Appendix II. An Empirical Tobit Model To Examine the Factors Influencing Adoption

A Tobit model (Tobin, 1958) was used to model factors that influence adoption of genetically engineered crops. This method estimates the likelihood of adoption and the extent (i.e., intensity) of adoption. The Tobit approach has been applied in previous studies of agricultural technology adoption, including studies of conservation adoption (Norris and Batie, 1987; Gould et al., 1989) and the adoption of alternative crop varieties (Adesina and Zinnah, 1993).

A two-limit Tobit model was used. The two-limit Tobit, originally presented by Rossett and Nelson (1975) and discussed in Maddala (1992) and Long (1997), is appropriate since the dependent variable is the proportion of the acreage with the technology; thus, the dependent variable must be between 0 and 1. The two-limit Tobit model can be represented as:

$$y_i^* = \beta' x_i + \in_i \qquad (1)$$

where y_i^* is a latent variable (unobserved for values smaller than 0 and greater than 1) representing the use of the technology; **x** is a vector of independent variables, which includes the factors affecting adoption; β is a vector of unknown parameters; and $\in_i$ is a disturbance assumed to be independently and normally distributed with zero mean and constant variance F; and i = 1, 2,…*n* (n is the number of observations). Denoting y_i (the proportion of acreage on which the technology is used) as the observed dependent (censored) variable:

$$y_i = \begin{cases} 0 & if \quad y_i^* \le 0 \\ y_i^* & if \quad 0 \le y_i^* \le 1 \\ 1 & if \quad y_i^* \ge 1 \end{cases} \qquad (2)$$

Using the two-limit Tobit, the extent of adoption was regressed against proxies for various factors hypothesized to influence producer adoption.

The McDonald-Moffit Decomposition for a Two-Limit Tobit. Unlike traditional regression coefficients, the Tobit coefficients cannot be interpreted directly as estimates of the magnitude of the marginal effects of changes in the explanatory variables on the expected value of the dependent variable. In a Tobit equation, each marginal effect includes both the influence of the explanatory variable on the probability of adoption as well as on the intensity of adoption. More explicitly, as Gould et al. (1989) observe, the total (marginal) effect takes into consideration that a change in an explanatory variable will affect simultaneously the number of adopters and the extent of adoption by both current and new adopters.

To obtain the decomposition for the case of a two-limit Tobit, begin with equation (1). Given the assumption that the disturbance $\in_i$ is independently and normally distributed with zero mean, the expected value of the latent variable for the two-limit Tobit is $E(y^* | x) = \beta' x$ and $\partial E(y^* | \mathbf{x})/\partial x_k = \beta_k$. However, the conditional expected value of the truncated outcome is (Long, 1997; Maddala, 1992) is:

$$E(y | \mathbf{x}, L < y^* < U) = \boldsymbol{\beta x} + \sigma \frac{\phi(Z_L) - \phi(Z_U)}{\Phi(Z_U) - \Phi(Z_L)} \qquad (3)$$

where L and U denote the lower and upper limit, respectively; $Z_L = (L - \boldsymbol{\beta x})/\sigma$ and $Z_U = (U - \boldsymbol{\beta x})/\sigma$; $\Phi(.)$ and $\phi(Z)$ are the cumulative distribution and density function for the standard normal. The expected value of the dependent variable (observed outcome) (Long, 1997) is:

$$E(y | x) = L \cdot Pr(y = L | x_i) + E(y | x, L < y^* > U, x) \cdot Pr(L < y^* > U | x_i) + U \cdot Pr(y = U | x_i) \qquad (4)$$

Substituting the expressions for $Pr(y = L | x_i) = \Phi(Z_L)$, $Pr(y = U | x_i) = 1 - \Phi(Z_U) = \Phi(-Z_U)$, into the equation above and taking the derivative, one obtains the marginal effect:

$$\frac{\partial E(y \mid \boldsymbol{x})}{\partial x_k} = E(y \mid x, L < y^* < U) \cdot \left[\frac{\partial[\Phi(Z_U) - \Phi(Z_L)]}{\partial X_k} \right]$$

$$+ \left[\Phi(Z_U) - \Phi(Z_L)\right] \cdot \left[\frac{\partial E(y \mid x, L < y^* < U)}{\partial X_k} \right] \qquad (5)$$

$$+ \frac{\partial \Phi(-Z_U)}{\partial x_k}$$

Equation (5) is the extension of the McDonald-Moffit decomposition for the case of a two-limit Tobit. It decomposes the total marginal effect of a change in an independent variable x_k on the expected value of the extent of adoption (i.e., the percent of the acreage under the technology) into three components:

(i) The change in the probability of adoption weighted by the conditional expected value of the percent acreage under adoption given that the farmer has adopted,

(ii) The change in the percent acreage under adoption for farmers that are already adopting weighted by the probability of adoption, and

(iii) The change in the probability of adopting on 100 percent of the acreage.

Substituting the expression for $E(y \mid \boldsymbol{x}, L < y^* < U)$ from equation (3), setting the lower limit L=0 and the upper limit U=1 and taking the derivatives, recalling that $\partial \Phi(Z)/\partial x_k = \phi(Z) \cdot (\beta_k/\sigma)$, one obtains the expression for the three components of the marginal effect:

$$\frac{\partial E(y \mid \boldsymbol{x})}{\partial x_k} = \left\{ (\beta x + \sigma \left[\frac{\phi(Z_L) - \phi(Z_U)}{\Phi(Z_U) - \Phi(Z_L)} \right] \right\} \cdot [\phi(Z_L) - \phi(Z_U)]$$

$$+ [\Phi(Z_U) - \Phi(Z_L)] \cdot \beta_k \cdot \left\{ 1 + \frac{Z_L \phi(Z_L) + Z_U \phi(Z_U)}{\Phi(Z_U) - \Phi(Z_L)} - \frac{[\phi(Z_L) - \phi(Z_U)]^2}{[\Phi(Z_U) - \Phi(Z_L)]^2} \right\} + \qquad (6)$$

$$+ \beta_k [\phi(-Z_U)/\sigma]$$

Simplifying, one obtains the total marginal effect: $\partial E(y \mid \boldsymbol{x})/\partial x_k = \beta_k . [\Phi(Z_U) - \Phi(Z_L)]$.

Data and Estimation. Data used to estimate the Tobit model are from USDA's 1998 ARMS. The definition of a farm, and thus the target population of the ARMS, is any business that produces at least $1,000 worth of agricultural production during the calendar year. The farm population used in this study includes those that grew corn or soybeans during 1998. Appendix table 2.1 shows the number of observations in each case. The ARMS data include information about the financial condition and management of the operation; demographic characteristics; and management and marketing strategies used on the operation. Important to this study is that the survey included questions about the extent to which alternative technologies were used in the farm business. Producers were asked for each crop grown whether they planted bioengineered seed and, if so, what type of seed was planted and on how many acres it was planted. The adoption of GE crops was defined in cases where herbicide-tolerant soybeans, herbicide-tolerant corn, and Bt corn were used. The extent of adoption was defined as the proportion of total harvested corn (soybean) acres in herbicide-tolerant corn (soybeans) as well as the proportion of total corn acres in Bt corn.

A total of three Tobit adoption models were estimated using the ARMS data, one for each of the three genetically engineered crop varieties. The estimating technique was consistent with the complex survey design of the ARMS (Dubman, 2000). The LIFEREG procedure of SAS with the weight option (using the survey weights) was used to estimate the parameters. A replication approach employing the delete-a-group jackknife method was used to estimate parameter standard errors (Kott and Stukel, 1997; Kott, 1998).

Variable Specification. While technology adoption has both static and dynamic aspects, our focus is from a cross-section, point-in-time (i.e., static) perspective at the micro (i.e., individual farm) level. At this level, each farm operator is assumed to decide whether to adopt a technology and, if adopted, to choose its intensity of use. Within this context, the analysis encompasses both the farm and operator characteristics that are hypothesized to influence the decision to adopt and to what extent. We also incorporate a proxy variable to account for farm location (i.e., a proxy for climate, soil type, topography, input/equipment dealer availability, etc.) similar to Fernandez-Cornejo et al. (1994) and Green et al. (1996).

The adoption rate of GE technologies was expected to be influenced by the following sets of factors: farmer risk attitudes; farmer management resources, including education, experience, and off-farm employment; farm size, land tenure; credit reserves; farm typology; use of contracting; degree of pest infestation (for the case of Bt corn); and a regional dummy variable. While the variables are defined in appendix table 2.1, some require additional clarification.

The main focus of this study is on the role of farm size in technology adoption. Farm size is defined as the number of corn and soybean acres harvested on the operation. To allow for the possibility that the effect of farm size on adoption may vary as size changes, both linear and quadratic terms for size are included. Following Kinnucan et al. (1990), one interprets the significant coefficients on the farm size terms in the estimated model, which control for other factors, as an indication of scale dependency associated with the adoption of the technology.

Identifying and quantifying producer risk preferences is a difficult task (Feder et al., 1985). To operationalize the concept of risk preferences using farmer attributes obtained from the survey, one uses a risk index constructed according to farmers' answers to a series of questions in the ARMS survey. The construction is based on the notion that risk attitudes are reflected by farmers' attitudes toward tools used for managing risk. Moreover, as Bard and Barry (1998) show, it is more appropriate to base the analysis of issues involving risk on how farmers react to risk than their self-assessment.

Ten questions were included in the ARMS survey questionnaire to elicit farmers' attitudes toward tools used for managing risk. The questions asked whether farmers strongly agreed, agreed, neither agreed, or disagreed, disagreed, or strongly disagreed with each of 10 statements. To prevent response bias, some of the questions were worded in such a manner that strong agreement implies willingness to accept more risk while other questions are phrased such that agreement with the statement implies that the farmer is more risk adverse. Thus, typically the questions begin with either "I never" or "I usually." Subjects of the questions are having cash on hand to pay bills, use of custom work, reliance on market information to make marketing decisions, spreading commodity sales throughout the year, having adequate liability insurance, having machinery new or in good repair, believing that concentration of farming operations in one geographic area "substantially increases" total risk, having sufficient backup management/labor to carry production for emergencies, having adequate hail/fire insurance, and hedging by using futures/options (Bard and Barry, 1998).

Categories of the ERS farm typology classification based on the occupation of farm operator were also included in the model (Hoppe, Perry, and Banker, 1999). The mutually exclusive typology categories were specified as a series of dummy variables that indicate whether or not the farm was classified as limited-resource, retirement, residential lifestyle, or a nonfamily farm. Limited-resource farms are constrained by low levels of assets and household income. Retirement farms are those with operators who report that they are retired (excluding limited-resource farms). Residential lifestyle farms are those with operators who report a major occupation other than farming (excluding limited-resource farms). Nonfamily farms are those organized as nonfamily corporations or cooperatives, as well as those operated by hired managers. These categories were included in the adoption model to account for the diversity of farm types by reflecting differences in operators' expectations from farming, stage in the life cycle, and dependence on agriculture.

A credit reserve variable was specified as the maximum feasible level of debt that the farm operator could service from income (Ryan, 1999). Credit reserves are hypothesized to positively influence adoption. Genetically engineered seeds are more expensive than traditional varieties and adoption may also be influenced by the operating investment. Also included was the proportion of operator and spouse hours worked off-farm.

The use of contracting was specified using a dummy variable indicating whether or not the farm sold corn (or soybeans) under a marketing contract, or produced corn (or soybeans) under a production contract. Contracting has been used in modeling adoption to reflect the level of risk management used by producers. In the context of biotech crops, contracting may indicate that the producer has locked a market channel for the crop and thus has reduced the uncertainty that these crops would be accepted in traditional marketing channels. Producers would be more likely to adopt biotech crops if they have contracts that ensure market access. Contracting may also be an indicator of the overall level of operator management.

A measure of State infestation level for the European corn borer (ECB) was included in the Bt corn adoption model to account for variation in the perceived need for pest control. As an infestation level proxy, we used a dummy variable equal to 1 for the States with the highest infestations, and 0 otherwise. Past infestation levels of corn fields by the ECB were calculated as the percentage of the State's corn acres infested with ECB at a treatable level (obtained from Pike, 1999) relative to the planted corn acreage.

Results. Results of the Tobit analysis for the adoption of genetically engineered crops are presented in Appendix tables 2.2 and 2.3. These tables include the estimated coefficients, standard errors, and calculated marginal effects. The marginal effects are used to calculate the elasticities.

Statistically significant variables in the adoption models varied among the individual technologies. Farm size was significant in the Bt corn and herbicide-tolerant corn, but not for herbicide-tolerant soybeans. The coefficients of the quadratic terms indicate that the probability of adoption for Bt corn and precision farming increased with farm size at a decreasing rate while adoption of herbicide-tolerant corn increased linearly with size (within the range of the data). The contracting variable was significant in two of the three adoption models. The expected extent of adoption was greater on operations that utilized marketing or production contracts than for other operations. Among operator characteristics, education and experience were significant in various adoption models. The expected extent of adoption associated with two of the three technologies increased significantly as operator education increased. The expected extent of adoption of herbicide-tolerant corn and soybeans increased with operator experience. The measure of operator risk aversion was only significant in the herbicide-tolerant soybean model. The negative coefficient on the risk variable indicates that the more risk-averse producers are expected to have a higher extent of adoption for these technologies. Location of the operation outside of the primary production area was associated with a lower expected adoption for herbicide-tolerant soybeans. Among the typology variables, only the limited-resource classification was significant in the model for herbicide-tolerant soybeans, suggesting that limited-resource farms were less likely to adopt. The corresponding indicator variable shows that corn borer infestation had a significant and positive influence on the expected adoption of Bt corn. Credit reserves, off-farm work, and land tenure were not significant in any of the adoption models.

Appendix table 2.1—Variable definitions and means

Variable name	Variable definition	Mean value: Soybean farms	Mean value: Corn farms
EDUCATION	Education of the operator: beyond high school/college = 1, 0 otherwise	0.422	0.424
EXPERIENCE	Operator experience, years on operation	23.52	23.98
CREDIT	Credit reserve (maximum debt repayment capacity), $1,000	232.8	228.2
OFF	Operator/spouse proportion of time worked off-farm	0.412	0.387
MARGINALR	Dummy variable equal to 1 if farm is located in marginal production region, 0 otherwise[1]	0.248	0.381
SIZE	Farm size, 1,000 acres of harvested soybeans/corn	0.195	0.164
SIZE_SQ	Farm size squared	0.121	0.086
TENURE	Farm tenure, ratio of owned to operated acres	0.489	0.553
RISK	Risk index, ranging from 12 (risk averse) to 48 (risk seeking)	28.63	28.38
LIMRES	Dummy variable equal to 1 if farm belongs to the “limited-resources” category of the ERS farm typology, 0 otherwise	0.042	0.042
RETIRE	Dummy variable equal to 1 if farm belongs to the “retirement” category of the ERS farm typology operator is, 0 otherwise	0.029	0.034
LIFEST	Dummy variable equal to 1 if farm belongs to the “residential/ lifestyle” category of the ERS farm typology, 0 otherwise	0.282	0.254
NONFAM	Dummy variable equal to 1 if farm belongs to the “nonfamily” category of ERS farm typology, 0 otherwise	0.026	0.022
CONTRACT	Dummy variable equal to 1 if farm uses soybeans/corn marketing or production contracts, 0 otherwise	0.121	0.131
HI_INF	Dummy variable equal to 1 if farm is in State with a high infestation level of European corn borer, 0 otherwise	na	0.248
Number of observations		2,321	1,719

[1] Marginal production regions are those outside of the primary areas where these crops are grown, defined using the ERS farm resource regions (box 1). Primary production regions for soybeans are the Heartland and Mississippi Portal. Primary production regions for corn are the Heartland and Prairie Gateway.
na = Not applicable.

Appendix table 2.2—Tobit estimates: Adoption of herbicide-tolerant soybeans, Bt corn, and herbicide-tolerant corn, 1998

Technology/ variable	Estimated coefficient	Standard error	t-statistic	Marginal effect $\partial E(y\|\mathbf{x})/\partial x_k$
Herbicide-tolerant soybeans:				
Intercept	0.10627	0.60357	0.18	—-
EDUCATION	0.40943	0.28592	1.43	0.081
EXPERIENCE	0.01234	0.00641	1.92*	0.002
CREDIT	0.00019	0.00025	0.78	0.000
OFF	0.13772	0.25491	0.54	0.027
MARGINALR	-0.38910	0.14220	-2.74**	-0.077
SIZE	0.03087	0.23659	0.13	0.006
SIZE_SQ	-0.07041	0.06751	-1.04	-0.014
TENURE	-0.35418	0.31678	-1.12	-0.070
RISK	-0.03684	0.01476	-2.50**	-0.007
LIMRES	-1.44391	0.44928	-3.21**	-0.284
RETIRE	-0.38311	0.56992	-0.67	-0.075
LIFEST	0.08242	0.32830	0.25	0.016
NONFAM	0.71062	0.42338	1.68	0.140
CONTRACT	0.36799	0.14653	2.51**	0.072
Bt corn:				
Intercept	-0.57717	0.36585	-1.58	—-
EDUCATION	0.22989	0.09624	2.39 **	0.037
EXPERIENCE	0.00384	0.00366	1.05	0.001
CREDIT	0.00011	0.00009	1.22	0.000
OFF	-0.16851	0.12394	-1.36	-0.027
MARGINALR	-0.11709	0.08728	-1.34	-0.019
SIZE	1.06147	0.25152	4.22 **	0.172
SIZE_SQ	-0.43925	0.12973	-3.39**	-0.071
TENURE	-0.09012	0.11267	-0.80	-0.015
RISK	-0.01537	0.01357	-1.13	-0.002
LIMRES	-0.02361	0.27252	-0.09	-0.004
RETIRE	-0.36465	0.31985	-1.14	-0.059
LIFEST	0.07478	0.17853	0.42	0.012
NONFAM	0.22157	0.23895	0.93	0.036
CONTRACT	0.09635	0.05515	1.77*	0.016
HI_INF	0.26938	0.10626	2.54 **	0.044
Herbicide-tolerant corn:				
Intercept	-2.24752	0.48173	-4.67**	—-
EDUCATION	0.54292	0.16289	3.33**	0.019
EXPERIENCE	0.01294	0.00651	1.99*	0.001
CREDIT	-0.00026	0.00013	-1.94*	-0.000
OFF	0.06968	0.38352	0.18	0.002
MARGINALR	-0.07962	0.13278	-0.60	-0.003
SIZE	1.16590	0.62184	1.87*	0.041
SIZE_SQ	-0.42077	0.44267	-0.95	-0.015
TENURE	-0.11399	0.30899	-0.37	-0.004
RISK	-0.01762	0.01583	-1.11	-0.001
LIMRES	0.24265	0.60202	0.40	0.008
RETIRE	-0.97222	5.22866	-0.19	-0.034
LIFEST	-0.12682	0.31294	-0.41	-0.004
NONFAM	0.25422	0.70038	0.36	0.009
CONTRACT	0.00255	0.14292	0.02	0.000

Note: Single and double asterisks (*) denote significance at the 10-percent and 5-percent levels, respectively. Using the delete-a-group jackknife variance estimator with 15 replicates, the critical t-values are 2.145 at the 5-percent level and 1.761 at the 10-percent level. —- = Not applicable.