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DECOMPOSING THE SIZE EFFECT ON THE ADOPTION OF INNOVATIONS: AGROBIOTECHNOLOGY AND PRECISION AGRICULTURE

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This paper examines the factors that influence the adoption of two emerging agricultural technologies, genetically engineered crops and precision agriculture in corn and soybean production, and contrasts the relative influence of various factors on the adoption decision for these two technologies, with special emphasis on the role of farm size.

Key Words: corn; genetically engineered crops; precision agriculture; soybeans; technology adoption; two-limit Tobit analysis.

Because technological change can affect the level of output, product quality, employment, trade, and real wages and profits, the adoption of new technologies offers economic opportunities and challenges. Consequently, technology adoption continues to interest economists, sociologists, and policymakers. Of particular interest to policymakers is the impact of new technologies on farm structure (i.e., farm size), and the role that farm structure, among other factors, plays in the adoption process (United States Department of Agriculture [USDA], 1998, p. 31). This study contrasts the adoption of two innovations—genetically engineered crops and precision agriculture—that are likely to shape United States agriculture in the present decade.

The objectives of this paper are to: (a) examine the factors that influence the adoption of two emerging agricultural technologies in corn and soybean production, genetic engineering (GE) and precision agriculture (PA); and (b) contrast the relative influence of various factors on the adoption decision for these two technologies, with special emphasis on the role of farm size.

Genetically Engineered Crops And Precision Agriculture

Although there are several types of genetically engineered (GE) crops commercially available, this paper focuses on the adoption of herbicide-tolerant corn and soybeans and *Bacillus thuringiensis* (Bt) corn. The most common herbicide-tolerant crops are resistant to glyphosate, a herbicide effective on many species of grasses and broadleaf weeds (Fernandez-Cornejo & McBride, 2000). A gene from the soil bacterium *Bacillus thuringiensis* provides Bt corn with protection against the European corn borer (ECB).

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Precision agriculture (PA) is often characterized as a suite of technologies used to manage variability within fields. Precision agriculture technologies include enabling technologies, such as computers, Geographic Information Systems, and Global Positioning Systems, as well as various sensors with geo-referencing capabilities, such as grid soil sampling, yield monitors and satellite images, and input applicators (e.g., seed, fertilizer, pesticides) that can vary rates across a field (Pierce & Nowak, 1999). These technologies can be used independently or as a package of technologies that includes, for example, the use of grid soil sampling, a variable-rate input applicator, and a yield monitor.

Numerous empirical technology adoption studies have been conducted over the last 40 years, beginning with the work of Griliches (1957) and Rogers (1961). Feder, Just, and Zilberman (1985) and Feder and Umali (1993) review many of these studies. However, only a few empirical analyses of the factors affecting the adoption of GE crops (Fernandez-Cornejo & McBride, 2000) and precision agriculture (Daberkow & McBride, 1998; Khanna, Epough, & Hornbaker, 1999) have appeared in the literature.

The Empirical Model

A Tobit model was used to model the adoption of GE and PA techniques (see appendix). This method estimates the likelihood of adoption and the extent (i.e., intensity) of adoption. The Tobit model is preferable to binary adoption models when the decision to adopt involves simultaneously the decision regarding the intensity of adoption (Feder & Umali, 1993), as it does with GE and PA technologies. The Tobit approach has been applied in studies of adoption of conservation tillage (Norris & Batie, 1987; Gould, Saupe, & Klemme, 1989) and adoption of alternative crop varieties (Adesina & Zinnah, 1993). A two-limit Tobit model (Rosett & Nelson, 1975; Maddala, 1992) is used in this study because the dependent variable is the proportion of the acreage (between 0 and 1) using the technology.

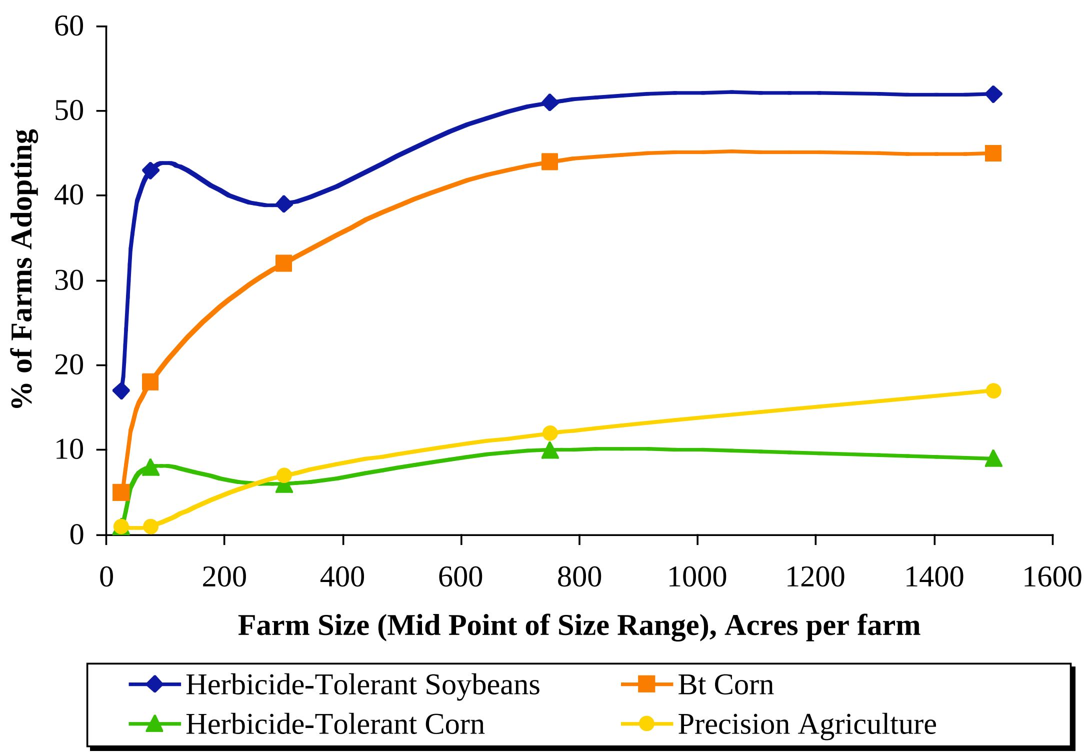
Unlike traditional regression coefficients, the Tobit coefficients cannot be interpreted directly as estimates of the magnitude of the marginal effects of changes in the explanatory variables on the expected value of the dependent variable. In a Tobit equation, each marginal effect includes both the influence of the explanatory variable on the probability of adoption as well as on the intensity of adoption. As Gould, Saupe, and Klemme (1989) observe, the total (marginal) effect takes into consideration that a change in a explanatory variable will affect simultaneously the number of adopters and the extent of adoption by both current and new adopters. According to the extension of the McDonald-Moffit decomposition for the case of a two-limit Tobit, the total marginal effect of a change in an independent variable on the expected value of the extent of adoption (i.e., the percent of the acreage under the technology) is equal to a weighted sum of: (a) the change in the probability of adoption (by nonadopters), (b) the change in the (percent) acreage under adoption for farmers that have already adopted, and (c) the change in the probability of adopting on 100% of the acreage.

Data And Estimation

Data used to estimate the Tobit model are from USDA's 1998 Agricultural Resource Management Study (ARMS). The ARMS is a multi-frame, probability-based survey in which sample farms are randomly selected from groups of farms stratified by attributes such as economic size, type of production, and land use (USDA, 2000). The population used in this study includes those farms that grew corn or soybeans during 1998.

The extent of adoption of GE crops 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. The extent of adoption of PA was defined as the proportion of total crop acres on which the variable rate technology (VRT) was applied for seeding, fertilizing, or applying chemicals. Farm adoption rates for each technology calculated directly from the 1998 ARMS data are shown by size of operation in figure 1. Overall, herbicide-tolerant soybeans were adopted by about one-third of soybean producers in 1998, while Bt corn was used on 20% of corn farms. Herbicide-tolerant corn was adopted by only 5% of corn farms and PA was used on only 6% of farms with corn or soybeans. Adoption rates generally increased with size of operation for all the technologies, but at different patterns. The adoption of herbicide-tolerant soybeans and corn was considerably higher among farms with 50 or more acres than among those with fewer than 50 acres. However, above 50 acres, adoption of the herbicide-tolerant technology was fairly stable (39-52% for soybeans and 6-10% for corn). In contrast, the adoption of Bt corn and PA showed a steady increase with size.

Figure 1: Adoption (Sample Averages) by Size of Operation, 1998.



Four Tobit adoption models were estimated using the ARMS data: one for each of the 3 GE crops, and one for PA (see appendix). In each case, the extent of adoption was regressed against proxies for various factors hypothesized to influence producers' adoption decisions. The adoption rate of GE and PA technologies was expected to be influenced by the following sets of factors: farm size, farmer risk attitudes, education, experience, off-farm employment, land tenure, credit reserves, farm typology, use of contracting, degree of pest infestation (for the case of Bt corn), and a regional dummy variable to account for farm location (e.g., a proxy for climate, soil type). Although the variables are defined in table 1, some require additional clarification.

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. To operationalize the concept of risk preferences using farmer attributes obtained from the survey, we use 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. Bard and Barry (1998) show that in issues involving risk it is more appropriate to base the analysis on how farmers react to risk than their self-assessment. Categories of the USDA Economic Research Service (ERS) farm typology classification based on the occupation of farm operator (Hoppe, Perry, & Banker, 1999) were included in the model as a series of dummy variables that indicate whether or not the farm was classified as limited-resource, retirement, residential lifestyle, or a non-family farm.

Table 1: Definitions and Means of Main Variables.

		Mean Value	
Variable Name	**Variable Definition**	**Soybean Farms**	**Corn Farms**
EDUCATION	1 if operator studied beyond high school, 0 otherwise.	0.422	0.424
EXPERIENCE	Operator experience, years on operation.	23.520	23.980
CREDIT	Credit reserve (maximum debt repayment capacity), thousand $.	232.800	228.200
OFF-FARM	Operator/spouse proportion of time worked off-farm.	0.412	0.387
MARGINALR	1 if farm is located in marginal production region.[1]	0.248	0.381
SIZE	Farm size, acres of harvested soybeans/corn, thousands.	0.195	0.164
RISK	Risk index, ranging from 12 (risk averse) to 48 (risk seeking).	28.630	28.380
LIMRES	1 if a "limited resources" farm of the ERS farm typology.	0.042	0.042
CONTRACT	1 if farm uses soybeans/corn marketing or production contracts.	0.121	0.131
HI_INF	1 if farm is in state with high infestation level of European borer.	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 (Hoppe, Perry, & Banker, 1999). 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.

Results

Results of the Tobit analysis for the adoption of GE crops and PA technologies are presented in table 2 expressed in the form of elasticities with respect to each of the significant explanatory variables (detailed parameter estimates, standard errors, t-statistics, and marginal effects are provided in the appendix). The elasticities presented in table 2 take into account that a change in an explanatory variable will simultaneously affect the number of adopters and the proportion of acreage under adoption. As an example of interpretation, a one-percent increase from the mean size (harvested acres) leads to an increase in the expected proportion of corn acres planted with Bt corn by 0.258%. The interpretation of the elasticity for binary variables is somewhat different. For example, a one-percent increase in the proportion of corn farmers pursuing education beyond high school would lead to an increase in the expected proportion of corn acres planted with herbicide-tolerant corn by 0.336%.

Table 2: Elasticities of Adoption with Respect to Variables Significant in the Tobit Analysis, 1998.

Variable	Herbicide-Tolerant Soybeans	Bt Corn	Herbicide-Tolerant Corn	Precision Farming
EDUCATION	0	0.179	0.336	0.149
EXPERIENCE	0.236	0	0.453	0
MARGINALR	-0.079	0	0	0
SIZE	0	0.258	0.279	0.281
RISK	-0.859	0	0	-1.594
LIMRES	-0.049	0	0	0
CONTRACT	0.036	0.022	0	0.048
HI_INF	NA	0.123	NA	NA

Notes. An elasticity of zero indicates an insignificant underlying coefficient. NA=not applicable

Decomposition of the elasticity of size for each technology is presented in table 3. According to the extension of the McDonald-Moffit decomposition for a two-limit Tobit, three components of the elasticity can be identified. The first component indicates how responsive the probability of adoption by non-users of the technology is to changes in size. For example, a one-percent increase in average size, the probability of adopting Bt corn by non-users would increase by 0.217%. The second component indicates how responsive the proportion of acreage under adoption by current users of the technology is to changes in size. As average size increases by one-percent, the proportion of acres with Bt corn would increase by 0.483% from current adopters. The final elasticity component, unique to the two-limit Tobit, indicates how responsive the probability of having all acreage under the technology is to changes in size. If size increases by one percent, the probability of using Bt on all corn acreage increases by 0.074%.

For the adoption of Bt corn and PA both linear and quadratic term are significant, the linear term positive and the quadratic term negative. This implies that in these two cases there a size beyond which adoption no longer increases with size. This maximum is reached at a size of 1,170 acres (about a fifth of the size of the largest farm in the sample) for the case of Bt corn (table 3). For the case of PA, the maximum is at about 1,600 thousand acres, while the largest farm is 7,000 acres. The maximum does not exist for herbicide-tolerant corn because only the linear term is statistically significant and for the case of herbicide-tolerant soybeans because it is invariant to size.

Table 3: The Size Effect on Adoption.

Item	Herbicide-Tolerant Soybeans	Bt Corn	Herbicide-Tolerant Corn	Precision Farming
Elasticity of size (measured at the means)				
Total elasticity of adoption with respect to size: Increase in percent of acreage under adoption for all farmers per 1% increase in size.	0	0.258	0.279	0.281
Decomposition of the elasticity of size				
Increase in the probability of adoption by non-adopters (in percent) per 1% increase in size.	0	0.217	0.442	0.181
Increase in percent of acreage under adoption for farmers that have already adopted per 1% increase in size.	0	0.483	0.242	0.514
Probability (in percent) of having all planted acres under adoption per 1% increase in size.	0	0.074	0.104	0.195
Size				
Size at which the elasticity of adoption becomes negative, thousand acres.	NA	1.170	∞	1.635
Largest farm in the sample, thousand acres.	7.00	5.890	5.890	7.0

Note. An elasticity of zero indicates an insignificant underlying coefficient.

Implications Of The Results

Genetically engineered crop technologies, which can easily incorporated into current production practices, suggest that adoption should be invariant to farm size. This was found to be the case of herbicide-tolerant soybeans. Conversely, PA technologies, which require substantial human and financial capital, suggest that adoption would be more likely on larger farms. Size was found to be positively associated with the adoption of PA. However, the adoption of herbicide-tolerant and Bt corn were also positively related to farm size, thus, the size-invariance of adoption of these technologies was not supported.

The estimated elasticities of size for Bt and herbicide-tolerant corn and PA technologies suggest that the impact of size on adoption is very similar. However, decomposition of the elasticities reveals how the impacts differ. The probability of adopting herbicide-tolerant corn by non-users was much more responsive to changes in size (0.442% per 1% increase in size) than for the other technologies. This may be because of the relative ease of access and use of the herbicide-tolerant crops, especially compared with PA. Non-users could be expected to easily adopt herbicide-tolerant crops with little financial or human capital investment. Among current adopters, the extent of adoption was most responsive to changes in size for users of PA techniques (0.514% per 1% increase in size). This may be attributed to the incentive that producers have to lower unit costs by spreading their fixed investment in PA over more acreage.[1] For possibly this same reason, the probability of having all their acreage under adoption was higher for PA than for the GE crop technologies. Also, this component of the Bt corn size elasticity may have been the lowest because of refuge requirements associated with Bt corn.

The different empirical results obtained for the adoption of herbicide-tolerant soybeans and herbicide-tolerant corn may be understood by examining their adoption rates. The 1998 adoption rate for herbicide-tolerant soybeans in the sample (34% of farms) implies that the adoption of herbicide-tolerant soybeans has progressed past innovator and early adopter stages into the realm where adopting farmers are much like the majority of farmers. On the other hand, adoption of herbicide-tolerant corn was quite low in 1998 (5% of farms), implying that adoption was largely confined to innovators and other early adopters who in general tend to control substantial resources and who are willing to take the risks associated with trying new ideas. It appears that despite the fact that herbicide-tolerant corn has characteristics similar to those of herbicide-tolerant soybeans, the adoption of herbicide-tolerant corn was size dependent while adoption of herbicide-tolerant soybeans was invariant to size, because the impact of farm size on adoption is highest at the early stages of the diffusion of an innovation (the case of the herbicide-tolerant corn), and becomes less important as diffusion increases. This result confirms Rogers' (1995) observation that adoption is more responsive to farm size at the innovator stage and the effect of farm size in adoption generally diminishes as diffusion increases. Moreover, this result was supported by the relatively high elasticity of adoption by non-users of herbicide-tolerant corn.

The results that are most difficult to interpret are those for Bt corn. Characteristics of the Bt corn technology are similar to those of other GE crops in that the investment requirements in both human and financial capital are relatively low. Also, the adoption of Bt corn in 1998 was at 20% of farms, a level beyond that including only innovators and other early adopters. However, magnitudes of the estimated adoption elasticities for Bt corn were more similar to those for PA than for any of the other GE crops. One important difference between Bt corn and the other technologies is that Bt corn is designed to target a problem that has much more regional variation than that of the other technologies.[2] European corn borer (ECB) infestations are quite severe in some areas and virtually nonexistent in others. In general, areas with higher ECB infestations, including states in the western Corn Belt and Great Plains, also have more corn acreage per farm than in other areas. Although we attempted to control for regional variability in ECB infestations, our measured impact of farm size on Bt corn adoption may have been influenced by the correlation between farm size and ECB infestations.

The use of contracting (marketing or production) was positively associated with adoption in most cases. The effect of contracting may be indicative of the greater importance placed on risk management by adopting farms. Contracting assures a market for GE crops, lessening price and any market access risk that could result from uncertainty about consumer acceptance of these crops. On the other hand, GE crops such as Bt corn can be regarded as risk management tools that reduce the likelihood of yield losses due to pest infestations.

Operators with more education were also more likely to adopt both GE crop technologies for corn and PA techniques. The complex nature of information collection and interpretation associated with PA suggests that more education would enhance the ability of the farm operator to utilize these technologies. The insignificance of education in the adoption of herbicide-tolerant soybeans is not surprising because of the low managerial requirement of this technology. However, the impact of education on GE crop adoption for both corn technologies exceeded that of PA, despite the fact that these crops require a much lower human capital investment. The level of operator education, like the contracting variable, may be an indication of the overall level of management on these operations. Operators with more experience were more likely to adopt herbicide-tolerant corn and soybeans, but not PA. Experience may also indicate management level in the sense that more experienced operators are more likely to understand that the greatest economic benefits of new technologies accrue to early adopters. Operator experience may not be associated with the adoption of PA because experience and age tend to be highly correlated. Older operators are probably less likely to adopt PA techniques because of their shorter planning horizon and the required investment in human and financial capital associated with precision agriculture.

Summary And Concluding Comments

This study contrasts the adoption of two innovations—genetically engineered crops and precision agriculture—that appear likely to shape US production agriculture in the next decade. A direct comparison of adoption models was made to draw inferences about how the different attributes of technologies may influence their adoption. The primary focus was on how the relationship between farm size and adoption differs for a presumed size-invariant technology (GE crops), and a presumed size-dependent technology (PA). A review of the technology adoption literature suggested that farm size is often a surrogate for many other factors. This study attempted to control for many of these factors in order to isolate the effect of farm size on adoption. Also, the analysis decomposed the elasticities of adoption with respect to size and compared them among the technologies in order to gain a better understanding of the role of farm size in technology adoption.

Our results suggest that the interrelationships between the attributes of innovations and the characteristics of adopters at different stages make it difficult to classify innovations as size-invariant or size-dependent because the classification depends on the extent of adoption. This difficulty is inherent to the data commonly available (and theoretically could be surmounted only if the model included all factors that characterize an innovator, so that the size effect could be totally isolated). This study also measured the role of farm size in adoption at only one point in time. Given these limitations, a comparison of these results with measurements at other points in the diffusion path would further the understanding of how the characteristics of these technologies influence their adoption by farms of various sizes.

Endnotes

[1] Responsiveness among current adopters was also high for Bt corn (0.483% per 1% increase in size) because once the decision to control the European corn borer is made, it is implemented across much of the operation.

[2] As a reviewer observed, another important difference between Bt corn and the herbicide-tolerant crops is that there are close substitutes for herbicide tolerant technologies (other herbicides) but there is no close substitute for Bt corn (no good chemical control for the European corn borer).

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Appendix: The Two-Limit Probit Model

A two-limit Tobit model was used in this study. Originally presented by Rosett and Nelson (1975) and discussed in Maddala (1983) and Long (1997), this model is appropriate because 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:

$$y_i^* = \beta' x_i + \varepsilon_i \tag{1}$$

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 ε_i, is a disturbance term assumed to be independently and normally distributed with zero mean and constant variance σ^2; and $i = 1, 2, \ldots n$ (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, we have:

$$y_i = \begin{cases} 0 & \text{if} \quad y_i^* \leq 0 \\ y_i^* & \text{if} \quad 0 < y_i^* < 1 \\ 1 & \text{if} \quad y_i^* \geq 1 \end{cases} \tag{2}$$

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

The Tobit parameters were estimated using minimum likelihood (ML) methods. Due to the complex survey design of the ARMS, a weighted option is used (the weight variable multiplies the contribution to the log likelihood of each observation). Even using this method, however, the standard error of the parameters would be biased. For this reason, a delete-a-group jackknife method was used to estimate parameter standard errors (Kott, 1998).

Results of the Tobit analysis for the adoption of genetically engineered crop and precision agriculture technologies are presented in tables 4 and 5. These tables include the estimated coefficients, standard errors, and calculated marginal effects. The marginal effects are used to calculate the elasticities.

Table 4: Tobit Estimates for the Adoption of Herbicide-Tolerant Soybeans, 1998.

Technology/Variable	Estimated Coefficient	Standard Error	*t*-Statistic	Marginal Effect $\partial E(y\|x)/\partial x_k$
Intercept	0.106	0.604	0.18	---
EDUCATION	0.409	0.286	1.43	0.081
EXPERIENCE	0.012	0.006	1.92*	0.002
CREDIT	0.000	0.000	0.78	0.000
OFF-FARM	0.138	0.255	0.54	0.027
MARGINALR	-0.389	0.142	-2.74**	-0.077
SIZE	0.031	0.237	0.13	0.006
SIZE_SQ	-0.070	0.068	-1.04	-0.014
TENURE	-0.354	0.317	-1.12	-0.070
RISK	-0.037	0.015	-2.50**	-0.007
LIMITED-RESOURCE	-1.444	0.449	-3.21**	-0.284
RETIREMENT	-0.383	0.570	-0.67	-0.075
LIFESTYLE	0.082	0.328	0.25	0.016
NON-FAMILY	0.711	0.423	1.68	0.140
CONTRACT	0.368	0.147	2.51**	0.072

Note. Single and double asterisks (*) denote significance at the 10% and 5% levels, respectively. Using the delete-a-group jackknife variance estimator with 15 replicates, the critical *t*-values are 2.145 at the 5% level and 1.761 at the 10% level.

Table 5: Tobit Estimates for the Adoption of Bt Corn, Herbicide-Tolerant Corn, and Precision Farming, 1998.

Technology/Variable	Estimated Coefficient	Standard Error	*t*-Statistic	Marginal Effect $\partial E(y\|x)/\partial x_k$
Bt Corn				
Intercept	-0.577	0.366	-1.58	---
EDUCATION	0.230	0.096	2.39**	0.037
EXPERIENCE	0.004	0.004	1.05	0.001
CREDIT	0.000	0.000	1.22	0.000
OFF-FARM	-0.169	0.124	-1.36	-0.027
MARGINALR	-0.117	0.087	-1.34	-0.019
SIZE	1.061	0.252	4.22**	0.172
SIZE_SQ	-0.439	0.130	-3.39**	-0.071
TENURE	-0.090	0.113	-0.80	-0.015
RISK	-0.015	0.014	-1.13	-0.002
LIMITED-RESOURCE	-0.024	0.273	-0.09	-0.004
RETIREMENT	-0.365	0.320	-1.14	-0.059
LIFESTYLE	0.075	0.179	0.42	0.012
NON-FAMILY	0.221	0.239	0.93	0.036
CONTRACT	0.096	0.055	1.77*	0.016
HI_INF	0.269	0.106	2.54**	0.044
Herbicide Tolerant Corn				
Intercept	-2.248	0.482	-4.67**	---
EDUCATION	0.543	0.163	3.33**	0.019
EXPERIENCE	0.013	0.007	1.99*	0.001
CREDIT	-0.000	0.000	-1.94*	-0.000
OFF-FARM	0.070	0.384	0.18	0.002
MARGINALR	-0.080	0.133	-0.60	-0.003
SIZE	1.166	0.622	1.87*	0.041

Table 5 Cont'd.: Tobit Estimates for the Adoption of Bt Corn, Herbicide-Tolerant Corn, and Precision Farming, 1998.

Technology/Variable	Estimated Coefficient	Standard Error	*t*-Statistic	Marginal Effect $\partial E(y\|x)/\partial x_k$
SIZE_SQ	-0.421	0.443	-0.95	-0.015
TENURE	-0.114	0.309	-0.37	-0.004
RISK	-0.018	0.016	-1.11	-0.001
LIMITED-RESOURCE	0.243	0.602	0.40	0.008
RETIREMENT	-0.972	5.229	-0.19	-0.034
LIFESTYLE	-0.127	0.313	-0.41	-0.004
NON-FAMILY	0.254	0.700	0.36	0.009
CONTRACT	0.003	0.143	0.02	0.000
Precision Farming				
Intercept	-2.262	1.126	-2.01*	---
EDUCATION	0.564	0.269	2.10*	0.020
EXPERIENCE	-0.004	0.013	-0.26	-0.000
CREDIT	0.000	0.000	0.56	0.000
OFF-FARM	0.713	0.438	1.63	0.025
MARGINALR	-0.511	0.501	-1.02	-0.018
SIZE	2.655	0.643	4.13**	0.093
SIZE_SQ	-0.892	0.228	-3.92**	-0.031
TENURE	0.112	0.572	0.20	0.004
RISK	-0.089	0.043	-2.10*	-0.003
LIMITED-RESOURCE	1.444	1.255	1.15	0.051
RETIREMENT	-1.180	12.148	-0.10	-0.041
LIFESTYLE	-0.465	0.608	-0.76	-0.016
NON-FAMILY	1.134	0.753	1.51	0.040
CONTRACT	0.605	0.225	2.68**	0.021

Note. Single and double asterisks (*) denote significance at the 10% and 5% levels, respectively. Using the delete-a-group jackknife variance estimator with 15 replicates, the critical *t*-values are 2.145 at the 5% level and 1.761 at the 10% level.