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Impacts of Bt Maize on Smallholder Income in the Philippines

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Bacillus thuringiensis (Bt) maize is the first genetically modified crop to be introduced to Philippine farmers. Since its commercialization in 2003, evidence has accumulated regarding the economic benefits of adopting Bt maize. Based on data collected from 466 farmers, this research focuses specifically on the selection and endogeneity bias that has not yet been explicitly addressed; it also tests the impacts of adoption on net farm income, off-farm income of the farmer, and total household income, including income from crops and livestock, off-farm income of the farmer, and income of all household members. Regression results are compared for OLS regress and two types of instrumental variables methods. Accounting for self-selection and endogeneity, adoption of Bt maize increases net farm income, off-farm income, and household income. The predicted probability that a household's income falls below the poverty line is lower among Bt maize adopters. However, we have not fully addressed placement bias.

Key words: Philippines, Bt maize, adoption, impact, off-farm income, household income, net farm income.

Introduction

Bt (*Bacillus thuringiensis*) maize is the first genetically modified crop to be introduced to Philippine farmers. Since its commercialization in 2003, there has been sustained public concern over its benefits for smallholder producers. Research about the economic impacts of Bt maize adoption among smallholder farmers in the Philippines has been conducted in an effort to address this concern and is now accumulating in the published literature.

In analyzing economic impacts of an agricultural technology, it is always the case that benefits streams vary over time and vary among farmers, so that a single cross-section of data provides only one snapshot in time. In addition, some of the initial results of research implemented in the Philippines were inconclusive due to potential bias associated with methods employed. Such limitations are not confined to research in the Philippines; they are shared by many of the analyses generated during the first decade of use of biotech crops in developing countries.

As described in the introductory article in this issue, measuring the economic impact of biotech crops in developing countries poses particular challenges, especially when adoption is still in the initial stages. These include the difficulty in establishing an appropriate counterfactual, placement bias associated with targeting of particular regions of the country by the seed industry and the likelihood that better-endowed farmers adopt first, which can bias the estimated benefits of the technology.

In 2004, in an ex ante approach applied with mixed-integer programming and data drawn from farmers purposively selected to represent 'typical' conditions, Cabanilla (2004) estimated the potential impact of Bt maize on farms. Initial ex post studies focused on partial budget analyses as a rough indicator of profitability (Gonzales, 2005). Yorobe and Quicoy (2006) published an ex post analysis based on 107 Bt and 363 non-Bt growers in four provinces of the country (Bukidnon, Camarines Sur, Isabela, and South Cotabato). The authors concluded that per-unit yields and incomes were higher among Bt growers, and insecticide expenditures were lower. Major determinants of adoption were risk perceptions, education, training, and use of hired labor. Yorobe and Quicoy (2006, p. 266) found that "increasing the probability of adoption by 10% increased net farm income by 4.1%," an adoption elasticity that was "higher than those observed in developed countries." Mutuc, Rejesus, and Yorobe (2011) found that Bt maize in the Philippines significantly reduced yield losses from pests—especially in poor weather conditions—and that the value of insecticide use is diminished when Bt maize is grown. Thus, Bt maize seed substitutes for insecticide use. These authors not only tested for endogeneity of pesticide use but also potential selectivity bias of adoption in their damage-abatement model, applying both a control function approach and a Heckman-type technique previously employed by Shankar and Thirtle (2005). They found that insecticide endogeneity may not be severe enough to cause significant bias in their results, but that selection bias may indeed constitute a problem.

In the research reported here, we seek to add new information to the existing body of research concerning the economic impacts of Bt maize in the Philippines. We estimate the impacts of adoption on net farm income, off-farm income, and total household income in the Philippines. A methodological contribution is that we employ a quasi-experimental approach with two types of instrumental variable estimation to account for selection and endogeneity issues. As instruments, we test the validity of seed price and distance to seed source.

We find that, after accounting for self-selection bias and endogeneity, adoption of Bt maize in the Philippines has a positive significant impact on net farm income, off-farm income, and household income. Nonetheless, because placement bias remains, as Bt maize diffuses, we call for public and private commitment to a sampling and research design that is nationally representative and permits the monitoring of selected impact indicators over time.

The following section summarizes the methodology, including the data design and econometric strategy. Results are then presented, followed by conclusions and a brief statement of some of the methodological challenges.

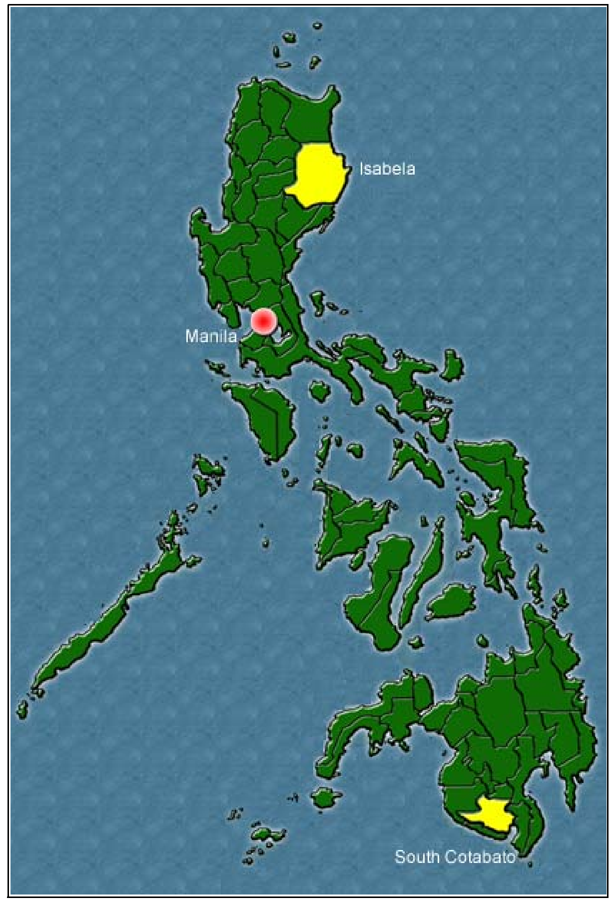

Figure 1. Location of study sites.

Methodology

Data Design

The data used in this study were collected in face-to-face interviews with maize producers in two major maize-producing provinces of the Philippines—Isabela and South Cotabato—from August 2007 to February 2008 (Figure 1).

The research team employed a three-stage sampling framework. In the first stage, two major maize-producing provinces (Isabela and South Cotabato) were selected according to several criteria. First, both are major maize-producing provinces in the country and adoption of hybrid maize varieties with the Bt trait was reported to be high. Second, confined field trials on Bt maize were conducted in these sites for regulatory compliance and private seed companies also maintain experimental areas for maize seed production. Third, seed companies originally introduced Bt maize in these areas because adoption rates for hybrid maize were known to be the highest in the country. Thus, site selection reflects a clear placement bias driven by contextual circumstances and the need to ensure that a sufficient number of Bt maize growers would be identified in a random sample. No pre-existing list of growers, census, or sampling frame was available.

In the second stage, major maize-producing villages in the province were selected. The 17 villages selected include four villages each in Tampakan and General Santos of South Cotabato province and Cauayan of Isabela province, as well as five villages in Ilagan (the capital of Isabela). The list of yellow-maize growers in the village was provided by the village head. Only smallholder maize farmers were included in the list. Smallholders were defined as those planting only 1-3 hectares in Isabela Province and 1-5 hectares in South Cotabato Province. These farm size ranges were based on mean maize area per farm in these villages. Farmers in selected villages also grow crops other than maize, including paddy rice, coconut, traditional fruit crops, and some vegetables.

Yellow-maize production is a primary farming activity in these villages and the density and contiguity of Bt (Yieldgard) and hybrid (Dekalb) users were reportedly high. The selection of the villages was carefully validated with the seed companies and the local agricultural offices. The variety was a major factor in the sampling scheme to maintain comparability in the analysis because Yieldgard was developed by backcrossing to the Dekalb isohybrid lines using the transformation event MON 810. The difference between the Dekalb hybrid and Yieldgard is only the Bt characteristic.

In the third stage, a total of 466 maize farmers were selected randomly from the list of smallholders in the 17 villages, consisting of 254 Bt and 212 hybrid users. A sampling fraction of not less than 15% was followed in each village. Applying a pre-tested questionnaire, enumerators surveyed the randomly chosen maize farmers and asked information on input utilization, varietal use, farming practices, yield, knowledge about Bt maize, other socio-economic characteristics, and income from maize production, livestock, and non-farm activities.

The survey instruments consisted of two components. In the first part, respondents were asked questions about their knowledge, attitudes, and perceptions of biotechnology, GM crops, and food. In the second section of the survey instrument, information about farming practices and the social and economic characteristics of farm households was collected. The information collected includes input utilization, varietal use, production, perceived yield losses, expenses, and income from maize production, livestock, and non-farm activities. All instruments are available from the first author.

Estimation Strategy

Early studies assessing the economic impact of biotech crops in developing agriculture often failed to address adequately the issue of selection bias and endogeneity problems, with the exception of some exemplary articles (Crost, Shankar, Bennett, & Morse, 2007; Qaim & de Janvry, 2005; Shankar & Thirtle, 2005). More recently, other approaches, such as propensity score matching, have been employed by authors (Ali & Abdulai, 2010).

Selection bias is related to the problem of identifying the appropriate counterfactual—the benchmark against which to compare the impact of adoption between adopters and non-adopters. Selection bias can result from the deliberate placement of development programs among certain farmers or from the choice of certain farmers to adopt. In either case, the sample of Bt maize growers is not assigned randomly. Then, the direct comparison of yield loss or insecticide use between Bt maize adopters and hybrid users may be biased. It is possible that the observed differences between the two groups cannot be wholly attributed to Bt maize adoption but partly to unobserved management abilities of both groups. By not controlling this selection issue, one can misattribute the effect of unobserved management ability as the effect of Bt maize adoption. Unless this is properly addressed in the estimation, the results could lead to incorrect inferences.

As originally conceptualized by Ravallion (1994), the dilemma of assessing impacts is essentially one of missing observations. We observe adopters after they have adopted, but are not able to observe their circumstances had they not adopted. We observe non-adopters, but these differ from adopters in both intrinsic and measurable ways. Selection bias on observables is introduced if, for example, farmers who are wealthier or whose yields are higher in the absence of adoption are also more likely to adopt. Unobserved (intrinsic) variables such as inherent management ability of the famer can also affect both the decision to adopt and income. In either case, the impact of using Bt maize seed on income could be overestimated.

Previously, Yorobe and Quicoy (2006) estimated the partial productivity impact of Bt maize by fitting a Cobb-Douglas production function. Recognizing that adopters self-select into the adoption group, they applied a two-stage Heckman procedure. In the first stage, they predicted adoption with a set of explanatory factors. In the second, they estimated the impact of adoption on net economic returns with an equation that included farm financial variables as well as the predicted probabilities from the first stage and the Inverse Mills Ratio.

Mutuc et al. (2011) then addressed the important methodological consideration that insecticide use, which Bt maize is intended to replace, is a damage-abating input. A statistical approach to estimating the impacts of a damage-abating input should model the indirect effect on yields through a reduction in crop losses rather than the direct impact on productivity (Lichtenberg & Zilberman, 1986). Following earlier research on Bt crops, Mutuc et al. (2011) estimated a logistic damage-control function and a Cobb-Douglas yield function for yield-enhancing inputs. They applied an instrumented, control-function approach to test the endogeneity of pesticide use, but found little evidence of bias. As did Shankar and Thirtle (2005), they also applied a Heckman-type test on adopter and non-adopter subsamples, finding strong evidence of selection bias on observed characteristics. Consequently, they used predicted values of adoption in their damage-abatement model, along with the Inverse Mills Ratio (IMR), which controls for the conditional probability of adoption.

Yorobe and Quicoy (2006) and Mutuc et al. (2011) use the Heckman model to handle selectivity bias—an approach that has been widely applied in the adoption literature. The Heckman selection model was originally proposed to control for the problem that wages observed in labor markets are observed only for the employed. Thus, the sample observations are incidentally truncated at some positive wage value. Where farmers are aware of an option to grow a certain type of seed but choose not to grow it—as in the case of Bt maize in the Philippines—a model that explicitly depicts non-adoption as a corner solution (a choice) is arguably more appropriate. The Heckman model has also been criticized for its distributional assumptions, and results are known to be sensitive to specification.

The problem of selection bias can be addressed through either experimental or quasi-experimental approaches, which have been extensively applied in the recent literature assessing the impacts of development programs. Experimental design refers to randomized, controlled trials (RCTs). When a study is conducted in an area where farmers have already adopted, as is the case in the Philippines, "rolling out" a new technology as in a RCT is not feasible. Two quasi-experimental approaches are generally applied by economists working with cross-sectional data (data collected from households at one point in time).

The first commonly used quasi-experimental approach is propensity score matching. Multivariate logit is used to predict the propensity of adopting farmers and non-adopting farmers to adopt, and, from both groups, the subsamples of farmers in a common range of the distribution of scores are selected. Actual adopters and non-adopters are effectively "matched" on observed characteristics. Differences in variables measuring impact are compared statistically between the two groups. This approach has been criticized on the grounds that it considers only the observable characteristics of farmers, ignoring the unobservable characteristics that also underlay the decision to adopt. In the context of this study, sample sizes are too small to permit a robust estimation of the distribution of propensity scores for the two groups.

A second approach that can be employed with cross-sectional data is the instrumental variables (IV) method, which is similar in some respects to the instrumented Heckman model because it treats correlated errors between a latent or unobserved variable and an observed (or outcome) variable. The instrumented-control function technique applied by Mutuc et al. (2011) is applied in the case of non-linear estimation.

We apply two methods of IV estimation to test the impact of Bt maize adoption using the following specification.

$$Y_i = X_i\beta + BT_i\delta + \varepsilon_i\,, \tag{1}$$

where Y_i is an impact outcome variable for Maize Farmer i in a sample size of n and X_i is a vector of observable control covariates. BT_i is a binary variable representing whether Farmer i adopted Bt maize (=1 if Bt maize adopter, 0 otherwise), β is a vector of parameters to be estimated, δ is the adoption impact parameter to be estimated, and ε_i is the unobserved error term. In this specification, selection or endogeneity bias arises when some unobserved covariates such as unobserved management ability affect both the decision to adopt Bt maize and the outcome variables (Yorobe et.al. 2011).

The decision to adopt Bt maize is specified as follows.

$$BT_{\mathrm{i}} = W_i\varphi + \mu_{\mathrm{i}}\,, \tag{2}$$

where W_i is a vector of instrumental variables that affect Bt maize adoption, φ is a vector of parameters to be estimated, and μ_i is the random error term.

In addition to the selection problem, the endogeneity problem exists if there are unobserved factors in μ_i and ε_i that cause these to be correlated (Greene, 2003; Rejesus, Palis, Lapitan, Chi, & Hossain, 2009). Estimating Equation 1 using Ordinary Least Squares (OLS) likely results in endogeneity problems. Endogeneity tests (Hausman, 1978) are performed to verify the existence of endogeneity (and/or selection) problems in the estimation.

For a more robust estimation procedure, two IV approaches were used to address the endogeneity and selection problems in Equation 1. The first IV method used, labelled as IV-1, is the more "traditional" IV approach where the predicted probabilities of Bt maize adoption (call this *Bt* hat) from a probit estimation of Equation 2 are used instead of the actual Bt maize binary variable (Dahl & Lochner, 2005; Nichols, 2007).

The second IV method used, labelled as IV-2, is a slight modification of the "traditional" approach. It is essentially a three-step procedure with a zero stage (Nichols, 2007). Initially, Equation 2 is estimated using probit regression, and the predicted values of Bt maize adoption (*Bt* hat) are calculated. But, instead of using the predicted values directly into Equation 1 to substitute for *Bt*, another probit regression is estimated where the binary variable *Bt* is regressed by OLS on the predicted values of *Bt* hat. The predicted values from this last regression (call this *Bt* tilde) are used in estimating Equation 1. This IV approach is more efficient than the "traditional" approach where *Bt* hat is directly substituted in place if *Bt* in Equation 1 (Wooldridge, 2002). Bootstrapping is used in this method to adjust the standard errors to account for the two-stage estimation procedure.

To successfully implement the above IV techniques, there should be valid instruments that are correlated with Bt adoption but are uncorrelated with the unobserved factors that affect the outcome. These instruments are included in Equation 2 but not in Equation 1 to assure identification. For this study, suitable instruments include distance to the maize market and seed price. Over-identification tests are used to check the validity of these instruments. Bootstrapping is also used to adjust the standard errors to account for the two-stage estimation procedure.

While the adoption model accounts for the endogenous selection, it has not eliminated the bias associated with the placement of Bt maize in specific administrative areas. We expect that this bias is minimal and may be insignificant, as placement of Bt maize in various areas of the country is primarily market driven and in the hands of the private seed suppliers. In other words, private seed suppliers provide seed in areas where they believe the likelihood that farmers conform to the profile of "adopters" is generally high.

In Equation 2, the dependent variable is binary (1=use of Bt maize and 0=use of maize hybrid). In the study area, more than half of the maize farmers were using the Bt variety with more than 17 years of experience farming maize. The maize hybrid refers to farmers using the Dekalb (818 and 9051 Isohybrid) varieties, the hybrid counterpart of Yieldgard. This varietal restriction was necessary to make the comparison more meaningful with the difference in outcomes attributable only to the Bt characteristic.

Dependent and observable covariates (explanatory variables) are shown in Table 1.

Dependent variables include net farm income above cash costs (in pesos per hectare), off-farm income (farmer income from sources outside of the farm, in pesos per month), and household income (income of all farm members, in pesos per month). Bt maize was introduced within the country essentially to reduce farm vulnerability to production losses attributed to the Asian corn borer. Field reports indicated that farms with high incidence of maize borer infestation reported higher yield losses and lower income. Net farm income above cash cost was used as an outcome variable to quantitatively measure the benefits that accrue to farmers from adopting. Previous studies have shown that using Bt maize in the Philippines increased farmers income by 14,849 pesos per hectare (Yorobe & Quicoy, 2006). This estimate, however, could be subject to the selection and endogeneity biases described above because these were not explicitly addressed by the authors. It is also important to note that more than 3 million farmers in the country depend on maize farming. Thus, increasing income through the Bt technology could substantially relieve poverty, particularly among smallholders. Other outcome variables include the off-farm income of the farmer and the income of all household members. In using the Bt technology, chemical application commonly performed by the farmer or members of his household is avoided. This opens up opportunities for the household members to engage in other off-farm and non-maize farming activities.

Table 1. Definition of explanatory variables.

Variable name	Definition
Net farm income	Net farm income above cash costs (in pesos per hectare)
Off-farm income	Farmer income outside the farm (in pesos per month)
Household income	Income of all farm household members (in pesos per month)
Bt	Dummy variable=1 if farmer adopted Bt maize, 0 if other
Gender	Gender of farmer (male=1, 0=otherwise)
Education	Farmer years of schooling
Experience	Years in maize farming
Extension	Attendance to pest management trainings (no)
Household size	No. of persons in the household
Seed price	Price of corn seeds (pesos per kilo)
Distance	Farm distance from seed source (km)
Credit	Amount of loan for corn production (pesos per hectare)
Capital	Value of household capital assets (pesos per hectare)
Labor management	Ratio of hired labor (man-day) to total labor (man-day)
Location	Dummy variable = 1 if Isabela and 0 if South Cotabato

Table 2. Summary statistics of explanatory variables.

	Full sample (n=466)		Bt users (n=254)		Non-Bt users (n=212)	
Variable name	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
Net farm income	20,932.67	17,300.77	24,700.05	16,342.02	16,418.94	17,373.96
Household income	25,563.80	27,111.92	30,600.45	29,545.08	19,529.32	22,497.09
Off-farm income	3,216.60	6,583.82	4,230.20	7,884.29	2,002.20	4,274.69
Bt maize	0.55	0.50	1.00	0.00	0.00	0.00
Gender	0.89	0.31	0.87	0.34	0.92	0.26
Education	7.32	3.19	7.65	3.30	6.92	3.02
Farming experience	16.82	11.38	17.80	11.23	15.64	11.47
Extension	0.38	0.49	0.42	0.49	0.34	0.47
Household size	4.51	1.61	4.41	1.55	4.63	1.68
Seed price	249.18	82.63	310.10	55.54	176.18	39.07
Distance	5.65	11.49	7.44	14.60	3.50	5.20
Capital assets	43,520.14	70,578.82	51,321.23	73,474.35	34,173.56	65,907.58
Credit	8,558.96	9,659.51	10,112.43	11,087.12	6,697.74	7,200.62
Labor management	0.70	0.25	0.72	0.46	0.63	0.27
Location	0.59	0.49	0.76	0.22	0.43	0.50

Source: Authors

Observable covariates include the gender of the household head, household size, human capital embodied in the farmer (years of education, years growing maize, attendance in pest management school), social capital of the farmer (group membership) and financial capital (value of capital assets in pesos), amount of loan for maize production in pesos per hectare, and a location dummy to account for sample heterogeneity. Type of labor management (proportion of hired labor to total labor) was included as a control covariate due to its influence on the adoption of pest management technologies (Beckmann & Wesseler, 2003; Irawan, Beckmann, Wesseler, 2007).

In the presence of endogeneity or selection problems, the IV approaches specified here require a first-stage probit estimation where the binary Bt adoption variable is regressed on valid instruments. Angrist and Krueger (2001) have shown that even when two-stage least squares (2SLS) specifications have a binary endogenous regressor, using linear regression in the first-stage generates consistent second-stage estimates. Seed price and distance to the seed source (in km) are the instrumental variables used for identification of the impact of adoption on the three income variables. We propose that these variables are likely to be correlated with Bt maize adoption but unlikely to be correlated with the unobservables in the error term of Equation 1. That is, they influence the income outcome only through their effect on Bt maize adoption. It is plausible that the farther the farm is from the maize seed source, the more likely that they are serviced by the technicians of the seed companies and still have access to the “financiers” in the area who provide input loans. Seed price was also expected to be highly correlated with Bt maize adoption, as increasing the Bt seed price would discourage farmers from using the variety.

Table 3. Diagnostics of first-stage Bt maize adoption probit model.

Variable	Parameter estimate	p-Value
Distance to seed source	0.02	0.07
Seed price	0.21	<0.01
Log-likelihood	-321.11	
Pseudo R-squared	0.63	
Akaike info. criterion	243.49	
Bayesian info. criterion	255.92	

Source: Authors; n=466

The summary statistics of the variables used in this study are given in Table 2. Bt maize producers showed higher levels of income than their non-Bt counterparts. They also appeared to be more educated and experienced in maize farming with more trainings attended. These data confirm the potential for selection bias in estimating the impacts of Bt maize adoption on any type of outcome variable. One reason why is that the average prices paid for the Bt seeds were almost twice that of non-Bt hybrids, and the seed source for the Bt seed is

Table 4. Impact of Bt maize adoption on net farm income per ha: OLS and two IV approaches.

	OLS		IV-1		IV-2	
Variable	**Par. estimate**	**p-Value**	**Par. estimate**	**p-Value**	**Par. estimate**	**p-Value**
Bt maize	4,300.05	0.01	4,353.53	0.07	3,553.51	0.11
Education	352.02	0.16	346.74	0.19	352.97	0.19
Household size	-597.61	0.21	-653.80	0.24	-653.89	0.24
Farming experience	-17.92	0.79	-20.09	0.75	-17.17	0.79
Extension	50.69	0.97	351.23	0.83	344.47	0.83
Gender	3,975.37	0.11	3,651.46	0.15	3,662.04	0.15
Capital assets	0.01	0.24	0.01	0.20	0.01	0.20
Credit	-0.05	0.51	-0.05	0.45	-0.05	0.47
Labor management	7,330.08	0.02	7,616.58	0.02	7,812.15	0.02
Location dummy	10,180.15	<0.01	9,974.09	<0.01	10,290.81	<0.01
Intercept	4,229.01	0.33	4,610.14	0.38	15,469.80	<0.01
No. of obs.	466		466		466	
Log-likelihood	-5,170.23		-5,171.46		-5,171.99	
R-squared	0.150		0.146		0.803	
Akaike info. criterion	10,362.46		10,364.93		10,365.98	
Bayesian info. criterion	10,408.05		10,410.52		10,411.57	

Note: p-values in the IV approaches calculated from bootstrapped standard errors (100 draws)
(Income in Philippine peso, $1US=41.40 pesos in 2007)
Source: Authors

relatively distant from the farm. At the time of this survey, only the more well-endowed farmers would have been able to use them. Accordingly, mean asset and loan values are considerably higher for Bt growers than non-Bt growers.

Results

The first-stage probit regression diagnostics for the two instrumental variables—distance from seed source and seed price—are shown in Table 3. Both instruments are statistically significant, which indicates that they are strongly correlated with the Bt maize adoption. The endogeneity tests (Wooldridge, 2003) indicate that endogeneity was present for net farm income (t statistic of 174.75 and p-value=<0.01), off-farm income (t statistic of -1.40 and p-value=0.10), and household income (t statistic of 2.34 and p-value=0.02).

Finally, the over-identification test of the instruments used for all of the outcome variables suggest that distance and seed price are not correlated with the error (with p-values > 0.20, leading to failure to reject the null hypothesis that the instrumental variables are valid).

Net Farm Income

To illustrate the consequences of selection and endogeneity bias, the results of three second-stage regressions (OLS, IV-1, IV-2) are shown in Table 4, including the estimated effects of the exogenous explanatory variables and the endogenous variable measuring Bt maize adoption.

Using OLS technique, the use of Bt maize has a statistically significant net-income increasing effect of 4,300.05 pesos per hectare. Other significant covariates that influence net farm income include labor management and location. Location was highly significant, indicating that Isabela corn farmers were earning more compared to their counterparts in South Cotabato. Labor management was also positively associated with net income to address the further need for labor given the increase in output.

Income effects, however, were found to be larger when endogeneity and selection problems have been controlled. When the first IV method (*Bt* hat) was applied, the increase in net farm income was statistically significant at 4,353.53 pesos per hectare. With the second IV method (*Bt* tilde), the gain in net farm income was not statistically significant. Other than Bt maize adoption, labor management, and location continue to be significant at the 1% or 2% level. Since both of these variables are predicted to have a sign (labor management is an indicator of labor constraints, and location is

Table 5. Impact of Bt maize adoption on off farm income per month: OLS and two IV approaches.

	OLS		IV-1		IV-2	
Variable	**Par. estimate**	**p-Value**	**Par. estimate**	**p-Value**	**Par. estimate**	**p-Value**
Bt maize	1,293.20	0.01	2,022.92	<0.01	1,852.75	<0.01
Education	451.53	<0.01	439.36	<0.01	438.95	<0.01
Household size	1,030.26	<0.01	1,012.26	<0.01	1,011.84	<0.01
Farming experience	68.49	<0.01	65.69	<0.01	66.47	<0.01
Extension	251.77	0.43	288.32	0.63	266.17	0.65
Gender	-1,886.55	0.06	-1,971.18	0.03	-1,961.24	0.03
Capital assets	<0.01	0.59	<0.01	0.61	<0.01	0.61
Credit	-0.02	0.33	-0.02	0.32	-0.02	0.33
Labor management	3,585.12	<0.01	3,457.07	<0.01	3,484.91	<0.01
Location	554.47	0.34	267.95	0.66	355.38	0.57
Intercept	-7,724.31	<0.01	-7,551.41	<0.01	-7,550.96	<0.01
No. of obs.	466		466		466	
Log-likelihood	-4,705.91		-4,704.69		-4,704.84	
R-squared	0.200		0.204		0.203	
Akaike info. criterion	9,433.91		9,431.39		9,431.68	
Bayesian info. criterion	9,479.41		9,476.97		9,477.27	

Note: p-values in the IV approaches calculated from bootstrapped standard errors (100 draws)
(Income in Philippine peso, $1US=41.40 pesos in 2007); Source: Authors

an indicator of heterogeneity), it is appropriate to apply one-tailed tests.

There is clearly a pronounced effect of Bt maize use on net farm income. This finding is consistent with other evidence that higher yields are obtained by farms using Bt maize due to lower yield losses (Mutuc et al., 2011). A major development goal of the Department of Agriculture in the present national government of the Philippines is to increase the level of farm income in agricultural communities. Previous studies revealed a high incidence of poverty in many of these communities, including maize (National Academy of Science and Technology, 2005). To evaluate whether the use of Bt maize could help alleviate poverty in the study sites, we show the kernel density of the predicted maize net farm income for both Bt maize and hybrid users in Figure 2. This is more informative than the observed net farm incomes since the values are conditional on the control covariates, thereby producing the pure effect of the Bt maize use. As shown, the density of predicted net farm income per hectare for Bt maize users lie to the right of those associated with non-Bt (hybrid) users. Observing the position of the rural poverty threshold in the Philippines (represented by the vertical red line) of 14,123 pesos in 2006 (National Statistical Coordination Board of the Philippines [NSCB], n.d.), the probability mass to the left of the poverty threshold is smaller for the Bt users compared to the hybrid users. Clearly, the result suggests that the probability of falling below the poverty threshold declines as one uses Bt maize.

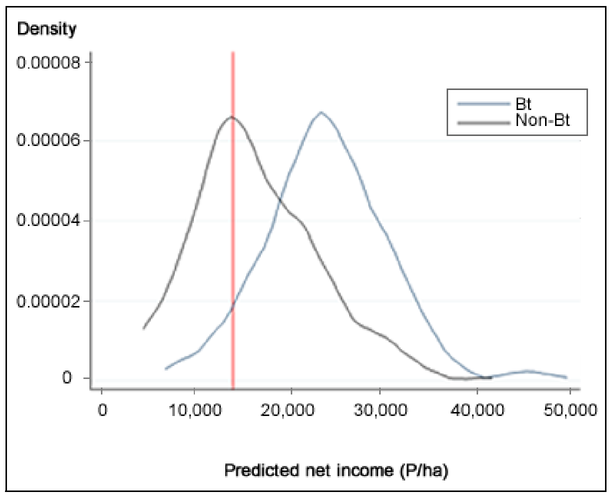

Figure 2. Kernel density of predicted net farm income.

Off-farm Income

The regression results using off-farm income as an impact outcome revealed a similarly significant income-increasing effect of growing Bt maize. Other statistically significant parameters include education, house-

Table 6. Impact of Bt maize adoption on household income per month: OLS and two IV approaches.

	OLS		IV-1		IV-2	
Variable	**Par. estimate**	**p-Value**	**Par. estimate**	**p-Value**	**Par. estimate**	**p-Value**
Bt maize	7,964.31	<0.01	7,367.49	0.03	7,138.37	0.02
Education	1,286.67	<0.01	1,287.19	0.01	1,279.29	0.01
Household size	795.00	0.38	691.98	0.45	689.68	0.45
Farming experience	152.87	0.15	150.94	0.19	152.65	0.18
Extension	-746.93	0.77	-137.78	0.95	-255.30	0.93
Gender	890.22	0.84	277.82	0.94	323.76	0.93
Capital assets	0.03	0.22	0.03	0.20	0.03	0.20
Credit	-0.14	0.19	-0.14	0.23	-0.14	0.23
Labor management	27,541.92	<0.01	28,281.44	<0.01	28,260.69	<0.01
Location	-4,769.03	0.12	-4,931.70	0.10	-4,729.07	0.11
Intercept	-1,275.99	0.09	-10,626.90	0.20	-389.25	0.96
No. of obs.	466		466		466	
Log-likelihood	-5,372.88		-5,375.17		-5,374.98	
R-squared	0.174		0.166		0.167	
Akaike info. criterion	10,767.77		10,772.36		10,771.98	
Bayesian info. criterion	10,813.35		10,817.94		10,817.56	

Note: p-values in the IV approaches calculated from bootstrapped standard errors (100 draws)
(Income in Philippine peso, 1US$=41.40 pesos in 2007)
Source: Authors

hold size, farming experience, gender, and labor management (Table 5).

Interestingly, the finding that Bt maize has a significant impact on off-farm income contradicts results reported by the National Research Council (2010). In that report, based on analyses undertaken among farmers in the United States, off-farm household income bore no statistically significant relationship with Bt maize adoption, as compared to HT soybeans. The management time saved is just too small to create an impact. On the contrary, the amount of labor freed due to the adoption of the Bt maize in a developing economy like the Philippines is significant enough for farmers to undertake other off-farm income-generating activities like driving, carpentry work, buying and selling merchandise, office employment, and others.

Needless to say, better education, a large household, and longer farming experience increases the opportunities for off-farm activities. It is interesting to note also that female farmers appear to have better capacities to generate off-farm income, considering the diversity of opportunities available to them. They were either employed in offices or undertaking buying and selling activities, which offers higher monthly income. The use of more hired labor also frees the operator and their family from farming work, thus giving them the opportunity to be employed elsewhere.

It was noted again that controlling for selection and endogeneity issues provided higher off-farm income estimates and that the estimate for IV-2 was in between that generated by OLS and by IV-1. The effect of the two IV methods was similar, which is an indication of the robustness of the methods to control for selection and endogeneity problems.

Household Income

The endogeneity of Bt adoption in household income could not be rejected, indicating that adoption was correlated with unobservables, and the 2SLS approach is more efficient than OLS (Wooldridge, 2003).

As shown in Table 6, parameter values of the three approaches are close. In the preferred OLS regression, Bt adoption, education, and the type of labor management adopted are statistically significant variables with one-tailed tests. The household income includes all on-farm (particularly income from the sale of livestock and poultry) and off-farm income of the farmer and his household members. Farmers using the Bt maize earned 7,964.31 pesos per month more than their hybrid counterparts. Although education was not a significant factor in influencing net farm income, the overall income of the household is greater with more education of the farmer. The hiring of laborers continues to serve the family in terms of greater total household income, which may—in part—reflect the life-cycle stage of the household.

Conclusions

This analysis adds to an accumulating literature on the impacts of Bt maize adoption in the Philippines in two ways. First, we estimate the impact of Bt maize use on net farm income, income from off-farm employment of the farmer, and household income from all household members. Second, we apply two instrumental variable models to control for self-selection and endogeneity problems.

Bt maize was commercially introduced in the Philippines to mitigate the damage brought about by the Asian corn borer. An early assessment of the impact conducted in two provinces in 2004 showed a positive effect on yield and net farm income (Yorobe & Quicoy, 2006), but the method used did not explicitly treat potential biases due to endogeneity and selection problems. Based on data collected from 466 smallholder maize farmers in Isabela and South Cotabato Provinces during 2007, we applied instrumental variables methods to control for both types of bias. Findings indicate that adoption of Bt maize increases net farm, off-farm, and household income. These results provide stronger evidence of the potential of Bt maize to enhance the total income of smallholders.

In the context of a developing agricultural economy, such findings bear important policy implications as they relate to government objectives to improve farming income in smallholder agricultural communities. The use of Bt maize reduces the predicted probability of falling below the poverty threshold compared to non-users.

Although the use of the improved maize variety was shown to have strong positive income impacts, it is important to note that it is not exclusive of other inputs and socio-economic variables. Human capital development and good management practices need also to be considered, as the use of Bt maize alone may not be a sufficient condition to increase yield and income. Access of farmers to better information, credit, and seed markets will also facilitate diffusion of this technology.

Related to diffusion, it is important to note that while selection and endogeneity bias were examined and treated in this article, placement bias was not. Findings are representative only of the highest adoption areas of the Philippines, as well as when comparing isogenic hybrids. We recommend private and public commitment to a nationally representative sampling frame and its use in monitoring of key impact indicators over time, as part of the Philippines agricultural development strategy. Any ad hoc surveys could then be grounded statistically in this frame.

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