Impacts of the Adoption of Genetically Engineered Crops on Farm Financial Performance

William D. McBride and Hisham S. El-Osta

ABSTRACT

The rapid adoption of genetically engineered (GE) crops by U.S. farmers suggests that these technologies have been perceived to improve farm financial performance. This study develops and applies an econometric model to data from corn and soybean producers in order to evaluate the financial impacts of the adoption of GE crops. Results indicate that the adoption of GE crops has had a limited impact on financial performance that varies by crop, type of technology, type of farm, and region of the nation. Factors other than the financial impacts appear to be important reasons for the rapid adoption of GE crops.

Key Words: *Bt, corn, farm financial performance, genetically engineered crops, herbicide-tolerant, soybeans, technology adoption.*

Genetically engineered (GE) crop varieties have been promoted by seed companies and scientists as more effective options for controlling pests, reducing pesticide use and costs, and in some cases increasing yields. Faced with reduced returns to crop production caused by low commodity prices, farmers are examining alternative technologies as potential ways to cut costs and improve financial performance. Rapid adoption of GE crop varieties among farmers suggests that these technologies are perceived to have economic advantages over traditional methods.

The most widely used GE crops are those with herbicide-tolerant and insect-resistant traits. Crops with herbicide-tolerant traits permit farmers to use herbicides that offer more effective weed control. Insect-resistant crops containing a gene derived from the soil bacterium *Bacillus thuringiensis* (BT) produce their own toxin to protect the plant from certain target insects. Although herbicide-tolerant and insect-resistant crops were only first commercially available in the U.S. during the mid-1990s, their adoption progressed to about 25 percent of corn acreage and about half of soybean acreage by the end of the decade (USDA, NASS 2000).

Corn and soybeans are leading users of agricultural pesticides at a substantial cost to U.S. farmers. These two crops comprised about 70 percent of the herbicide poundage and more than 20 percent of the insecticide poundage used on major U.S. field crops in 1995 (Fernandez-Cornejo and Jans). Average chemical costs for corn, at \$28 per acre, are nearly 20 percent of operating costs. Chemical costs average about \$25 per acre for soybeans, comprising about a third of total operating costs (USDA, ERS). GE crops have the potential for reducing these costs, and possibly

The authors are economists with the USDA. Economic Research Service, Washington, D.C. The views expressed here are not necessarily those of the Economic Research Service or the U.S. Department of Agriculture.

increasing yields, at a time when low commodity prices have squeezed profit margins in crop production. However, these benefits do not come without a cost. GE seed is more expensive than traditional seed and farmers are usually charged a fee to cover the development of the technology (i.e. technology fee).

This study attempts to examine the economic impacts of GE crop adoption on the U.S. farm sector. More specifically, the objective of this study is to address the following questions: (1) Has the adoption of GE crop varieties impacted the financial performance of U.S. farm businesses? (2) If so, how has the impact varied across the U.S. farm sector? To accomplish this objective the impacts of adoption on corn and soybean producers were evaluated. These results were then used to evaluate possible reasons for observed GE crop adoption patterns.

Background

Crops with herbicide-tolerant traits are designed to survive exposure to certain herbicides that previously would have destroyed the crop along with the targeted weeds. The most common herbicide-tolerant crops are Roundup Ready crops resistant to glyphosate, a highly effective broad-spectrum herbicide. Roundup Ready crops are designed to allow farmers to limit herbicide treatments to as few as a single post-emergence application of glyphosate, while a conventional weed-control program can involve multiple applications of several herbicides. Other advantages of glyphosate are its relatively low cost and favorable environmental features. Glyphosate binds to the soil rapidly, preventing leaching; is biodegraded by soil bacteria; and has extremely low toxicity to mammals, birds, and fish (Malik, Barry, and Kishore). Also, because herbicidetolerant crops do not rely on preplant incorporated herbicides, they encourage the use of minimum tillage practices which reduce soil erosion and chemical runoff (Owen). Corn and soybeans with herbicide-tolerant traits were first made commercially available in 1996. By 2000, herbicide-tolerant soybeans were planted on about half of U.S. soybean acreage, but only on about 7 percent of corn acreage (USDA, NASS 2000).

Bt crops contain a gene from a soil bacterium, Bacillus thuringiensis, that is toxic when ingested by certain Lepidopteran insects. The Bt technology is a novel approach to controlling insects because the insecticide is produced throughout the plant over its entire life. Therefore, the insecticide is more effective than conventional and biological insecticides because it can't be washed off by rain or broken down by other environmental factors. Corn with the inserted Bt trait is designed for protection from the European Corn Borer (ECB). For this protection from ECB, farmers pay a premium for Bt corn relative to traditional varieties. Therefore, the value of Bt corn relative to traditional varieties depends primarily upon the yield loss than can be attributed to the ECB.

Bt corn was first made commercially available in 1996 and was planted on 25 percent of U.S. corn acreage in 1999. However, planted Bt corn acreage fell to less than 20 percent in 2000 (USDA, NASS 2000). Concerns about the safety of GE corn, especially in Europe and Japan, may be a factor in reduced Bt plantings. Also, farmers could have adopted more Bt corn in 1999 than was economical given the ECB pressure and then corrected for this in 2000.

Related Research

Published research about the financial impacts from using herbicide-tolerant crops has been mixed. Data from field trials in West Tennessee were used in an economic analysis of Roundup Ready soybeans (Roberts, Pendergrass, and Hayes). Comparing per-acre net returns from 14 trials, the returns from the Roundup system were 13 percent higher than the returns for the second most profitable system. Higher returns from the Roundup system resulted from both higher yields and lower herbicide costs. Research results from experimental trials in Mississippi (Arnold, Shaw, and Medlin) also showed higher yields and net returns from Roundup Ready soybeans versus conventional varieties. Other partial budgeting

results also showed higher returns from Roundup Ready versus conventional weed control for soybeans (Marra, Carlson, and Hubbell; Reddy and Whiting). However, research using experimental data on Roundup Ready and conventional corn varieties in Kentucky did not show a significant difference in returns above seed, herbicide, and fixed costs (Ferrell, Witt, and Slack).

While economic analyses based on experimental data have mostly favored herbicidetolerant crops over conventional varieties, results from producer surveys have not been as definitive. Research using data from 1997 and 1998 cost-of-production surveys in Mississippi suggested that pesticide costs were lower with Roundup Ready soybeans, but lower pesticide costs were offset by the added technology fee (Couvillion et al.). McBride and Brooks (2000) compared mean seed and pest control costs estimated from a 1997 national survey of soybean producers. Results of the comparison did not indicate a cost advantage or disadvantage for herbicide-tolerant versus other soybean varieties. In extending the analvsis of this data, Fernandez-Cornejo, Klotz-Ingram, and Jans examined the impact of adoption on net returns after other factorsincluding cropping practices, agronomic conditions, and producer characteristicswere statistically controlled. Results of this study also did not show a significant change in net returns to soybean production from the adoption of herbicide-tolerant soybeans. Similar results were obtained in an analysis of the impacts from adopting herbicide-tolerant corn (Fernandez-Cornejo and Klotz-Ingram).

Published research about the economic benefits from using Bt corn suggests that the value of Bt corn relative to traditional varieties depends primarily upon the yield loss that can be attributed to damage from the ECB. Results from field trials controlling the level of ECB infestation indicated that, at the highest ECB injury level, Bt corn hybrids yielded more than 10 bushels per acre more than conventional varieties (Graeber, Nafziger, and Mies). The authors concluded that at \$2.25 per bushel for corn and \$12 per acre for the Bt technology, it takes about five bushels per acre more yield to pay for the ECB protection. Similar results were reported by Rice and Pilcher who showed how returns to Bt corn vary with the expected corn yield, the number of corn borers per plant, and the effectiveness of pest control. Because the economic benefits from Bt corn are tied to the level of ECB infestation, studies in some areas have found that the value of protection from Bt corn is not likely to exceed its cost. Hyde et al. (1999) found that the value of protection offered by Bt corn under Indiana conditions is generally lower than the premium paid for Bt seed corn. Similarly, research under Wisconsin conditions suggests that Bt seed may not be worth the additional cost because of a low probability of infestation (Lauer and Wedberg). Research by Hyde et al. (2000) suggests that the value of Bt corn relative to conventional varieties increases as one moves from east to west in the Corn Belt, because ECB infestations are much more frequent and severe in the western Corn Belt.

Data and Methods

Data used in this study are from USDA's 1998 Agricultural Resource Management Survey (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. Each selected farm represents a known number of farms with similar attributes. Weighting the data for each surveyed farm by the number of farms it represents is the basis for calculating estimates for all U.S. farms. The definition of a farm, and thus the target population of the ARMS, is any business that produces at least \$1000 worth of agricultural production during the calendar year. The farm population of interest in this study includes those that grew corn or soybeans during 1998.

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 GE technologies were used in the



Figure 1. Economic Research Service Farm Resource Regions

farm business. Producers were asked for each crop grown whether they planted GE 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 analysis of the impact of the adoption of GE corn (soybeans) was conducted on two segments of the farm population: (1) operations that harvested one or more acres of corn (soybeans), and (2) operations that specialized in the production of corn (soybeans). Specialized corn (soybean) farms were defined as those on which corn (soybeans) accounted for more than 50 percent of the total value of farm production. The population of specialized farms was examined in addition to all growers because the impact of GE technologies on farm financial performance is likely to be greatest on operations that specialize in the target commodities.

Spatial variation in the impact of GE crop adoption was examined using the ERS farm resource regions (Fig. 1). Because pest infestations differ across the U.S., one would expect that the impacts of pest control measures such as GE crops to be greatest where target pest pressures are most severe. Research suggests that the value of Bt corn relative to conventional varieties increases as one moves from east to west in the Corn Belt because ECB infestations are much more frequent and severe in the western Corn Belt (Hyde et al. 2000). Also, weed pressure tends to be greatest in the eastern and southern U.S. because of the hot, moist climate and the longer growing season. Therefore, the expected value of herbicide-tolerant crops would be greater in these areas because of higher conventional weed control costs. The farm resource regions are used to reflect agro-climatic variation across the U.S. and the differences in pest pressures this creates. One change to the regional delineation is that the Heartland is divided along the Mississippi River into the East Heartland and the West Heartland (Fig. 1). This change better reflects the difference in weed and ECB pressure between these areas.

Conceptual Framework and Empirical Technique

At the most basic level, a farm business is faced with the task of selecting for each production period the combination of inputs and products that will maximize the difference between expected receipts and costs subject to the technical rules given by its production function and to other production constraints. Under the assumption that the farm business is producing only one commodity while utilizing a yield damage-control input (e.g., input to control pest or weed pressure), its planning problem may hence be stated as (see Maumbe and Swinton):¹

(1) max
$$\Pi = p_y Y^e(p_y, p_a, p_y, I, L, K, C)$$

 $- p_a X^a - p_y X^o$
 s.t. $Y = f(X^a, X^o) - D(N)[1 - k(X^a)]$
 $L \le L_r + L_b$
 $I_r = f(A, H)$

where Π is expected short-run net returns; Y^e and Y are expected and actual crop yields, respectively; p_{λ} is commodity price; p_{a} is purchase price of damage-control input X^a which is designated here as a GE seed technology; p_x includes prices for variable inputs X^o (e.g., conventional seed, labor, chemicals, fertilizer, credit, etc.); K is fixed physical capital such as land; C represents conditioning factors (e.g., soil type; rainfall; operator's education, experience and managerial capacity); $D(\cdot)$ represents the pest/weed damage function (it expresses the relationship between pest/weed pressure and yield loss); N is the pest/weed pressure; and $k(X^a)$ is the "kill function" and is used here to describe the efficacy of the introduced technology in controlling pest/weed infestation (i.e., $k(X^a) = 1$ denotes that the technology is completely effective, or $Y^e = Y$; 0 otherwise): L is total effective labor requirement; L_r is total family labor (paid and unpaid); L_h is total hired labor input; and I_t denotes operator's knowledge about GE seed technology; A represents operator's access to information regarding GE seed technology (e.g., farm management consultant, input provider, extension service/county agent, *etc.*); H is operator's human capital endowment as defined by age, education, and experience.

Utilizing first-order conditions for a firm maximizing (1) allows for the derivation of a factor demand function for X^a as in:

(2)
$$X^a = g(p_y, p_x, p_a, K, C, L, I)$$

Equation (2) specifies that the demand for the damage control agent depends on commodity and input prices, on farm resources (K, L), on conditioning characteristics including those of the farm business and of the operator (C), and GE crop awareness (I).

This conceptual framework, when generalized to include operator risk preferences and to cover a production process with multiple outputs, provides the basis for estimating farm financial performance with the adoption of GE technologies. The method entails first the specification of the following general model:²

(3.a) II =
$$X\beta + G\alpha + \epsilon_1$$

(3.b) G = $Z\gamma + \epsilon_2$

where Π is a vector denoting net returns; *X*, a matrix of exogenous variables affecting farm's financial performance (as described by *K* and by the elements of *C* in (1), among others); *G*, a binary vector denoting the adoption of GE crop (i.e., G = 1 if technology adoption occurs, 0 otherwise); *Z*, a matrix of variables affecting the adoption of *GE* crop; and ϵ_1 and ϵ_2 are vectors of errors.

Several sources of potential econometric concerns must be considered if (3.a) and (3.b) are estimated separately, particularly if $E[\epsilon_1\epsilon_2] \neq 0$. First is the possibility that the decision to adopt the GE crop is determined jointly with net returns, which if left uncorrected would lead to simultaneous equation bias. Specifically, as shown in (1), adoption of a GE

¹ The farm business is assumed here to be a price taker with neutral preferences toward risk.

² The following discussion benefits greatly from the work of Burrows and of Aldrich and Nelson.

crop impacts productivity and/or cost of production, which in turns impacts net returns. In the same vein, technology choice is impacted by net returns, since declining expected net returns due to insect/weed pressure might entice operators to adopt the GE crop. This and the fact that technology choice is a function of factors that impact net returns--such as attributes of the technology itself (including its price, p_a), of the conditioning characteristics (C), of the extent of insect/weed pressure, among others (see (2))—indicate that Π is a component of Z. Simultaneous bias will also occur if correlation exists among some unmeasured variables common to both Π and Z. Examples of such variables are the extent of the insect/weed pressure, insect/weed resistance, and operator perception about alternative insect/weed control methods.

The first step in attending to the simultaneity concern inherent in these equations is to underscore the probabilistic nature of (3.b). A farm operator will choose to adopt a GE crop if expected net returns (π_a) from doing so exceeds some threshold (π_{na}), which is interpreted as the expected net returns of non-adoption plus a premium for risk or inconvenience in switching to a new technology (Burrows). Although observations on both π_a and π_{na} are not available, they nevertheless can be used to represent the act of adopting the GE crop. which itself is observable. Accordingly, the *ith* (i = 1, ..., n) operator would choose the GE crop if $\pi_a > \pi_{na}$ and would choose the traditional crop if $\pi_a < \pi_{aa}$. This process may be modeled by assuming that operator preference toward the GE technology is a linear function of exogenous variables as in:

(4)
$$\pi_{i,a} = \sum \gamma_{k,a} Z_{ik} + \upsilon_{i,a} \text{ and }$$
$$\pi_{i,na} = \sum \gamma_{k,na} Z_{ik} + \upsilon_{i,na}$$

The ν_i 's in (4) denote unmeasured factors, approximation errors, and/or random aspect of behavior (Aldrich and Nelson). For the *ith* farm operator, $\pi_{i,a}$ will be greater than $\pi_{i,na}$ if $\pi_{i,a} - \pi_{i,na} > 0$ and it will be less than $\pi_{i,na}$ if $\pi_{i,a} - \pi_{i,na} < 0$. Suppose we let π_i be this difference, then:

(5)
$$\pi_{i} = \pi_{i,a} - \pi_{i,na}$$

= $\sum (\gamma_{k,a} - \gamma_{k,na}) Z_{ik} + (\upsilon_{i,a} - \upsilon_{i,na})$

Equation (5) can be simplified by letting $\gamma_k = (\gamma_{k,a} - \gamma_{k,na})$ and $u_i = (\nu_{i,na} - \nu_{i,a})$ as in:

$$(6) \qquad \pi_i = \sum \gamma_k Z_{ik} - u_i.$$

The connection between the model of GE crop adoption in (3.b) and equation (6) is obvious. For example, $G_i = 1$ if $\pi_i > 0$, = 0 otherwise. In other words, the *ith* farm operator chooses the GE crop over the conventional crop if $\Sigma \gamma_k Z_{ik} - u_i > 0$, i.e., if $u_i < \Sigma \gamma_k Z_{ik}$. To the extent that $\pi_{i,mi}$ varies randomly across individual operators, then π_i is also random, which when expressed in terms of the probability of adopting GE crop ($P(\cdot)$), leads to the following representation:

(7)
$$P(G_i = 1) = P(\pi_i > 0) = P(u_i < \sum \gamma_k Z_{ik}).$$

Under the assumption that u_i is a continuous random variable, estimation of $P(G_i)$ is as follows:

(8)
$$P(G_i = 1) = F(z_i) = \int_{-\infty}^{z_i} f(u_i) du_i$$

where $F(z_i)$ is the cumulative distribution function, $f(u_i)$ is the probability density function of the random variable u_i , and where $z_i = \sum \gamma_k Z_{ik}$. In the context of this study, and because of the large sample size in the ARMS, u_i is assumed to follow the normal distribution. This allows for the specification of the model described in (6) as a probit. Because the probit model is associated with the standard cumulative distribution function $\Phi(\cdot)$, parameter estimates for (6) which are obtained by a maximum likelihood technique (MLT) allow for the estimation of the probability (\hat{P}_i) that the *i*th farmer selects the GE crop over the traditional crop as in the following:³

The objective of MLT here is to find the estimator $\hat{\gamma}$ that maximizes the likelihood of observing the pattern of GE crop adoption observed in the sample.

(9)
$$\hat{P}_{i} = \Phi(\hat{z}_{i}) = \int_{-\infty}^{\gamma} \varphi(u_{i}) du_{i}$$

= $\int_{-\infty}^{\gamma} (2\pi)^{-1/2} \exp(-u_{i}^{2}/2) du_{i}$

where $\varphi(\cdot)$ is the probability density function of the standard normal, u_i is a random variable with mean zero and unit variance, and $\hat{z} = \Sigma \hat{\gamma}_k Z_k$.

What has been accomplished so far is to demonstrate that the model described in (3.a) and in (3.b) is complex, as it requires estimation procedures for a probit within a simultaneous equation system. Although many studies have suggested techniques to deal with this difficulty (Amemiya; Heckman 1979; Nelson and Olson; Madalla), the fact remains that it may be impossible to obtain a unique solution for the endogenous variable without placing restrictions on the model. Instead, Burrows suggested a way to circumvent this problem. First make (3.b) a reduced-form equation through the exclusion of 11 from Z. Second, estimate (3.b) using its surrogate, namely the probit in (6), for the purpose of estimating the predicted probabilities (\hat{P}_i) of adopting a GE crop as in (9). The final step is to use \hat{P}_i as an instrument in the single-equation estimation of II. Parameter estimates obtained from this last step using weighted least squares are consistent and free from simultaneous equation bias.

A second econometric concern in estimating (3.b) is the likely occurrence of a selection bias due to "self-selection." For example, farm operators may select the GE crop because they are more aware of its effectiveness in abating pest problems, are able to afford the added costs, and/or are more capable of withstanding the possibility of yield losses due to failure of the GE crop technology. As was discussed earlier, the primary motive for adoption considered here is the perception by adopters that expected net returns from adoption (π_a) exceed that of non-adoption (π_{na}). Accordingly, and because of this self-selection, farm operators are not assigned randomly to the two groups: GE crop adopters and non-adopters. A consequence of this is that the two groups are systematically different. These differences may manifest themselves in farm financial performance and could be confounded with differences due to GE crop adoption (see Fernandez-Cornejo). If this self-selectivity problem is left uncorrected, results from estimating net returns using regression procedures could be biased. Heckman (1979) proposed a twostage estimation method to test and to correct for self-selectivity in linear regression models.

In this study the first stage of Heckman's technique involves the estimation of a GE crop-adoption model using the probit analysis (see equation (6)). Estimated parameters from the probit model are then used to estimate a random variable ($\hat{\lambda}_i$), also known as *the inverse Mills ratio* (IMR), as in the following:

$$\begin{aligned} 10) \quad \hat{\lambda}_{i} &= \frac{\phi(\hat{z}_{i})}{\Phi(\hat{z}_{i})} & \text{if } \mathbf{G}_{i} &= 1 \\ \hat{\lambda}_{i} &= \frac{\phi(\hat{z}_{i})}{(1 - \Phi(\hat{z}_{i}))} & \text{if } \mathbf{G}_{i} &= 0 \end{aligned}$$

In the second stage of Heckman's technique, $\hat{\lambda}_i$ is used as a regressor in the linear regression model in (3.a). The significance of $\hat{\lambda}_i$ can be interpreted as a test for selectivity bias, and its inclusion allows for the consistent estimation of the model's parameters.

In this study, attending to the simultaneity and self-selectivity concerns when estimating farm net returns is accomplished by appending to (3.a) the predicted probabilities (\hat{P}_i) of adopting a GE crop technology and the IMR ($\hat{\lambda}_i$) as additional regressors as in the following:

(11)
$$II_i = \beta_0 + \sum \beta_j X_{ij} + \gamma_j \hat{P}_{i1} + \varsigma_j \hat{\lambda}_{ij} + \epsilon_i$$

The model presented in (11) allows for the estimation of net returns using least squares when the technology adoption decision involves only one choice. In the case when multiple and independent technology choices are involved, equation (11) can be extended to reflect these additional choices by appending both the separate predicted probabilities reflecting these choices and their corresponding IMRs.

Model Specification and Estimation

The impact of the adoption of GE crops on farm financial performance is assessed by statistically controlling for several other factors that may also affect financial performance. That is, the effect of economic and environmental conditions, management practices, and operator characteristics are accounted for in order to isolate the effect of GE crop adoption on farm financial performance. To control for factors other than GE crop adoption, multipleregression is used in a two-stage econometric model of adoption and the adoption impact. The first stage of the model consists of an adoption-decision model that describes what factors influence the likelihood of adopting GE crops. Results of the first stage provide input for the second stage model that is used to estimate the impact of GE crops on farm financial performance.

The adoption-decision model was estimated by a probit analysis of GE crop adoption for each of the corn and soybean farm populations (i.e. all growers and specialized operations). Separate models were estimated for (1) herbicide-tolerant corn, (2) Bt corn, and (3) herbicide-tolerant soybeans. The models were specified using variables that have shown to be related to technology choice in the previous literature (Feder, Just, and Zilberman; Feder and Umali). Variables regressed against the decision to adopt each technology included operator education, age, primary occupation, risk preference, management level, farm size, specialization in the target commodity, and land tenure (Table 1). Operator preference toward risk was specified using a risk index constructed according to farmers' answers to a series of survey questions about how they react toward risk, including the use of risk-management tools (Bard and Barry). The operator's management level was specified as higher if the operator reported the use of budgeting or other record keeping methods to manage cash flows or control costs. Variables for geographic location were also included in the model to account for the impact that differences in soil, climate, production practices, and pest pressures would have on adoption.

The adoption-impact model was next estimated for each of the farm populations by regressing the set of explanatory variables, plus information obtained from the decision model, on alternative measures of farm financial performance obtained from the decision model. Several measures of farm financial performance were examined, but results are reported for only two measures: modified net farm income per tillable acre and crop operating margin per tillable acre.⁴ Modified net farm income (MNFI) was measured from the ARMS data as:

- MNFI = Net Farm Income (NFI) + interest expense
- NFI = Gross farm income total farm operating expenses (excluding marketing expenses)

Where:

Gross farm income = gross cash farm income + net change in inventory values + value of farm consumption + imputed rental value of operators dwelling

Total farm operating expenses = total cash operating expenses + estimate of non-cash expenses for paid labor + depreciation on farm assets

Crop operating margin (COM) was measured using the ARMS data as:

COM = Gross value of crop production – total farm chemical and seed expenses

Where:

Gross value of crop production = the production of each crop commodity produced on the farm operation valued at the stateaverage price received by farmers (USDA, NASS 1999).

⁴ Other financial performance measures examined in this study were an estimate of operator labor and management income (net farm income less charges for unpaid labor and capital) per tillable acre and rate of return to assets. These results were very similar to those obtained for the net farm income measure.

Variables	Definition	Corn (at least one harvested acre)	Corn (specialized operations)	Soybean (at least one harvested acre)	Soybean (specialized operations)
EDYEARS	Education of farm operator (years)	12.99	13.42	13.03	12.77
OPAGE	Age of farm operator (years)	51	50	50	50
OCCUPF	Occupation of farm operator (=1 farming; 0 otherwise)	0.68	0.55	0.65	0.42
SIZE	Farm size, measured as total harvested acres (100 acres)	4.44	4.47	4.82	2.94
SIZESQ	Farm size, squared	59.25	54.06	65.64	31.08
SPECIALIZ	Value of sales of relevant commodity/Total value of sales	0.30		0.40	
RISKPERCP	Operator's risk perception (index: $10 = \text{least}$, $50 = \text{most risk taking}$)	28.37	27.83	28.62	30.79
BUDGET	Operator's management level (= 1 use budgeting or other record keeping to manage cash flow and/or control cost; 0 otherwise)	0.74	0.76	0.72	0.55
TENURE	Rented acres/Total operated acres	0.61	0.61	0.55	0.61
HRTLNDW	Farm location (= 1 West Heartland; 0 otherwise)	0.30	0.42	0.31	0.23
NCRESCNT	Farm location (= 1 Northern crescent; 0 otherwise)	0.24	0.12	0.15	0.14
PRGATEWY	Farm location (= 1 Prairie Gateway; 0 otherwise)	0.07	0.06		_
MISSPORT	Farm location (= 1 Mississippi Portal; 0 otherwise)	_	_	0.04	0.06
$OTHREGN^1$	Farm location (= 1 Other Crop Producing region; 0 otherwise)	0.15	0.06	0.15	0.08
MNFI	Modified net farm income per tillable acre (\$)	101.47	82.23	99.07	65.40
СОМ	Crop value less cost of chemicals and seed per tillable acre (\$)	163.87	206.48	170.38	162.71
ADOPT_HT	Herbicide-tolerant seed (= 1 adoption; 0 otherwise)	0.05	0.06	0.37	0.35
ADOPT_Bt	Bt seed (= 1 adoption; 0 otherwise)	0.20	0.30		
Sample size		2719	535	2321	395
Population		460,210	118,158	400,542	112,975

Table 1. Means and Definitions of Variables, 1998

Note: $ADOPT_HT = 1$ and $ADOPT_Bt = 1$ include a small fraction of farms that used stacked trait seeds.

OTHREGN in the case of corn includes Northern Great Plains, Eastern Upland, Southern Seaboard, Fruitful Rim, and Basin and Range regions, and in the case of soybcans includes Northern Great Plains, Prairie Gateway, Eastern Upland, Southern Seaboard, Fruitful Rim, and Basin and Range regions. The East Heartland was the deleted group in the regression analysis.

Net farm income has been used as a measure of financial performance in several studies (Mishra, El-Osta, and Johnson; El-Osta and Johnson; Haden and Johnson; Seger and Lins). Net farm income was modified in this study by adding back interest expenses so that variation in farm debt did not influence the financial comparison among farms. The adoption of GE crops does not require a capital investment that would be reflected in the farm debt position. MNFI measures the return to operator and unpaid family labor, management, and capital (both equity and borrowed).

MNFI is a comprehensive measure of financial performance that can be influenced by many aspects of the farm business other than the adoption of GE crops. The impact on MNFI from livestock production or farm-related income activities (e.g. custom work, government payments) could easily overshadow the influence of GE crop adoption unless the influence was very strong. Therefore, crop operating margin was also used to measure financial performance in this study because it more closely isolates the limited impact that GE crop adoption has on financial performance. Most of the financial impacts of adopting GE crops result from changed crop yields, reduced chemical costs, and/or increased seed costs. COM is a component of net farm income that filters the impact that other farm activities such as livestock production, custom work, and government program participation have on financial performance. Other studies on the relative economies of GE and conventional crops have used returns above seed and chemical costs as the benchmark for comparison (e.g. Fernandez-Cornejo and McBride; Couvillion et al.; Rice and Pilcher). However, results from models specified with COM, compared to those using MNFI, provide a weaker test of the influence that GE crop adoption has had on farm financial performance.

To ascertain the impact of GE crop adoption on financial performance, the predicted probabilities of adoption estimated from the adoption-decision model were also included in the adoption-impact model. Because technology adoption and farm financial performance are jointly determined, the predicted probability of adoption for each technology provided an instrument for the adoption-decision that mitigates bias due to simultaneity concerns (Zepeda). The predicted probabilities were also specified as interaction terms with the geographic location variables. These interaction terms provided a means by which regional differences in the financial impact of adoption could be evaluated. A hypothesis is that regions with greater pest pressures would benefit more from GE crops than other regions. Selectivity variables for each technology were also estimated and added to the adoption-impact model to allow for unbiased and consistent parameter estimates (Lee). Heckman's two-step procedure (1976) was used to estimate the two-equation model, using weightedregression procedures and a jackknife variance estimator designed to be used with the ARMS data (Dubman).

Results

Probit parameter estimates for the herbicidetolerant and the Bt corn adoption-decision models are presented in Table 2, while parameter estimates for the herbicide-tolerant soybean adoption-decision models are shown in Table 3. The higher log-likelihood value (less negative) and greater McFadden R-squared of each model for the population of specialized corn and soybean producers indicate that the overall model fit was better than it was for the population of all producers of each crop.

The adoption of herbicide-tolerant corn among all corn growers was significantly impacted by many operator characteristics, including age, education, and farm occupation (Table 2). Greater education, higher age, and having farming as a major occupation were associated with a higher likelihood of adopting herbicide-tolerant corn. These results are consistent with adoption literature, except that older farm operators generally have a lower likelihood of adopting new technologies. The adoption of herbicide-tolerant corn was also more likely among growers in the western Heartland region relative to those in the eastern Heartland (the deleted group). However,

	Corn (at least one harvested acre)		Corn (specialized operations)		
Variables	ADOPT_HT1	ADOPT_Bt ²	ADOPT_HT ¹	ADOPT_Bt ²	
INTERCEPT	-3.7157***	-1.2133*	-4.2668***	-2.3750**	
EDYEARS	0.0982***	0.0414	0.0956	0.1198*	
OPAGE	0.0113***	-0.0005	0.0091	0.0111	
OCCUPF	0.2482**	0.1146	0.3076	0.2332	
RISKPERCP	-0.0087	-0.0299*	0.0164	-0.0400**	
SIZE	0.0140	0.0740***	0.0683	0.0899***	
SIZESQ	-0.0001	-0.0013***	-0.0019	-0.0016***	
TENURE	-0.2405	-0.0415	-0.5373	-0.1294	
SPECIALIZ	0.2450	0.4268***			
HRTLNDW	0.4386***	0.6355***	0.2207	0.6601***	
NCRESCNT	0.1224	-0.0336	0.7398**	0.2841	
PRGATEWY	0.2100	0.0451	0.4027	0.2579	
OTHREGN ³	0.2068	-0.1205	0.5633	-0.0587	
Log-likelihood	-86,106	-202,864	-23,667	-60,904	
McFadden's R ²	0.07	0.13	0.11	0.14	
Percent correct	94.9	80.2	94.1	74.2	
Sample size	2719		535		
Population	460,2	210	118,158		

 Table 2. Probit Estimates of the Technology Adoption-Decision Model in Corn Production,

 1998

⁺ADOPT_HT (= 1 Adoption of herbicide-tolerant seed; 0 otherwise).

² ADOPT_Bt (= 1 Adoption of Bt seed; 0 otherwise).

Note: $ADOPT_HT = 1$ and $ADOPT_Bt = 1$ include a small fraction of farms that used stacked trait seeds.

³ OTHREGN includes Northern Great Plains, Eastern Upland, Southern Seaboard, Fruitful Rim, and Basin and Range regions.

* Significant at 10%. *** Significant at 5%. *** Significant at 1%.

when the population was restricted to specialized corn operations, the only significant factor was a higher probability of adopting herbicide-tolerant corn in the Northern Crescent region.

Operator characteristics were less important in explaining the adoption of Bt corn, but farm size, specialization, operator risk perception, and region were significant (Table 2). The likelihood of adopting Bt corn increased as farm acreage increased at a decreasing rate. This relationship between farm size and technology adoption is consistent with most adoption literature. Also, increasing a farm's specialization in corn production increased its likelihood of adopting Bt corn. Coefficients on the risk perception variable indicate that more risk-adverse producers were more likely to adopt the Bt technology. While this result is counter to the common profile of technology adopters as more risk taking, the more risk-averse producers may be attracted to the Bt corn technology because of the insurance it offers against the threat of ECB infestations. Producers in the western Heartland region were also found to be more likely to adopt Bt corn than were producers in the eastern Heartland. This result was expected due to the higher incidence and severity of ECB infestations in portions of the western Heartland.

In contrast to corn, very few of the variables in either the model for all soybean growers or the model for specialized soybean growers were significant (Table 3). A possible reason for this lack of explanatory power is the significant diffusion of this technology across the population. The farm adoption rates for herbicide-tolerant soybeans in this study, 37 percent of all soybean farms and 35 percent of specialized soybean farms, were significantly greater than for the other technologies.

Variables	Soybean (at least one harvested acre) ADOPT_HT ¹	Soybean (specialized operations) ADOPT_HT ¹
INTERCEPT	-0.4520	-0.4053
EDYEARS	0.0671	0.1003
OPAGE	0.0051	0.0116
OCCUPF	0.1414	0.5938*
RISKPERCP	-0.0392^{***}	-0.0604
SIZE	0.0168	0.0211
SIZESQ	-0.0003	-0.0008
TENURE	-0.1662	
SPECIALIZ	0.2577	-0.6471
HRTLNDW	0.0515	0.0297
NCRESCNT	-0.2734	0.1755
MISSPORT	-0.0692	-0.2625
OTHREGN ²	-0.3005	-0.3874*
Log-likelihood	-249,038	-60,603
McFadden's R ²	0.06	0.17
Percent correct	63.8	70.8
Sample size	2321	395
Population	400,542	112,975

Table 3. Probit Estimates of the Technology Adoption-Decision Model in Soybean Production,

 1998

 $^{+}ADOPT_{HT}$ (= 1 Adoption of herbicide-tolerant seed: 0 otherwise).

Note: $ADOPT_HT = 1$ includes a small fraction of farms that used stacked trait seeds.

² OTHREGN includes Northern Great Plains, Prairie Gateway, Eastern Upland, Southern Seaboard, Fruitful Rim, and Basin and Range regions.

* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

Thus the adoption of herbicide-tolerant soybeans has progressed past innovator and early adopter stages into the realm where adopting farmers are much more like the majority of farmers (Rogers).

Parameter estimates for the adoption-impact models for corn are presented in Table 4, while those for soybeans are shown in Table 5. The overall model fit was very poor for both corn and soybean populations that included all producers, with an R-squared ranging from 0.003 to 0.10 among these models. Goodness of fit improved among the specialized corn and soybean populations, but was substantially lower for MNFI than for COM. This result was not surprising since MNFI accounted for the costs and returns of all farm enterprises, while COM included only crop returns and the costs that would be most impacted by the adoption of GE crops. Overall, the model fit was the best for the COM model estimated on the populations of specialized corn farms and specialized soybean farms (R-squared of 0.36 and 0.33, respectively).

Nearly all of the explanatory variables were insignificant in both adoption-impact models estimated on the population of all corn producers and on the model using MNFI among specialized corn producers (Table 4). The impact of GE crop adoption was not significantly different from zero in any of these models.⁵ However, several factors, including GE crop adoption, were found to affect COM on specialized corn farms. COM increased with size of operation at a decreasing rate, increased with operator age, and was higher for

⁵ Specification of the adoption-impact models included several variables, some of which were correlated (e.g. SIZE and SIZESQ; EDYEARS and OPAGE). This multicollinearity in the sample may have contributed to the lack of significant coefficients in several of the models. However, this is not to say that if the degree of multicollinearity were lower, more estimated coefficients would have been significant.

	Corn (at least one harvested acre)		Corn (specialized operations)		
Variables	<i>MNFT</i>	COM ²	MNFT	COM	
INTERCEPT	285.87	146.07	47.04	372.58***	
EDYEARS	5.17	-21.55	10.50	0.10	
OPAGE	-1.25	1.56	2.31	1.05***	
OCCUPF	52.38*	-4.40	-14.15	-21.29	
SIZE	-1.53	-12.23	6.01	4.76***	
SIZESQ	0.06	0.18	-0.07	-0.05^{***}	
SPECIALIZ	-33.90	56.42			
RISKPERCP	-5.77	1.87	-6.49	-7.69***	
BUDGET	8.90	51.55	8.91	26.46	
HRTLNDW	117.63	-62.78	49.73	17.69	
NCRESCNT	18.27	97.42	31.21	-99.97***	
PRGATEWY	138.03	-25.51	-18.59	-108.72***	
OTHREGN ³	25.53	24.21	216.55	-96.97***	
PHT^{4}	-655.40	961.73	126.73	1402.03***	
PBt^{5}	-309.58	840.17	-345.66	-319.70***	
PHT*HRTLNDW	100.67	-504.50	-114.24	-731.63***	
PHT*NCRESCNT	-1215.14	1660.49	-1144.22	-812.51**	
PHT*PRGATEWY	128.54	-1413.79	352.02	-325.27	
<i>PHT*OTHREGN</i>	-1425.66	30.13	-212.97	-746.41*	
PBt*HRTLNDW	-50.94	-290.62	36.53	131.65*	
PBt*NCRESCNT	436.13	-1265.58	402.22	155.08	
PBt*PRGATEWY	-361.46	120.11	-27.54	97.76	
PBt*OTHREGN	375.03	-135.87	-900.09*	-15.29	
LAMBDAHT	-9.59	0.19	-3.99	3.47	
LAMBDABt	6.09	3.92	-0.98	16.31***	
R ²	0.02	0.003	0.07	0.36	
Sample size	2	719	535		
Population	460,210		118,158		

Table 4. Regression Estimates of the Adoption-Impact Model in Corn Production	on, J	199	18
--------------------------------------------------------------------------------------	-------	-----	----

¹ MNFI denotes modified net farm income per tillable acre.

² COM denotes crop operating margin defined as returns above cost of chemicals and seed per tillable acre.

³ OTHREGN includes Northern Great Plains, Eastern Uplands, Southern Seaboard, Fruitful Rim, and Basin and Range regions.

⁴ PHT is the predicted probability of adopting herbicide-tolerant corn estimated from the adoption-decision model.

⁵ PBt is the predicted probability of adopting Bt corn estimated from the adoption-decision model.

* Significant at 10%. ** Significant at 5%. *** Significant at 1%.

producers who more actively managed risk. Farm location was significant and indicated that the COM was lower among specialized corn farms in regions outside of the Heartland. Very few explanatory variables were significant in any of the adoption-impact models for soybeans (Table 5).

The impact of GE crops on the COM of specialized corn farms varied by regions. To illustrate the impacts, elasticities were estimated to show the percentage change in COM from a change in the probability of adoption (Table 6). The elasticity of 0.27 for the adoption of herbicide-tolerant corn on all specialized corn farms indicates that as adoption increases by 10 percent, COM increases 2.7 percent. The greatest impact of the adoption of herbicide-tolerant corn was in the eastern Heartland, where a 10-percent increase in adoption increases COM by 4.1 percent, significantly greater than in most other regions. This result was not unexpected due to relatively high weed pressures in the east. In contrast to herbicide-tolerant corn, the adoption of

	Soybean (at least one harvested acre)		Soybean (specialized operations)		
Variables	MNFI		MNFI	COM	
INTERCEPT	789.19***	158.26***	506.5***	302.85***	
EDYEARS	20.14	3.82	-3.58	-1.64	
OPAGE	-0.88	-0.13	-0.08	-1.09**	
OCCUPF	35.30	-8.85	60.79**	31.24	
SIZE	0.72	3.31	-3.98	~1.66	
SIZESQ	-0.02	-0.04	0.08	0.04	
SPECIALIZ	61.01	38.20			
RISKPERCP	-17.37**	-2.88	-9.78^{***}	-2.45	
BUDGET	-17.10	6.07	-44.19*	-16.04	
HRTLNDW	135.76	25.40	-31.26	4.28	
NCRESCNT	-142.56	-34.10	53.07	18.72	
MISSPORT	302.94	67.21	100.30	-82.94***	
OTHREGN ³	-145.95	48.41	-156.67	-59.34*	
PHT^{\downarrow}	-1029.13	118.60	-237.00	67.54	
PHT*HRTLNDW	-203.92	-108.73	100.10	-27.15	
PHT*NCRESCNT	158.07	-31.68	-68.15	-64.77	
PHT*MISSPORT	-687.93	-214.74	-410.68	7.25	
PHT*OTHREGN	93.24	-263.77	226.29	-35.52	
LAMBDAHT	2.59	2.73	-15.76	8.83	
R ²	0.03	0.10	0.19	0.33	
Sample size	23	321	395		
Population	400.5	542	112,9	75	

Table 5. Regression Estimates of the Adoption-Impact Model in Soybean Production, 1998

¹ MNFI denotes modified net farm income per tillable acre.

² COM denotes crop operating margin defined as returns above cost of chemicals and seed per tillable acre.

³ OTHREGN includes Northern Great Plains, Prairie Gateway, Eastern Upland, Southern Seaboard, Fruitful Rim, and Basin and Range regions.

PHT* is the predicted probability of adopting herbicide-tolerant soybcans estimated from the adoption-decision model. * Significant at 10%. ** Significant at 5%. * Significant at 1%.

Table 6. Elasticities of Crop Operating Margin (COM) with respect to the Probability of GE Crop Adoption among Specialized Corn Farms, by Region, 1998

	СОМ			
Region	Herbicide- tolerant corn	Bt corn		
<u>U.S.</u>	0.27	-0.34		
Eastern Heartland	0.41	-0.46		
Western Heartland	0.19	-0.27		
Northern Crescent	0.17	-0.24*		
Prairie Gateway	0.31*	-0.32*		
Other Regions	0.19	-0.49*		

* Indicates that underlying coefficient is not significantly different from that of the Eastern Heartland region.

Bt corn resulted in a decrease in COM among the specialized corn farms. The overall elasticity of -0.34 suggests that as the probability of adoption increases 10 percent, COM declines by 3.4 percent. The negative impact of adoption was significantly less in the western Heartland compared to the eastern Heartland (-0.27 versus -0.46), expected because of greater pressure by the ECB in portions of the western Heartland.

Conclusions

This study attempted to measure the farm financial impacts of GE crop adoption on U.S. corn and soybean producers using a model that corrects for the simultaneity of technology adoption and farm financial performance and for the self-selectivity of technology adoption. Moreover, the model was specified to estimate the spatial variation of adoption impacts due to regional differences in pest pressures. Elasticities of financial performance with respect to GE crop adoption were estimated where possible in order to quantify and compare the impacts among regions.

Results of the analysis using broad financial performance measures, such as net farm income, to evaluate the effects of GE crop adoption showed little impact. GE crop technologies do not require a capital-intensive investment and thus have an impact on farm finances that is mainly limited to changes in variable costs and returns. This is most likely why the adoption-impact models explained much less of the variation in net farm income than the variation in the crop operating margin. Previous studies have had much more success in explaining the variation in net farm income (Mishra, El-Osta, and Johnson: El-Osta and Johnson: Haden and Johnson). However, these studies generally did not attempt to isolate the impact of specific technologies, or they focused on technology adoption for enterprises that comprised a substantial portion of whole-farm business activity (e.g. dairy). Business activity from enterprises unrelated to the GE crops, such as livestock, could have interfered with the measurement of any impact that GE crop adoption had on net farm income.

Perhaps the biggest issue raised by the results of this study is how to explain the rapid adoption of GE crops when the evidence about farm financial impacts is not clear or counterintuitive. Results of this study suggest that the adoption of herbicide-tolerant corn improved farm financial performance among specialized corn farms, but farm adoption of herbicidetolerant corn is relatively low. In contrast, the adoption of herbicide-tolerant soybeans and Bt corn has been rapid even though positive financial impacts could not be demonstrated. The positive financial impacts of adopting herbicide-tolerant corn may be due in part to seed companies setting low premiums relative to conventional varieties in an attempt to expand market share. Also, the limited acreage on which herbicide-tolerant corn has been used is likely acreage with the greatest comparative advantage for this technology. In the case of herbicide-tolerant soybeans, the results of this study are not inconsistent with findings from studies using other producer surveys. This suggests that at the current state of adoption, about 50 percent of acreage, factors other than economics may be driving adoption. Other research has suggested that the simplicity and flexibility of the herbicide-tolerant program have been the primary reasons that growers are adopting (Carpenter and Gianessi). Also, growers may have initially responded to the potential for savings from herbicide-tolerant soybeans that have since been diminished by price cuts on conventional herbicides.

The economic potential of Bt corn on an individual farm is more difficult to evaluate because returns to Bt corn are realized only if the density of ECBs is large enough to cause economic losses greater than the premium paid for the Bt seed. This requires farmers to have knowledge about past infestations because the adoption decision must be made before planting, prior to observing an infestation. Indicators of ECB infestations suggest that only about 25 percent of corn acreage was infested at a treatable level in 1997 (Pike), while Bt corn adoption rates were 20 percent in 1998 and 25 percent in 1999 (USDA, NASS 2000). Results of this study show that the adoption of Bt corn had a negative impact on the farm financial performance of specialized corn farms in 1998. This suggests that Bt corn may have been used on some acreage where the value of ECB protection was lower than the Bt seed premium. Possible reasons for this "over-adoption" are annual variations in ECB infestations, lack of knowledge about infestation levels and the yield loss due to infestations, and the desire to insure against losses due to the ECB. A reduction in the Bt corn adoption rate for 2000, to 18 percent, may be due in part to producers gaining experience with determining how this technology can be used profitably.

Finally, the implications of this study should be regarded carefully and only within the constraints of the analysis. Just one year of data was examined. As mentioned previously, the financial impacts of GE crops would vary with several factors, most notably annual pest infestations, seed premiums, prices of alternative pest control programs, and any premiums paid for segregated crops. These factors have changed and will likely continue to change over time as technology, marketing strategies for GE and conventional crops, and consumer perceptions of GE crops continue to evolve.

References

- Aldrich, J. and F.D. Nelson. *Linear Probability, Logit, and Probit Models.* Sage University Paper Series on Quantitative Applications in the Social Sciences, 07-45. Sage Publications: Beverly Hills and London. 1984.
- Amemiya, T. "Qualitative Response Models: A Survey." *Journal of Economic Literature* 19(December 1981):1483–1536.
- Arnold, J.C., D.R. Shaw, and C.R. Medlin. "Roundup Ready⁽³⁾ Programs Versus Conventional Programs: Efficiacy, Varietal Performance, and Economics." *Proceedings of the Southern Weed Science Society* 1998. pp. 272– 73.
- Bard, S.K. and P.J. Barry. "Developing a Scale for Assessing Farmers Risk Attitudes." Unpublished manuscript, Center for Farm and Rural Business Finance, University of Illinois, Urbana, IL, November 1998.
- Burrows, T. M. "Pesticide Demand and Integrated Pest Management: A Limited Dependent Variable Analysis." *American Journal of Agricultural Economics* 65(November 1983):806–10.
- Carpenter, J. and L. Gianessi. "Herbicide-Tolerant Soybeans: Why Growers are Adopting Roundup Ready Varieties." AgBioForum. 2(1999):65–72.
- Couvillion, W.C., F Kari, D. Hudson, and A. Allen. A Preliminary Economic Assessment of Roundup Ready Soybeans in Mississippi. Mississippi State University, Research Report 2000-005, May 2000.
- Dubman, R.W. Variance Estimation with USDA's Farm Costs and Returns Surveys and Agricultural Resource Management Study Surveys. U.S. Department of Agriculture, Economic Research Service, Staff Paper AGES 00-01, April 2000.
- El-Osta, H.S. and J.D. Johnson. Determinants of Financial Performance of Commercial Dairy Farms. U.S. Department of Agriculture, Eco-

nomic Research Service, Technical Bulletin Number 1859, 1998.

- Feder, G. and D.L. Umali. "The Adoption of Agricultural Innovations: A Review." *Technological Forecasting and Social Change* 43(1993): 215–239.
- Feder, G., R. J. Just, and D. Zilberman. "Adoption of Agricultural Innovations in Developing Countries: A Survey." *Economic Development* and Cultural Change 2(1985):255–98.
- Fernandez-Cornejo, J. and W.D. McBride. Genetically Engineered Crops for Pest Management in U.S. Agriculture: Farm-Level Effects. U.S. Department of Agriculture, Economic Research Service, Agricultural Economic Report No. 786, 2000.
- Fernandez-Cornejo, J. and S. Jans. Pest Management in U.S. Agriculture. U.S. Department of Agriculture, Economic Research Service, Agricultural Handbook No. 717, 1999.
- Fernandez-Cornejo, J., C. Klotz-Ingram, and S. Jans. "Farm-Level Effects of Adopting Genetically Engineered Crops in the U.S.A." NE-165 Conference Proceedings, Transitions in Agbiotech: Economics of Strategy and Policy, edited by William H. Lesser, 2000, pp. 57–74.
- Fernandez-Cornejo, J., and C. Klotz-Ingram. "Economic, Environmental, and Policy Impacts of Using Genetically Engineered Crops for Pest Management." Paper presented at the Northeastern Agricultural and Resource Economics Association meetings, Ithaca, NY, June 1998.
- Fernandez-Cornejo, J. "The Microeconomic Impact of IPM Adoption: Theory and Application." Agricultural Resources Economic Review 25(October 1996):149-60.
- Ferrell, J.A., W.W. Witt, and C.H. Slack. "Integrating Glyphosate into Corn Weed Management Strategies." *Proceedings of the Southern Weed Science Society* 1999. pp. 27–28.
- Graeber, J.V., E.D. Nafziger, and D.W. Mies. "Evaluation of Transgenic, Bt-Containing Corn Hybrids." *Journal of Production Agriculture* 12(1999):659–663.
- Haden, K.L. and L.A. Johnson. "Factors Which Contribute to Financial Performance of Selected Tennessee Dairies." Southern Journal of Agricultural Economics 21(1989):104–112.
- Heckman, J.J. "Sample Selection Bias as a Specification Error." *Econometrica* 47(1979):153– 61.
- Heckman, J.J. "The Common Structure of Statistical Models of Truncation, Sample Selection, and Limited Dependent Variables and a Simple Estimator for Such Models." Annals of Eco-

nomic and Social Measurement 5(1976):475-91.

- Hyde, J., M.A. Martin, P.V. Preckel, C.R. Edwards, and C.L. Dobbins. "Estimating the Value of Bt Corn: A Multi-State Comparison." Paper presented at the American Agricultural Economics Association meetings, Tampa. FL. July–Aug. 2000.
- Hyde, J., M.A. Martin, P.V. Preckel, and C.R. Edwards. "The Economics of Bt Corn: Valuing Protection from the European Corn Boer." *Review of Agricultural Economics* 21(1999):442– 454.
- Lauer, J. and J. Wedberg. "Grain Yield of Initial Bt Corn Hybrid Introductions to Farmers in the Northern Corn Belt." *Journal of Production Agriculture* 12(1999):373–376.
- Lee, L. "Generalized Econometric Models with Selectivity Bias." *Econometrica* 51(1983):507– 12.
- Maddala, G.S. Limited-Dependent and Qualitative Variables in Econometrics. Cambridge University Press, 1983.
- Malik, J.M., G.F. Barry, and G.M. Kishore. "The Herbicide Glyphosate." *BioFactors* (1989):17– 25.
- Marra, M., G. Carlson, and B. Hubbell. Economic Impacts of the First Crop Biotechnologies. Internet site: http://www.ag.econ.ncsu.edu/faculty/ marra/online.html (Accessed April 4, 2001).
- Maumbe, B. M., and S. M. Swinton. "Why Do Smallholder Cotton Growers in Zimbabwe Adopt IPM? The Role of Pesticide-Related Health Risks and Technology Awareness" Paper presented at the American Agricultural Economics Association meetings, Tampa, FL. July– Aug. 2000.
- McBride, W.D. and N. Brooks. "Survey Evidence on Producer Use and Costs of Genetically Modified Seed." Agribusiness 16(2000):6–20.
- Mishra, A.K., H.S. El-Osta, and J.D. Johnson. "Factors Contributing to Earnings Success of

Cash Grain Farms." Journal of Agricultural and Applied Economics 31(1999):623–637.

- Nelson, F. D., and L. Olson. "Specification and Estimation of a Simultaneous Equation Model with Limited Dependent Variables." *International Economic Review* 19(1978):695–709.
- Owen, M.D.K. "Midwest Experience with Herbicide-resistant Crops." *Proceedings of the Western Society of Weed Science*, 1997, pp. 9–11.
- Pike, D.R. Personal communication, University of Illinois, August 1999.
- Reddy, K.N. and K. Whiting. "Comparison of Weed Control in Roundup Ready, STS, and Conventional Soybeans." *Proceedings of the Southern Weed Science Society*, 1999, pp. 210.
- Rice, M.E. and C.D. Pilcher. "Potential Benefits and Limitations of Transgenic Bt Corn for Management of the European Corn Borer (Lepidoptera: Crambidae)." *American Entomologist* 44(1998):75–78.
- Roberts, R.K., R. Pendergrass, and R.M. Hayes. "Economic Analysis of Alternative Herbicide Regimes on Roundup Ready Soybeans." *Journal of Production Agriculture* 12(1999):449– 454.
- Rogers, E. Diffusion of Innovations, 4th Edition. New York: Free Press, 1995.
- Seger, D.J. and D.A. Lins. "Cash Versus Accrual Measures of Farm Income." North Central Journal of Agricultural Economics 8(1986): 219–226.
- U.S. Department of Agriculture, Economic Research Service. Internet site: http://www.ers.usda.gov/ data/costsandreturns/ (Accessed April 12, 2001).
- U.S. Department of Agriculture, National Agricultural Statistics Service. *Prospective Plantings* Cr Pr 2-4. March 2000.
- U.S. Department of Agriculture, National Agricultural Statistics Service. *Agricultural Prices*— 1998 Summary Pr 1-3. July 1999.
- Zepeda, L. "Simultaneity of Technology Adoption and Productivity." *Journal of Agricultural and Resource Economics* 19(1994)1:46–57.