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# Revisiting the Impact of Bt Corn Adoption by U.S. Farmers

By

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#### **ABSTRACT**

This study examines the impact of adopting Bt corn on farm profits, yields, and insecticide use. The study employs an econometric model that corrects for self-selection and simultaneity. The model is estimated using nationwide farm-level survey data for 2005. Regression analysis confirms that Bt adoption is associated with increased profits, yields and seeding rates. However, the results of this analysis suggest that Bt adoption is not significantly related to insecticide use.

**Key Words:** Genetically engineered corn, insect resistance, Bt corn, insecticide use, technology adoption, yields.

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## Revisiting the Impact of Bt Corn Adoption by U.S. Farmers

Genetically engineered (GE) crop varieties with enhanced pest management traits, such as insect resistance and herbicide tolerance are being adopted by U.S. farmers at a very rapid rate. 

Insect resistant crops (Bt crops) contain a gene from a soil bacterium, *Bacillus thuringiensis* (Bt), which produces a protein that is toxic to specific insects. Bt corn with traits to control the European corn borer was introduced commercially in 1996. By the year 2000, Bt corn accounted for 19 percent of corn planted acres. Bt corn with traits to control corn rootworms was commercially introduced in 2003. By 2010 Bt corn accounted for approximately 63 percent of domestic corn acres (figure 1).

Estimating the costs and benefits associated with Bt corn use is complicated by the high degree of variability in regional factors such as weather, infestation levels and seed costs.

Moreover, the impact of Bt adoption is often confounded with the effect of other production practices such as conservation tillage, crop rotation, and other pest-management practices.

Several studies have analyzed how Bt corn affects pesticide use, yields, costs, and profits (Marra et al. 1998; Duffy, 2001; McBride & El-Osta, 2002; Fernandez-Cornejo and McBride, 2002; Pilcher et al., 2002; Fernandez-Cornejo and Li, 2005). Generally speaking, these studies have found that Bt corn yields are higher for adopters than for growers of conventional varieties (table 1). For instance, Marra et al. (1998) showed that yields were approximately 7.1 bushels per acre higher for Bt adopters in Iowa, and 18.2 bushels per acre higher for Bt adopters in Minnesota.

Duffy (1999) found that Bt corn yields were approximately 13 bushels per acre higher than conventional yields. Mitchell et al. (2004) found that adoption increased yields by 2.8 to 6.6 %.

<sup>&</sup>lt;sup>1</sup> Insect resistance and herbicide tolerance are classified as first generation, or input, characteristics. First generation characteristics usually increase yields and/or confer costs savings to farmers.

Dillehay et al. (2004) found that adoption increased yields by 5.5 % in Pennsylvania and Maryland. Fernandez-Cornejo and Li (2005) found that, on average, adopters had 12.5 bushels per acre higher corn yields that nonadopters. Several studies also concluded that adopters used less insecticide than nonadopters (table 1).

However, most studies have analyzed data collected in the first 5 years of adoption (1996-2001). As a recent report by the NRC concludes "The environmental, economic, and social effects on adopters and nonadopters of GE crops changed over time..." However, empirical research into the environmental and economic effects of changing market conditions and farmer practices have not kept pace." This paper presents the results of a study conducted to estimate the farm-level effects of adopting Bt corn. The study uses farm level data collected nationally in 2005.

#### The Data

The data were obtained from the 2005 nationwide Agricultural Resource Management Survey (ARMS) developed and conducted by the USDA. The ARMS survey has a multi-phase, multi-frame, stratified, probability-weighted design. In other words, farmers with specific characteristics are administered different phases of the ARMS survey during and after each survey year. After data collection, NASS generates probability weights to help ensure that the ARMS sample accurately represents the population of US famers.

The ARMS survey has three phases. The ARMS Phase I survey is administered in the summer of the survey year. Phase I verifies that all respondents operate a farm or plant a specific crop. The ARMS Phase II survey is administered in the fall or winter of the survey year. This commodity-based, field level survey collects data on production practices and input use.

The ARMS Phase III is administered in the spring following the survey year. Phase III gathers data on debt, revenue, operating costs and expenditures.

After merging the Phase II and Phase III datasets and excluding observations with missing values, 1156 observations from 19 major corn-producing states were available for analysis. Five hundred and sixty four of the operations sampled were located in the Heartland region. The Heartland Region encompasses western Ohio, Indiana, Illinois, western Kentucky, northern Missouri, Iowa, northeastern Nebraska, southeastern South Dakota, and southern Minessota.

According to the 2005 ARMS corn survey, 76.5 percent of the farmers adopting Bt corn indicated that they did so in order to increase yields. Other adopters reported reasons for adopting Bt corn were to decrease pesticide costs (11.3 percent), to save management time (3.3 percent). Approximately ten percent of adopters reported using Bt corn for other reasons.

Survey results indicate that, on average, actual corn yields were 17 bushels per acre (12.3 percent) higher for adopters than for non-adopters, seed use was 0.02 bushels per acre (4.8 percent) higher for adopters than for non-adopters, insecticide use was 0.04 pounds per acre (43 percent) of active ingredients lower for adopters than for non-adopters, and variable profits were 18.84 dollars per acre (8.75 percent) higher for adopters than for non-adopters (table 2), Differences in the unconditioned means suggest that Bt adoption may increase profits, yields, and seeding rates, while decreasing insecticide use.

The geographical distribution of average corn yields and Bt adoption rates are shown in Figures 1 and 2, respectively. We also show the location of the ERS designated Heartland Region, where the yields and Bt adoption rates appear highest (particularly in the northwestern heartland region).

Table 3 contrasts insecticide use in 2005 with insecticide use in 2001. Total pounds applied declined by approximately 4.5 million pounds (or 50 percent) over this time period. Usage declined most in Chlorpyrifos and Terbufos. Chlorpyrifos and Terbufos are used to control corn rootworms and other insects (Wilson et al., 2005).<sup>2</sup> Given that Bt corn can be used to control the European corn borer (since 1996) and the corn rootworm (since 2003), it is likely that that decreased demand for corn insecticides is due to Bt adoption.

Mean comparisons are illustrative. However, definite conclusions should not be drawn from these comparisons unless the data is generated under carefully controlled experimental settings, where factors other than adoption are "controlled for" by making them as similar as possible (Fernandez-Cornejo and Li, 2005; Fernandez-Cornejo and McBride, 2002). Clearly, this is not the case with survey data. After all, surveyed farmers were not randomly assigned to a treatment group (adopters) and a control group (non-adopters). Consequently, adopters and nonadopters may be systematically different from one another (for example, in terms of management ability). This situation, called self-selection, biases the statistical results, unless it is corrected. For these reasons, we specify an econometric model that accounts for self-selection and endogeneity.

#### The Model

In this section, we briefly discuss the theoretical framework of the model and present the specifications used in the empirical analysis.

This study employs a two-stage framework. The first stage, which is referred to as the *adoption decision model*, is used to determine factors that influence farmers' decision to use Bt

<sup>2</sup> http://www.chlorpyrifos.com/benefits-by-crop.htm

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seeds. The second stage, or *impact model*, is used to estimate the impact of how adopting Bt seeds has on yields, seed demand, insecticide demand, and farm profits.

## The Adoption Decision Model

Because adoption decisions involve a binary choice (experimenting with a new technology or retaining an old one), a probit specification is used in this stage of the analysis. Formally, if F denotes the normal distribution, the probability of adopting a seed with Bt traits is  $P(I_{Bt} = 1) = F(\delta'_{BT}Z)$  where  $I_{Bt}$  is an indicator for whether the farmer chooses Bt seeds,  $\delta$  is a vector of parameter estimates, and Z is a vector of explanatory variables. The specification for the adoption equation is:  $I_{Bt} = \delta_{Bt}'Z + \varepsilon_{Bt}$  where the residuals,  $\varepsilon_{Bt}$  are normally, identically and independently distributed. Elements of Z may include: (i) the relative price of Bt seeds, (ii) farm size, (iii) operator experience, (iv) use of crop insurance (which is used in many studies as a proxy for risk aversion), and (v) operator knowledge about pest infestations.

## The Impact Model

The second stage of the model examines how Bt adoption affects pesticide use, yields, and variable profits. To do this in a manner consistent with farmers' optimization behavior, we use the well-developed restricted profit function (Diewert, 1974). Using the Hotteling-Shephard lemma, the output supply and input demand functions can be derived from the profit function.

For the empirical model, we use a normalized quadratic restricted profit function (Diewert and Ostensoe, 1988). Considering land as a fixed input, imposing symmetry by sharing parameters, imposing linear homogeneity by normalization (using the price of labor as the numeraire), and appending disturbance terms, the per-acre profit function  $(\pi)$ , the supply (yield)

equation (Y), the per-acre demand equation for seeds  $(X_1)$ , and the per-acre demand equation for insecticides  $(X_2)$  are:

(1) 
$$\pi = A_0 + A_y P + \sum_k C_k R_k + .05 G_{yy} P^2 + \sum_j G_{yj} P W_j + \sum_k F_{yk} P R_k + .05 \sum_j \sum_i G_{ij} W_i W_j + \sum_k \sum_j E_{jk} W_j R_k + \varepsilon_{\pi}$$

(2) 
$$Y = A_y + G_{yy}P + \sum_{i} G_{yj}W_j + \sum_{k} F_{yk}R_k + \varepsilon_y$$

(3) 
$$X_1 = A_1 + G_{y1}P + \sum_j G_{1j}W_j + \sum_k E_{1k}R_k + \varepsilon_1$$

(4) 
$$X_2 = A_2 + G_{y2}P + \sum_j G_{2j}W_j + \sum_k E_{2k}R_k + \varepsilon_2$$

where P and W are output and input prices (respectively) and A, C, E, F and G are parameters (Fernandez-Cornejo, 1996). The vector R contains a measure of Bt adoption (as discussed in the next section) as well as exogenous variables to control for pest infestation levels and management characteristics.

## Self Selection

As discussed in a previous section, since farmers are not randomly assigned to a treatment group and a control group, adopters and nonadopters may be systematically different from one another. If these differences affect both farm performance and Bt adoption, they will confound the analysis (Fernandez-Cornejo, 1996). This is a classic case of self-selection (Greene, 1997).

Self-selection is a type of endogeniety (Maddala, 1983; Green, 1997). Endogeneity arises when there is a correlation between the explanatory variables and the model's residuals.<sup>3</sup>

<sup>&</sup>lt;sup>3</sup> The residuals represent "noise" generated by random processes, but also contain variation caused by all unspecified or unobservable variables.

If endogeniety is not accounted for (for instance, through the use of instrumental variable techniques), the results of the analysis will be biased.

For simplicity, consider self selection in the context of determining whether Bt adoption affects seed demand. Let the true model be,

(5) 
$$X_{Seed_i} = \beta_1 S_i + \propto Bt_i + \gamma_1 RA_i + e_i$$

(6) 
$$Bt_i = \beta_2 Z_i + \gamma_2 RA_i + v_i$$

Where  $X_{Seed_i}$  represents seed use,  $Bt_i \in \{0,1\}$  represents the farmer's decision to adopt Bt seeds,  $S_i$  and  $Z_i$  are vectors of (exogenous) explanatory variables,  $RA_i$  represents an unobserved variable (e.g., the farmers desire to avoid risk),  $\beta_1, \beta_2, \infty$ ,  $\gamma_1$  and  $\gamma_2$  are vectors of parameter estimates, and  $e_i$  and  $v_i$  are error terms.

RA is assumed to be unobserved. Thus, it is necessary to estimate:

(7) 
$$X_{Seed_i} = \beta_1 S_i + \propto Bt_i + \varepsilon_1$$
, where the error term is  $\varepsilon_1 = (\gamma_1 RA_i + e_i)$ 

(8) 
$$Bt_i = \beta_2 Z_i + \varepsilon_2$$
, where the error term  $\varepsilon_2 = (\gamma_2 RA_i + v_i)$ 

Consider Equation 7. Notice that neither  $E[Bt_i, \varepsilon_1]$  nor  $E[X_{Seed_i}, \varepsilon_1]$  equals 0 because  $RA_i$  influences both Bt adoption and seed demand (as specified in Equations 5 and 6). This correlation is the source of the self-selection problem. Regressing Equation 7 without accounting for this correlation will generate biased parameter estimates.

## Controlling for Endogeneity/Self Selection

There are several methods of controlling for self-selection. The approach used in this study

(sometimes called an instrumental variables approach) is to calculate predictions of  $Bt_i$  (denoted by  $\widehat{Bt}_i$ ) using the parameters estimated from equation 8 and to substitute these predictions into Equation 7. Because the variables in  $Z_i$  are exogenous,  $\widehat{Bt}_i$  is uncorrelated with  $e_i$ , and  $\propto$  is an unbiased estimator.<sup>4</sup>

## Estimation

The Adoption Model was calculated using the weighted probit routine in LIMDEP. The system of profit, yield, and derived demand equations (equations 1-4) were jointly estimated using a seemingly unrelated regression (SUR) framework.

The Impact model was estimated using the Conditional Mixed Process Module (cmp) developed for STATA by David Roodman (Roodman, 2009).<sup>5</sup> The CMP module fits Seemingly Unrelated Regression Models with normally distributed error terms. Unlike many of the SUR routines available in Stata or SAS, this program enables the estimation of mixed models, allowing linear, probit, ordered probit, multinomial probit, Tobit, interval regression, and truncated-distribution regressions to be jointly estimated within the context of a seemingly unrelated system of equations. For the purposes of this analysis, the profit, yield, and seed demand equations were assumed to have uncensored, linear specifications. Because approximatley 80% of the farmers in the sample do not use insecticides, a tobit specification was

Since  $E[S_i, e_i] = E[Bt_i, e_i] = E[\widehat{RA}_i, e_i] = 0, \propto$  is an unbiased estimator.

<sup>&</sup>lt;sup>4</sup> An alternate approach (sometimes called a generalized residuals approach) involves explicitly modeling  $RA_i$ , the endogenous component of  $\varepsilon_1$ . Assuming that the residuals from Equation 8 are normally distributed, a probit equation can be used to estimate Equation 8. The generalized residuals are obtained from the first order condition (or score function) of the probit's log likelihood function. A simple derivation demonstrates that the score function simplifies to the inverse mills ratio for the entire sample. The inverse mills ratio is strongly correlated with  $RA_i$ . Consequently, the inverse mills ratio can be used as a proxy, or an instrument. Including the inverse mills ratio (denoted  $\widehat{RA}_i$ ) in Equation 5 yields:

<sup>(9)</sup>  $X_{Seed_i} = \beta_1 S_i + \propto Bt_i + \theta \widehat{RA}_i + e_i$ 

Though this approach relies on parametric assumptions (the normality of  $v_i$ ),  $\hat{\theta}$  provides valuable information about how farm performance is effected by unobserved variation.

<sup>&</sup>lt;sup>5</sup> This module is based on work by Cappellari and Jenkins (2003), Gates (2006), Geweke (1989), Hajivassiliou (1998), and Keane (1992,1994).

used to model insecticide demand. As in the Adoption Model, a weighted least squares technique was used to estimate the Impact Model.

After estimating the Impact Model using the full sample, the standard errors were reestimated using the delete-a-group jackknife method described in Kott (1998), and employed in other analyses of ARMS data (Fernandez et al., 2005; Fernandez and Li, 2005; Fernandez 2002). It is well known that standard errors estimated using the jackknife method are conservative, and "may understimate the significance of variables under some circumstances (Fernandez et al., 2005). For this reason, standard errors calculated using both the standard estimation procedure and the jackknife method are reported below. The P-values used in this analysis were calculated using the jackknifed standard errors.

#### **Model Results**

The Adoption Decision Model

Table 4 presents results from the Adoption Model. Generally speaking, these results corroborated a priori assumptions. For instance, previous work has established that large operations are more likely than small operations to adopt agricultural innovations (Feder et al, 1985; Fernandez et al, 2002; Fernandez-Cornejo and Li, 2005). Previous work has also established that farmers who purchase crop insurance are more likely than their uninsured counterparts to purchase Bt seeds (Fernandez and McBride, 2002). Similarly, it is well known that the opportunity cost of pest infestations tends to be higher on irrigated operations, operations

Cornejo, Hendricks, and Mishra; 2005).

<sup>7</sup> Bt seeds and crop insurance both reduce expected losses from pest infestations.

<sup>&</sup>lt;sup>6</sup> NASS partitions the sample into 15 groups of observations. 15 "replicate" groups of observations are formed by excluding one of the 15 original groups from the full sample. NASS calculates sampling weights for the full sample, as well as each of the replicates. In order to estimate the model, parameter estimates are estimated using the full sample. To calculate the standard errors, the model is run 15 additional times (using each of the 15 subsamples and the appropriate replicate weights). The standard errors estimated from each subsample are saved and used to calculate the adjusted standard errors (see Fernandez-

in the heartland (that tend to have highly productive soils), and other operations with high expected yields. Finally, it is not surprising that farmers expecting yield loses from corn borers are more likely to plant insect resistant seeds than those who do not expect these loses. In other words, we expected the parameter estimates on Size, Crop Insurance, Irrigation, Heartland, and Ind\_cbor to be positive and significant.

It should be mentioned that some of the results did not corroborate our a priori hypotheses. For instance, we expected the parameter estimates for operator experience and the price of corn to be positive. However, both of these parameter estimates were negative and significant.

Insofar as operator experience is concerned, while we usually expect a positive association of adoption with experience, we also expect a negative association of adoption with age. In this study, adopters had an average of 33.48 years of experience, while nonadopters had an average of 37.74 years of experience (see table 2). This implies that many of the survey respondents are in their sixties. It is not surprising that older farmers are less likely to adopt a new technology than their "younger" counterparts.

Insofar as the price of corn is concerned, our results indicate that there is a negative association between the price of corn and the use of Bt corn. This result mirrors the difference between the unconditioned means in corn prices for nonadopters (\$2.01) and adopters (\$1.95) (see table 2). The fact that farmers received higher prices for conventional corn may reflect the fact that consumers are willing to pay a premium for non-GE corn. An alternative explanation stems from the fact that corn prices exhibit a high degree of spatial correlation (this would violate the assumption that corn prices are independently distributed). In cases where there is a high degree of spatial correlation, p-values for parameter estimates may be spuriously high. In

other words, there might not be a strong statistical relationship between corn prices and seed choice. Future work should further explore these possibilities.

## The Impact Model

The Impact Model fits the data relatively well. While it appears that there is no consensus regarding the best measure of "goodness of fit" for Mixed Process Models (Kramer, 2005), pseudo-R<sup>2</sup> statistics are good alternatives to traditional R<sup>2</sup> values.<sup>8</sup> As discussed in Magee (1990), there are many different methods of calculating pseudo R<sup>2</sup> statistics, all of which provide slightly different values.

One possibility involves calculating the likelihood ratio for a parameterized (unrestricted) model and an unparameterized (restricted) model (Magee, 1990). More specifically, it can be shown that:

Pseudo 
$$R^2 = 1 - \exp\left(\frac{-2}{n}\log\left(\frac{L_u}{L_r}\right)\right) = 1 - \exp\left(\frac{-2}{n}(\log L_u - \log L_r)\right)$$

where, n is the number of observations,  $L_u$  is the log-likelihood of the fully parameterized model and  $L_r$  represents the log-likelihood of the intercept only model. Using this measure, the Pseudo-R<sup>2</sup> of the model is 0.77.

An alternative involves directly computing the sum of squared residuals and dividing them by the sum of squared means. While identical to the formula used to calculate the traditional  $R^2$  value, it does not have the same interpretation:

<sup>8</sup> Pseudo R<sup>2</sup> values resemble traditional R2 values in that they are bounded on the [0,1] interval and higher values indicate better model fit. However, these values cannot be interpreted as one would interpret a traditional R2, because the parameter estimates were not calculated to minimize variance (rather they were calculated via maximum likelihood or an alternative, iterative method). Different methods of calculating pseudo R<sup>2</sup>'s can provide very different values.

Generalized 
$$R^2 = 1 - \frac{\text{SSE}}{\text{SSM}} = 1 - \frac{|e'e|}{|m'm|}$$

where e is a nxl matrix of residuals (with n = to the number of observations in the system, and l = to the number of equations in the system), m is a nxl matrix of the difference in means  $(y - \bar{y})$ , and |e'e| represents the determinant of e'e. Using this measure, the Generalized R<sup>2</sup> of the model is 0.83.

In addition to the pseudo  $R^2$  calculations, several Likelihood Ratio tests were also used to test the performance of our model (see table 5). These tests strongly reject the following null hypotheses:

- 1) That all of the parameter estimates in the model equal 0.
- 2) That all of the parameter estimates for Bt adoption equal 0.

These tests confirm that our model has explanatory power, and that Bt adoption is strongly correlated with measures of on-farm performance.

Most of the results derived from the parameter estimates corroborate a priori expectations. Increases in seed prices decrease seed demand. Increases in insecticide prices decrease insecticide demand. Increases in corn prices increase per-acre supply (yields). Pest infestation is associated with decreased yields, while being located in the Heartland region and high precipitation rates are associated with increased yields (table 6). Notably, increases in insecticide prices appear to decrease seed demand. This implies that seeds and insecticides are complements in the production process.

Insofar as the impact of Bt adoption is concerned, this study's findings suggest that Bt seed use increases profits, yields, and seed demand (tables 6 and 7). More specifically, a 10%

<sup>&</sup>lt;sup>9</sup> Parameter restrictions ensure that G12 equals G21. This ensures that the effect insecticide prices have on seed demand is equivalent to the effect seed prices have on insecticide demand.

increase in the probability of adoption was associated with a 1.3 percent (2.89 dollars/acre) increase in profits, a 1.2 percent (1.72 bushels/acre) increase in yields, and a 0.6 percent (0.002 bushels /acre) increase in seed demand (table 8).

In contrast to the findings reported in Fernandez-Cornejo and Li (2005) (which were based on 2001 data), this study finds that Bt adoption does not have a statistically significant impact on insecticide demand (table 5). This result appears to be related to the fact that insect infestation levels were lower in 2005 than they were in 2001 (see for example Hutchinson et al, 2010). Because infestation levels were low, most farmers applied substantially fewer insecticides in 2005 than they did in 2001. In fact (as previously mentioned), 80% of the farmers in the sample did not use insecticides at all. This may have reduced the impact of Bt adoption on insecticide use. After all, farmers only use insecticides if treating pest infestations is expected to be profitable. In other words, farmers only use insecticides if infestation levels are above a certain threshold. Below this threshold, Bt adoption should not affect insecticide use.

## **Concluding Comments**

This study estimates how adopting Bt corn affects profits, yields, seeding rates, and insecticide demand using an econometric model that corrects for self-selection and simultaneity. The model is estimated using 2005 national survey data.

Survey results indicate that, on average, variable profits were \$18.84 per acre higher for adopters than for non-adopters, corn yields were 17 bushels per acre higher for adopters than for non-adopters, seed demand was 0.02 bushels per acre higher for adopters than for non-adopters,

 $<sup>^{10}</sup>$  Average insecticide use was 0.07 pounds per acre in 2005 (table 1) compared with about 0.15 pounds per acre in 2001 (Fernandez-Cornejo and Li (2005).

<sup>&</sup>lt;sup>11</sup> This threshold may differ for adopters and non-adopters.

and insecticide demand was 0.04 pounds of active ingredients lower for adopters than for non-adopters. Differences in the unconditioned means suggest that Bt adoption increases profits, yields, and seeding rates, while decreasing insecticide use.

Regression analysis confirms that Bt adoption is positively associated with increased profits, yields and seeding rates. However, our results suggest that Bt adoption is not significantly related to insecticide use. This result appears to be related to the fact that insect infestation levels were lower in 2005 than they were in earlier years.

The implications of these results should be regarded carefully, and only within the constraints of this analysis. The economic impacts of adopting GE crops vary with pest infestations, seed premiums, and prices of alternative pest control programs. Future work should incorporate other inputs (for instance, fertilizer) and cropping practices (particularly the role of crop rotations and conservation tillage).

#### References

Cappellari, L, and S Jenkins. "Multivariate probit regression using simulated maximum likelihood." *Stata Journal* 3.3 (2003): 278-294.

Darr, D.A., and W.S. Chern. "Estimating Adoption of GMO Soybeans and Corn: A Case Study of Ohio." *Department of Agricultural, Environmental and Development Working Paper* AEDE-WP-0003-00 (2000): 1-24.

Diewert, W.E.. "Applications of Duality Theory." *Frontiers of Quantitative Economics*. Amsterdam: North-Holland, 1974. 106-171.

Diewert, W.E., and L. Ostensoe. "Flexible Functional Forms and Global Curvature Conditions." In *Dynamic Econometric Modeling*. W. Barnett, E. Berndt, and H. White, eds., Cambridge Univ. Press. 1988.

Dillehay, B. L., G. W. Roth, D. D. Calvin, R. J. Karatochvil, G. A. Kuldau, and J. A. Hyde. "Performance of Bt Corn Hybrids, their Near Isolines, and Leading Corn Hybrids in Pennsylvania and Maryland." *Agronomy Journal* 96.204 (2004): 818-824.

Duffy, M. "Does Planting GMO Seed Boost Farmers' Profits." Iowa State, Leopold Center for Sustainable Agriculture, Leopold Letter 11 (1999).

Duffy, M. "Who Benefits from Biotechnology." American Seed Trade AssociationElectronic (2001): 1-.

Feder, G, R Just, and D Zilberman. "Adoption of Agricultural Innovations in Developing Countries: A Survey." *Economic Development and Cultural Change* 33.2 (1985): 255-298.

Fernandez-Cornejo, J. "The Microeconomic Impact of IPM Adoption: Theory and Adoption." *Agricultural and Resource Economics Revue* 25 (1996): 149-160.

Fernandez-Cornejo, J, C Hendricks, and A Mishra. "Technology Adoption and Off-Farm Household Income: the Case of Herbicide-Tolerant Soybeans." *Journal of Agricultural and Applied Economics* 37.2 (2005): 549-63.

Fernandez-Cornejo, J, C Klotz-Ingram, and S Jans. "Farm-Level Effects of Adopting Herbicide-Tolerant Soybeans in the U.S.A." *Journal of Agricultural and Applied Economics* 34.1 (2002): 149-163.

Fernandez-Cornejo, J, and Jiayi Li. "The Impacts of Adopting Genetically Engineered Crops in the USA." *Paper Presented at the American Agricultural Economics Association* July 24-27 (2005): 1-25.

Fernandez-Cornejo, Jorge, and William McBride. "Adoption of Bioengineered Crops." *Department of Agriculture* Agricultural Economic Report Number 810 (2002): 1-61.

Gates, R. "A Mata Geweke-Hajivassiliou-Keane multivariate normal simulator." Stata Journal 6.2 (2006): 190-213.

Geweke, J. "Bayesian inference in econometric models using Monte Carlo integration." Econometrica 57 (1989): 1317-1339.

Greene, W. Econometric Analysis. 3<sup>rd</sup> ed. Upper Saddle River, NJ: Prentice-Hall, 1997.

Hajivassiliou, V., and D. McFadden. "The method of simulated scores for the estimation of LDV models." Econometrica 66 (1998): 863-896.

Heckman, James. "Sample Selection Bias as a Specification Error." *Econometrica* 47.1 (1979): 153-161.

Hutchinson, W. D., E. C. Burkness, R. L. Hellmich, L. V. Kaster, T. E. Hunt, R. J. Wright, K. Pecinovsky, T. L. Rabaey, B. R. Flood, E. S. Raun, P. D. Mitchell, R. D. Moon, T. W. Leslie, S. J. Fleischer, M Abrahamson, K. L. Hamilton, K. L. Steffey, and M. E. Gray. "Areawide Suppression of European Corn Borer with BT Maize Reaps Savings to Non-Bt Maize Growers." *Science* 330 (2010): 222.

Hyde, Jeffrey, Marshall Martin, Paul Preckel, and Richard Edwards. "The Economics of Bt Corn: Valuing Protection from the European Corn Borer." *Review of Agricultural Economics* 21.2 (1999): 442-454.

Keane, M. P. "A computationally practical simulation estimator for panel data." Econometrica 62 (1994): 95-116.

Keane, M. P. "A note on identification in the multinomial probit model." Journal of Business and Economics Statistics 10.2 (1992): 193-200.

Kramer, M. "R2 statistics for mixed models." *Proceedings of the Conference on Applied Statistics in Agriculture* 17 (2005): 148-160.

Kott, P.S.. "Using the Delete-A-Group Jackknife Variance Estimator in NASS Surveys." *USDA*, *NASS*, *RD Research Report* RD-98-01 (1998).

Leung, Siu Fai, and Shihti Yu. "On the choice between sample selection and two-part models." *Journal of Econometrics* 72 (1996): 197-229.

Maddala, G. S. . Limited Dependent and Qualitative Variables in Econometrics. Cambridge, UK: Cambridge University Press, 1983.

Magee, L. "R2 Measures Based on Wald and Likelihood Ratio Joint Significance Tests." *The American Statistician* 44.3 (1990): 250-253.

Marra, M, P Pardey, and J Alston. "The Payoffs to Transgenic Field Crops: An Assessment of the Evidence." AgBioForum 5.2 (2003): 43-50.

McBride, W, and H El-Osta. "Impacts of the Adoption of Genetically Engineered Crops on Farm Financial Performance." Journal of Agricultural and Applied Economics 34.1 (2002): 175-191.

McBride, William D., and Nora Books. "Survey Evidence on Producer Use and Costs of Genetically Modified Seed." *Agribusiness* 16.1 (2000): 6-20.

Mitchell, P, T Hurley, and M Rice. "Is Bt Corn Really a Drag? Bt Corn yield Drag and Yield Variance." *Faculty Paper Series* FP 04-01. Department of Agricultural Economics, Texas A&M University (2004).

Pilcher, C. D., M. E. Rice, R. A. Higgins, K. L. Steffey, R. L. Hellmich, J. Witowski, D. Calvin, K. R. Ostlie, and M. Gray. "Biotechnology and the European corn borer: Measuring historical

farmer perceptions and adoption of transgenic Bt corn as a pest management strategy." *Journal of Economic Entomology* 95 (2002): 878-892.

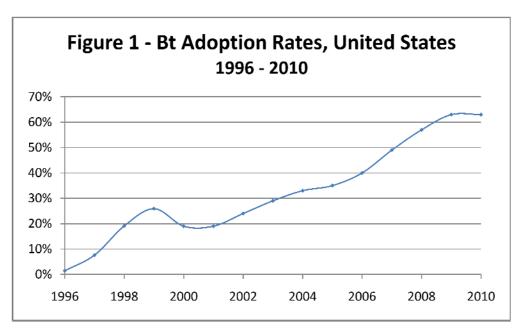
Roodman, David . "Estimating Fully Observed Recursive Mixed-Process Models with cmp." *Center for Global Development Working Paper* Number 168 (2009): 1-53.

Scandizzo, Pasquale L., and Sara Savastano. "The Adoption and diffusion of GM Crops in United States: A Real Option Approach." *AgBioForum* 13.2 (2010): 142-157.

Vella, Francis. "A Simple Estimator for Simultaneous Models with Censored Endogenous Regressors." *International Economic Review* 34.2 (1993): 441-457.

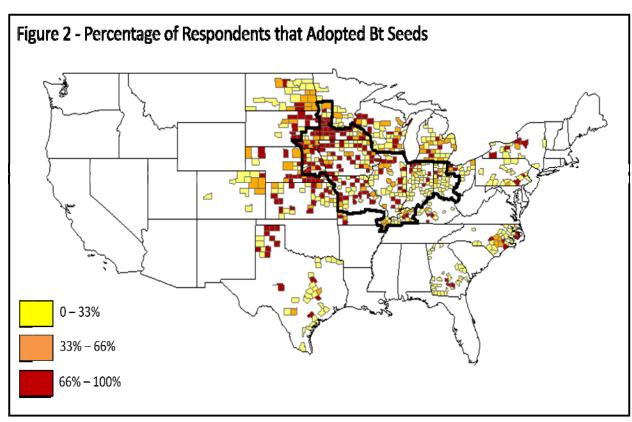
Vella, Francis. "Estimating Models with Sample Selection Bias: A Survey." *The Journal of Human Resources* 33.1 (1998): 127-169.

Wilson, Ted, Marlin Rice, Jon Tollefson, and Clinton Pilcher. "Transgenic Corn for Control of the European Corn Borer and Corn Rootworms: a Survey of Midwestern Farmers' Practices and Perceptions." *Journal of Economic Entomology* 98.2 (2005): 237-247.



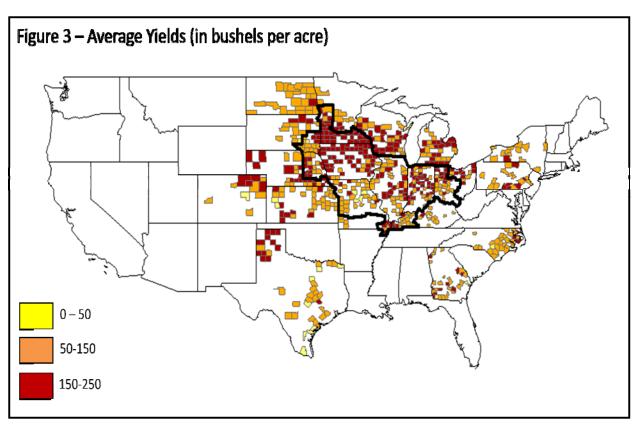
Source: NASS/ERS ARMS Data, the NASS Objective Yield Survey, and the NASS June Agricultural Survey

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Source: NASS/ERS 2005 ARMS Corn Data

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Source: NASS/ERS 2005 ARMS Corn Data

Summary of Previous Studies on the Effects of Bt Corn on Yields, Insecticide Use, and Returns

Table 1.

		Effects on		
Researchers / Date of Publication	Data Source	Yield	Insecticide Use	Returns
Rice and Pilcher, 1998	Survey	Increase	Decrease	Depends on infestation
Marra et al., 1998	Survey	Increase	Decrease	Increase
McBride & El-Osta, 2002 <sup>1</sup>	Survey	Na	Na	Decrease
Duffy, 2001	Survey	Increase	Na	Same
Pilcher et al., 2002	Survey	Increase	Decrease	Na
Baute, Sears, and Schaafsma, 2002	Experiments	Increase	Na	Depends on infestation
Dillehay et al., 2004 <sup>2</sup>	Experiments	Increase	Na	Na
Fernandez-Cornejo and Li, 2005	Survey	Increase	Decrease	Na

Na = not available

Source: Fernandez-Cornejo and Li, 2005

	Sample Means and Definition of Selected
Table 2.	Variables Corn Producers, 2005

Variable	Description	All Obs	Std Dev	Bt Adopters	Non Adopters
Yield	Per Acre Yields, in bushels	144.76	40.54	155.44	138.33
Seed Use	Seed, in bushels per acre	0.35	0.05	0.36	0.34
Insecticide Use	Insecticides, in pounds AI per acre	0.07	0.27	0.05	0.09
Bt Corn	Dummy Variable = 1 if the operator planted seeds with Bt traits	0.38	0.48		
Crop Insurance	Dummy Variable = 1 if the operator has crop ins	0.76	0.43	0.88	0.69
Seed Price	Seed Price, dollars per bushel	109.23	24.01	120.30	102.53
Insecticide Price	Insecticide Price, in dollars per pound Al	16.24	13.14	17.08	15.73
Corn Price	Corn Price, dollars per bushel	1.99	0.24	1.95	2.01
Operator Experience	Years of operator experience	36.14	13.92	33.48	37.74
Conservation Tillage	Dummy Variable = 1 if the operator uses conservation tillage practices	0.65	0.48	0.68	0.63
Heartland	Dummy Variable = 1 if the operation is located in the ERS designated Heartland region	0.69	0.46	0.74	0.65
Insecticide	Dummy Variable = 1 if insecticides are applied	0.20	0.40	0.21	0.19

Source: 2005 ARMS Corn Survey

<sup>&</sup>lt;sup>1</sup> Results using 1998 data

<sup>&</sup>lt;sup>2</sup> Results using 2000 - 2002 data

Major Insecticides Used on Corn, **Table 3.** 2001<sup>1</sup> and 2005<sup>2</sup>

Active Ingredient	Area Applied		Total A	Applied	
	Percent			ısand ınds	
	<u>2001</u>	<u>2005</u>	<u>2001</u>	<u>2005</u>	
Bifenthrin	2	2	67	72	
Carbofuran	*	*	476	113	
Chlorpyrifos	4	2	3,663	2,047	
Cyfuthrin	4	7	16	38	
Dimethoate	*	*	164	68	
Esfenvalerate	*	*	1	8	
Fipronil	3	1	259	88	
Lambda-cyhalothrin	2	1	23	25	
Methyl parathion	1	*	386	82	
Permethrin	3	1	236	116	
Propargite	*	*	156	289	
Tebupirimphos	4	6	371	573	
Tefluthrin	6	7	466	637	
Terbufos	3	*	2,491	331	
Petroleum Distillate	*	NA	56	NA	
Phorate	*	NA	73	NA	
Zeta-cypermethrin	NA	*	NA	11	
Other			100	351	
Total	8,904	4,498			
Planted Acres (in thous	76,470	70,745			

<sup>\*</sup> Area applied is less than one percent.

Source: NASS Agricultural Chemical Usage Reports,

Field Crop Summaries, 2005 and 2001

<sup>&</sup>lt;sup>1</sup> Planted Acres in 2001 for the 19 program states were 70.7 million acres. States included are CO, GA, IL, IN, IA, KS, KY, MI, MN, MO, NE, NY, NC, ND, OH, PA, SD, TX and WI.

<sup>&</sup>lt;sup>2</sup> Planted Acres in 2005 for the 19 program states were 76.5 million acres. States included are CO, GA, IL, IN, IA, KS, KY, MI, MN, MO, NE, NY, NC, ND, OH, PA, SD, TX and WI.

Table 4.	Predicting Bt Adoption	- Corn Producers, 2005
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Observations :1156Log Likelihood :-638.30Restricted Log Likelihood:-765.95Wald Chi-Squared :255.31Prob > chi2 :P<.0001</td>

Variable	Parameter E	stimates
Constant	0.58	
Acres Planted	0.005	***
Operator Experience	-0.01	***
Relative Price of Bt Seeds	-0.06	
Corn Price	-0.96	***
Debt to Asset Ratio	0.19	
Contract	0.12	
Crop Insurance	0.44	***
Conservation Tillage	0.03	
Irrigation	0.84	***
Crop Rotation	0.19	
Ind_Cbor	0.69	***
Ind_Cwrm	0.08	
Heartland	0.26	***

<sup>\*\*\*</sup> indicates that P<.01, \*\* indicates that P<.05, \* indicates that P<.1 Source: Model Results

 Table 5.
 Log Likelihood Tests, Parameters from the Impact Model

Null Hypothesis	Description of the Null Hypothesis	Test Statistic	P-value
A0, Ay, A1, A2, C1, C2, C3, C4, C5, C6, C7, Gyy, Gy1, Gy2, Fy1, Fy2, Fy3, Fy4, Fy5, Fy6, Fy7, G11, G12, G22, E11, E12, E13, E14, E15, E16, E17, E21, E22, E23, E24, E25, E26, E27 = 0	Ho: The variables in the impact model do not have explanatory power	1720.89	<.00001
C1, Fy1, E11, E21 = 0	Ho: Bt Adoption does not affect Profits, Yields, Seed Demand, or Insecticide Demand	108.99	<.00001

Source: Model Results

Results from the Impact Model -- Corn Producers, 2005

Table 6.Derived Output and Input Equations

i abic o.	Derived Ot	itput and	mput	Lquations					
Variable	Parameter	Yiel	d¹	Parameter	Seed	) <sup>1</sup>	Parameter	Ins	1
Corn Price	Gyy	134.53	***	Gy1	0.48	***	Gy2	1.73	**
Seed Price	Gy1	0.48	***	G11	-0.004	***	G21	-0.002	
Insecticide Price	Gy2	1.73	**	G12	-0.002		G22	-0.006	
Bt Corn	Fy1	45.84	***	E11	0.05		E21	0.19	
Other Insect Infestations	Fy2	-28.34	**	E12	-0.014	***	E22	0.253	
Ind_Cbor	Fy3	-0.96		E13	0.01	**	E23	-0.27	
Ind_Cwrm	Fy4	-0.04		E14	0.01		E24	0.04	
Heartland	Fy5	17.22	***	E15	0.025		E25	0.03	
Precipitation	Fy6	1.33		E16	-0.003	***	E26	-0.05	**
Education	Fy7	2.72		E17	0.02	*	E27	0.19	
Constant	Ay	67.67	***	A1	0.26	**	A2	-0.87	***

<sup>&</sup>lt;sup>1</sup> P-values were calculated using the jackknifed standard errors. \*\*\* indicates that P<.01, \*\* indicates that P<.05, \* indicates that P<.1

Source: Model Results

# Results from the Impact Model -- Corn Producers, 2005 Profit Equation

Table 7.

Variable	Parameter	Parameter Estimate <sup>1</sup>		SE, using standard method	SE, using Jackknife method	
Constant	A0	-4.45	**	0.77	1.70	
Corn Price	Ay	67.67	***	6.36	9.04	
Seed Price	A1	0.26	***	0.01	0.03	
Insecticide Price	A2	-0.87	***	0.20	0.29	
Bt Adoption	C1	-2.47	**	0.57	0.96	
Other Insect Infestations	C2	1.84		0.92	1.55	
Ind_cbor	C3	-0.13		0.63	1.18	
Ind_cwrm	C4	-1.59		0.75	1.31	
Heartland	C5	-1.20	**	0.25	0.49	
Precipitation	C6	0.20	*	0.07	0.10	
Education	C7	-0.69		0.39	0.68	
(Corn Price)^2	Gyy	134.53	***	15.10	21.78	
Corn Price*Seed Price	Gy1	0.48	***	0.04	0.08	
Corn Price*Insecticide Price	Gy2	1.73	**	0.38	0.59	
Corn Price*Bt Adoption	Fy1	45.84	***	4.82	11.17	
Corn Price*Other Insect Infestations	Fy2	-28.34	**	8.22	9.52	
Corn Price*Ind cbor	Fy3	-0.96		5.71	7.99	
Corn Price*Ind cwrm	Fy4	-0.04		6.55	8.85	
Corn Price*Heartland	Fy5	17.22	***	2.20	5.42	
Corn Price*Precipitation	Fy6	1.33		0.54	0.91	
Corn Price*Education	Fy7	2.722		3.41	5.78	
(Seed Price)^2	, G11	-0.004	***	0.00	0.00	
Seed Price*Insecticide Price	G12	-0.002		0.00	0.00	
(Insecticide Price)^2	G22	-0.006		0.01	0.01	
Seed Price*Bt Adoption	E11	0.054	***	0.01	0.01	
Seed Price*Other Insect Infestations	E12	-0.0136	**	0.01	0.01	
Seed Price*Ind_cbor	E13	0.009		0.01	0.01	
Seed Price*Ind cwrm	E14	0.01		0.01	0.02	
Seed Price*Heartland	E15	0.025	***	0.00	0.00	
Seed Price*Precipitation	E16	-0.003	*	0.00	0.00	
Seed Price*Education	E17	0.02	**	0.00	0.01	
Insecticide Price*Bt Adoption	E21	0.19		0.14	0.31	
Insecticide Price*Other Insect Infestations	E22	0.25		0.22	0.33	
Insecticide Price*Ind_cbor	E23	-0.27		0.18	0.28	
Insecticide Price*Ind_cwrm	E24	0.04		0.14	0.35	
Insecticide Price*Heartland	E25	0.03		0.07	0.11	
Insecticide Price*Precipitation	E26	-0.05	**	0.02	0.02	
Insecticide Price*Education	E27	0.19		0.11	0.29	

<sup>&</sup>lt;sup>1</sup> P-values were calculated using the jackknifed standard errors. \*\*\* indicates that P<.01, \*\* indicates that P<.05, \* indicates that P<.1 Source: Model Results

The Impact of Adoption of Insect Resistant Corn, Corn Producers 2005

Table 8.	2005	,
Elasticity of		Elasticity with respect to the probability of adoption
Profit	_	0.13
Yield		0.12
Seed		0.06
Ins		NA

Source: Model Results