Journal of Agricultural and Applied Economics, 44,1(February 2012):117–135

Impact Assessment of Bt Corn Adoption in the Philippines

Maria Erlinda M. Mutuc, Roderick M. Rejesus, Suwen Pan, and Jose M. Yorobe, Jr.

This article examines the impact of Bt corn adoption in the Philippines using an econometric approach that addresses simultaneity, selection, and censoring problems. Although previous literature emphasizes the importance of simultaneity and selection problems, this is the first study that addresses the issue of censoring in estimating the effects of Bt corn adoption at the farm in a developing country context. We show that Bt corn adoption provides modest but statistically significant increases in farm yields and profits. Furthermore, our results provide some evidence of inference errors that can potentially arise when censoring in the pesticide application variable is ignored in the estimation procedures.

Key Words: Bt, censoring, corn, farm level impacts, genetically modified crops, pesticide use, technology adoption

JEL Classifications: Q12, Q16

Only about a fifth of the 42 million hectares allocated to genetically-modified (GM) corn worldwide are in developing countries – Argentina, Honduras, Philippines, South Africa, and Uruguay; the remainder are in developed countries such as the United States, Canada, Australia, Portugal, among others (GMO Compass, 2010). With less than a million hectares devoted to Bt corn in developing countries, not including Argentina, fairly narrow farm-level survey data are subsequently available that lend to limited ex-post farm impact studies of Bt corn adoption in a developing country context (See Gouse et al., 2005, 2006; Yorobe and Quicoy, 2006). Although a number of papers have examined the yield and pesticide use impacts of Bt crops in general using various econometric methods, none (to the best of our knowledge) has raised the issue of censoring and its potential effects on inference.

Previous studies have pointed out the importance of addressing selection bias and simultaneity in input use decisions (i.e., simultaneity of pesticide application and yields) when estimating the impact of Bt technology (Crost et al., 2007; Fernandez-Cornejo and Li, 2005; Huang et al., 2002; Qaim and de Janvry, 2005; Shankar and Thirtle, 2005; Yorobe and Quicoy, 2006), but have fallen short of the censoring issue. Censoring may be an important issue in evaluating the impact of Bt corn because adoption of this

---

Maria Erlinda M. Mutuc is postdoctoral research associate, Department of Agricultural and Applied Economics, Texas Tech University, Lubbock, TX. Roderick M. Rejesus is associate professor, Department of Agricultural and Resource Economics, North Carolina State University, Raleigh, NC. Suwen Pan is senior economist, World Agricultural Economic and Environmental Services, Columbia, MO. Jose M. Yorobe, Jr. is associate professor, Department of Agricultural Economics, University of the Philippines at Los Baños, Philippines.

We gratefully acknowledge the helpful comments of the editor Darrell Bosch and three anonymous reviewers.

technology makes it possible for farmers to *not* apply any pesticide due to the insect resistance afforded by the Bt variety that subsequently affects the range of yields and/or profits farmers could attain (See Wu, 2006). When a large proportion of farmers do not apply pesticides, censoring becomes critical and ignoring it may affect the consistency and efficiency of impact parameter estimates and the resulting inferences about the farm-level impact of Bt corn technology.

This paper provides evidence about the effect of Bt corn adoption on yield and pesticide use in the Philippines using an econometric approach that explicitly accounts for censoring in the pesticide use data. In particular, a system of output supply and input demand equations derived from a flexible profit function specification is estimated to assess the impact of Bt corn adoption, and at the same time tackle potential selection, simultaneity, and censoring problems in the estimation. It is shown that potential inference errors could arise when censoring is not taken into account in the impact analysis of Bt crops.

Corn Production and Bt Technology in the Philippines

Corn is the second most important crop in the Philippines after rice, and approximately a third of Filipino farmers' (1.8 million) major source of livelihood. Yellow corn is the most important type and accounts for about 60% of total corn production (the residual is white corn); this is the corn type considered in this study. Most of the yellow corn produced in the Philippines is sold to the livestock and poultry feed mill industries, albeit some farmers keep a small proportion of output for human consumption in times of very poor harvest (Gerpacio et al., 2004).

Typically grown rainfed in lowland, upland, and rolling-to-hilly agro-ecological zones of the Philippines, corn has two cropping seasons per year – wet season (usually from March/April to August) and dry season (from November to February). Most corn farmers in the Philippines are small, semi-subsistence farmers with average farm size ranging from less than a hectare to about 4 hectares (Gerpacio et al., 2004; Mendoza and Rosegrant, 1995). Corn producing households usually grow other cash crops as a small percentage of their cultivated area; some engage in small-scale (backyard) poultry and livestock production to augment income and supply home needs (Gerpacio et al., 2004; Mendoza and Rosegrant, 1995).

The most destructive pest in the major corn-producing regions of the Philippines is the Asian corn borer (*Ostrinia furnacalis* Guenee) (see Morallo-Rejesus and Punzalan, 2002). Over the past decade or so, corn borer infestation has occurred yearly (i.e., infestation is observed in at least one region yearly) with pest pressure constant to increasing over time. Farmers report that yield losses from this pest range from 30% to almost 100%. Even amidst the Asian corn borer, insecticide application has been moderate relative to other countries in Asia (i.e., China) and corn farmers in major producing regions in the Philippines only apply insecticides when infestation is high. Also, trader-financier loan arrangements sometimes limit the availability of insecticides when needed (i.e., priority given to paying customers) (Gerpacio et al., 2004).

Bt corn was first introduced in the Philippines in 1996 on a limited trial basis only. Between 1999 and 2002, after approval from the National Committee on Biosafety in the Philippines, field trials of Bt corn were conducted in the major corn-producing areas in the country. Finally, in 2002, the Philippine Department of Agriculture approved the commercial distribution of Bt corn (specifically Monsanto's Yieldgard™ 818 and 838). This made the Philippines the first country in Asia to commercialize Bt corn. Primarily in response to the Asian corn borer, Bt corn is anticipated to potentially improve corn productivity in the country since corn yields have remained low (2 metric tons/ha) and corn imports have increased over time.

Econometric Issues and Estimation Strategies

Accounting for Simultaneity and Selection Problems

A first naive approach is to estimate the effect of Bt corn adoption on farm profits using

Ordinary Least Squares (OLS) with the following specification:

$$(1) \qquad \pi_i = \mathbf{x}_i\boldsymbol{\beta} + I_i\alpha + \varepsilon_i,$$

where π_i is the profits for farm i, $\mathbf{x}_i$ is a vector of explanatory variables (i.e., farmer/farm characteristics, etc.), $\boldsymbol{\beta}$ is a conformable parameter vector, I_i is a binary variable equal to one if the producer adopts Bt corn ($I_i = 1$) and zero ($I_i = 0$) otherwise, α is a scalar parameter (to be estimated) that measures the impact of Bt corn, and ε_i is a random error term. But, as McBride and El-Osta (2002) indicated, the decision to adopt Bt corn and profits may be jointly determined and there may be unobserved factors that affect both I_i and π_i, which, if not properly addressed, may lead to simultaneity bias and incorrect inferences about the impact of Bt corn adoption.

If the Bt corn adoption decision is modeled as:

$$(2) \qquad I_i = \mathbf{z}_i^1\boldsymbol{\gamma}_1 + v_i$$

where $\mathbf{z}_i^1$ is a vector of explanatory variables that affect Bt corn adoption, $\boldsymbol{\gamma}_1$ is a conformable parameter vector to be estimated, ν_i is a random error term; then simultaneity bias may exist if π_i is part of $\mathbf{z}_i^1$ (i.e., both variables are jointly determined) and/or unobservable factors are both in ε_i and ν_i (i.e., unobserved pest pressure) that make the errors correlated (see Burrows, 1983). To control for simultaneity bias due to these factors, Equation (2) can be estimated in reduced form using a probit model that does not include π_i, then Equation (1) can be estimated by OLS using the predicted adoption probabilities $\hat{I}_i$ as an instrument for I_i (Burrows, 1983; McBride and El-Osta, 2002):

$$(3a) \qquad \pi_i = \mathbf{x}_i\boldsymbol{\beta}_1 + \hat{I}_i\alpha_1 + \varepsilon_i^1.$$

Still, Equation (3a) does not consider other sources of simultaneity bias. For example, profits and yields can be considered as jointly determined; Equation (3a) can be estimated as a system of equations:

$$(3b) \qquad y_i = \mathbf{x}_i\boldsymbol{\beta}_2 + \hat{I}_i\alpha_2 + \varepsilon_i^2,$$

where y_i is a yield variable. In this case, iterated seemingly unrelated regression (ITSUR) can be used to simultaneously estimate the parameters from Equations (3a) and (3b). But Equations (3a) and (3b) are still a "sparse" model because they ignore the potential simultaneity of profits, yields, Bt corn adoption, and pesticide (or other input) application. As noted above, pesticide decisions depend on whether or not Bt corn is adopted. To address this other potential source of simultaneity bias, a system of corn output supply and pesticide input demand functions derived from an appropriately specified profit function can be estimated using the ITSUR technique (Fernandez-Cornejo and Li, 2005; Fernandez-Cornejo, Klotz-Ingram, and Jans, 2002). In particular, a quadratic restricted profit function is a properly specified profit function where corn output supply and pesticide input demand equations can be derived and estimated together as a system using ITSUR (Diewert and Ostensoe, 1988; Fernandez-Cornejo and Li, 2005)[1]:

$$(4a) \qquad \begin{aligned} \pi = {} & A_0 + A_y P + \sum_j A_j w_j + \sum_k C_k R_k \\ & + 0.5 G_{yy} P^2 + \sum_j G_{yj} P w_j + \sum_k F_{yk} P R_k \\ & + 0.5 \sum_j \sum_i G_{ij} w_i w_j + \sum_k \sum_j E_{jk} w_j R_k \\ & + 0.5 \sum_i C_{ik} R_i R_k + \varepsilon_\pi, \end{aligned}$$

$$(4b) \qquad y = A_y + G_{yy} P + \sum_j G_{yj} w_j + \sum_k F_{yk} R_k + \varepsilon_y,$$

$$(4c) \qquad x_1 = A_1 + G_{y1} P + \sum_j G_{1j} w_j + \sum_k E_{1k} R_k + \varepsilon_1.$$

In Equations (4a) to (4c) above, π is farm profit, y is corn yield, and x_1 is the amount of pesticide applied. Further, P and w are output and input prices, while A, C, E, F, and G are parameters to be estimated. The vector R in Equations (4a) to (4c) can contain other explanatory factors affecting either π, y, or x_1 (e.g., socio-demographic/farm characteristics). If the predicted probabilities of Bt corn adoption $(\hat{I}_i)$ are included in the vector R, then the simultaneity between the Bt corn adoption decision and the

[1] As in Fernandez-Cornejo and Li (2005), restrictions based on economic theory (i.e., symmetry) are imposed.

dependent variables in Equations (4a) to (4c) is addressed.

The system of equations above can be expanded to accommodate other inputs (i.e., fertilizer, labor, seeds, etc.) with additional input demand equations (i.e., x_2, x_3, etc.) similar to Equation (4c). Hence, another advantage of using the "system" profit function approach above is that the impact of Bt corn adoption on other inputs (i.e., fertilizer, labor, seeds) can also be estimated (in addition to its effect on farm-level profits, yields, and pesticide use).[2]

The systematic differences between adopters and non-adopters can also manifest themselves in realized profits, which in turn can potentially bias our impact estimates (i.e., selection bias). An approach to address this problem (see McBride and El-Osta, 2002) is similar to Heckman's (1979) two-step procedure using the full sample (rather than just the selected sample, as in the classical Heckman two-step approach) and appending the inverse mills ratio ($\hat{\lambda}_i$) to each equation in the profit function system in Equations (4a) to (4c). However, this can produce inconsistent impact estimates when both censoring and self-selection are present in the system of censored equations to be estimated (Shonkwiler and Yen, 1999). Another practical estimation concern that arises is the presence of multicollinearity caused by the high correlation between $\hat{I}_i$ and $\hat{\lambda}_i$. This occurs because both terms are calculated based on the probit equation in Equation (2) and, therefore, both are functions of the vector $\mathbf{z}_i^1$. In addition, Fernandez-Cornejo and Li (2005) and Fernandez-Cornejo, Klotz-Ingram, and Jans (2002) indicated that the approach of simply using the predicted probabilities $(\hat{I}_i)$ in the impact equation(s) may be sufficient to control for self-selection that is caused by the non-random assignment of Bt corn adopters and non-adopters. In light of these three issues, we opted not to include $\hat{\lambda}_i$ in our final model specifications.

Accounting for Censoring Problems

As Bt technology allows for farmers to *not* apply pesticides, this censoring mechanism can contaminate and bias the impact parameter estimates embedded in the system of Equations (4a) to (4c) above. As a number of farmers discontinue the use of pesticides after Bt adoption, x_i in Equation 4(c) is truncated (see Huffman, 1988; Lee and Pitt, 1984). We do not observe x_i for all observations, but rather a censored version, x_i^{cen}. Following Rigobon and Stoker (2007), the indicator d_i describes the censoring process, with $d_i = 0$ as an uncensored observation and $d_i = 1$ a censored one, for which we observe the value $\xi = 0$. That is, pesticide use is 0 and we observe:

$$(5) \qquad x_i^{cen} = (1 - d_i)x_i + d_i\xi.$$

The probability of censoring is denoted as $p = \Pr\{d = 1\}$ and $0 < p < 1$. If we ignore that x_i^{cen} is not x_i and estimate Equations 4(a)–4(c), the bias can easily be seen to depend on the censoring process and censoring value $\xi = 0$. If we estimate Equations 4(a)–4(c) and drop the censored observations (use observations with $d_i = 0$), the distribution of the error terms in the system (ε_π, ε_y, ε_1) is altered. When the mean of the error terms varies with d_i, then there exist biases from truncation.

One approach to address censoring in a system of equations is the two-step procedure of Shonkwiler and Yen (1999). This is a computationally tractable procedure that produces consistent results relative to the simple Heckman-type procedures. However, a number of studies have questioned the efficiency properties of this approach (see Chen and Chen, 2002; Tauchmann,

[2] This approach assumes a risk-neutral profit maximizing behavior. Studies indicate that actual input choices of Philippine farmers are more consistent with a risk-neutral profit maximizing behavior than a risk-averse, safety-first behavior (see Mendoza, Brorsen, and Rosegrant, 1992; Rosegrant and Herdt, 1981; Roumasset, 1976; Smith et al., 1989). Notwithstanding, the validity of a risk-neutral profit maximizing behavioral assumption in the profit function approach may be affected by significant credit constraints and crop diversification (i.e., also planting conventional corn). Our survey data indicate that over 60% of producers had access to loans and only less than 1% (27 producers) did not (i.e., due to high interest rates or no collateral); the remainder did not need loans. Also, Bt farmers in the sample that "diversified" did so only in very small areas of their farm and only to "experiment" and compare yields with Bt corn.

2005). Another approach is to use maximum likelihood (ML) procedures to jointly estimate the whole system of equations in Equations (4a) to (4c) above. But ML approaches to the censoring problem require evaluation of a partially integrated multivariate normal probability density function (i.e., multiple probability integrals in the likelihood function) (see, for example, Lee and Pitt, 1986, 1987; Pudney, 1989; Yen, Lin, and Smallwood, 2003). This notwithstanding, advances in simulation procedures (see Borsch-Supan and Hajivassiliou, 1993; Geweke, 1991; Keane, 1994) have allowed for ML approaches to be more computationally tractable. One common procedure is to use a simulated ML (SML) procedure that utilizes the Geweke-Hajivassiliou-Keane (GHK) algorithm for simulating multiple probability integrals. However, as Roodman (2009) explains, the drawback of using this SML procedure is that convergence problems occur especially when there are collinear regressors in the model specification.[3]

In view of the foregoing (and in footnote 3), we utilize an estimation strategy that combines the procedures of Perali and Chavas (2000) and Belasco, Ghosh, and Goodwin (2009), which has characteristics of both a two-step and an ML approach. First, we run a recursive bivariate probit model where the Bt adoption decision in Equation (2) is estimated simultaneously with the following pesticide use equation:

$$(6) \qquad x^B = \mathbf{z}_i^2 \boldsymbol{\gamma}_2 + \omega_i,$$

where $x^B = 1$ if pesticide application is greater than zero and $x^B = 0$ otherwise. This procedure is utilized to account for the potential correlation of the Bt adoption decision and the pesticide use decision (see following section). This would then allow one to calculate the predicted probabilities of Bt corn adoption $\left(\hat{I}_i\right)$ that will be included in the vector R to control for simultaneity problems between Bt corn adoption and the dependent variables.

Next, we follow the procedure of Perali and Chavas (2000) to first estimate parameters of each equation one-by-one without imposing any cross-equation restrictions using standard ML procedures. In the case of the censored pesticide variable in Equation (4c) a univariate Tobit procedure is used to estimate the parameters of that equation. As Perali and Chavas (2000) argued, equation-by-equation estimation of the parameters by ML methods without cross-equation restrictions would be consistent and asymptotically efficient absent model misspecification.

Third, using the vector of parameters estimated equation-by-equation in the first step, the error correlation/covariance between each pair of equations in the system can then be consistently estimated using nonlinear least squares procedures (Perali and Chavas, 2000). The aforementioned steps allow for consistent estimation of all the unrestricted parameters (i.e., the parameters in each equation and the error correlation/covariance matrix). However, by estimating the system equation-by-equation, it is not possible to impose the cross-equation restrictions required by theory (i.e., symmetry conditions), which necessitates the fourth step below.

Fourth, we use the censored multivariate regression procedure (also called multivariate Tobit) used by Belasco, Ghosh, and Goodwin (2009) to re-estimate our parameter vector, while imposing the necessary theoretical cross-equation restrictions. This fourth step also makes it possible to impose the error correlation/covariance structure estimated in the third step to avoid over-parameterization, ease the computational burden, and avoid convergence problems. As in Belasco, Ghosh, and Goodwin (2009), the structure of our system of equations is amenable to ML methods because we only have one censored dependent variable (pesticide use) that leads to only two regimes – censored and uncensored (instead of 2^m regimes where m is the number of censored variables) (see Chavas and Kim, 2004). To implement the quasi-ML procedure in Belasco, Ghosh, and Goodwin (2009), we

[3] In previous versions of this paper, we used the two-step procedure of Shonkwiler and Yen (1999) and found fairly similar results as the ones presented here. We also ran the SML approach described above. But plausibly due to the collinearity of our left-hand side variables (i.e., prices of inputs, outputs, and their interactions are more than likely correlated), we encountered convergence problems that precluded us from getting a valid variance-covariance matrix.

first let the model specified in Equations (4a) to (4c) above to be more compactly specified as follows: $Y_i = X_iB_i + e_i$, where the vector of dependent variables is defined as $Y_i = [\pi_i, y_i, x_{1i}]$ for each observation *i*, X_{i} is a matrix of independent variables, B_i is a matrix of unknown parameters, and e_i is a vector of errors assumed to have a mean zero and covariance matrix Σ_i. Each observation must then be ordered as censored or uncensored and, consequently, Y_i needs to be partitioned into its censored $\left(Y_i^{(1)}\right)$ and uncensored $\left(Y_i^{(2)}\right)$ variables noting the associated covariance matrix Σ_i and Σ_{22i} for each. The sample log-likelihood function needed to estimate the parameters in Equations (4a) to (4c) and the compact formulation above becomes:

$$
\begin{aligned}
LL = & \sum_{Pesticide(x_1)>0} \{\ln[\phi(Y_i;\mu_i,\Sigma_i)]\} \\
& + \sum_{Pesticide(x_1)=0} \left\{\ln\left[\phi\left(Y_i^{(2)};\mu_i^{(2)},\Sigma_{22i}\right)\right]\right\} \\
& + \ln[\Phi(0;g_i,\eta_i)]
\end{aligned}
\tag{7}
$$

where ϕ (Y; μ, Σ) refers to the multivariate normal probability density function with mean vector μ and variance-covariance matrix Σ, while $\Phi(0; g_i,\eta_i)$ denotes the univariate cumulative distribution function evaluated at zero with mean g_i and variance η_i.

Following the detailed definitions of g_i and η_i in Belasco, Ghosh, and Goodwin (2009), and utilizing the initial estimates of the parameter vector and imposing the error correlation/covariance matrix in the previous steps, a tractable likelihood function based on Equation (7) can be derived and maximized to estimate the parameters in Equations (4a) to (4c) and at the same time impose the restrictions required by economic theory (i.e., symmetry conditions).

Data Description and Empirical Specification

Data Description

The data used in this study is from the International Service for the Acquisition of Agri-Biotech Applications Corn Survey. It is a farm-level survey of 107 Bt and 363 non-Bt corn farmers (i.e., total of 470 farmers surveyed) undertaken through face-to-face interviews during the wet and dry seasons of crop year 2003–2004 in four major yellow corn growing provinces in the Philippines: Isabela, Camarines Sur, Bukidnon, and South Cotabato. Detailed data on quantities and prices of corn outputs (e.g., production, prices received in Philippine Pesos (PhP)), purchased inputs (e.g., fertilizer, insecticides, hired labor), and non-purchased inputs (e.g., unpaid family labor) were gathered, as well as information on household socio-demographic characteristics and subjective questions on Bt technology (i.e., their perception of the risks of Bt). The survey team used pre-tested questionnaires before actual data collection.

To arrive at the sample of Bt respondents to be surveyed, we first chose three towns and then three barangays (the smallest political unit in the Philippines) per town in each of the four selected provinces based on the density of Bt corn adopters in the area. Using a list of Bt farmers from local sources (i.e., local Monsanto office), we used simple random sampling (SRS) to determine the Bt corn respondents within the selected barangays. The only exception was in Camarines Sur and Bukidnon where complete enumeration of Bt corn respondents was used due to the small number of Bt corn users in the selected barangays in those provinces.

The non-Bt sample was then selected by randomly sampling from a list of non-Bt farmers in the proximity of the chosen Bt farmers (i.e., typically within the same barangay) to minimize the agro-climatic difference between the subsamples. To facilitate comparability, physical and socio-economic factors were compared with assurance that the Bt adopters and non-adopters were “similar” in terms of yield, area, farming environment, input use, pesticide use, costs and returns, reasons for adoption, knowledge about Bt corn, information sources, and perceptions in planting Bt corn. About 2–4 non-Bt farmers were sampled for every Bt farmer selected. The sampling procedure for non-Bt respondents was partly motivated by our desire to reduce potential selection problems and “placement bias” related to the promotion programs of seed companies only in certain locations. However, as Bt seeds were promoted uniformly across the major corn-producing provinces included in the survey (based on consultation with Philippine social scientists working in those areas), we believe placement bias does not pose as a critical issue.

Though the full sample of respondents was not drawn using SRS, the approach we use is a variant of the stratified random sampling procedure that facilitates comparability (and ultimately the analysis) of Bt and non-Bt adopters. This sampling procedure remains a valid method for choosing a sample that ensures adequate representation of the groups under study (see Qaim and de Janvry, 2005 for a study that used a similar sampling approach). In the end, out of the 470 respondents, only 407 (101 Bt adopters and 306 non-Bt adopters) were used in the analysis due to incomplete information and missing data issues.

Empirical Specification: Bivariate Probit Model

Following McBride and El-Osta (2002), Fernandez-Cornejo and Li (2005), and Yorobe and Sumayao (2006), the explanatory variables in the Bt corn adoption (i.e., $\mathbf{z}_i^1$) model are: education, farm size, corn output price, fertilizer and pesticide price (represented by barangay medians of unit values), number of years of farming, amount of off-farm income, a dummy for extension personnel contact, a risk perception dummy,[4] a season dummy, province dummies (Camarines Sur province is the omitted province category), and provincial level rice prices (production substitute for corn). Note that rice price is included in the Bt corn adoption equation but not in the pesticide equation to act as a variable that helps to identify the Bt equation (since rice price is expected to influence Bt adoption and not the pesticide use decision).

The explanatory variables in the pesticide adoption (i.e., $\mathbf{z}_i^2$) equation, on the other hand, are the same as in the Bt corn adoption equation, except that we exclude the rice price variable and include a late planting dummy and a Bt adoption dummy in the pesticide use equation. We include a late planting dummy in the specification since corn planted later is more susceptible to pest losses and farmers tend to compensate for this by increasing pesticide applications. See, for example, Kirimi and Swinton (2004) where a late planting dummy is used to explain inefficiency among corn farmers in Kenya and Ghana. Note that the inclusion of the Bt adoption dummy in the pesticide equation (while not including the pesticide use dummy in the Bt adoption specification) implies that the bivariate probit model is essentially a recursive, simultaneous equation model (Greene, 2003, p. 715). Given our cross-section data, this recursive model is appropriate since at that time when the pesticide use decision is being made (usually within the season) the Bt adoption decision has been made (i.e., Bt adoption influences pesticide use decision). However, at the time the Bt decision is being made (usually before or at planting), the decision to adopt pesticide use in the season has not been made. Also, if we simultaneously include the pesticide use dummy in the Bt equation and the Bt adoption dummy in the pesticide use equation, the model becomes unidentified (Greene, 2003). With this identification problem and timing of the Bt adoption decision, an alternative would have been to use data on the farmer's expectation about the amount of pesticide application based on information from previous seasons. However, these data are not available and the recursive model is the best approach in this case. Furthermore, as argued in Maddala (1983, p. 123) and Greene (2003, pp. 715–16), the endogeneity of the Bt dummy in the pesticide equation can be ignored due to the nature of the log-likelihood and the fact that ML is used to estimate the model (rather than least squares regression).

Empirical Specification: Restricted Profit Function Model

We use restricted farm-level profits (PhP/ha), corn yields (kg/ha), amount of pesticide application (kg/ha), amount of fertilizer application (kg/ha), amount of seed used (kg/ha), and

[4] The "risk perception" dummy here is binary variable equal to one if the producers answered "No" to the following question: "As far as your information about Bt corn was concerned, did you see some risks in the Bt GMO? Yes or No." (GMO = genetically modified organism.) This variable does not represent the risk behavior of the individual farmer.

amount of hired labor utilized (in man-days/ha) as dependent variables in the system of equations associated with the profit function impact model (Equations (4a) to (4c) and Equations (7a) to (7c)). Restricted farm profits are calculated by subtracting the costs of purchased and non-purchased inputs from the reported total revenues (quantity produced multiplied by output price). Purchased input expenditures (i.e., seeds, fertilizers, pesticides, hired labor) were reported by the farmers. Non-purchased labor expenditures (i.e., unpaid family and operator labor) are calculated based on the man-days of work and prevailing hired labor wage rate reported by the farmer. Profits are calculated and then divided by the farm size to derive profits per hectare.[5]

The pesticide amount refers to the aggregated amount of insecticides, herbicides, and fungicides used and is measured in terms of kilograms of material per hectare (kg/ha). If left disaggregated, there would not have been enough non-zero values in the dataset. A single pesticide variable with sufficient non-zero values also facilitates the convergence of the multi-step estimation procedure used in the study. Note that using a "lumped" pesticide variable should not be problematic since insecticide value is still the dominant component of the pesticide variable used in this study. In the Philippines, 51% of agri-chemicals used are insecticides, 21% herbicides, 14% fungicide, and the remaining 14% are others (Chemical Industries Association of the Philippines, 2009).

Corn output prices and input prices (i.e., pesticide price, seed price, fertilizer price, labor price) serve as explanatory variables in the profit function impact model. Unit values (derived by dividing expenditure by quantity) for pesticides, fertilizer, and labor are used instead of actual prices of these inputs. Because actual data on pesticide price is not available given that we had to use a single pesticide variable, a "unit value" estimate of pesticide price is computed. Also, since we had to aggregate the costs of several kinds of fertilizers and the costs of labor for different practices to calculate single measures of fertilizer use and labor use, unit values for these two inputs are computed as well. However, the use of unit values can lead to inconsistent estimates due to the common measurement errors across the independent and dependent variables in the impact model. At the same time, there is price (or unit value) variation because farmers buy inputs from different geographical sources; hence, the presence of outliers. A way to minimize the effect of outliers is to use unit value cluster means or medians as in Klemick and Lichtenberg (2008). In this case, we use the barangay as the cluster; the medians of all unit values traced to farmers in a particular barangay (barangay median) are used as proxies for prices of pesticides, fertilizers, and labor. Actual data on seed prices are used since we did not aggregate different seed types. In addition, the predicted probabilities of Bt corn adoption are included as an element included in vector R to be able to assess the impact of Bt corn adoption.

Summary statistics for all the pertinent variables are presented in Table 1. About 55% of Bt corn adopters (and 47% of the non-adopters) did not use pesticides; this validates our concern regarding potential inference problems that can arise due to censoring in the pesticide data.

Results and Discussion

Bivariate Probit Model Results

Estimation results for the bivariate probit model are presented in Table 2. The statistically significant variables that influence the Bt adoption decision include average corn price received by farmers, rice price, fertilizer and pesticide prices, off-farm income, the season dummy, the risk perception dummy, and some location dummies. Higher corn output prices tend to increase the likelihood of Bt corn adoption. This is consistent with the adoption literature (Feder, Just, and Zilberman, 1985) where more profitable operations (due to the higher prices received) are more likely to adopt agricultural

[5] Consistent with the definition of a restricted profit function in the conceptual framework, "profit" here is defined as revenues less variable costs. Fixed costs are not included.

Table 1. Summary Statistics: Full Sample, Bt Corn Adopters, Non-Bt Corn Adopters

Variables	Full Sample (407 farmers)	Bt Adopters (101 farmers)	Non-Bt Adopters (306 farmers)
Seeds per hectare (kg/ha)	18.97	18.77	19.04
	(10.61)	(4.58)	(11.96)
Seed price (PhP/kg)	144.95	227.90	117.57
	(57.32)	(33.69)	(31.17)
Hired labor per hectare (man-days/ha)	48.36	52.19	47.09
	(30.21)	(25.40)	(31.58)
Hired labor price (PhP/man-day)	111.20	123.35	107.19
	(22.20)	(17.43)	(22.16)
Fertilizer/hectare (kg/ha)	422.30	452.01	412.49
	(179.53)	(180.72)	(178.34)
Fertilizer price (PhP/kg)	11.11	11.72	10.90
(barangay median/unit value)	(0.87)	(0.51)	(0.87)
Pesticides applied per hectare	0.81	0.62	0.87
(kg material/ha)	(1.43)	(1.03)	(1.53)
Pesticide price (PhP/kg)	548.06	594.32	532.80
(barangay median/unit value)	(217.80)	(200.34)	(221.46)
Average corn price received (PhP/kg)	8.02	8.84	7.75
	(1.07)	(0.90)	(0.98)
Rice price, province level (PhP/kg)	8.77	9.03	8.69
	(0.51)	(0.32)	(0.53)
Yield (kg/ha)	3917.83	4849.50	3610.32
	(1537.64)	(1607.04)	(1384.99)
Profit (PhP/kg)	13933.87	21650.59	11466.64
	(13043.74)	(14763.64)	(11366.39)
Corn area planted (ha)	2.04	2.39	1.92
	(3.12)	(3.34)	(3.03)
Age	46.10	45.05	46.45
	(12.13)	(11.53)	(12.32)
Off-farm income (PhP)	3.24	5.14	2.61
	(10.26)	(17.67)	(6.01)
Years in farming	18.17	17.46	18.41
	(11.72)	(10.93)	(11.98)
Years of education	8.38	9.53	7.97
	(3.39)	(3.72)	(3.18)
Extension contact dummy	0.83	0.94	0.79
(= 1 with contact)	(0.37)	(0.23)	(0.40)
Season dummy (= 1 if 1st crop	0.30	0.07	0.37
/wet season)	(0.45)	(0.25)	(0.48)
Late planting dummy	0.25	0.34	0.23
(= 1 if late)	(0.43)	(0.47)	(0.41)
Risk perception dummy	0.46	0.92	0.31
(= 1 if no risk perceived)	(0.49)	(0.27)	(0.46)

Table 1. Continued.

Variables	Full Sample (407 farmers)	Bt Adopters (101 farmers)	Non-Bt Adopters (306 farmers)
Location dummies			
1 = Bukidnon	0.29	0.13	0.35
	(0.45)	(0.33)	(0.47)
2 = Cotabato	0.32	0.38	0.31
	(0.46)	(0.48)	(0.46)
3 = Isabela	0.25	0.48	0.18
	(0.43)	(0.50)	(0.38)
Bt dummy	0.25		
(= 1 if planted Bt)	(0.43)		
Pesticide dummy	0.51	0.45	0.53
(= 1 if used pesticides)	(0.50)	(0.50)	(0.50)

Note: Standard errors in parentheses.

innovations (Fernandez-Cornejo, Klotz-Ingram, and Jans, 2002). Higher rice prices, on the other hand, increase the opportunity cost of planting Bt corn and hence reduce the likelihood of Bt corn adoption. Our results further indicate that higher fertilizer prices increase the likelihood of Bt adoption among corn farmers. Higher fertilizer prices significantly increase the marginal cost of using fertilizer so that farmers tend to substitute Bt for fertilizer due to Bt's potential yield increasing effect that would otherwise have been had with more fertilizer use. Although significant and negative (which is unexpected), the effect of the pesticide input price on Bt corn adoption seems to be negligible.

Table 2 further reveals that farmers with higher off-farm income are more likely to adopt the Bt variety. This may be because farmers that have off-farm income may be more willing to try out a new technology given that they have additional income "buffer" in case their use of Bt results in lower profits. Also, farmers who face a tradeoff between the time spent working on and off the farm are able to substitute engaging in multiple income-generating activities (economies of scope) for economies of scale, given the enhanced yields from the Bt variety (Fernandez-Cornejo, Hendricks, and Mishra, 2005). Corn planting in the wet season (the season dummy = 1) increases the likelihood of Bt adoption since more severe infestation of corn usually occurs during the wet or rainy season. The positive and significant parameter estimate associated with the risk perception dummy suggests that farmers that do not perceive Bt corn as risky (i.e., risk perception dummy = 1) are more likely to adopt Bt corn. The positive sign for the second and third location dummies indicate that farmers in the province of South Cotabato and Isabela are more likely to adopt Bt corn than those farmers in Camarines Sur.

The negative statistically significant sign associated with the Bt corn adoption dummy in the pesticide use equation is important because it provides evidence that Bt corn adoption significantly reduces the odds of applying pesticides. As expected, the pest resistance afforded by Bt technology leads to a reduction in the likelihood of farmers using pesticides and is consistent with previous studies (see Fernandez-Cornejo and Li, 2005; Marra, Pardey, and Alston, 2002; Pilcher et al., 2002; Rice and Pilcher, 1998). Other variables that affect pesticide use are off-farm income, pesticide price, the extension dummy, and the location dummy for Bukidnon. The negative and significant effect of pesticide price on the pesticide use decision is consistent with economic theory. The positive extension contact dummy may indicate that farmers who communicate with extension personnel are more comfortable applying pesticides.

Table 2. Estimated Parameters of Bivariate Probit Model: Bt Corn Adoption and Pesticide Use (Bt dummy in the pesticide equation)

	Bt Corn Adoption Dummy		Pesticide Use Dummy	
Variables	Parameter Estimate	Marginal Effect	Parameter Estimate	Marginal Effect
Constant	−19.998*		−2.350	
	(4.160)		(2.085)	
Years of education	0.059	0.002	0.020	0.008
	(0.040)	(0.002)	(0.027)	0.010
Corn area planted (ha)	0.010	0.000	0.035	0.014
	(0.030)	(0.001)	(0.024)	(0.009)
Average corn price received (PhP/kg)	0.858*	0.030***	0.025	0.010
	(0.208)	(0.018)	(0.126)	0.050
Fertilizer unit value (PhP/kg)	1.333*	0.047***	0.165	0.066
(barangay median)	(0.315)	(0.026)	(0.135)	(0.053)
Pesticide unit value (PhP/kg)	−0.003*	0.000***	−0.001*	−0.001*
(barangay median)	(0.001)	(0.000)	(0.000)	(0.000)
Years in farming	−0.004	0.000	0.013***	0.005***
	(0.011)	(0.000)	(0.007)	(0.002)
Off-farm income (PhP)	0.051*	0.002	−0.005	−0.002
	(0.018)	(0.001)	(0.007)	(0.003)
Season dummy (= 1 if 1st crop)	3.708*	0.586*	0.963**	0.364*
	(0.899)	(0.194)	(0.416)	(0.142)
Extension contact dummy	1.626*	0.029***	0.568**	0.222**
(= 1 if with contact)	(0.615)	(0.017)	(0.289)	(0.107)
Risk perception dummy	2.086*	0.146*	−0.097	−0.039
(= 1 if no risk is perceived)	(0.320)	(0.055)	(0.228)	(0.090)
Location dummy 1	0.797	0.043	−1.082*	−0.406*
	(0.861)	(0.065)	(0.357)	(0.117)
Location dummy 2	3.753*	0.692*	0.744	0.284
	(1.188)	(0.268)	(0.506)	(0.179)
Location dummy 3	3.138*	0.553***	0.581	0.225
	(1.088)	(0.289)	(0.480)	(0.176)
Rice price, province level (PhP/kg)	−0.958*	−0.034***		
	0.331	0.019		
Late planting dummy (= 1 if late)			−0.184	−0.073
			(0.480)	(0.068)
Bt dummy (= 1 if farmer plants Bt)			−0.814***	−0.310***
			(0.488)	(0.167)
Rho	0.26			
	(0.34)			
Log likelihood	−269.71			

Note: Standard errors in parentheses. Single, double, and triple asterisks denote statistical significance at the 1%, 5%, and 10% levels.

Another thing to note from Table 2 is the insignificant error correlation measure (ρ) between the Bt corn adoption and pesticide use decision, which suggests that when we explicitly control for the recursive structure of the decisions (i.e., by including the Bt dummy in the pesticide use equation) and given the other control variables in the specification, the empirical specification is rich enough to eliminate unobserved factors that may cause endogeneity

Table 3. Estimated Parameters of the Profit Function: Non-Censored and Censored Models

Variables	Non-Censored	Censored
Constant	−2563.930*	−28569.000
	(2538.929)	(36751.000)
Corn price	754.188	1826.713*
	(977.492)	(391.625)
Labor price	74.378*	−50.034
	(13.940)	(153.361)
Fertilizer price	831.078*	3459.380
	(120.768)	(6678.096)
Pesticide price	2.134**	27.809***
	(0.730)	(16.761)
Seed price	9.123***	−163.171***
	(5.003)	(92.775)
Bt_hat	−4894.052	67684.000*
	(3673.259)	(437.220)
(corn price)^2	170.027*	104.136*
	(40.857)	(42.519)
Corn price*labor price	4.853	12.140*
	(3.368)	(3.533)
Corn price*fertilizer price	96.099	249.390*
	(90.657)	(66.974)
Corn price*pesticide price	0.065	0.282
	(0.312)	(0.339)
Corn price*seed price	−0.710	8.158*
	(1.449)	(1.580)
Corn price*Bt_hat	1122.039*	478.631*
	(305.817)	(53.219)
(labor price)^2	−0.469*	−0.350*
	(0.068)	(0.072)
Labor price*fertilizer price	−0.483	−33.465
	(0.405)	(27.594)
Labor price*pesticide price	0.002	0.441*
	(0.003)	(0.069)
Labor price*seed price	0.006	0.799*
	(0.020)	(0.266)
(fertilizer price)^2	−25.833**	−294.049
	(10.493)	(622.425)
Fertilizer price*pesticide price	−0.070**	−5.366*
	(0.036)	(0.198)
Fertilizer price*seed price	−0.239	25.293*
	(0.173)	(8.796)
(pesticide price)^2	−0.0002	−0.010 ***
	(0.0003)	(0.006)
Pesticide price*seed price	0.000	−0.088
	(0.001)	(0.255)
(seed price)^2	−0.049*	−0.580*
	(0.011)	(0.119)
Labor price*Bt_hat	7.933	−42.462
	(6.053)	(104.826)
Fertilizer price*Bt_hat	123.022**	−5675.414*

Table 3. Continued.

Variables	Non-Censored	Censored
	(39.982)	(3466.414)
Pesticide price*Bt_hat	−0.161	−0.648*
	(0.308)	(0.106)
Seed price*Bt_hat	0.159	−10.284
	(2.369)	(52.134)
$(\text{Bt\_hat})^2$	−3177.088*	37420.000*
	(6985.025)	(517.640)

Note: Standard errors in parentheses. Single, double, and triple asterisks denote statistical significance at the 1%, 5%, and 10% levels.

of the Bt corn and pesticide use decision. This also validates the recursive structure used in the study.[6]

Impact Model Results

The parameter estimates for the profit function impact model for both the censored and non-censored versions are shown in Tables 3 and 4, respectively.[7] To facilitate interpretation, we calculated the elasticity of different impact variables with respect to the probability of Bt corn adoption (Table 5). For example, in the non-censored profit function impact model, we calculate the elasticity of yield with respect to the probability of Bt corn adoption by taking the first derivative of Equation (4b) with respect to the probability of Bt corn adoption ($\partial y / \partial R_1 = F_{y1}$) and multiplying it with the ratio of the means of Bt corn adoption probability and corn yield $\left(\bar{R}_1/\bar{y}\right)$. Standard errors of these elasticity estimates are derived using the delta method. Similar elasticity calculations are used for the other impact variables of interest. Own-price output supply and input demand elasticities are also reported in Table 5.

Based on the impact model elasticities in Table 5, notice that when censoring is not addressed Bt corn adoption has a statistically significant effect only on profits, yield, and fertilizer. However, when censoring is accounted for, our impact model suggests that Bt corn adoption also has a statistically significant effect on pesticide application, in addition to its effect on profits, yields, and fertilizer. Moreover, we find that the effect of Bt on fertilizer use is negative in the censored model while the non-censored model shows a positive Bt effect on fertilizer. These differences in the results between the non-censored and censored models are suggestive of potential inference errors that could occur when censoring is disregarded.

The strong positive impact of Bt corn adoption on yields is consistent with the literature (see Baute, Sears, and Schaafsma, 2002; Dillehay et al., 2004; Duffy, 2001; Fernandez-Cornejo and Li, 2005; Marra, Pardey, and Alston, 2002; Pilcher et al., 2002; Rice and Pilcher, 1998). The magnitudes of the elasticity estimate from our model also tend to be fairly similar to the elasticity estimates from previous studies and the non-censored model. In particular, our 0.015 yield elasticity estimate is fairly close to the elasticity estimate of Fernandez-Cornejo and

[6] As a check we ran the "flip-side" model where the pesticide use dummy is included in the Bt adoption equation and the Bt dummy is not included in the pesticide use equation (available upon request). We find that the pesticide use dummy in the Bt adoption equation is significant and negative (which is expected). But in this specification the error correlation measure is significant at the 10% level. This indicates that there may be unobserved factors affecting both decisions that are not captured in the specification and therefore the other recursive specification may be more appropriate. It is impossible to meaningfully estimate a specification where the pesticide dummy is in the Bt equation and the Bt adoption dummy is in the pesticide use equation.

[7] Following the J-test (Davidson and MacKinnon, 1981), we found that $u = 0.973$ (with standard error = 0.017); this is statistically significantly different from zero for the comparison between the non-censored and the censored impact models. However, (1-u) is statistically insignificant for this comparison. The likelihood ratio (−34) indicates that the censored impact model is a more suitable model for this specific data.

Table 4. Estimated Parameters of the Yield and Input Demand Functions: Non-Censored and Censored Models

Equation	Yield		Labor Demand		Fertilizer Demand		Pesticide Demand		Seed Demand	
Variables	Non-Censored	Censored	Non-Censored	Censored	Non-Censored	Censored	Non-Censored	Censored	Non-Censored	Censored
Constant	754.19	1826.71*	74.37*	−50.03	831.07*	3459.38	2.134*	27.38	9.12***	−163.17***
	(977.49)	(391.62)	(13.94)	(153.36)	(120.76)	(6678.09)	(0.73)	(28.27)	(5.01)	(92.77)
Corn price	170.02*	104.13*	3.41*	14.69	−2.98	489.22	−0.07	0.29	2.33*	−6.66
	(40.86)	(42.51)	(1.18)	(21.65)	(9.96)	(239.10)	(0.07)	(0.15)	(0.47)	(4.26)
Labor price	4.85	12.14*	−0.46*	−0.35*	−0.48	−33.46	0.002	0.44*	0.01	0.79*
	(3.36)	(3.53)	(0.07)	(0.07)	(0.40)	(27.59)	(0.00)	(0.06)	(0.02)	(0.26)
Fertilizer	96.09	249.39*	−0.48	−33.46	−25.83**	−294.04	−0.07**	−5.36*	−0.23	25.29*
price	(90.65)	(66.97)	(0.40)	(27.59)	(10.49)	(622.42)	(0.04)	(0.19)	(0.17)	(8.79)
Pesticide	0.06	0.28	0.002	0.44*	−0.07**	−5.36*	−0.000	−0.01***	0.00	−0.08
price	(0.31)	(0.33)	(0.00)	(0.06)	(0.03)	(0.19)	(0.00)	(0.001)	(0.00)	(0.25)
Seed price	−0.71	8.15*	0.006	0.79*	−0.23	25.93*	0.00	−0.08	−0.04*	−0.58*
	(1.44)	(1.58)	(0.02)	(0.26)	(0.17)	(8.79)	(0.00)	(0.25)	(0.01)	(0.11)
Bt_hat	1122.03*	478.63*	7.93	−42.46	123.02*	−5675.41*	−0.16	−0.64*	0.15	−10.28
	(305.81)	(232.19)	(6.05)	(104.82)	(39.98)	(3466.84)	(0.31)	(0.10)	(2.37)	(52.13)

Note: Standard errors in parentheses. Single, double, and triple asterisks denote statistical significance at the 1%, 5%, and 10% levels.

Table 5. Elasticities with Respect to Bt Adoption and Own-Price

	Non-Censored Model		Censored Model	
Variables	Bt	Own-price	Bt	Own-price
Profits	0.088**		0.094*	
	(0.044)		(0.040)	
Yield	0.063*	0.348*	0.015*	0.213*
	(0.017)	(0.084)	(0.007)	(0.087)
Labor	0.036	−1.079*	−0.106	−0.805*
	(0.028)	(0.156)	(0.262)	(0.165)
Fertilizer	0.065*	−0.679**	−1.622*	−7.736
	(0.021)	(0.276)	(0.458)	(16.375)
Pesticide	−0.013	−0.036	−0.049*	–3.455***
	(0.020)	(0.06)	(0.008)	(2.110)
Seed	0.002	−0.377*	−0.065	–4.522*
	(0.028)	(0.088)	(0.332)	(0.925)

Notes: Elasticities calculated at sample averages, except for the pesticide elasticity where the mean used accounted for censoring. Standard errors in parentheses. Single, double, and triple asterisks denote statistical significance at the 1%, 5%, and 10% levels.

Li (2005) for the United States at 0.03. This strong positive effect of Bt on yields is also consistent with the results from the earlier study of Yorobe and Quicoy (2006) in the Philippines.

In contrast to the consistent positive Bt corn impact on yields, there is no strong consensus in the literature as to the effect of Bt corn on profits. Marra, Pardey, and Alston (2002), for example, found that Bt corn increases profits, but studies by McBride and El-Osta (2002) indicate that Bt corn negatively affects profits. Fernandez-Cornejo and Li (2005), on the other hand, did not find any statistically significant Bt corn effect on profits. But note that these previous studies have not controlled for some (or all) of the econometric issues addressed in this article (i.e., simultaneity, selection, and censoring problems). Nevertheless, our elasticity estimate based on the censored profit function model suggests that Bt corn adoption provides a positive, statistically significant impact on farm level profits that is consistent with earlier findings in the Philippines (Cabanilla, 2004; Yorobe and Quicoy, 2006). Note, however, that the magnitude of the profit impact of Bt in the censored model is similar to the estimate in the uncensored model.

Our results in Table 5 indicate that Bt corn adoption has a statistically significant negative effect on pesticide use. This is corroborated by previous studies on Bt corn where Bt was found to have a statistically significant pesticide use reducing effect (see Fernandez-Cornejo and Li, 2005; Marra, Pardey, and Alston, 2002; Pilcher et al., 2002; Rice and Pilcher, 1998). In this particular case, the negative and statistically significant pesticide demand elasticity suggests that Bt corn in the Philippines tends to be an input-saving technology, in addition to being a yield-enhancing technology. Moreover, notice that the pesticide elasticity estimate is not significant when censoring is not accounted for, which again underscores the importance of this issue in impact estimation of Bt crops.

Another interesting result from Table 5 is the statistically significant fertilizer-reducing effect of Bt corn adoption when censoring is accounted for and the statistically insignificant effect of Bt corn on seed and labor demand. The potential yield-enhancing effects of Bt corn adoption may have contributed to the decreased fertilizer demand. Farmers we interviewed expected more vigorous plant growth with Bt corn, which may have led them to reduce fertilizer use. In addition, given a constant budget constraint and the higher cost of Bt seeds, it seems reasonable to expect a reduction in the use of fertilizer because these farmers may have heard of the potential yield-enhancing effect of the technology and consequently reduced fertilizer use to remain within their budget constraint. Reduced fertilization when using Bt corn is consistent with the study of Wortmann et al. (2011) that suggests that economically optimal fertilizer rates may be lower for Bt corn relative to conventional corn because of its improved fertilizer uptake efficiency. Morse, Bennett, and Ismael (2007) also found that farmers using Bt cotton have lower fertilizer expenditures relative to non-Bt users.

Confirmation of Theoretical Properties

The estimated profit function predicts positive profits for about 90 percent of the farmers. Furthermore, the estimated profits are non-decreasing in output price and non-increasing in input prices for majority of the observations. The signs of the own-price elasticities of input demand and the own-price elasticity of output supply are consistent with theoretical expectation (although most of the inputs are complements). However, the Hessian matrix of second partial derivatives of the profit function was not positive semi-definite which may be the result of the nature of the technological relationships between inputs in corn farming (Williamson, Hauer, and Luckert, 2004). In most empirical work, the satisfaction of convexity has been problematic but most empirical studies simply note this limitation and cautiously consider the results from the analysis as valid (Bernard et al., 1997; Diewert and Wales, 1987; Shumway, 1983; Williamson, Hauer, and Luckert, 2004). As such, the results in this study should be interpreted against this potential limitation.

Robustness Check: The Damage Abatement Approach

Due to the convexity limitation, we estimate the damage abatement specification as a means to check the robustness of our main result – that Bt corn has a statistically significant positive effect on yields.[8] Following Shankar and Thirtle (2005) and Qaim and de Janvry (2003), a Cobb-Douglas production function with a logistic damage function, and a quadratic production function with a logistic damage function are estimated. As argued by Shankar and Thirtle (2005), a logistic damage abatement specification may be preferred over other specifications (i.e., specifically the exponential) due to its flexibility. In both models, we find that the Bt damage control parameter is positive and statistically significant, which implies that the Bt variety increases pest damage abatement and subsequently increases yield. This corroborates the yield increasing effect of Bt we find in our profit function approach.

Concluding Comments

This article estimates the impact of Bt corn adoption in a developing country context applying econometric procedures that control for simultaneity, selection, and censoring problems using cross-sectional survey data on corn producers in the Philippines. Results of our analysis suggest that initial Bt corn adoption in the Philippines provides a modest but statistically significant increase in farm yields and profits. In addition, Bt corn adoption has a negative effect on the likelihood of pesticide use (based on the bivariate probit model) and pesticide demand is significantly reduced by Bt corn adoption (based on our elasticity estimates). Bt corn adoption is also shown to have a statistically significant fertilizer-reducing effect. As a net importer of corn, the positive yield and profit effects from the initial release of Bt corn point to the potential of the Bt technology as a means to improve productivity of the local corn sector and increase local grain supply and eventually reduce the country's reliance on foreign corn.

The empirical analysis in the study underscores the importance of addressing censoring in the pesticide application variable in estimating the economic impacts of Bt technology. This is especially important in developing countries where pesticide use is more limited, such as the Philippines and South Africa (as pointed out in Shankar and Thirtle (2005)). Our results demonstrate that censoring may be a potential source of inference error when not properly accounted for in the estimation. Utilizing a multi-step estimation strategy based on Perali and Chavas (2000) and Belasco, Ghosh, and Goodwin

[8] Results are available from authors upon request.

(2009) to control for censoring, we find considerably different elasticity estimates of the impact of Bt when censoring of the pesticide application variable is ignored in the estimation procedures.

These results, however, reflect the "initial" impact of Bt corn adoption in the first year of its availability when overall adoption is still low. It would be interesting to track if the positive yield and profit impacts are sustained in the medium- to longer-term with the availability of panel data. The lack of data on the level of pest infestation at the time of the survey also limits the interpretation of the results. Notwithstanding, the positive yield and profit effects based on data from 2003/2004 are signals that Bt adoption would progress in subsequent years. In fact, from an adoption level of 1.27% (of total corn area) in 2003/2004, the adoption level of Bt (including Bt stacked traits) increased to as much as 21.9% in 2009/2010 (Philippine Department of Agriculture Biotech Team, 2011).

[Received October 2010; Accepted September 2011.]

References

Baute, T.S., M.K. Sears, and A.W. Schaafsma. "Use of Transgenic *Bacillus thuringiensis* Berliner Corn Hybrids to Determine the Direct Economic Impact of the European Corn Borer (Lepidoptera: Crambidae) on Field Corn in Eastern Canada." *Journal of Economic Entomology* 95(2002):57–64.

Belasco, E., S.K. Ghosh, and B.K. Goodwin. "A Multivariate Evaluation of Ex-Ante Risks Associated with Fed Cattle Production." *American Journal of Agricultural Economics* 91(2009):431–43.

Bernard, J.T., L. Bouthillier, J. Catimel, and N. Gelinas. "An Integrated Model of Quebec-Ontario-U.S. Northeast Softwood Lumber Markets." *American Journal of Agricultural Economics* 79(1997):987–1000.

Borsch-Supan, A., and V.A. Hajivassiliou. "Smooth Unbiased Multivariate Probability Simulators for Maximum Likelihood Estimation of Limited Dependent Variable Models." *Journal of Econometrics* 58(1993):347–68.

Burrows, T.M. "Pesticide Demand and Integrated Pest Management: A Limited Dependent Variable Analysis." *American Journal of Agricultural Economics* 65(1983):806–10.

Cabanilla, L.S. "Bt Corn in the Philippines: How Much Will Farmers Expect to Gain". Paper presented in the Philippine Agricultural Economics and Development Association Convention, Quezon City, Philippines, October 12, 2004.

Chavas, J., and K. Kim. "A Heteroskedastic Multivariate Tobit Analysis of Price Dynamics in the Presence of Price Floors." *American Journal of Agricultural Economics* 86(2004): 576–93.

Chemical Industries Association of the Philippines. Agrichemicals and Fertilizers Industry. Internet site: http://spik-ph.org/index.php/the-industry/agrichemicals-fertilizers-industry/ (Accessed April 10, 2009).

Chen, K., and C. Chen. "Cross Product Censoring in a Demand System with Limited Dependent Variables: A Multivariate Probit Model Approach." Staff Paper 00-02, Department of Rural Economy, University of Alberta, 2002.

Crost, B., B. Shavani, R. Bennett, and S. Morse. "Bias from Farmer Self-Selection in Genetically Modified Crop Productivity Estimates: Evidence from Indian Data." *Journal of Agricultural Economics* 58(2007):24–36.

Davidson, R., and J.G. MacKinnon. "Several Tests for Model Specification in the Presence of Alternative Hypotheses." *Econometrica* 49(1981):781–93.

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

Diewert, W.E., and T.J. Wales. "Flexible Functional Forms with Global Curvature Conditions." *Econometrica* 55(1987):43–68.

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(2004):818–24.

Duffy, M. *Who Benefits from Biotechnology*. Chicago, IL: American Seed Trade Association, 2001.

Feder, G., R. Just, and D. Zilberman. "Adoption of Agricultural Innovations in Developing Countries: A Survey." *Economic Development and Cultural Change* 33(1985):255–98.

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(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(2002):149–63.

Fernandez-Cornejo, J., and J. Li. "The Impacts of Adopting Genetically Engineered Crops in the USA: The Case of Bt Corn." Selected Paper, 2005 Agricultural and Applied Economics Association Annual Meetings, Providence, RI, July 24–27, 2005.

Gerpacio, R.V., J.D. Labios, R.V. Labios, and E.I. Diangkinay. *Maize in the Philippines: Production Systems, Constraints, and Research Priorities*. Mexico: International Maize and Wheat Improvement Center, 2004.

Geweke, J. "Efficient Simulation from the Multivariate Normal and Student-t Distributions Subject to Linear Constraints." *Computer Science and Statistics: Proceedings of the Twenty-Third Symposium on the Interface*. E.M. Keramidas, ed. Fairfax: Interface Foundation of North America, Inc., 1991.

GMO Compass. Internet site: http://www.gmo-compass.org (Accessed April 7, 2009).

Gouse, M., C.E. Pray, J. Kirsten, and D. Schimmelpfenning. "Three Seasons of Subsistence Insect-Resistant Maize in South Africa: Have Smallholders Benefited?" *AgBioForum* 9(2006):15–22.

———"A GM Subsistence Crop in Africa: The Case of Bt White Maize in South Africa." *International Journal of Biotechnology* 7(2005): 84–94.

Greene, W.H. *Econometric Analysis*, 5th ed. Upper Saddle, NJ: Prentice Hall, 2003.

Heckman, J.J. "Sample Selection Bias as a Specification Error." *Econometrica* 47(1979):153–61.

Huang, J., R. Hu, S. Rozelle, F. Qiao, and C. Pray. "Transgenic Varieties and Productivity of Smallholder Cotton Farmers in China." *The Australian Journal of Agricultural and Resource Economics* 46(2002):367–87.

Huffman, W. "An Econometric Methodology for Multiple-Output Agricultural Technology: An Application of Endogenous Switching Models." *Agricultural Productivity: Measurement and Explanation*. Washington, DC: Resources for the Future. S. Capalbo and J. Antle, eds. 1988.

Keane, M.P. "A Computationally Practical Simulation Estimator for Panel Data." *Econometrica* 62(1994):95–116.

Kirimi, L., and S.M. Swinton. "Estimating Cost Efficiency among Maize Producers in Kenya and Uganda." Selected Paper Presentation, American Agricultural Economics Association Annual Meeting, Denver, CO, August 1–4, 2004.

Klemick, H., and E. Lichtenberg. "Pesticide Use and Fish Harvests in Vietnamese Rice Agroecosystems." *American Journal of Agricultural Economics* 90(2008):1–14.

Lee, L.F., and M.M. Pitt. "Microeconomic Models of Rationing, Imperfect Markets and Non-Negativity Constraints." *Journal of Econometrics* 36(1987):89–110.

———. "Microeconomic Demand Systems with Binding Nonnegativity Constraints: The Dual Approach." *Econometrica* 54(1986):1237–42.

———. "Microeconometric Models of Consumer and Producer Decisions with Limited Dependent Variables." Discussion paper, University of Minnesota, Department of Economics, 1984.

Maddala, G. *Limited Dependent and Qualitative Variables in Econometrics*. New York, NY: Cambridge University Press, 1983.

Marra, M., P. Pardey, and J. Alston. "The Payoffs to Transgenic Field Crops: An Assessment of the Evidence." *AgBioForum* 5(2002):43–50.

McBride, W., and H.S. El-Osta. "Impacts of the Adoption of Genetically Engineered Crops on Farm Financial Performance." *Journal of Agricultural and Applied Economics* 34(2002): 175–91.

Mendoza, M.S., B.W. Brorsen, and M.W. Rosegrant. "Aggregate Corn Area Response under Risk: Some Implications for Price Stabilization Programs." *Journal of Philippine Development* 35(1992):99–111.

Mendoza, M.S., and M.W. Rosegrant. *Pricing Behavior in Philippine Corn Markets: Implications for Market Efficiency*. Washington, DC: International Food Policy Research Institute, 1995.

Morallo-Rejesus, B., and E.G. Punzalan. *Corn*. Los Baños: National Crop Protection Center. University of the Philippines at Los Baños, 2002.

Morse, S., R. Bennett, and Y. Ismael. "Inequality and GM Crops: A Case-Study of Bt Cotton in India." *AgBioForum* 10(2007):44–50.

Perali, F., and J. Chavas. "Estimation of Censored Demand Equations from Large Cross-Section Data." *American Journal of Agricultural Economics* 82(2000):1022–37.

Philippine Department of Agriculture Biotech Team. Personal Communication, May 2011.

Pilcher, C.D., M.E. Rice, R.A. Higgins, K.L. Steffey, R.L. Hellmich, J. Witkowski, 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):878–92.

Pudney, S. *Modelling Individual Choice*. Oxford, UK: Basil Blackwell, 1989.

Qaim, M., and A. de Janvry. "Bt Cotton and Pesticide Use in Argentina: Economic and Environmental Effects." *Environment and Development Economics* 10(2005):179–200.

———. "Genetically Modified Crops, Corporate Pricing Strategies, and Farmers′ Adoption: The Case of Bt Cotton in Argentina." *American Journal of Agricultural Economics* 85(2003):814–28.

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.

Rigobon, R., and T. Stoker. "Estimation with Censored Regressors: Basic Issues." *International Economic Review* 48(2007):1441–58.

Roodman, D. "Estimating Fully Observed Recursive Mixed-Process Models with *cmp*," Working Papers 168, Center for Global Development, 2009.

Rosegrant, M., and R. Herdt. "Simulating the Impacts of Credit Policy and Fertilizer Subsidy on Central Luzon Rice Farms, the Philippines." *American Journal of Agricultural Economics* 63(1981):655–65.

Roumasset, J.A. *Rice and Risk: Decision Making Among Low-Income Farmers*. Amsterdam, North-Holland: Elsevier, 1976.

Shankar, B., and C. Thirtle. "Pesticide Productivity and Transgenic Cotton Technology: The South African Smallholder Case." *Journal of Agricultural Economics* 56(2005):97–116.

Shonkwiler, J.S., and S.T. Yen. "Two-Step Estimation of a Censored System of Equations." *American Journal of Agricultural Economics* 81(1999):972–82.

Shumway, R. "Supply, Demand, and Technology in a Multiproduct Industry: Texas Field Crops." *American Journal of Agricultural Economics* 65(1983):748–60.

Smith, J., G. Umali, M. Rosegrant, and A.M. Mandac. "Risk and Nitrogen Use on Rainfed Rice: Bicol, Philippines." *Fertilizer Research* 21(1989):113–23.

Tauchmann, H. "Efficiency of Two-Step Estimators for Censored Systems of Equations: Shonkwiler and Yen Reconsidered." *Applied Economics* 37(2005):367–74.

Williamson, T., G. Hauer, and M.K. Luckert. "A Restricted Leontief Profit Function Model of the Canadian Lumber and Chip Industry: Potential Impacts of US Countervail and Kyoto Ratification." *Canadian Journal of Forest Research* 34(2004):1833–44.

Wortmann, C., R. Ferguson, G. Hergert, T. Shaver, and C. Shapiro. *Do Bt Corn Hybrids Require More Fertilizer?* University of Nebraska-Lincoln Extension CropWatch, January 17, 2011. Internet site: http://cropwatch.unl.edu/web/cropwatch/archive?articleID=4424846.

Wu, F. "An Analysis of Bt Corn's Benefits and Risks for National and Regional Policymakers Considering Bt Corn Adoption." *International Journal of Technology and Globalisation Special Issue on Genetically Modified Crops in Developing Countries – Institutional and Policy Challenges* 2(2006):115–36.

Yen, S.T., B. Lin, and D.M. Smallwood. "Quasi and Simulated Likelihood Approaches to Censored Demand Systems: Food Consumption by Food Stamp Recipients in the United States." *American Journal of Agricultural Economics* 85(2003):458–78.

Yorobe, J.M., Jr., and C.B. Quicoy. "Economic Impact of Bt Corn in the Philippines." *The Philippine Agricultural Scientist* 89(2006): 258–67.

Yorobe, J.M., Jr., and B.R. Sumayao. "Determinants of Adoption of Bt (Bacillus thuringiensis) Corn in the Philippines." Unpublished manuscript, University of the Philippines at Los Baños, 2006.