October 1989 No. 310

MODELING SEQUENTIAL BINARY RESPONSES: AN APPLICATION TO WISCONSIN FARMERS' ATTITUDES TOWARD AGRICULTURAL OPTIONS

By

Amr N. Shiha, Thomas L. Cox and Gerald R. Campbell*/
University of Wisconsin-Madison

---

*/ Amr N. Shiha is a Graduate Research Assistant, Thomas L. Cox is Assistant Professor of Agricultural Economics and Gerald R. Campbell is Professor of Agricultural Economics, University of Wisconsin-Madison. This research was funded by the Wisconsin Agricultural Experiment Station, College of Agricultural and Life Sciences.

Modeling Sequential Binary Responses: An Application to Wisconsin Farmers' Attitudes Toward Agricultural Options

INTRODUCTION

Appropriate techniques for modeling sequential binary responses have been the subject of debate in the econometric literature. In such models, a positive response on a binary dependent variable determines the inclusion in a subsample on which another binary dependent variable is observed. Given a bivariate normal distribution for the two disturbance terms in the population, there is concern over the possible correlation of the disturbance terms. If the disturbance terms are correlated and the corresponding regression equations are not estimated jointly, a problem of biased estimates of the population parameters may result. This problem is due to a possible nonrandom inclusion in the censored sample. Alternatively, if the assumption of bivariate normal structure is theoretically inconsistent with a non-zero correlation coefficient in such models, then estimating each equation separately will provide unbiased estimates and will be more conceptually appealing.

The literature shows two different approaches to deal with these problems. The first starts with a maintained hypothesis of correlated dependent variables. It then applies a joint probit estimation technique to capture interdependence between the error terms and to correct for selectivity bias in the parameter estimates. Examples include Van De Ven and Van Praag (1981), Danzon and Lillard (1982), Catsiapis and Robinson (1982) and Tunali (1983). However, Lee and Maddala (1983) have pointed out conceptual difficulties of assuming correlated dependent variables. They show that in sequential binary response models the disturbance terms must be independent if they have a joint normal distribution. Accordingly, the estimation procedure should start with an assumption of zero correlation coefficient and then apply univariate probit on each equation repeatedly. This paper compares the empirical implications of both approaches. It applies both techniques to study the factors that influence Wisconsin farmers knowledge and use of agricultural options where a farmer's decision of whether or not to use options is observed only if he knows about them.

It has been argued that a well functioning options market could provide an alternative to price support programs (Gardner, p. 990).[1/] The initiation of exchange traded options on agricultural futures raises concern about farmers knowledge of these types of contracts. Low actual use of such contracts has reinforced the suggestion that limited knowledge about what options markets offer limits their use (Heifner and Sporleder, p. 35). The present study sheds some light on the factors that contribute to farmers knowledge and use of options in Wisconsin. The methodological issues of sequential binary response models arise when trying to analyze responses of farmers who know about options and within that population, farmers who have actually traded options. The factors examined include size of the grain business, private hedging practice, market information and educational attainment of the farmer.

THE CONCEPTUAL MODEL AND ESTIMATION PROCEDURES

Assume that the propensities of a Wisconsin farmer to know about and to use options are given by the following two linear equations:

$$y^*_{1i} = \beta_1' \underline{x}_i - \epsilon_{1i} \tag{1}$$

$$y^*_{2i} = \beta_2' \underline{x}_i - \epsilon_{2i} \tag{2}$$

where y^*_{ji}, $(j=1,2)$, represents the ith farmer's utility index of knowing about and using options respectively, $\underline{x}_i$ is a 1xK vector of explanatory variables, β_j is a 1xK vector of parameters and ϵ_{ji} is a disturbance term which is assumed to have a standard normal distribution, independent of $\underline{x}_i$, with $E(\epsilon_{ji}) = 0$ and $Cov(\epsilon_{ji}, \epsilon_{ji'}) = 0$ for $i \neq i'$. For the ith farmer we assume that ϵ_1 and ϵ_2 have a bivariate normal distribution with zero means and covariance matrix:

$$\Sigma = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$$

However, y_2^* 2/ is not directly observable. For y_1^* we observe the following dichotomous variable:

$$y_1 = \begin{cases} 1 & \text{iff} \quad y_1^* > 0 \\ 0 & \text{iff} \quad y_1^* \leq 0. \end{cases}$$

Further, since a farmer must first know about options before deciding whether or not to use them, y_2^* is defined only for the subpopulation of Wisconsin farmers who know about options. Thus the observed dichotomous variable for y_2^* is given by:

$$y_2 = \begin{cases} 1 & \text{iff} \quad y_1^* > 0,\ y_2^* > 0 \\ 0 & \text{iff} \quad y_1^* > 0,\ y_2^* \leq 0. \end{cases}$$

The above structure represents a sequential decision model where the variables y_1 and y_2 determine the break down of the sample observations into three groups:

S_1: those who do not know about options ($y_1 = 0$).

S_2: those who know about options and do not use them ($y_1 = 1$, $y_2 = 0$).

S_3: those who know about options and use them ($y_1 = 1$, $y_2 = 1$).

Our objective is to estimate the parameters of equations 1 and 2. We recognize, however, that given the above sample structure and the observability condition (i.e. y_2 is observed iff $y_1 = 1$), biased estimates of the population parameters may result if the disturbance terms (ϵ_1, ϵ_2) have a nonzero correlation coefficient, ρ, and the parameters are not estimated jointly. This problem is due to nonrandom inclusion in the subsample of observations who know about options, Heckman (1979). For this purpose we consider two different methods for estimating bivariate probit with sample selection.

The first method, as followed by Van De Ven and Van Praag (1981) and Tunali (1983), attempts to correct for selectivity bias and to incorporate interdependence between the disturbance terms in sequential binary response models. This approach starts with a maintained hypothesis of a nonzero correlation coefficient. The parameters of the two decision equations are then estimated jointly utilizing an information loss likelihood function.

Given our sample observability condition, we have a case of information loss where the joint occurrence of ($y_1 = 0$, y_2) is not observable. Thus, the probabilities P_k that a respondent belongs to the k^{th} group ($k = 1,2,3$) are given by:

$$P_1 = Pr(Y_1 = 0) = Pr(Y_1^* \le 0) = F(-\underline{\beta}_1'\underline{x})$$
$$P_2 = Pr(Y_1 = 1, Y_2 = 0) = Pr(Y_1^* > 0,\ Y_2^* \le 0) = G(\underline{\beta}_1'\underline{x}, -\underline{\beta}_2'\underline{x}; -\rho)$$
$$P_3 = Pr(Y_1 = 1, Y_2 = 1) = Pr(Y_1^* > 0,\ Y_2^* > 0) = G(\underline{\beta}_1'\underline{x},\ \underline{\beta}_2'\underline{x};\ \rho)$$

where $F(.)$ and $G(.,..,;.)$ are the standard univariate and bivariate normal distribution functions respectively. The likelihood function with information loss is given by:

$$L = \prod_{S_1} F(-\underline{\beta}_1'\underline{x}) \prod_{S_2} G(\underline{\beta}_1'\underline{x}, \underline{\beta}_2'\underline{x}; -\rho) \prod_{S_3} G(\underline{\beta}_1'\underline{x}, \underline{\beta}_2'\underline{x};\ \rho). \qquad (3)$$

Maximizing the above likelihood function and solving for its parameters we get the maximum likelihood estimates for the population parameters $\underline{\beta}_1$, $\underline{\beta}_2$ and ρ.

Van De Ven and Van Praag used the above likelihood function in estimating the demand for health insurance deductibles in the Netherlands. They considered a sequential binary decision model where the first decision of a respondent was whether or not to fill in the questionaire completely and the second was whether or not to prefer insurance deductibles with less premium. Tunali also applied the same approach in analyzing migration decisions. The dichotomous variables D_1 and D_2 denoted the break down of the sample observations into stayers ($D_1=0$), one time movers ($D_1=1, D_2=0$) and frequent movers ($D_1=1$, $D_2=1$).

However, Lee and Maddala (1983) criticize the above approach. They show that in estimating bivariate probit with sample selection the starting assumption should be a zero correlation coefficient. Since (ϵ_1, ϵ_2) have a bivariate normal distribution over population, their distribution defined on subpopulation $y_1=1$ is truncated normal with joint density given by:

$$g(\epsilon_1, \epsilon_2) = \frac{h(\epsilon_1, \epsilon_2)}{F(\underline{\beta}_1'\underline{x})} \tag{4}$$

where $h(.,.)$ is the population normal joint density of ϵ_1 and ϵ_2. Thus, the marginal densities of ϵ_1 and ϵ_2 defined on subpopulation $y_1=1$ are given by:

$$g_1(\epsilon_1) = \frac{h(\epsilon_1)}{F(\underline{\beta}_1'\underline{x})} \tag{5}$$

and

$$g_2(\epsilon_2) = \int_{-\infty}^{\underline{\beta}_1'\underline{x}} \frac{h(\epsilon_1, \epsilon_2)}{F(\underline{\beta}_1'\underline{x})} \, d\epsilon_1 \tag{6}$$

where $h(\epsilon_1)$ is the population normal marginal density for ϵ_1. Equation 6 shows that if ϵ_2 has a normal distribution then ϵ_1 and ϵ_2 defined on subpopulation $y_1=1$ must be independent. This is so since ϵ_2 is normal iff $\rho = 0$. In other words, if $g_2(\epsilon_2)$ is the normal marginal density function of ϵ_2 then $g_2(\epsilon_2) = h(\epsilon_2)$. But this is the same as saying that $h(\epsilon_1, \epsilon_2) = h(\epsilon_1)h(\epsilon_2)$, i.e., ϵ_1 and ϵ_2 are independent.[3/] Thus in sequential binary decision models we cannot simultaneously assume bivariate normal disturbances and a nonzero correlation coefficient.

Starting with the assumption that $\rho = 0$, the probability P_k that a sample observation belong to group k can be rewritten as:

$$P_1 = F(-\underline{\beta}_1'\underline{x})$$
$$P_2 = F(\underline{\beta}_1'\underline{x})\ F(-\underline{\beta}_2'\underline{x})$$
$$P_3 = F(\underline{\beta}_1'\underline{x})\ F(\underline{\beta}_2'\underline{x}).$$

Using these results, the likelihood function in (3) can be rewritten as:

$$L = \prod_{S_1} F(-\underline{\beta}_1'\underline{x}) \prod_{S_2} F(\underline{\beta}_1'\underline{x})\ F(-\underline{\beta}_2'\underline{x}) \prod_{S_3} F(\underline{\beta}_1'\underline{x})\ F(\underline{\beta}_2'\underline{x}). \tag{7}$$

Maximizing the above likelihood function is equivalent to maximizing the likelihood functions of the two dichotomous variables repeatedly. The parameter vector $\underline{\beta}_1$ is first estimated from the entire sample by dividing it into those who know about options and those who do not. Next, $\underline{\beta}_2$ is estimated from the subsample of observations who know about options by dividing it into those who use options and those who do not.

DATA: THE SURVEY OF WISCONSIN CASH GRAIN FARMERS

In the Fall of 1986, a random sample from a population defined as those Wisconsin farmers who had 100 acres or more of corn and one or more acres of soybeans was surveyed with mail questionnaires. The purpose was to learn about Wisconsin cash grain farmers knowledge of commodity options and related marketing alternatives. The sample was stratified among crop reporting districts. We received 835 responses out of 2228 farmers surveyed in a mail survey with telephone follow up.[4]

The questionnaire asked farmers: "Have you heard of agricultural options?" If the answer was yes, the follow up question was: "Have you used agricutural options in grain marketing?" For the 796 usable responses, 389 knew about options. Of the latter number, only 27 reported that they had used them.

Our objective is to study the factors that influence a Wisconsin farmer's knowledge and use of options. A major factor expected to influence a farmer's attitudes toward options was the size of grain business (SIZE). An option contract is lumpy trading in units of 1000 ot 5000 bushels. This necessitates relatively large volumes of grain sales in order to use such a tool proportionately to cash grain sales. Further, large scale grain operations have a larger absolute potential loss from price declines. This provides an economic incentive to learn about options and to use them if appropriate.

A second factor considered was a farmer's previous private hedging practices (HEDGE). Like futures and forward contracts, put options can provide a forward pricing device for the farmer. Options have the advantage that they need not be exercised in the case of favorable cash market changes. Thus, frequent use of forward and futures contracts in hedging is expected to increase a farmer's awareness of forward pricing tools and to increase the probability of options as part of a forward pricing strategy.

A third major factor expected to influence farmer knowledge of options is (EDUCATION). Options contracts are an abstract concept. Understanding how the options market works is expected to be easier for farmers with more formal education. Education is thus expected to positively influence both farmers general behavior in learning about and understanding how to use new marketing tools.

A final major factor expected to influence farmer knowledge and use of options is their behavior in seeking market information. Farmers who are more active in seeking price and economic outlook information are more market oriented. These farmers would be expected to be aware of new marketing techniques and their potential uses in their marketing strategies.

To analyze the farmer responses, we divided the sample into two groups of responses: Those who did not know and those who knew about options. The latter subsample was further divided into: Those who did not use options and those who used them. Positive (know or use) and negative (don't know or don't use) responses were coded by one and zero respectively. The resulting sample distributions of responses on farmers' knowledge about and use of options are given in Tables 1 and 2, respectively.

The variables AREA and INCOME were used to represent SIZE. The HEDGE factor was represented by FORWARD1, FORWARD2, and FUTURES. The effect of INFORMATION was accounted for by EXP1 and EXP2. Observations with missing values on any variable considered were deleted. Description of the explanatory variables, their measurements and expected impacts are provided in Table 3. Their descriptive statistics are shown in Table 4.

Table 1. Distribution of Sample Responses on Knowledge About Options.

Response on: Do You Know About Options?	Number of Observations	Percent
No	284	55.6
Yes	227	44.4
Total	511	100

Table 2. Distribution of Responses on Options Use As a Subsample of Those Who Knew About Them.

Response on: Have You Used Options?	Number of Observations	Percent
No	211	93
Yes	16	7
Total	227	100

Table 3. Description of the Explanatory Variables, Their Measurements and Expected Impacts on Wisconsin Farmers' Attitudes Toward Commodity Options.

Factor	Variable	Description	Measurement	Expected Impact on: Knowledge About Options	Expected Impact on: Use Of Options
---		Intercept			
SIZE	AREA	Area planted to field crops	1 = more than 259 acres 0 = less than 259 acres	+	+
	INCOME	Importance of cash grain sales in the income structure of the farm	1 = if cash grain sales contribute more than 40% to farm income 0 = otherwise	+	+
HEDGE	FORWARD1	Low frequency of using forward contracts to hedge cash grain during the five years preceding the survey	1 = if the respondent had used forward contracts one to four times 0 = otherwise	+	+
	FORWARD2	High frequency of using forward contracts during the five years preceding the survey	1 = if the respondent has used forward contracts five times or more 0 = otherwise	+	+
	FUTURES	Use of future contracts to hedge during the five years that preceded the survey	1 = if respondents had used futures in the last four years 0 = otherwise	+	+

Table 3 (continued).

Factor	Variable	Description	Measurement	Expected Impact on Knowledge About Options	Expected Impact on Use Of Options
INFORMATION	EXP1	Low annual expenditures to acquire market information (e.g. telephone hot lines and special market letters)	1 - if the respondent spends up to $200 annually 0 - otherwise	+	+
	EXP2	High annual expenditure to acquire market information	1 - if the respondent spends more than $200 0 - otherwise	+	+
EDUCATION	EDUCATION	Educational attainment	1 - if the respondent has more than a more 12 years formal education 0 - otherwise	+	+

Table 4. Descriptive Statistics for the Explanatory Variables on Wisconsin Farmers' Attitudes Toward Agricultural Options.

	Whole Sample		Subsample of Observations Who Know About Options	
Variable	Mean	Standard Deviation	Mean	Standard Deviation
AREA	0.739	0.439	0.833	0.374
INCOME	0.243	0.429	0.317	0.466
FORWARD1	0.086	0.281	0.159	0.366
FORWARD2	0.043	0.203	0.093	0.290
FUTURES	0.059	0.235	0.119	0.324
EXP1	0.189	0.3923	0.264	0.442
EXP2	0.063	0.243	0.115	0.319
EDUCATION	0.286	0.452		

RESULTS

Applying Both Estimation Techniques to the Wisconsin Data

Both joint and univariate probit estimation techniques were applied to the Wisconsin data. Joint probit estimation is assumed to capture interdependence between the disturbance terms of the selection and outcome equations (i.e., those of equations 1 and 2). Univariate probit assumes independence and employs the approach suggested by Lee and Maddala in estimating sequential binary response models.

Comparison between the parameter estimates from both techniques is provided in Table 5. The numerical values of the coefficients of equation 1 and their standard errors are very close in both cases implying the same significance pattern. This result does not apply to the coefficients of equation 2, however. The magnitudes are different in both cases with standard errors being higher in the joint case. In addition, none of the coefficients of the joint estimation use equation are statistically significant at conventional alpha levels.

As a result, while both approaches yield very close predicted probabilities of knowing about options with parallel significance levels, discrepancies occur for the probabilities of using options. The comparison provided in Table 6 shows that univariate probit estimation gives higher predicted probabilities of using options with lower prediction errors.

It is interesting to note that the estimated correlation coefficient is not significantly different from zero ($\alpha = 0.05$). This contradicts the hypothesis of interdependent disturbances. Moreover, the maximized value of the likelihood functions are almost the same under both methods (Table 5). As such, both approaches provide little empirical difference regarding interdependence of the error terms and the probabilities of knowing about options. However, univariate estimation gives more efficient estimates of the parameters of the options use equation. The same applies to the predicted probabilities of its binary variable. These findings support the use of the univariate approach in estimating the parameters of sequential binary decision models; a technique which has the additional advantages of theoretical appeal and computational ease.

Table 5. Coefficient Estimates and Standard Errors ( ) for the Joint and Univariate Probit Estimation Techniques.

Variable	Estimation Method			
	Univariate Probit Estimation Log Likelihood = -340.76[a]		Joint Probit Estimation Log likeliihood = -340.63	
	Know	Use	Know	Use
ONE	-0.997 (0.144)[b]	-1.868 (0.429)[b]	-0.995 (0.147)[b]	-2.364 (2.501)
AREA	0.593 (0.144)[b]	-0.591 (.446)	0.592 (0.147)[b]	-0.397 (1.988)
INCOME	0.404 (0.149)[b]	-0.104 (0.369)	0.389 (0.150)[b]	-0.017 (.697)
FORWARD1	0.947 (0.248)[b]	0.626 (.456)	0.939 (0.262)[b]	0.807 (.750)
FORWARD2	1.188 (0.549)[b]	1.100 (0.532)[b]	1.200 (0.594)[b]	1.259 (0.967)
FUTURES	0.383 (0.418)	0.756 (0.451)[c]	0.378 (0.479)	0.766 (0.541)
EXP1	0.322 (0.160)[b]	0.485 (0.414)	0.326 (0.166)[b]	0.530 (.564)
EXP2	0.342 (.336)	0.681 (.543)	0.327 (0.351)	0.717 (.711)
EDUCATION	0.395 (0.135)[b]	---	0.400 (0.137)[b]	---[d]
Correlation Coefficient, ρ			0.545 (5.178)	

[a] The figure corresponds to the likelihood function given by equation 7.
[b] Coefficient is significant at 0.05 level.
[c] Coefficient is significant at 0.10 level.
[d] For identification in estimating β_1 and β_2 jointly, the coefficient on EDUCATION was set to zero in equation 2.

Table 6. Predicted Probabilities of Knowing About Options, $F(\hat{\beta}_1'\underline{x})$, and Of Using Them, $F(\hat{\beta}_2'\underline{x})$, Evaluated at Selected Values of the Independent Variables and at Samples Means Using the Joint and Univariate Probit Estimates (Standard Error in Parentheses)

Variable Values									$F(\hat{\beta}_1'\underline{x})$		$F(\hat{\beta}_2'\underline{x})$[a]	
One	Area	Income	Forward1	Forward2	Futures	Exp1	Exp2	Education	Univariate Probit	Joint Probit	Univariate Probit	Joint Probit
1	0	1	0	0	0	0	0	0	0.277 (0.053)[b]	0.272 (0.053)[b]	0.024 (.0249)	0.008 (0.051)
1	0	0	1	0	0	1	0	0	0.607 (0.1080)[b]	0.607 (0.1082)[b]	0.291 (0.142)[b]	0.152 (0.525)
1	1	0	0	1	1	0	1	0	0.934 (.079)[b]	0.934 (0.109)[b]	0.531 (0.1972)[b]	0.4928 (0.316)
1[c]	0.739	0.234	0.046	0.043	0.059	0.189	0.063	.286	0.456 (.025)[b]	0.456 (0.030)[b]	---	---
1	0.833	0.317	0.159	0.093	0.119	0.264	0.115		---	---	0.029 (0.014)[b]	0.016 (.030)

a Does not include education.

b Significant at $\alpha = 0.05$.

c Figures in the last two rows are the means of the explanatory variables for the whole sample and subsample $y_1 = 1$, respectively.

Interpreting Univariate Estimation Results

In discussing and interpreting the estimated coefficients further, we concentrate on the univariate estimation results. AREA, INCOME, FORWARD1, FORWARD2, EXP1 AND EDUCATION have significant positive impacts on the probability of knowing about options. FUTURES and EXP2 have the expected positive sign but their coefficients are not significant at the α=.05. The SIZE variables (AREA, INCOME) have negative, but insignificant, impacts on the probability of using options. FORWARD2 and FUTURES have statistically significant impacts on this probability with the expected positive signs.

In order to get further insight into the significance of different factors, we conduct zero null hypotheses tests on each of the subvectors of parameters corresponding to the factors considered. The results, provided in Table 7, show that the size of grain business is a significant determinant of the probability of knowing about options. Large size grain commitments promotes the economic significance of protection against price declines and appears to enhance a farmer's incentive to know about options as a new marketing alternative. As expected, previous experience with forward pricing through either cash forward or futures trading contributes to the awareness of options as an additional marketing tool. The results also show that formal education is a significant determinant of the probability of knowing about options. However, a farmer's expenditure on market information is not a statistically significant determinant of this probability.[5/]

When we turn to those farmers reporting that they use options our major influencing factors show somewhat different results. Previous forward pricing experience in cash forward contracts and futures is significantly related to options use. We thus have limited evidence that those who have used these other instruments may find the use of options a "natural" extension of their marketing tools package. This supports the expectation that experience with related abstract marketing tools and the transaction involved in their use would encourage the use of options. In the case of SIZE and INFORMATION, the lack of a significant contribution to options use could have many explanations. One explanation is that even if farmers can get greater potential returns and they understand how to put together a complex marketing plan this does not mean they will choose a particular tool. During the time of our survey agricultural options were new and had very stiff competition as price protection devices from federal feed grain programs. The participation rate in feed grain programs by respondents to our survey was 75%, indicating that most of the farmers in our study had already chosen an element of their marketing plan which gave them some of the same price protection as options. Further, the income supplement feature of farm programs meant that the benefits were even greater than price protection. It can be argued that all the variables hypothesized to positively influence options use also positively influence feed grain program participation.

Table 7. Results of the Zero Null Hypothesis Test for the Subvectors of Coefficients on SIZE, HEDGE, INFORMATION and EDUCATION.

Pre-conditioned Factor	Null Hypothesis	Chi-square[a] Statistic for Knowing Options	Chi-square Statistic for Using Options
SIZE	$\beta_2 = \beta_3 = 0$	(19.957)[b]	1.765
HEDGE	$\beta_4 = \beta_5 = \beta_6 = 0$	(21.318)[b]	(10.597)[b]
INFORMATION	$\beta_7 = \beta_8 = 0$	4.562	1.813
EDUCATION	$\beta_9 = 0$	(8.561)[b]	

[a] Degrees of freedom equal to the number of parameters being tested.

[b] Subvector is significant at $\alpha = 0.05$.

Applying the Results to the Average Farmer

To get an indication about the probability that the average farmer in Wisconsin knows about options, we evaluated $F(\hat{\underline{\beta}}_1'\underline{x})$ at the mean values of the sample observations. The same was applied to the subsample of those who knew about options to get a prediction for $F(\hat{\underline{\beta}}_2'\underline{x})$ at the data means. Table 6 shows a moderate value, 0.456, for the former probability and a rather small value, 0.029, for the latter.[6/] This low probability of options trading may be explained in part by the easy access to the USDA Feed Grain Program cited above. At the time of the survey the USDA Feed Grain Program of 1985 had also provided a significant degree of indirect price protection even to those outside the program. This could have further discouraged farmers from using options. Also, options contracts had only been traded for about two years at the time of the survey. Thus, farmers had limited time to investigate and observe their use.

To compare the importance of different factors in influencing the probabilities of knowing about and using options we employed marginal impact analysis for selected variables. A variable's marginal impact is defined as the change in predicted probability that results from a change in the variable's value from zero to one holding all other variables constant at their sample means. Here we consider only factors with significant chi-square statistics. Marginal impacts are given in Table 8 for the whole population and for subpopulation of farmers who knew about options. From these results it becomes clear that in our sample the effect of a farmer's previous forward pricing practice is more important than the effect of the size of grain business and education in determining a farmer's awareness of options. A simultaneous increase in FORWARD2 and FUTURES from zero to one, other things being equal, causes the probability of knowing about options to increase by 128.2%, while for EDUCATION and SIZE these impacts are 26.38% and 21.18% respectively. Within the HEDGE factor, FORWARD2 and FUTURES are more important determinants of the probability of using options than FORWARD1. The more active the farmer in using forward pricing, the greater the likelihood that he will use options as a part of a marketing plan.

Table 8. Marginal Impacts of a Change in an Explantory Variable from Zero to One on the Probabilities of Knowing About and Using Options Holding All Other Variables Constant at Their Sample Means.[a]

Factor	Variable	Marginal Impact on $F(\underline{\beta}_1'\underline{x})$ Absolute	Percentage	Marginal Impact on $F(\underline{\beta}_2'\underline{x})$ Absolute	Percentage
SIZE	AREA	0.0593	13.96		
	INCOME	0.0315	7.42		
HEDGE	FORWARD1	0.3239	76.27	0.0991	173.56
	FORWARD2	0.4017	94.58	0.2239	392.12
	FUTURES	0.1428	33.62	0.1270	222.42
EDUCATION	EDUCATION	0.1112	26.18	---	---

a We considered only those variables that correspond to significant preconditioned factors for the whole sample and subsample $y_1 = 1$.

CONCLUSIONS

This paper explores some methodological issues in modeling sequential binary responses. The results show that in estimating the parameters of such models a starting assumption of uncorrelated disturbance terms is a reasonable one. The univariate probit estimation technique gave more efficient estimates for the parameters of the use of options equation as well as lower prediction errors for the probability of its binary variable. Both methods showed little empirical differences regarding the interdependence of the error terms and the probabilities of knowing about options. Thus, these results support the univariate approach as a preferred method, offering conceptual appeal as well as computational ease. We recognize, however, that the small number of observations with positive responses on the use decision may have biased the results. Further studies with larger sample sizes may add additional insights into the empirical implications of both approaches.

The paper also examines factors that influence Wisconsin cash grain farmers knowledge and use of options. The results indicate that size of the commitment to cash grain, previous forward contracting experience and education are all related to Wisconsin farmers knowledge of the existence of agricultural options contracts. The single most important factor in influencing this probability is previous experience using similar marketing tools (e.g. futures and forward contracts). The results also show a moderate value for the probability that the average Wisconsin farmer knows about options. As we attempted to explore factors influencing the use of options decision, the results are less revealing. Only previous forward pricing experience was significantly related to use. In addition, the average farmer's chance of using options was rather low. We would acknowledge that the jump from knowing about to using options is a large one. Our survey techniques only begin to explore the use decision and much deeper investigation will be required to sort out how this new tool will be combined in farmers marketing plans.

REFERENCES

Campbell, Gerald R. and Amr Shiha. "Wisconsin Corn and Soybean Producers' Knowledge and Use of Options and Related Marketing Instruments." Working Paper No. 276, Madison: Department of Agricultural Economics, University of Wisconsin (1987).

Catsiapis, G. and C. Robinson. "Sample Selection Bias with Multiple Selection Rules." Journal of Econometrics, 18 (1982), pp. 351-368.

Danzon, P. M. and L. A. Lillard. The Resolution of Medical Malpractice Claims - Modeling the Bargaining Process, R-2792-ICJ, The Institute for Civil Justice, Rand Corporation, Santa Monica, 1982.

Gardner, Bruce L. "Commodity Options for Agriculture." American Journal of Agricultural Economics, 59(1977), pp. 986-992.

Heckman, James J. "Sample Selection Bias as a Specification Error." Econometrica, 47(1979), pp. 153-62.

Heifner, Richard and Thomas L. Sporleder. "Alternative Public Programs to Increase Farmers' Awareness and Potential Use of Forward Markets." in: Options, Futures, and Agricultural Commodity Programs, USDA Report No. AGES 870911, Washington, DC, (February 1988), pp. 34-44.

Lee, Lung-Fei and G. S. Maddala. Sequential Selection Rules and Selectivity in Discrete Choice Econometric Models, Unpublished manuscript, University of Minnesota, 1983.

Tunali, I. "A Common Structure for Models with Double Selection." Social Systems Research Institute, Report No. 8304, University of Wisconsin, Madison, 1983.

Van De Ven, Wynard P.M.M. and Bernard M.S. Van Praag. "The Demand for Deductibles in Private Health Insurance: A Probit Model with Sample Selection." Journal of Econometrics, 17(1981), pp. 229-252.

ENDNOTES

1/ Current government programs contain elements of price support and direct income transfer. Options markets can help provide price insurance but they are not automatic vehicles for income transfer.

2/ Henceforth, we drop the subscript i to avoid notational clutter.

3/ This, however, does not necessarily mean uncorrelated decision rules. But there are underidentification problems if only dichotomous indicators are observed. According to Lee and Maddala the correlation between the two decision equations can be identified if ϵ_2 is not normally distributed on subpopulation $y_1=1$ and if either y_1^* and y_2^* are observed or there exists another continuous variable, y, that depends on y_1 and y_2.

4/ For details on the survey, see Campbell and Shiha (1987).

5/ While our measures for all the major factors can be criticized the measure of information is especially weak. The survey question concentrated on price outlook information which is only one element of the information acquisitiveness of farmers. Thus, we may not have given the information seeking behavior a fair test.

6/ Considering only the statistically significant factors in evaluating $F(\underline{\beta}_2'\underline{x})$ does not alter these results much and yields a predicted probability of 0.046 for using options by the average Wisconsin farmer.