. The probabilities of participation in the program given a schedule of incentive payments can be obtained as $P_i = F_\epsilon(\Delta_i)$.[5] Because rates of adoption at a particular incentive payment value may vary among the practices, from a cost effectiveness standpoint, the optimal rate of adoption may not be the same across the practices.

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[4] 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, we believe that the WTA questions analyzed here may be more incentive compatible than many WTP survey questions. Some level of incentive compatibility is likely as, given that the survey was administered by the USDA, many of the respondents may quite rationally believe that their responses may influence the policy setting. If so, then exaggerating their WTA can suggest to the government that the program is too expensive and increase the probability that the program will be dropped or reduced in magnitude. Underreporting WTA can result in the program being accepted by the government but with offered payments lower than their reservation price.

[5] Hanemann (1984, 1989) provides formulas for estimating mean WTA. For this article, the median (and mean if we assume that WTA can be less than zero as well) is $-\gamma/\alpha$.

Table 1. Descriptions of the Farm Management Practices Addressed in the Analysis

Practice	Description
Conservation tillage (*CONTILL*)	Tillage system in which at least 30% of the soil surface is covered by plant residue after planting to reduce soil erosion by water; or where soil erosion by wind is the primary concern, at least 1,000 pounds per acre of flat small grain residue-equivalent are on the surface during the critical erosion period.
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.
Legume crediting (*LEGCR*)	Nutrient management practice involving the estimation of the amount of nitrogen available for crops from previous legumes (e.g., alfalfa, clover, cover crops) and reducing the application rate of commercial fertilizers accordingly.
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.
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.

Data Description

The 1992 area studies project is a data collection and modeling effort undertaken jointly by the Economic Research Service (ERS), the U.S. Geological Survey (USGS), the National Agricultural Statistical Service (NASS), and NRCS. 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 USGS's National Water Quality Assessment (NAWQA) sites.

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 WTA question, the bids (per acre) offered for all of the practices except conservation tillage are ($2, $4, $7, $10, $15, and $20). For conservation tillage the bids are ($4, $6, $9, $12, $18, and $24). The bid ranges were chosen to cover what we perceived to be the likely range of

Table 2. Definition of Explanatory Variables

Variable	Description	Mean	SD
BIDVAL	Bid offer ($) in the WTA question	6.78	8.45
TACRE	Total areas operated	1,112.09	1,624.04
EDUC	Formal education of operator	3.20	1.39
FLVALUE	Estimated market value per acre of land	1,354.35	689.36
EXPER	Farm operator's years of experience	24.84	12.87
BPWORK	Number of days annually operator worked off the farm	43.51	86.28
NETINC	Operation's net farm income in 1991	28,108.40	20,443.19
SNT	Soil nitrogen test performed in 1992 (dummy)	0.10	0.31
TISTST	Tissue test performed in 1992 (dummy)	0.03	0.17
CONTILL	Conservation tillage used in 1992 (dummy)	0.47	0.50
PESTM	Destroy crop residues for host free zones (dummy)	0.13	0.32
ANIMAL	Farm type beef, hogs, sheep (dummy)	0.22	0.41
ROTATE	Grasses and legumes in rotation (dummy)	0.05	0.22
MANURE	Manure applied to field (dummy)	0.15	0.36
HEL	Highly erodible land (dummy)	0.19	0.39
IA	Eastern Iowa or Illionis basin area (dummy)	0.72	0.45
ALBR	Albermarle-Pamlico drainage area (dummy)	0.09	0.29
IDAHO	Upper Snake River basin area (dummy)	0.12	0.33

WTA. The bids were randomly assigned with equal probability to the surveys.[6] The specific DC-CVM question asked of 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, which identifies current users at the $0 payment, is "Is this practice [listed in the survey] currently in use on your farm?" (Answer yes or no.) The appendix provides a more detailed facsimile of the set of contingent behavior questions as well as the question designed to identify current users and the number of acres on which they use the practice.

Explanatory variables are defined in table 2. Deciding which farm activity variables to include in the regressions for each of the practices was based on whether or not the variables appeared justified from a farm management standpoint. For instance, soil nitrogen testing (*SNT*) is not included in the regressions for integrated pest management (*IPM*), since the former should have little to do with the latter. On the other hand, highly erodible land (*HEL*) is included in the regressions for conservation tillage (*CONTILL*) because one would expect that farmers are more likely to adopt it on highly erodible land. A priori, economic theory does not give much of a guide as to what the expected sign of most demographic variables will be in the adoption equations. Nonetheless, since they can add to the predictive power of the regressions, they are included. In sum, except for income and price (bid variable), which are automatically included in all the regressions, every variable available from the USDA survey that was significant in at least one regression was included in the regressions, subject to the proviso that the variable make some sense from a farm management standpoint. Table 2 presents sample statistics for these variables for all the farmers in the sample.

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

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 could lead to biased 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).

One-Way-Up Model

Ideally, in pooling the revealed and stated preference data, the user and nonuser groups should have the same utility function and associated coefficients (Adamowicz, Louviere, and Williams), when adjusted for differences in variances between the two groups, although a case can be made that this pooling is useful even if the two groups are not equivalent (see footnote 2). In general, one can test this hypothesis with a likelihood ratio test, namely, $LR = -2^*(LL_r - LL_u)$, on the adoption equation log-likelihood (LL) estimates for current nonusers (LL_1), current users (LL_2), where unrestricted $LL_{ur} = LL_1 + LL_2$, and an equation pooling both groups (LL_r). However, since there is no variance, by definition, in the dependent variable for current adopters, this test is not possible (for current nonadopters, on the other hand, we have responses to the offered bids). Instead, to test the equality of parameters between users and nonusers, we used the *LR* test above on GLS regressions for users, nonusers, and pooled users and nonusers, in which the dependent variable is acres on which the practice is applied (*stated acres* for respondents who are current nonusers or *actual acres* for respondents who are current users) and the explanatory variable sets are those from table 4. When we adjust for variance differences between users and nonusers, the null hypothesis of parameter equality between the two groups cannot be rejected for four of the five practices tested (the null hypothesis was rejected for *CONTILL*).[7]

Although the likelihood ratio tests suggest that the two groups may have similar coefficients, we cannot use traditional probit to estimate the adoption equation. Because the CVM question is asked only to nonusers, the probability of a yes response to the hypothetical bid is conditional on the nonusers already replying no to the \$0 offer (as implied by their answer to the first question, which asked them if they currently use the practice). On the other hand, the Prob(accept \$0) for current users is implied by the response to the first question and is unconditional. In other words, for nonusers, Prob(yes to hypothetical $\$Bid_i$) = Prob($WTA \leq Bid_i \mid WTA > \$0$). Given this conditional probability (i.e., we already know that nonusers will not accept the \$0 bid offer), the inequality Prob(yes to hypothetical incentive offer greater than $\$0 | WTA > \$0$) < Prob(yes to \$0) can occur, a direction of inequality which does not suggest WTA in a simple

[7] The assumption for the error term is $\text{var}(e_i) = \sigma^2 e^{\gamma_0 + \gamma_1 z_i}$, where $z = 1$ if nonuser and $z = 0$ if user. The test results are available from the author.

single-bound framework. Hence, to avoid biased regression coefficients, the adoption model must consider the conditionality of the hypothetical responses.

That the Prob(yes) to the CVM question is conditional on a Prob(no to \$0), suggests a two-step or one-way-up (OWU) model for the MLE.[8] For an early example of a mulitple-bound model (in this case double bound) for purely hypothetical data, see Hanemann, Loomis, and Kanninen. In our OWU context, there are three possible responses and probabilities of those responses:

1. Yes (i.e., respondent is a current user, at \$0 bid); $Pyes = \text{Prob}(WTA \leq \$0)$.
2. No-Yes (the respondent is not a current user [at \$0 bid] but says yes to the hypothetical offer); $Pno\text{-}yes = \text{Prob}(\$0 < WTA \leq \$bid) = P(WTA \leq \$bid) - P(WTA \leq \$0)$.
3. No-No (the respondent is not a current user [at \$0 bid] and says no to the hypothetical offer); $Pno\text{-}no = \text{Prob}(\$0 < WTA \text{ and } WTA > \$bid) = P(WTA > \$bid)$.

Given these possibilities, the likelihood function for this one-way-up model:

$$(2) \qquad L = \prod_{i}^{n} P_{yes_i}^{IY_i} P_{no\text{-}yes_i}^{INY_i} P_{no\text{-}no_i}^{INN_i},$$

where IY, INY, and INN are the binary indicator variables. Assuming a normal distribution, the gradient is, summed from $i = 1$ to n,

$$(3) \qquad \partial \text{Ln } L/\partial\beta = \sum_{i=1}^{N} [IY_i\phi(\beta' x_{0i})/\Phi(\beta' x_{0i})]x_{0i} + [INY_i/(\Phi(\beta' x_i) - \Phi(\beta' x_{0i}))]$$
$$\times [\phi(\beta' x_i)x_i - \phi(\beta' x_{0i})x_{0i}] - [INN_i\phi(\beta' x_i)/(1 - \Phi(\beta' x_i))]x_i,$$

where x_{0i} is the (1xk) vector of explanatory variables where $Bid_i = \$0\ \forall i$, x_i is the (kx1) vector of explanatory variables, and Bid_i = hypothetical value for current nonusers and \$0 otherwise.[9]

The likelihood function and the analytic gradients were programmed into Gauss Version 3.1 and the Gauss Maxlik package was used for estimation. The one-way-up results are presented in table 3. The coefficient on *BIDVAL* is of the correct sign and significant at the 1% level for all the practices. With t-statistics of 10 to 14, the bid coefficients indicate that *BIDVAL* strongly outperforms the other explanatory variables in explaining adoption. This strong performance is not surprising since all the respondents to the contingent questions, in particular, are directly responding to the bid value. No other coefficients were significant across all the practices. *FLVALUE*, the value of the market value of the land per acre, was significant and negative for four of the five practices, suggesting that farmers with higher value lands may see the offered practices as detrimental to profitability, though only by a small amount since the coefficients are quite small. *NETINC*, net income, is significant in only two cases, and the sign is positive. However, little can be said about this performance as, a priori, it is difficult to predict the signs of *NETINC* (and *FLVALUE*). Note that the correlation between *NETINC* and *FLVALUE* is low for our data sets. *TACRE*, total acreage, was significant only for *IPM*, indicating that farm size is not a good predictor of adoption of most BMPs, though one

[8] The "one-way-up" name refers to fact that the model proceeds to the next (higher) bound only if the answer to the first bound is no.

[9] Using more explicit notation than in equation (2), the log-likelihood function is $\ln L = \Sigma^n IY_i \ln[\Phi(\beta' x_{0i})] + INY_i \ln[\Phi(\beta' x_i) - \Phi(\beta' x_{0i})] + INN_i[\ln(1-\Phi(\beta' x_i)]$.

Table 3. One-Way-Up Adoption Model Combining Current Users and Nonusers

Variables	Coefficient Estimates				
	CONTILL	*IPM*	*LEGCR*	*MANTST*	*SMTST*
CONSTANT	−21.34	−107.1	−159.5	−206.2	−110.5
	(−0.8)	(−5.4)	(−5.8)	(−7.5)	(−4.8)
BIDVAL	2.82	3.52	2.23	4.36	5.85
	(11.4)	(13.1)	(10.0)	(11.4)	(13.6)
EDUC	0.51	21.14	16.68	9.86	4.57
	(0.2)	(7.3)	(5.7)	(3.1)	(1.4)
TISTST	—	—	14.05	−60.78	—
			(0.6)	(−1.5)	
CTILL	56.25	—	—	—	—
	(6.6)				
HEL	6.54	—	—	—	—
	(0.6)				
EXPER	−0.30	−0.30	0.04	−0.30	−0.65
	(−1.0)	(−1.0)	(0.1)	(−0.9)	(−1.9)
PESTM	0.17	41.37	—	—	—
	(0.0)	(3.7)			
ROTATE	5.79	11.19	32.33	—	—
	(0.3)	(0.6)	(2.0)		
MANURE	−12.25	—	18.34	27.62	—
	(−1.3)		(2.0)	(2.7)	
ANIMAL	−4.11	−27.83	−1.35	30.91	−11.28
	(−0.4)	(−3.6)	(−0.2)	(3.5)	(−1.2)
TACRE	0.00	0.00	0.00	0.00	0.00
	(−1.0)	(1.8)	−0.7	(−0.1)	(−0.2)
FLVALUE	0.00	−0.01	−0.02	−0.02	−0.01
	(0.0)	(−2.1)	(−3.6)	(−3.5)	(−2.4)
IA	69.97	15.63	116.49	105.13	−27.47
	(3.5)	(1.0)	(5.4)	(5.0)	(−1.7)
ALBR	71.09	−13.15	−14.59	12.53	−118.5
	(2.7)	(−0.6)	(−0.6)	(0.5)	(−5.6)
IDAHO	27.82	−37.17	55.14	7.21	21.00
	(1.3)	(−1.9)	(2.3)	(0.3)	(1.2)
BPWORK	−0.07	−0.10	−0.12	−0.07	−0.06
	(−1.4)	(−2.2)	(−2.7)	(−1.4)	(−1.1)
NETINC	0.00	0.00	0.00	0.00	0.00
	(1.9)	(0.8)	(−1.2)	(−1.1)	(3.5)
Sum ln*L*	−751.6	−935.4	−857.7	−637.6	−676.5
%*CUser*	74.9	70.7	73.4	92.4	91.0
%*CAd*	82.1	79.6	85.5	88.8	85.5

Note: The figures in parentheses are coefficients/standard errors. The numbers of observations for each regression are 1,059; 1,021; 1,024; 1,010; and 1,006; respectively. Coefficients are scaled up by a factor of 100 for ease of presentation.

could expect the scale of farm operation to be an important determinant of adoption of *IPM*.

The statistic %*CUser* is the percentage of the time the estimated model correctly predicts whether or not the farmer is a current user of the practice, while %*CAd* is the percentage of correct predictions (where the nonadoptor's response to the offer is the

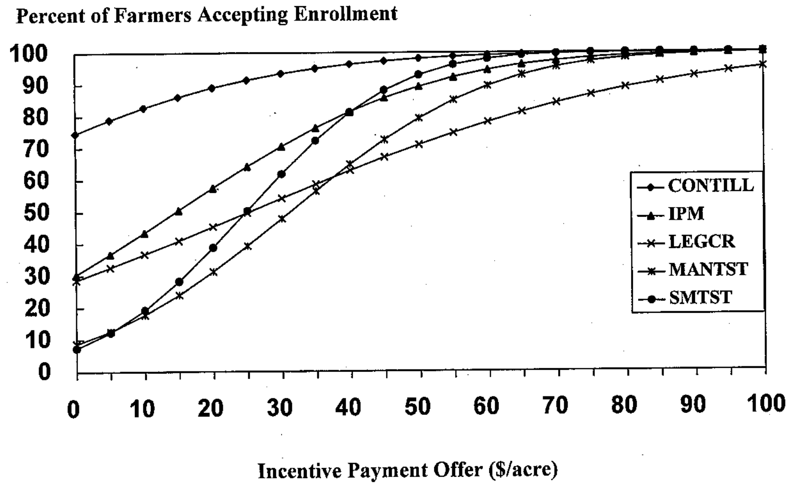

Figure 1. Response curves for the subsidized practices (analysis of actual users combined with CVM survey data)

"true" value) of adoption for current nonadoptors. Using the estimates of the γs (0.663, -0.516, -0.564, -1.362, and -1.454, respectively, for each practice), the coefficient estimates on *BIDVAL* (α) in table 3, and the equation in footnote 5, the estimated median WTAs are $-\$23.51$, \$14.65, \$25.28, \$31.26, and \$24.86, respectively for each practice. The negative sign on the median WTA for *CONTILL* suggests that farmers would be willing to pay to continue using the practice. Given that over 70% of farmers surveyed currently use this practice without any payment, and given their investments in machinery are necessary for this practice, this result is not surprising.

Figure 1 graphs the percentage of farmers adopting the practices as a function of the offered incentive payment. Current levels of adoption of the practice are shown vertically on a line through the \$0 incentive offer. *IPM* and *LEGR* have flatter response curves than *MANTST* and *SMTST,* indicating less sensitivity to the offer values. Given its high current use among farmers, *CONTILL* has the flattest response curve, even though it does not have the smallest *BIDVAL* coefficient. These results can be compared with those from doing a single-bound (SB) probit regression only on the hypothetical data and then, given the estimated coefficients, predict the number of current nonusers who adopt at each offer price and then add them to the number of current users to come up with a schedule similar to that in figure 1. For example, the number of farmers using conservation tillage at the \$10 offer is the number of farmers who currently use the practice plus the number of current nonusers who will adopt the practice with a bid offer of \$10. In figure 2, the SB probit results predict lower enrollment levels for any given bid offer, except the lowest ones, compared with the one-way-up model. For example, based on the SB results, *LEGCR, MANTST,* and *SMTST* all need greater than \$45 incentive payments to reach 50% adoption, while with the combined actual-hypothetical results, no practice requires greater than approximately \$31 per acre to achieve 50% adoption. Enrollment at the \$0 bid offer is higher in figure 2 as the SB probit model predicts positive enrollment by current nonusers at \$0 bid—a result which can only be defensible if some current nonusers who where uninformed of the BMPs before are now informed about

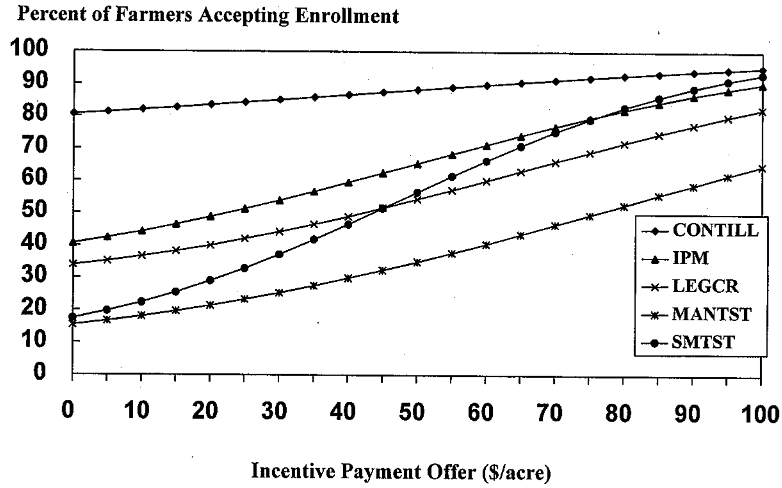

Figure 2. Response curves for the subsidized practices (analysis of CVM survey data only)

them and may use them even at $0 bid—while the OWU model predicts only current (actual) use at $0 bid and hence is more conservative.

Continuous Model Combining the Actual and Hypothetical Data

The next step is to incorporate the one-way-up results into a continuous model regression, a regression with acres on which the practices are used as the dependent variable. Specifically, the dependent variable is *stated acres* allocated to the practice for current nonusers of the practice and *actual acres* allocated to the practice for current users, which for farmer i can be stated as:

$$PACRES_i = z_i' \theta + u_i, \tag{4}$$

where $PACRES_i$ is the amount of acres in the preferred practice, z_i is a vector of explanatory variables, and u_i is a disturbance with mean zero. As with the discrete choice model, 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. Since economic theory does not suggest any a priori reasons why the *PACRES* equation should have different explanatory variables than the adoption equation, the same variables are used. To reduce the potential of some possible form of heteroskedasticity associated with the total acreage (*TACRE*) variable, $PACRES_i$ is divided by $TACRE_i$ for the regressions.

Ordinary least squares (OLS) estimates of (4) may be biased. Because $PACRES_i$ is only observed for the farmers who are current users or are willing to adopt at the offered incentive payment, the sample for the regression equation may not be drawn randomly from the population who answered the survey, implying sampling bias due to omitted $PACRES_i$. In addition to being potentially biased, OLS estimates are inefficient (Greene 1990). The Heckit procedure (Greene 1990) can be used to correct (4) for nonrandom sampling by using information from the one-way-up qualitative variable regression. Since

$PACRES_i$ is observed only when $y_i = 1$ (for current users and for hypothetical users), (4) should be rewritten as:

$$(5)\qquad \begin{aligned} E[PACRES_i|z_i, \text{ in sample}] &= E[PACRES_i|z_i, y_i = 1], \\ &= E[PACRES_i|z_i, \epsilon_i \geq \Delta V_i], \quad \text{or} \\ &= z_i'\theta + E[u_i|\epsilon_i \geq \Delta V_i]. \end{aligned}$$

To estimate this continuous model in a sample selection framework, the Mills ratio calculated from the one-way-up model is added as an explanatory variable (Greene 1990). Variables which are highly correlated (using a standard of correlation coefficient greater than or equal to 0.5) with the Mills ratio explanatory variables are removed, resulting in one or two variables being removed from each continuous model equation.

Because the dependent variable $PACRES_i/TACRE_i$ is censored to fall between 0 and 1, OLS estimation of the above Heckit model may be biased and inconsistent. Hence, a tobit version of the Heckit model is estimated with the lower and upper limits set at 0 and 1, respectively. To correct for heteroskedasticity between users and nonusers, the variance of the error term is $\text{var}(e_i) = \sigma^2 e^{\gamma_1 z_i}$, where $z_i = 1$ if respondent i is a nonuser and 0 if a user.[10]

The tobit model results are presented in table 4. For four of the five BMPs, the coefficient on *BIDVAL* is significant and of the expected sign, either through its impact in the Mills ratio (as in *CONTILL*) or through the *BIDVAL* (for practices *LEGCR*, *MANTST*, and *SMTST*). Note that for the Mills ratio variable λ_i, $\partial\lambda_i/\partial BIDVAL_i$ is negative. Based on the results from table 3, the negative sign on the Mills ratio coefficient for *CONTILL* shows the expected result that an increase in the cost share for conservation tillage leads to an increase in the percentage of total acres on which conservation tillage is used. For the other BMPs, since the Mills ratio is not significant, sample selection bias is unlikely to be a concern. A large majority of the farmers in the sample use conservation tillage, while a minority of farmers use the other practices, which may have some bearing on producing significant sample selection bias in the former but not in the latter. Of the other explanatory variables, none was significant for every practice, implying that the relevant set of explanatory variables differs for each practice. For example, the coefficient on *ANIMAL* was significant and negative for four of the five cases, suggesting logically that farmers with animal operations are less likely to be interested in using the offered practices. However, *ANIMAL* is not significantly different from 0 in the manure testing (*MANTST*) practice; while a positive coefficient may be predicted a priori, a negative sign would have been quite unusual. On the other hand, the coefficient on *MANURE* (farmer applies manure to field) is significant only for *MANTST* and is positive, which is not surprising as one could expect that farmers who apply manure to their fields may have a strong interest in *MANTST*.

As expected, since a great majority of farmers already use conservation tillage, the *CONTILL* equation is not particularly sensitive to the cost-share offer. An increase in the cost share from the current level of \$0 to \$10 results in only 2.6% more acres using the practice. On the other hand, for manure testing, which is currently used by a small

[10] Note that $\text{var}(e_i)$ cannot be written as $\sigma^2 e^{\gamma_0+\gamma_1 z_i}$ where $z_i = 1$ if respondent is a nonuser and 0 if respondent is a user. In the Limdep 6.0 (Greene 1992) tobit model with heteroskedasticity correction we used, γ_0 needs to be set equal to 0 since σ is a free parameter in this program, and thus, the inclusion of a constant in the variance of the error term model will cause a singular covariance matrix.

Table 4. Tobit Continuous Stage Regression for Acreage under BMP

Variables	Coefficient Estimates				
	CONTILL	*IPM*	*LEGCR*	*MANTST*	*SMTST*
CONSTANT	63.53	44.49	43.42	33.43	55.39
	(5.8)	(4.4)	(2.9)	(1.6)	(2.4)
BIDVAL	−0.45	0.24	1.25	1.34	0.84
	(−1.2)	(0.7)	(2.7)	(2.4)	(1.6)
EDUC	0.31	—	−1.95	−2.51	−2.69
	(0.3)		(−1.0)	(−1.0)	(−1.2)
TISTST	—	—	2.25	26.35	—
			(0.3)	(1.7)	
HEL	0.59	—	—	—	—
	(0.2)				
EXPER	−0.24	−0.27	−0.19	−0.52	−0.28
	(−2.4)	(−1.5)	(−1.0)	(−1.5)	(−1.0)
PESTM	−1.34	4.55	—	—	—
	(−0.4)	(1.0)			
ROTATE	−4.67	3.15	2.62	−5.76	−0.19
	(−0.9)	(0.4)	(0.3)	(−0.4)	(−0.0)
MANURE	1.58	—	7.33	45.23	—
	(0.4)		(1.0)	(4.8)	
ANIMAL	−6.59	−17.15	−9.84	−3.35	−26.09
	(−2.0)	(−2.9)	(−1.6)	(−0.4)	(−3.0)
FLVALUE	0.00	0.00	0.01	0.00	0.00
	(2.4)	(1.5)	(3.7)	(0.3)	(0.0)
SNT	—	—	8.62	−13.22	—
			(1.1)	(−1.4)	
IA	13.46	33.20	—	—	18.73
	(1.7)	(4.4)			(1.8)
ALBR	−22.05	2.76	—	−7.65	—
	(−2.8)	(0.4)		(−0.6)	
IDAHO	16.47	28.24	7.92	19.16	25.51
	(2.6)	(3.7)	(1.4)	(1.5)	(2.6)
BPWORK	−0.01	0.01	0.10	0.06	0.11
	(−0.6)	(0.5)	(2.5)	(1.2)	(2.1)
NETINC	0.00	0.00	0.00	0.00	0.00
	(−0.8)	(−0.2)	(−0.2)	(−1.4)	(−0.6)
MILLS	−20.87	7.31	−9.34	9.70	5.37
	(−2.1)	(0.9)	(−1.1)	(0.7)	(0.6)
FMUSE	−11.11	4.35	−16.39	−32.51	9.36
	(−0.9)	(0.4)	(−1.1)	(−1.9)	(0.5)
Sigma	35.75	32.34	42.33	37.95	32.33
	(8.7)	(10.7)	(7.2)	(7.4)	(8.7)
Obs.	794	366	291	128	159
Sum ln*L*	−307.9	−166.1	−145.4	−49.6	−71.7
Sum ln*L* w/out Mills	−310.2	−166.6	−146.3	−50.0	−71.9

Notes: The figures in parentheses are coefficients/standard errors. Dependent variable = (actual or hypothetical acres the practice is used on)/(total farm acreage), where tobit lower and upper limits are set to 0 and 1, respectively. Coefficients are scaled up by a factor of 100 for ease of presentation.

percentage of farmers, an increase in the cost share from the current level of \$0 to \$10 results in 13.3% more acres using the practice. Legume crediting (*LEGCR*) shows similar increases over the same offer range, while soil moisture testing (*SMTST*) shows an 8.4% increase and *IPM* a 2.4% increase.

Conclusion

Using farmer responses to CVM survey data from four watershed regions in the United States, I estimate the minimum incentive payments a farmer would accept in order to adopt more environmentally friendly best management practices. In a departure from the traditional CVM survey approach, since data on actual users of the BMPs (i.e., farmers who currently use the BMPs with no incentive payments or, in other words, at \$0 bid offers) exist, I extend the traditional CVM survey analysis by combining this actual market data with the hypothetical, or contingent behavior analysis. Doing so, I add information to the regression, thereby most likely increasing the reliability of the results compared with that from the contingent behavior survey response data only. From a policy standpoint, getting relevant farmers to adopt the BMPs is likely the most difficult hurdle. However, what also matters from an environmental standpoint is how many acres are enrolled in the practice, given the decision to participate. Hence, given the results from the adoption equations, I also model the number of acres enrolled in the BMPs as a function of the incentive payments. As with the discrete choice functions, I combine the actual and the contingent behavior data.

For the data sets used in this article, adoption rates predicted with the combined data model are significantly higher over a wide range of offers than those predicted using a single-bound probit analysis of the hypothetical data only. Hence, using the traditional CVM analysis results to determine payments to attain a given level of adoption may result in overpayment. Still, the high cost to the government of attaining much higher than current levels of adoption suggests that incentive payments may not be a particularly feasible policy option in this period of shrinking agricultural budgets. This hypothesis is only enforced by the somewhat flat response the bid offers in terms of the number of acres enrolled given the decision to adopt the practice. However, we need more information on the valuation of the environmental benefits of adopting the BMPs in order to know whether the incentive payment schemes can yield benefits greater than costs for any of the BMPs. If incentive payment schemes are used to promote adoption, basing payments on the combined data model instead of the contingent behavior data only model can result in substantial cost savings for the government.

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Appendix: Example of Survey Questions for Adoption of a Practice

a. Is this practice currently in use on your farm? *[Enter 1 if Yes. If No, please skip to item e.]*

b. When did you begin using this practice? *[Please enter approximate month and year, for example 0190 for January of 1990.]*

c. Was this practice cost-shared when you adopted it? *[If YES enter dollars per acre (total cash share for cols. 10–12). If NO leave blank.]*

d. On how many acres do you use this practice? *[Enter number of acres and skip to item j.]*

e. Would you adopt this practice if you received a $24/acre incentive to do so? *[Enter 1 if Yes.]*

f. How many acres would you apply this practice on?