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Farm Level Impacts of Bt Corn Adoption in a Developing Country: Evidence from the Philippines

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ABSTRACT

This article examines the ex post farm-level impacts of Bt corn adoption in the Philippines. Using an econometric approach that addresses simultaneity, selection, and censoring problems, we show that Bt corn adoption provides modest but statistically significant increases in farm-level yields and profits. Furthermore, our results suggest that farm-level yield and profit impacts of Bt corn adoption are underestimated when censoring in the pesticide application variable is not considered in the estimation procedures. Previous literature have emphasized the importance of simultaneity and selection problems but this is the first study that have raised the issue of censoring problems in estimating the farm-level effects of Bt corn adoption.

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

JEL Classification: Q12; Q16

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Introduction

A decade after its first commercialization, genetically modified (GM) crops are now grown in 11 industrial and 11 developing economies (James 2006).[1] But even though the number of GM crop adopters has increased globally, adoption rates for a number of these crops have still been slow and limited for most developing countries. One such GM crop is insect-resistant corn that contains a gene from the soil bacterium *Bacillus Thuringiensis* (Bt).[2] One reason for the slower adoption of this particular GM crop (and most GM crops in general) is the institutional constraints and restricted capacity typically faced by a number of developing countries (Byerlee and Fischer, 2002; Lele, 2003; Traxler, 2004; Qaim, 2005). The controversy regarding environmental risk and consumer safety may have also delayed adoption and commercialization of Bt corn in less developed nations (Gaskell, 2000; Gouse et al., 2005).

The slow adoption of Bt corn worldwide is evidenced by the fact that in 2005 only eight nations have approved the commercial production and trade of Bt corn in their respective countries (Brookes and Barfoot, 2006). Of the total area planted to Bt corn in the world, only 20% are in developing countries (e.g. Argentina, Honduras, Philippines, South Africa, Uruguay) and the remaining 80% are in industrialized countries (e.g. Canada, Spain, and USA). In light of the smaller planted area in developing countries (less than a million hectares except for Argentina), there has been limited farm-level survey data available for Bt corn in these countries and, consequently, only a handful of studies have examined the *ex post* farm impact of this crop

[1] Specifically, these countries, in order of planted area (in hectares) are: the U.S., Argentina, Brazil, Canada, India, China, Paraguay, South Africa, Uruguay, Philippines, Australia, Romania, Mexico, Spain, Colombia, France, Iran, Honduras, Czech Republic, Portugal, Germany and Slovakia.
[2] Hereinafter, we refer to this insect-resistant corn as Bt corn. Note that Bt corn was genetically engineered so that it is resistant to the corn stem borer.

in a developing country context. In fact, the study by Gouse et al. (2005) is the only study we found that utilized farm-level survey data to examine the impact of Bt corn in a developing country (South Africa in this case). Majority of studies that use survey data to rigorously examine farm-level impacts of Bt corn focused mainly on US farmers (See McBride and El-Osta, 2002; Fernandez-Cornejo and Li, 2005), not developing country farmers.

The objective of this article is to determine the *ex post* farm-level impact of Bt corn adoption in a developing country environment. In this article, we provide evidence based on farm-level survey data from the Philippines. The Philippines is an ideal developing country to investigate because it has only recently approved (in 2002) the commercial distribution of Bt corn, which in turn allows one to see the *ex post* impact immediately after initial adoption of the technology. In addition, using Philippine data allows us to advance the literature since no study (as far as we know) has yet looked at Bt corn impact in the context of a less developed country in Asia.

Rigorous econometric techniques that controls for simultaneity, self-selection, and censoring issues is used in this article to more precisely measure the farm level effects of Bt corn adoption in the Philippines. Note that only the US studies (e.g. McBride and El-Osta, 2002; Fernandez-Cornejo and Li, 2005) utilized similar econometric procedures to analyze Bt corn impacts at the farm level. However, the econometric approach used in these US studies only accounted for simultaneity and self-selection, not censoring. Censoring may be an important issue in evaluating the impact of Bt corn because adoption of this technology makes it possible for farmers to not apply any pesticide (due to the insect resistance afforded) and, consequently, this affects the range of yields and/or profit they could attain (i.e. the range of possible yields/profits that can be realized may be different if pesticides are not used vs. if they are used, even in the presence of Bt technology) (See Wu, 2006).

Not accounting for the censoring in the data may affect the consistency and efficiency of the impact parameter estimates and, consequently, the inferences about the farm-level impacts of the Bt corn technology. Hence, this article also contributes to the literature by providing an econometric approach that accounts for censoring, as well as simultaneity and self-selection, in the analysis of the farm-level impacts of Bt corn adoption. This type of analysis allows us to examine the extent of inference error when censoring is not accounted for in the analysis.

Econometric Issues and Estimation Strategies

The purpose of this article is to accurately estimate the farm-level profit impact of Bt corn adoption based on cross-section survey data from the Philippines. More formally, the effect of Bt corn adoption on farm profits can initially be modeled as:

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

where π_i is the profits for farm *i*, $\mathbf{x}_i$ is a vector of explanatory variables (i.e. farmer characteristics, farm size etc.), $\boldsymbol{\beta}$ is a conformable parameter vector, I_i is a binary variable that is equal to one if one adopts Bt corn (I_i =1) and zero (I_i =0), otherwise, α is a scalar parameter that measures the impact of Bt corn, and ε_i is a random error term. However, 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) $$I_i = \mathbf{z}_i^1\boldsymbol{\gamma}_1 + v_i ,$$

where $\mathbf{z}_i^1$ is a vector of explanatory variables that affects Bt corn adoption, $\boldsymbol{\gamma}_1$ is a conformable parameter vector, v_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 v_i (i.e. unobserved pest pressure) that makes the errors correlated (See Burrows, 1983). To control for simultaneity bias due to these factors, one approach is to estimate (2) in reduced form using a probit model that do not include π_i, then estimate (1) by Ordinary Least Squares (OLS) using the predicted adoption probabilities $\hat{I}_i$ as an instrument for I_i (Burrows, 1983; McBride and El-Osta, 2002):

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

However, the model in (3a) above does not consider other sources of simultaneity bias. For example, profits and yields can be considered as jointly determined and (3a) above can be estimated as a system of equations with:

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

where y_i is a yield variable. In this case, iterated seemingly unrelated regression (ITSUR) can be used to simultaneously estimate the parameters from (3a) and (3b).

Equations (3a) and (3b) is a "sparse" model because it still ignores the potential simultaneity of profits, yields, and Bt corn adoption with pesticide application. As noted above, pesticide decisions can simultaneously change depending on whether or not Bt corn is adopted. To further address this other 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 (See Fernandez-Cornejo and Li, 2005; Fernandez-Cornejo, Klotz-Ingram and Jans, 2002). In particular, a normalized quadratic restricted profit function (see complete specification below) 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)[3]:

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

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

$$\tilde{x}_1 = A_1 + G_{y1} P + \sum_j G_{1j} w_j + \sum_k E_{1k} R_k + \varepsilon_1 \,. \tag{4c}$$

In (4a) to (4c) above, $\tilde{\pi}$ is farm profit, $\tilde{y}$ is the corn yield, and $\tilde{x}_1$ is the amount pesticide input application. Further, *P* and *w* are the output and input prices, while *A*, *C*, *E*, *F*, and *G* are parameters. The vector *R* in equations (4a) to (4c) can contain other explanatory factors affecting either $\tilde{\pi}$, $\tilde{y}$, or $\tilde{x}_1$ (e.g. socio-demographic variables, farm characteristics). If the predicted probabilities of Bt corn adoption ($\hat{I}_i$) are included in the vector *R*, then the simultaneity among the Bt corn adoption decision and the dependent variables in (4a) to (4c) is being addressed.

Censoring in the pesticide equation (4c) above (and its consequent implication to impact estimation) is another issue that has not been addressed in the Bt corn adoption literature. As mentioned in the introduction, the adoption of Bt technology makes it possible for farmers not to apply pesticides and this censoring mechanism can contaminate and bias the impact parameter estimates embedded in the system of equations (4a) to (4c) above. To control for the effect of pesticide censoring in the system, we use Shonkwiler and Yen's (1999) two-step procedure for

[3] In equations (4a) to (4c) we follow the notation of Fernandez-Cornejo and Li (2005) for comparability. In this system, we consider land to be a fixed input with corn as the only output. As in Fernandez-Cornejo and Li (2005), symmetry and homogeneity assumptions are imposed.

addressing censoring in a system of equations.[4] First, we can estimate a probit model of pesticide usage as follows:

$$\tilde{x}^B = \mathbf{z}_i^2 \boldsymbol{\gamma}_2 + \omega_i , \tag{5}$$

where $\tilde{x}^B = 1$ if pesticide application is greater than zero and $\tilde{x}^B = 0$ otherwise. But since we know that pesticide adoption and Bt corn adoption are likely to be correlated, a bivariate probit model where equations (2) and (5) are estimated simultaneously is used here instead of simply using equation-by-equation probit.

Second, we calculate $\phi(\mathbf{z}_i^2 \boldsymbol{\gamma}_2)$ and $\Phi(\mathbf{z}_i^2 \boldsymbol{\gamma}_2)$, in order to re-specify the system of equations in (4a) to (4c) such that it will account for pesticide censoring (a'la Shonkwiler and Yen (1999)):

$$\begin{aligned}\tilde{\pi} = \Phi(\mathbf{z}_i^2 \boldsymbol{\gamma}_2)\Bigg[& A_0 + A_y P + \sum_j A_j w_j + \sum_k C_k R_k + 0.5 G_{yy} P^2 + \sum_j G_{yj} P w_j + \sum_k F_{yk} P R_k \\ & + 0.5 \sum_j \sum_i G_{ij} w_i w_j + \sum_k \sum_j E_{jk} w_j R_k + 0.5 \sum_i C_{ik} R_i R_k \Bigg] + \delta \phi(\mathbf{z}_i^2 \boldsymbol{\gamma}_2) + \varepsilon_\pi ,\end{aligned} \tag{6a}$$

$$\tilde{y} = \Phi(\mathbf{z}_i^2 \boldsymbol{\gamma}_2)\left[A_y + G_{yy} P + \sum_j G_{yj} w_j + \sum_k F_{yk} R_k \right] + \delta \phi(\mathbf{z}_i^2 \boldsymbol{\gamma}_2) + \varepsilon_y , \tag{6b}$$

$$\tilde{x}_1 = \Phi(\mathbf{z}_i^2 \boldsymbol{\gamma}_2)\left[A_1 + G_{y1} P + \sum_j G_{1j} w_j + \sum_k E_{1k} R_k \right] + \delta \phi(\mathbf{z}_i^2 \boldsymbol{\gamma}_2) + \varepsilon_1 . \tag{6c}$$

Again, the predicted probabilities of Bt corn adoption ($\hat{I}_i$) are included in the vector R to control for simultaneity problems between Bt corn adoption and the dependent variables. The system in (6a) to (6c) can then be estimated using the ITSUR procedure. Note that the Shonkwiler and Yen

[4] Note that Shonkwiler and Yen (1999) showed that their procedure produces consistent estimates as compared to just using the simpler Heckman-type procedures to control for censoring and self-selection in systems of censored equations. There are still several studies that question the efficiency of the Shonkwiler and Yen (1999) procedure, but this approach has still been applied in many applied economic studies and there is yet to be any consensus in the literature as to which approach is best for estimating censored systems of equations.

(1999) procedure can also be applied to the “sparse” model in (3a) and (3b) to account for the effect of pesticide censoring:

(7a) $$\pi_i = \Phi(\mathbf{z}_i^2\boldsymbol{\gamma}^2)\left[\mathbf{x}_i\boldsymbol{\beta}^1 + \hat{I}_i\alpha^1\right] + \delta^1\phi(\mathbf{z}_i^2\boldsymbol{\gamma}^2) + \varepsilon_i^1,$$

(7b) $$y_i = \Phi(\mathbf{z}_i^2\boldsymbol{\gamma}^2)\left[\mathbf{x}_i\boldsymbol{\beta}^2 + \hat{I}_i\alpha^2\right] + \delta^2\phi(\mathbf{z}_i^2\boldsymbol{\gamma}^2) + \varepsilon_i^2.$$

Another econometric problem that has been mentioned in previous literature is the selection problem due to the non-random assignment of Bt corn adoption. The systematic difference between the adopters vs. non-adopters can manifest themselves in the profits realized, which in turn biases our impact estimates. One approach that has been used in the past to address this problem (See McBride and El-Osta, 2002) is to use an approach 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). This is done by appending the inverse mills ratio ($\hat{\lambda}_i$) to equation (3a) and (3b) (and consequently in (7a) and (7b)) for the sparse model or in the vector R for the profit function impact model in (6a) to (6c). The inverse mills ratio ($\hat{\lambda}_i$) is calculated from (2) as follows:

(8) $$\hat{\lambda}_i = \frac{\phi(\mathbf{z}_i^1\hat{\boldsymbol{\gamma}}_1)}{\Phi(\mathbf{z}_i^1\hat{\boldsymbol{\gamma}}_1)} \text{ if } I_i = 1, \text{ and } \hat{\lambda}_i = \frac{\phi(\mathbf{z}_i^1\hat{\boldsymbol{\gamma}}_1)}{1-\Phi(\mathbf{z}_i^1\hat{\boldsymbol{\gamma}}_1)} \text{ if } I_i = 0;$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are standard normal probability density function (pdf) and cumulative density function (cdf), respectively.

However, this approach was shown by Shonkwiler and Yen (1999) to produce inconsistent impact estimates when both censoring and self-selection is present in the system of censored equations to be estimated. Another practical estimation concern that arises when using the inverse mills ratio is the multicollinearity problem caused by the high correlation between $\hat{I}_i$

and $\hat{\lambda}_i$. This correlation occurs because both terms are calculated based on the probit equation in (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 due to 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. But we contend that the two models represented by (6a) to (6c) and by (7a) to (7b) sufficiently accounts for problems caused by censoring, simultaneity, and self-selection.

As mentioned in the introduction, censoring has not been addressed in previous studies that examined the impact of Bt corn adoption. Hence, in this paper, we estimate the models that control for censoring vs. the models that do not account for this issue (i.e., we compare the parameter estimates from equations (6a) to (6c) vs. (4a) to (4c) for the profit function impact model; and equations (7a) and (7b) vs. equations (3a) and (3b) for the sparse impact model).

Data Description and Model Specification

Data

The data used in this study is from the International Service for the Acquisition of Agri-Biotech Applications (ISAAA) Corn Survey. It is a farm-level survey of 107 Bt and 363 non-Bt corn farmers undertaken during the wet and dry seasons of crop year 2003-2004 in four major corn growing provinces in the Philippines, namely: Isabela, Camarines Sur, Bukidnon, and South Cotabato. In each province, at least three towns and three barangays (the smallest political unit in the Philippines) per town were chosen based on the density of Bt corn adopters. Complete enumeration was used in Camarines Sur and Bukidnon due to the small number of Bt corn users while simple random sampling was used in other barangays.

Non-Bt adopters in the proximity of the chosen Bt farms were randomly selected to minimize the agro-climatic difference between the sub-samples. In addition, to facilitate comparability, physical and socio-economic factors were compared in order to assure that the Bt adopters and non-adopters were “similar”. The factors compared include 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. Note that the survey team used pre-tested questionnaires before actual data collection was implemented. Information on farming systems and environment, input-output relations, costs and benefits, and socioeconomic factors affecting Bt corn adoption were collected in the actual survey.

Model Specification

To implement the empirical approach in the previous section, we first need to identify the key explanatory variables in the Bt corn adoption (i.e. $\mathbf{z}_i^1$) and pesticide adoption (i.e. $\mathbf{z}_i^2$) models, which is estimated simultaneously using a bivariate probit. Following the work of McBride And El-Osta (2002), Fernandez-Cornejo and Li (2005), and Yorobe and Sumayao (2006), the explanatory variables used in the Bt corn adoption model are: education, age, farm size, corn output price, a risk perception dummy, a season dummy, and a couple of location dummies that represent the sample from southern regions of the Philippines (See Table 1). On the other hand, the explanatory variables in the pesticide adoption model are: education, age, farm size, a risk perception dummy, fuel cost, non-agricultural income, and a Bt adoption dummy. Note that the inclusion of the Bt adoption dummy in the pesticide equation implies that the bivariate probit model is essentially a recursive, simultaneous equations model (Greene, 2003, p. 715). As argued by Maddala (1983, p. 123) and Greene (2003, p. 715-716), 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 the maximum likelihood estimation is used to estimate the model (rather than least squares regression).

The variables in both the sparse impact model (equations (7a)-(7b) and (3a)-(3b)) and the profit function impact model (equations (4a) to (4c) and equations (6a) to (6c)) need to be specified as well. For the sparse model, the dependent variables are the profit or net income from corn production and the natural logarithm of corn yield. The explanatory variables for the sparse model are the natural logarithms of output price, seed price, fertilizer price, pesticide price, labor price. As explained above, the predicted probabilities of Bt corn adoption is included in the sparse model as well. For the profit function impact model based on the normalized quadratic restricted profit function (equations (6a)-(6c) and (4a)-(4c)), we use the variables specified in (6a) to (6c) and use the predicted probability of Bt corn adoption as the element included in vector *R*.

A detailed description of all the variables described above is shown in Table 1. Summary statistics for the pertinent variables are also presented in Tables 2a to 2c (for the whole sample, the Bt corn adopters, and non-Bt corn adopters). Notice that only 55% of the Bt corn adopters did not use pesticides and this validates our concern regarding the potential implications of censoring in this data.

Results and Discussion

Bivariate Probit Model Results

Table 3 presents parameter estimates of the bivariate probit model. Our results indicate that Bt corn adoption and pesticide use decisions are endogenous based on the statistically significant ρ . This suggests that there may be unobserved factors that affect both the Bt corn adoption decision and the pesticide use equation (e.g., unobserved pest pressure). Hence, our use of a bivariate probit model to estimate the two equations is warranted in this case.

The statistically significant variables that affect Bt corn adoption are education, farm size, corn output price, farmer's risk perception, and location dummy 1. The positive farm size and education variables corroborate previous findings that larger farm operations and highly-educated producers are the ones more likely to adopt technological innovations (Just and Zilberman, 1983; Feder and O'Mara, 1981; Feder, Just, and Zilberman, 1985).[5] Higher corn output price tend to increase the likelihood of Bt corn adoption. This follows the adoption literature (Feder, Just, and Zilberman, 1985) where more profitable operations (due to the higher prices) are more likely to adopt agricultural innovations (Fernandez-Cornejo, Klotz-Ingram, and Jans, 2002). The parameter 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 negative sign for the first location dummy indicates that households in Bukidnon are less likely to adopt Bt corn.

Among the statistically significant variables that affect the likelihood of pesticide use, the negative statistically significant sign associated with the Bt corn adoption dummy is important because it provides evidence that Bt corn adoption significantly reduces pesticide use. This follows our expectation that the pest resistance afforded by Bt technology leads to a reduction in the likelihood of farmers using pesticide and this is consistent with previous studies (See Rice and Pilcher, 1998; Marra, Pardey and Alston, 2002; Pilcher et al., 2002; Fernandez-Cornejo and Li, 2005). Other statistically significant variables that affect pesticide use are age, the risk perception dummy, and non-agricultural income of the household.

[5] However, there are other studies that suggest that benefits derived from the adoption of transgenic crop varieties are unbiased against smaller farm operations and are scale neutral (Pray, Huang, and Qiao, 2001; Qaim and Traxler, 2005). But there is no strong and consistent result in the literature so far.

Impact Model Results

The parameter estimates for the sparse impact model and the profit function impact model are seen in Tables 4 and 5, respectively. Note that parameter estimates for both the censored and non-censored versions of these two impact models are presented in these tables. To facilitate interpretation, we calculated the elasticity of different impact variables with respect to the probability of Bt corn adoption (Table 6). 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($\partial \tilde{y} / \partial R_1 = F_{y1}$) and multiplying it with the ratio of the means of Bt corn adoption probability and corn yield ($R_1 / \tilde{y}$). Similar calculations are used for the other impact variables of interest. Note that yield and profit elasticities (with respect to output and input prices) could also be calculated and these figures are presented in Appendix Tables 1 and 2.

For both the sparse and the profit function impact model in Table 6, notice that Bt corn adoption do not significantly affect profits when censoring is not addressed in the estimation. But when censoring is accounted for, both the sparse and the profit function impact model indicate positive statistically significant effects of Bt corn adoption on profits. Note that the effect of Bt corn adoption on yields are statistically significant whether or not censoring is accounted for. In addition, the magnitudes of the impact of Bt corn adoption on both yields and profits are underestimated when censoring in the pesticide application variable is not accounted for. Hence, this result is indicative of the importance of censoring when estimating the yield and profit impact of Bt corn adoption.

Note that the strong positive impact of Bt corn adoption on yields is consistent with the literature where majority of studies found that Bt corn positively affects yields (See Rice and

Pilcher, 1998; Marra, Pardey and Alston, 2002; Duffy, 2001; Pilcher et al., 2002; Baute, Sears, and Schaafsma, 2002; Dillehay et al., 2004; Fernandez-Cornejo and Li, 2005). The elasticity estimate from the censored profit function model indicates that a 10% increase in the probability of Bt corn adoption increases yields by 4.1%. This is slightly higher than the estimate of Fernandez-Cornejo and Li (2005) for the US (which is 0.039), but this is expected since their estimation procedure did not account for censoring. But notice that our non-censored result is very similar in magnitude to theirs.

In contrast to the consistent positive Bt corn impact on yields, the literature does not have a consistent result relative 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. 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. A 10% increase in the probability of Bt corn adoption increases profits by 0.8%.

As mentioned above, one advantage of the richer profit function model is that it gives us the ability to calculate the effect of Bt corn adoption on pesticide demand, as well as the demand for other inputs (i.e. labor, fertilizer, and seed). Our results indicate that Bt corn adoption does not significantly affect pesticide demand, although the negative sign indicates that Bt corn adoption leads to decreases in pesticide use (which is consistent with previous studies: See Rice and Pilcher, 1998; Marra, Pardey and Alston, 1998; Pilcher et al., 2002; Fernandez-Cornejo and Li, 2005). In this particular case, the non-significant pesticide demand elasticity suggests that Bt corn in the Philippines may be a yield-enhancing technology but not an input-saving technology.

Other interesting results from Table 6 are the statistically significant labor-increasing and fertilizing decreasing effects of Bt corn adoption (when censoring is accounted for). The labor increasing effect can be attributed to the farmers being wary about the new technology and its true effectiveness in controlling corn borer. The farmers we interviewed indicated that they utilized more labor in terms of scouting these pests to make sure their populations are down within the season; and also in harvesting/handling costs so that they can examine the yield effects of the technology more accurately. 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, which then may have led some to reduce fertilizer use. Although not statistically significant, the negative sign of the seed demand is consistent with the higher prices associated with Bt corn seeds relative to non-Bt corn seeds.

Concluding Comments

This article estimates the farm-level impacts of Bt corn adoption in a developing country context using econometric procedures that controls for simultaneity, selection, and censoring problems. A cross-sectional survey data from corn producers in the Philippines is used to achieve this objective. Results of our analysis suggest that Bt corn adoption provides a modest but statistically significant increase in farm yields and profits. In addition, although Bt corn adoption significantly affects whether or not pesticide is used (based on the probit models), our elasticity estimates indicates that pesticide demand is not significantly affected by Bt corn adoption per se. However, Bt corn adoption seem to significantly increase labor demand and decrease fertilizer demand.

The results of our analysis also point to the importance of addressing censoring in the pesticide application variable when one is interested in estimating the impacts of Bt corn adoption. Previous literature has pointed to the importance of controlling for simultaneity issues and selection problems when estimating impact of Bt technology, but not censoring. Our results show that censoring may also be a potential source of inference error when not properly accounted for in the estimation. Utilizing the general approach of Shonkwiler and Yen (1999) to control for censoring, our analysis suggests that yield and profit elasticity estimates tend to be underestimated when censoring of the pesticide application variable is ignored in the estimation procedures.

One limitation of the study that should always be kept in mind is the use of a single-cross sectional data collected immediately after approval of Bt production in the Philippines. Hence, the results here reflect the “initial” impact of Bt corn adoption during the first year of its availability where adoption in the country is still low overall. Hence, it would be interesting to see whether or not the positive yield and profit impacts can be sustained in the medium- to longer-term. Collection of panel data would enable modeling of the dynamics of adoption and provide further insights as to the sustainability of impacts (Besley and Case, 1993; Doss, 2006). Furthermore, availability of panel data in the future may allow explicit consideration of risk and uncertainty in the modeling process. Notwithstanding these limitations, the positive yield and profit impacts is a good indication that Bt corn adoption in the Philippines may expand in the future.

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Table 1. Variable Definitions

Variable Name	Definition
Profits	Profits (income less costs) in PhP/ha
Yield	Corn Yield in kg/ha
Pestapp	Pesticide application (in kg/ha)
Educ	Years of education for household head
Age	Age of household head
Farm Size	Total land of the household
Corn price	Corn price for Bt/non –Bt (PhP/kg.)
Fuel Cost	Total cost of gas/diesel/oil (in PhP)
Non-Ag. Income	Total income earned outside of agricultural activities (in 1000 PhP)
Seed price	Price of seed (in Php/kg)
Fertilizer price	Price of fertilizer (in Php/kg)
Pesticide Price	Price of pesticide (in Php/kg)
Labor price	Price of hired labor (in PhP/man-day)
Season dummy	Season dummy = 1 if wet season (first cropping); = 0 otherwise
Location dummy 1	Location dummy 1=1 if household is in Bukidnon; =0 otherwise
Location dummy 2	Location dummy 2=1 if the household is in South Cotabato; =0 otherwise
Risk Perception dummy	Risk perception dummy = 0 if perceive Bt as risky; = 1 otherwise
Bt dummy	Bt corn adoption dummy = 1 if adopt Bt corn; = 0 otherwise
Pesticide dummy	Pesticide dummy = 1 if use pesticide (>0); = 0 otherwise

Table 2a. Summary Statistics: Full Sample (n = 407)

Variable	Mean	St. Dev.	Min.	Max
Profits	13993.87	13043.74	-24346.88	65509.83
Yield	3917.83	1537.64	525.00	10533.00
Pestapp	483.89	1078.16	0.00	15000.00
Educ	8.36	3.39	0	17
Age	46.10	12.13	19	79
Farm Size	2.83	4.85	0	70
Corn output price	8.02	1.07	5.67	10.50
Fuel Cost	181.39	1891.45	0	34920
Non-Ag. Income	3.23	10.26	0	166.67
Seed price	140.48	184.35	3.37	1911.11
Fertilizer price	3.16	17.02	0	313.85
Pesticide Price	1530.98	20232.32	0	405405.41
Labor price	77.09	51.18	0.66	319.44
Season dummy	0.30	0.46	0	1
Location dummy 1	0.29	0.46	0	1
Location dummy 2	0.32	0.47	0	1
Risk perception. dummy	0.46	0.50	0	1
Bt dummy	0.25	0.43	0	1
Pesticide use dummy	0.50	0.50	0	1

Table 2b. Summary Statistics: Bt Corn adopters (n = 101)

Variable	Mean	St. Dev.	Min.	Max
Profits	21650.59	14763.64	-9098.71	65509.83
Yield	4849.50	1607.04	650	10533.33
Pestapp	384.97	703.71	0.08	5000
Educ	9.53	3.73	0	17
Age	45	11.54	25	79
Farm Size	3.76	5.36	0.75	32
Corn output price	8.85	0.90	6.50	10.50
Fuel Cost	511.32	3550.52	0	960
Non-Ag. Income	5.14	17.67	0	166.67
Seed price	258.02	315.03	4.88	1911.11
Fertilizer price	7.64	4.51	0	22.80
Pesticide Price	1.11	3.14	0	30
Labor price	89.74	53.26	11.51	289.24
Season dummy	0.07	0.26	0	1
Location dummy 1	0.05	0.22	0	1
Location dummy 2	0.38	0.49	0	1
Risk perception. dummy	0.92	0.27	0	1
Bt dummy	1.00	0	1	1
Pesticide use dummy	0.45	0.50	0	1

Table 2c. Summary Statistics: Non-Bt Corn Adopters (n = 306)

Variable	Mean	St. Dev.	Min.	Max
Profits	11466.65	11366.39	-24346.88	50505.20
Yield	3610.31	1385.00	525	8400
Pestapp	516.54	1175.02	0.02	15000
Educ	7.97	3.18	0	16
Age	46.45	12.32	19	77
Farm Size	2.53	4.64	0	70
Corn output price	7.75	0.98	5.67	10.05
Fuel Cost	72.50	762.36	0	12750
Non-Ag. Income	2.61	6.01	0	62
Seed price	101.68	81.34	3.36	622.22
Fertilizer price	1.69	19.24	0	313.85
Pesticide Price	2035.94	23321.02	0	405405.41
Labor price	72.92	49.86	0.66	319.44
Season dummy	0.37	0.48	0	1
Location dummy 1	0.37	0.48	0	1
Location dummy 2	0.30	0.46	0	1
Risk perception. dummy	0.31	0.46	0	1
Bt dummy	0	0	0	0
Pesticide use dummy	0.52	0.50	0	1

Table 3. Results of the Bivariate Probit Model: Bt Corn Adoption and Pesticide Use

Variable	Bt Corn Adoption Dummy		Pesticide Use Dummy	
	Parameter Estimate	St. Error	Parameter Estimate	St. Error
Intercept	-5.54*	1.27	-0.29	0.26
Educ	0.06*	0.03	-0.026	0.02
Age	-0.005	0.008	0.01*	0.005
Farm size	0.032*	0.015	-0.017	0.016
Corn output price	0.43*	0.13		
Risk perception dummy	1.88*	0.21	-0.68*	0.18
Season dummy	0.22	0.33		
Location dummy 1	-1.32*	0.29		
Location dummy 2	-0.02	0.21		
Fuel Cost			0.31*	0.17
Non-Ag. Income			-0.013*	0.008
Bt dummy			-0.71*	0.29
ρ			-0.51*	0.19
Log-Likelihood Value	-387.82			

Notes: (1) * Significant at 10% level.

(2) The parameter ρ represents the correlation between the errors of the Bt corn adoption equation and the pesticide use equation.

Table 4. ITSUR Estimates of Non-Censored and Censored Sparse Impact Model

	Non-Censored Sparse Impact Model		Censored Sparse Impact Model	
	Ln(*Yield*)	*Profits*	ln(*Yield*)	*Profits*
Intercept	6.88*	-14.63*	2.72*	-25.93*
	(0.32)	(1.77)	(1.56)	(3.83)
ln(*Corn output price*)	0.57*	8.41*	-0.22	13.35*
	(0.15)	(0.87)	(0.73)	(1.80)
ln(*Seed price*)	-0.20*	-1.05*	-0.31*	-1.56*
	(0.03)	(0.15)	(0.12)	(0.30)
ln(*Fertilizer price*)	-0.10*	-0.97*	-0.10	-1.84*
	(0.02)	(0.12)	(0.11)	(0.27)
ln(*Pesticide price*)	-0.001	-0.03	-0.05*	-0.011
	(0.007)	(0.04)	(0.03)	(0.08)
ln(*Labor price*)	-0.12*	-0.97*	-0.45*	-2.65*
	(0.02)	(0.12)	(0.13)	(0.31)
Prob. of Bt Corn Adoption ($\hat{I}_i$)	0.35*	0.86	3.60*	3.77*
	(0.15)	(0.86)	(0.76)	(1.86)
PDF of Pesticide Adoption ($\phi(\mathbf{z}_i^2\boldsymbol{\gamma})$)			17.25*	4.61*
			(0.41)	(1.01)

Note: (1) Standard Errors in Parenthesis
(2) * Significant at the 10% level.

Table 5. ITSUR Estimates of Non-Censored and Censored Profit Function Impact Model

	Non-Censored Profit Function Impact Model		Censored Profit Function Impact Model	
	Parameter Estimate	Standard Error	Parameter Estimate	Standard Error
A0	-10.27*	1.58	-3.94*	1.89
Ay	7.42*	0.28	5.20*	1.34
A1	2.42*	0.36	0.62	0.41
A2	8.67*	0.60	-2.96*	0.71
A3	-0.09	0.39	0.99*	0.53
A4	1.60*	0.39	-1.13*	0.42
C1	-2.23	5.95	-3.35	3.87
Gyy	0.38*	0.13	1.59*	0.63
Gy1	-0.14*	0.02	-0.23*	0.11
Gy2	-0.01	0.02	-0.37*	0.10
Gy3	0.01	0.01	-0.05	0.03
Gy4	-0.02	0.02	-0.39*	0.11
G11	0.14*	0.08	0.05	0.08
G12	-0.20*	0.09	-0.24*	0.10
G13	0.06	0.04	0.01	0.03
G14	-0.20*	0.07	-0.03	0.09
G22	0.93*	0.09	-1.34*	0.09
G23	0.01	0.07	-0.12*	0.07
G24	-0.39*	0.10	-0.37*	0.11
G33	-0.13*	0.06	0.16*	0.10
G34	-0.03	0.04	-0.04	0.04
G44	-0.06	0.08	-0.35*	0.08
Fy1	0.54*	0.15	4.90*	0.71
E11	0.15	0.74	1.78*	0.65
E22	-8.65*	1.25	-14.77*	1.34
E33	-0.83	0.68	-0.29	0.44
E44	-0.82	0.82	-0.82	0.71
PDFP	--	--	5.02*	0.82
PDFY	--	--	17.61*	0.37
PDFI1	--	--	8.23*	0.32
PDFI2	--	--	35.31*	0.53
PDFI3	--	--	8.47*	0.56
PDFI4	--	--	12.54*	0.34

* *PDFP*, *PDFY*, *PDFI1*, *PDFI2*, *PDFI3*, and *PDFI4* are the pdfs of pesticide adoption in the profit, yield, and input equations (seed, fertilizer, pesticide, and labor demand), respectively.

Table 6. Elasticity of Selected Impact Variables with Respect to Probability of Bt Adoption

Impact Variables	Non-Censored Sparse Impact Model	Censored Sparse Impact Model	Non-Censored Profit Function Impact Model	Censored Profit Function Impact Model
Yield	0.06*	0.30*	0.09*	0.41*
Profits	0.05	0.11*	0.04	0.08*
Labor demand			0.02	0.15*
Fertilizer demand			-1.40*	-1.24*
Seed demand			-0.14	-0.02
Pesticide demand			-0.13	-0.07

* Significant at the 10% level

Appendix Table 1. Output and Input Price Elasticities of Yield

Elasticity of Yields with Respect to:	Non-Censored Sparse Impact Model	Censored Sparse Impact Model	Non-Censored Profit Function Impact Model	Censored Profit Function Impact Model
Output price	0.57*	-0.11	0.38*	0.80*
Labor price	-0.12*	-0.23*	-0.14*	-0.02*
Fertilizer price	-0.10*	-0.05	-0.01	-0.12*
Seed price	-0.20	-0.15*	0.01	0.005
Pesticide price	-0.0007	-0.03*	-0.02	-0.02*

* Significant at the 10% level

Appendix Table 2. Output and Input Price Elasticities of Profit

Elasticity of Profits with Respect to:	Non-Censored Sparse Impact Model	Censored Sparse Impact Model	Non-Censored Profit Function Impact Model	Censored Profit Function Impact Model
Output price	2.95*	2.36*	2.94*	1.88*
Labor price	-0.34*	-0.48*	-0.51*	-0.52*
Fertilizer price	-0.34	-0.33*	-0.22*	-0.35*
Seed price	-0.37*	-0.28*	-0.24*	-0.13*
Pesticide price	-0.01*	-0.002	-0.12*	-0.25*

* Significant at the 10% level