Production Risk, Farmer Welfare, and Bt Corn in the Philippines

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ABSTRACT

This article examines the production risk effects and welfare implications of Bt corn adoption in the Philippines by specifically considering the impact of Bt on the mean, variance, and skewness of yields. Assessing the skewness effects of Bt provides further inferences about the downside risk protection of this technology in a developing country context. Stochastic production function estimation is utilized to achieve the study objective, including an approach that allows for examining the skewness effects of Bt within a damage abatement specification. Our results indicate that Bt corn do not have a statistically significant risk-reducing (i.e., variance-reducing) or downside risk-reducing (i.e., skewness-increasing) effect, the main benefit is through its mean yield increasing effect. But we find that the probability of suffering a profit loss is lower for Bt farmers than for non-Bt farmers. Based on risk premium and certainty equivalent welfare measures, Bt corn farmers in the Philippines is still better-off (in welfare terms) relative to non-Bt farmers given Bt corn's dominant yield increasing effect and lower probability of profit loss.

Keywords: Bt corn, Damage Abatement, GM crop, Production Risk, Downside risk, Skewness, Stochastic Production Function

JEL Codes: Q12; Q1

Introduction

Insect-resistant crops that have a gene from the soil bacterium *Bacillus thuringensis* (Bt) are now one of the most widely adopted genetically-modified (GM) crop variety in the world. In particular, single-trait Bt corn and cotton varieties have been used in a number of developed and developing countries primarily to control lepidopteran pests that can damage these crops (e.g., Asian/European corn borer, cotton bollworn). Given the widespread use of these Bt crops, there have been a number of studies in both developed and developing countries that investigated the yield and insecticide use impacts of this Bt technology (See Smale et al., 2007 and Qaim, 2009 for a comprehensive review of this literature).

In general, these studies found that first generation Bt crops have yield-increasing and pesticide-reducing effects. For example, the yield-increasing effects for Bt cotton are observed to be largest for countries that typically underutilize pesticides, such as in Argentina, India, and South Africa (Qaim and de Janvry, 2005; Qaim, 2003; Shankar and Thirtle, 2005). While in countries where pesticide use is typically high, such as China and the United States (US), the pesticide-reducing effect of Bt cotton is much more dominant than the yield effect (Huang et al., 2002; Falck-Zepeda et al., 2000). Although there have been fewer studies that examined the impacts of Bt corn, the existing literature also show similar yield-increasing and insecticide-reducing effects, albeit with a smaller magnitude (Brookes and Barfoot, 2005, Gouse et al., 2006; Fernandez Cornejo and Li, 2005; Yorobe and Quicoy, 2006; Qaim, 2009).

Aside from the yield and insecticide use impacts of Bt crops, there have also been recent studies that examine the production risk impact of using Bt technology.[1] Hurley et al., (2004) developed a theoretical model that shows that Bt corn can be risk increasing or risk decreasing

[1] We follow the definition in the literature where an input is considered to be risk decreasing (increasing) if it decreases (increases) the variance of output (See Just and Pope, 1979; Shankar et al., 2007, 2008)

and then used a simulation model for two counties in the US to empirically verify their theoretical results. Crost and Shankar (2008), using panel data and a stochastic production function approach, observed a risk reducing effect for Bt cotton in India, but they did not find any conclusive evidence for the risk effects of Bt cotton in South Africa. Using a stochastic production function approach with a single-year of cross sectional data, Shankar et al. (2007; 2008) also investigated the production risk effects of Bt cotton in South Africa and found that Bt cotton significantly increases yield (or output) risk. The empirical finding of a risk increasing effect is somewhat contrary to the notion that Bt technology should reduce risk given that it reduces the probability of damage from lepidopteran pests (i.e., the so-called ‘insurance’ function of Bt). But note that there have been empirical studies that shows that pest control inputs (like Bt and insecticides) could either be risk increasing (Horowitz and Lichtenberg, 1993) or risk decreasing (Smith and Goodwin, 1996).

Even with these studies that investigated the production risk impacts of Bt technology, there is still a gap in our knowledge given that only Bt cotton in developing countries was the main focus of all the studies that used a stochastic production function approach to empirically estimate the risk effect of the technology. Note that Hurley et al. (2004) did study the risk impacts of Bt corn, but they used a simulation-based empirical approach within the context of a developed country environment (the US). To the best of our knowledge, there has been no study that have investigated the production risk impact of Bt corn (instead of cotton) in a developing country context like the Philippines using a stochastic production function approach.

Moreover, the papers that have studied production risk effects of Bt only considered the mean yield and yield variance impact of Bt technology (i.e., a mean-variance approach). None have examined the effect of Bt technology on the skewness of yields. Although useful information about the risk effects of Bt can be gathered from understanding its impact on yield variance, analyzing the variance effect alone would not enable one to distinguish between unexpected bad events and unexpected good events. Hence, it is also important to analyze the effect of Bt corn on skewness as well. An increase in the skewness of yields means a reduction in downside risk (i.e., a decrease in the probability of crop failure).[2] Farmers that have decreasing absolute risk aversion (DARA) preferences,[3] would be more averse to being exposed to downside risk (Menezes et al., 1980; Antle, 1987) and will have more incentives to adopt Bt crops if we find evidence that it does significantly increase yield skewness.

The objective of this paper is to determine the production risk effects of Bt corn in the Philippines. Specifically, we examine the impact of Bt corn on the mean, variance, and skewness of yields, and then evaluate the welfare implications of these effects using risk premium and certainty equivalent measures. The analysis relies on two separate farm-level survey data collected in Philippines in the 2003/2004 and 2007/2008 crop years (i.e., these are two separate cross-sectional data sets, rather than a panel data set). We first utilize the moment-based approach developed in Di Falco and Chavas (2006, 2009) to estimate a stochastic production function that disentangles the mean, variance, and skewness effects of Bt technology. This approach is an extension of the Just-Pope stochastic production function (Just and Pope, 1979), but it is more general since it includes a skewness component. In addition, we also use the stochastic production function approach of Saha et al. (1997) to analyze the risk effects of Bt

[2] An input is considered to be downside risk decreasing (increasing) if it increase (decrease) the skewness of output (See Di Falco and Chavas 2006, 2009). The effect of an input on the skewness of output provides additional information that is not apparent when only looking at the effect of input on the variance of output. For example, a variance increasing input does not necessary lead to higher risk premiums if the input also increases the skewness of output (i.e. downside risk reduction that lowers risk premium) and the skewness effect dominates the variance effect.

[3] Previous literature suggests that most decision-makers (and, more specifically, farmer-decision-makers) exhibit decreasing absolute risk aversion (DARA) (also alternatively called constant relative risk aversion (CRRA)) behavior (See Binswanger, 1981; Saha et al., 1994; Chavas, 2004; Chavas and Holt, 1996; Escalante and Rejesus, 2008). Hence, assumptions of DARA preferences for farmers seem reasonable.

corn. This model allows us to recognize the 'damage abating' nature of pesticide inputs and Bt.[4] However, since the original model in Saha et al. (1997) do not accommodate the skewness effect, we also extended Saha et al.'s (1997) model to be able to study the downside risk effects of Bt corn within a damage abatement specification. This extension is also a contribution to the literature because, to the best of our knowledge, this is a new approach to analyze the downside risk effects of damage abating technologies.

Our empirical results indicate that the main benefit of Bt corn in the Philippines is through its mean yield increasing effect. We did not find any evidence that Bt corn has an impact on yield variance and skewness. This indicates that Bt corn in the Philippines do not have a statistically significant risk reducing or downside risk reducing effect. But our certainty equivalent measure indicate that Bt corn farmers in the Philippines still tend to be better off than non-Bt farmers given Bt corn's dominant yield increasing effect, even if there is no statistically significant risk benefits to adoption of the technology.

Conceptual Framework

For a stochastic production function: $y = g(x,v)$, where x is a vector of inputs and v is a vector of unobserved factors not under the control of the producer (i.e., unobserved weather variables, production or pest conditions). The profit of the producer is $\pi = p \cdot g(x,v) - c(x)$, where $p > 0$ is the output price and $c(x)$ is the cost of inputs x. Assume that the utility of the farmer depends on profit (e.g., $U(\pi)$) and is characterized by a von Neumann-Morgenstern utility function. Expected utility of the farmer can then be defined as (Pratt, 1964):

(1) $$EU(\pi) = EU[p \cdot g(x,v) - c(x)] = U\left[E(\pi) - R\right],$$

[4] The Saha et al. (1997) model allows for the so-called 'damage control' or 'damage abatement' specification of the stochastic production function (Lichtenberg and Zilberman, 1986), which is not accounted for in the standard Just-Pope specification and the stochastic production function approach in Di Falco and Chavas (2006, 2009).

where R is the risk premium that measures the cost of private risk bearing. And the certainty equivalent (CE), the sure amount of profit that the farmer would be willing to receive that would give the same utility as the expected value of the random profit:

(2) $$CE = E(\pi) - R = E\left[p \cdot g(x,v)\right] - c(x) - R.$$

From equations (1) and (2), the risk premium *(R)* and the certainty equivalent *(CE)* depend on the moments of profit which depends on the moment of the production function $g(x, v)$. By taking a Taylor series approximation on equation (1) evaluated at the point $E(\pi)$ (See Di Falco and Chavas, 2006, 2009):[5]

(3) $$U\left(E(\pi)\right) + \tfrac{1}{2}\left(\tfrac{\partial^2 U}{\partial \pi^2}\right) E[\pi - E(\pi)]^2 + \tfrac{1}{6}\left(\tfrac{\partial^3 U}{\partial \pi^3}\right) E[\pi - E(\pi)]^3 \approx U\left(E(\pi)\right) - \left(\tfrac{\partial U}{\partial \pi}\right) R.$$

From (3), the risk premium R can be approximated as follows:

(4) $$R_a = \frac{1}{2} r_2 M_2 + \frac{1}{6} r_3 M_3$$

where $M_i = E\left[\pi - E\left(\pi\right)\right]^i$ is the i^{th} central moment of the profit distribution,

$r_2 = -\left(\partial^2 U / \partial \pi^2\right) / \left(\partial U / \partial \pi\right)$ is the Arrow-Pratt coefficient of absolute risk aversion, and

$r_3 = -\left(\partial^3 U / \partial \pi^3\right) / \left(\partial U / \partial \pi\right)$, all evaluated at E($\pi$). Equation (3) and (4) allows us to decompose the effect of variance and skewness on the risk premium of the producer. Under risk aversion behavior (i.e., when $\partial^2 U / \partial \pi^2 < 0$ and $r_2 > 0$), an increase in profit variance would result in higher risk premium (or higher cost of private risk bearing). For the effect of the skewness of the profit distribution on the risk premium, Di Falco and Chavas (2006, 2009) shows that the risk premium tends to decrease with a rise in skewness, assuming that farmers have downside risk aversion (i.e., when $\partial^3 U / \partial \pi^3 > 0$ and $r_3 < 0$).

[5] We only use a third-order Taylor series expansion in approximating the left hand side of equation (2) as the additional terms from fourth-order (or higher-order) Taylor series expansion are close to zero for DARA/CRRA behavior.

We can empirically estimate the effect of Bt corn on risk premiums (and *CE*) from equation (4) by assuming that p is known (i.e., risk only depends on the moments of the production distribution) and then using the production function developed in Di Falco and Chavas (2006, 2009) that disaggregates the mean, variance, and skewness effects of Bt technology. The Di Falco and Chavas (2006, 2009) production function allows one to see the effect of Bt corn on the first three moments of the production distribution and, consequently, on the risk premium and CE measures. From Di Falco and Chavas (2006, 2009), consider the following econometric specification of $g(x, v)$:

$$g(x,v) = f_1\left(x,\beta_1\right) + \left[f_2(x,\beta_2) - \left[\frac{f_3(x,\beta_3)}{k}\right]^{\frac{2}{3}} \right]^{\frac{1}{2}} e_2(v) + \left[\frac{f_3(x,\beta_3)}{k}\right]^{\frac{1}{3}} e_3(v), \tag{5}$$

where $f_2(x,\beta_2) > 0$ and the random variables e_2 and e_3 are independently distributed and satisfies the following conditions: $E\left[e_2(v)\right] = E\left[e_3(v)\right] = 0$, $E\left[e_2(v)^2\right] = E\left[e_3(v)^2\right] = 1$, $E\left[e_2(v)^2\right] = 0$, and $E\left[e_3(v)^3\right] = k > 0$. Note that Di Falco and Chavas (2006, 2009) has shown that the specification in (5) is a more general expression that expands the traditional Just-Pope production function (Just and Pope, 1978, 1979) to also account for skewness. From (5), it follows that the mean, variance, and skewness of $g(x,v)$ can be represented as:

$$E\left[g\left(x,v\right)\right] = f_1\left(x,\beta_1\right) \tag{6a}$$

$$E\left[\left(g\left(x,v\right) - f_1\left(x,\beta_1\right)\right)^2\right] = f_2\left(x,\beta_2\right) \tag{6b}$$

$$E\left[\left(g\left(x,v\right) - f_1\left(x,\beta_1\right)\right)^3\right] = f_3\left(x,\beta_3\right). \tag{6c}$$

Equations (6a) - (6c) provide a flexible representation of the effects of inputs (including the Bt corn technology) on the distribution of output under uncertainty. We generally expect that the mean function in (6a) to be increasing and concave in inputs x. However, the effect of inputs x

on the variance and skewness of output is largely an empirical issue (i.e., the *i*th input could be variance increasing, neutral, or decreasing and/or skewness increasing, neutral, or decreasing). Of particular interest in this paper is the effect of Bt corn technology (represented as a dummy variable) on the variance and skewness of output.

The limitation of the Di Falco and Chavas (2006, 2009) representation of the stochastic production function in (5) is that it does not recognize the damage abating nature of insecticides and Bt corn technology. Lichtenberg and Zilberman (1986) argues that damage abating inputs (like pesticides) are different from conventional inputs (like fertilizer) in that they affect output only indirectly, by reducing the extent of damage in the event that damage occurs. In contrast, conventional outputs such as fertilizer and labor increase output directly. Hence, we extend the Di Falco and Chavas (2006, 2009) specification by using the model in Saha et al. (1997) to account for the damage abating nature of pesticides and Bt, while at the same time having a flexible risk representation that allows us to ascertain the effects of conventional and damage abating inputs on output variance and skewness.

The damage abatement production function as presented in Saha et al. (1997) is:

(7) $$y = f\left(x, \beta\right) h\left(z, \alpha, e\right) \exp\left(\varepsilon\right),$$

where *x* is a vector of conventional inputs, *z* is a vector of damage abating inputs, β and α are parameters to be estimated, and *e* and ε are error terms. Note that *e*, which is associated with the damage abatement function $h\left(\cdot\right)$, represent pest- and pesticide-related randomness ordered from good states to bad states (i.e., lower to higher unobserved pest density) and ε represent randomness related to crop growth conditions ordered from bad states to good states (e.g., poor rainfall to good rainfall). Following Saha et al. (1997), we make two assumptions on (7) to facilitate identification and estimation: (i) the damage abatement function is specified as:

$h(z,\alpha,e) = \exp\left[-A(z,\alpha)e\right]$ where $A(\cdot)$ is a continuous and differentiable function, and (ii) the two error terms have the following properties: $\varepsilon \sim N(0,1)$, $e \sim N(\mu,1)$, and $\operatorname{cov}(\varepsilon,e) = \rho$. Under these assumptions, the natural logarithm of output has a normal distribution:

(8) $$\ln(y) \sim N\left[\left[\ln(f(x,\beta)) - \mu A(\cdot)\right], B(\cdot)\right],$$

where $B(\cdot) \equiv \left[1 + A(\cdot)^2 - 2A(\cdot)\rho\right]$ and is defined as the variance of $\ln(y)$. The implication of (8) is that output *y* is log-normally distributed (Saha et al., 1997).[6] Thus, utilizing the moment formulas for the log-normal distribution (Johnson, Kotz, and Balakrishnan, 1994), the mean, variance, and skewness of the output distribution from the damage abatement specification can be derived as follows:[7]

(9a) $$E(y) = f(\cdot) \times \left[\exp\left(\tfrac{B(\cdot)}{2} - \mu A(\cdot)\right)\right]$$

(9b) $$V(y) = E\left[y - E(y)\right]^2 = \left(E(y)\right)^2 \times \left[\exp\left(B(\cdot)\right) - 1\right]$$

(9c) $$S(y) = E\left[y - E(y)\right]^3 = \left(E(y)\right)^3 \times \left[\exp\left(B(\cdot)\right) + 1\right] \times \left[\exp\left(B(\cdot)\right) - 1\right]^2.$$

The specification above allows the damage abating inputs and technologies in $h(\cdot)$ to have marginal effects on the variance and skewness of output that are independent of the marginal effects on the expected value of input. Hence, flexibility with respect to risk is retained while maintaining the damage abatement specification.

[6] Although there may be other parametric or non-parametric distributions that can characterize farm output better, the log-normal distribution have a history of being used in empirical agricultural economics studies (see, for example, Tirupattur et al., 1996; Shankar et al., 2007)

[7] The detailed derivation of the moment conditions from the damage abatement production functions are presented in the Appendix.

Empirical Setting and Data

Data

Corn is the second most important crop in the Philippines after rice, with approximately one-third of Filipino farmers (~1.8 million) depending on corn as their major source of livelihood. Yellow corn, which accounts for about 60% of total corn production (white corn accounts for the rest), is the corn type that is considered in this study. Corn in the Philippines is typically grown rainfed in lowland, upland, and rolling-to-hilly agro-ecological zones of the country. There are two cropping seasons per year – wet season cropping (usually from March/April to August) and dry season cropping (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 (Mendoza and Rosegrant, 1995; Gerpacio et al., 2004).

The most destructive pest in the major corn-producing regions in the Philippines is the Asian corn borer (*Ostrinia furnacalis Guenee*) (Morallo-Rejesus and Punzalan; 2002). Over the past decade or so, corn borer infestation occurred yearly (i.e., infestation is observed in at least one region yearly) with pest pressure being constant to increasing over time. Farmers report that yield losses from this pest range from 20% to 80%. Although the Asian corn borer is a major pest in the country, insecticide application has been moderate compared to other countries in Asia (i.e., China) (Gerpacio et al., 2004). Gerpacio et al. (2004) also report that corn farmers in major producing regions only apply insecticides when infestation is high.

With the Asian corn borer as a major insect pest for corn in the country, the agricultural sector was naturally interested in Bt corn technology as a means of control. In December 2002, after extensive field trials, the Philippine Department of Agriculture (DA) provided regulations for the commercial use of GM crops and approved the commercial distribution of Bt corn (specifically Monsanto's *Yieldgard*^{TM} *818* and *838*). In the first year of its commercial adoption, 2002, Bt corn were grown in only 1% of the total area planted with corn – on about 230,000 hectares. In 2008, about 12.8% of corn planted was Bt, and in 2009 this increased to 19% equal to about 500,000 hectares (GMO Compass, 2010). Apart from Monsanto, Pioneer Hi-Bred (since 2003) and Syngenta (since 2005) sell Bt corn seeds in the Philippines.

The data used in this study come from two sources: (1) the International Service for the Acquisition of Agri-Biotech Applications (ISAAA) corn surveys for crop years 2003/2004 in the Philippines and (2) the International Food Policy Research Institute (IFPRI) corn surveys for crop years 2007/2008 in the Philippines. These are two separate cross-section data sets with different samples in 2003/2004 and 2007/2008 (i.e., it is not a panel data set). Data collected in the survey included information on corn farming systems and environment, inputs and outputs, costs and revenues, marketing environment, and other factors related to Bt corn cultivation were collected (i.e., subjective perceptions about the technology). Actual data collection was implemented through face-to-face interviews using pre-tested questionnaires.

The 2003/2004 survey considered four major yellow corn growing provinces: Isabela, Camarines Sur, Bukidnon, and South Cotabato. To arrive at the sample of Bt respondents to be surveyed, three towns and three barangays (i.e, the smallest political unit in the Philippines) within each town were initially chosen in each of the four provinces based on the density of Bt corn adopters in the area. Using a list of Bt corn farmers from local sources (i.e., local Monsanto office), simple random sampling was used to determine Bt corn respondents within selected barangays. The exceptions were in Camarines Sur and Bukidnon where all Bt respondents were included due to the small number of Bt corn farmers in the selected barangays within these two provinces (Note that 2003/2004 is only the second season that Bt corn was available in the

Philippines). The non-Bt sample was then selected by randomly sampling from a list of non-Bt farmers in the proximity of the selected Bt farmers (i.e., typically within the same barangay) to minimize agro-climatic differences between the subsamples. In addition, to facilitate comparability, physical and socio-economic factors were compared to assure that adopters and non-adopters were “similar”. The factors compared include yield, area, farming environment, input use, insecticide use, costs and returns, reasons for adoption, knowledge about Bt corn, information sources, and perceptions on planting Bt corn.[8] After removing observations due to incomplete information and missing data issues, 407 observations (out of the 470 randomly selected respondents) are used in the analysis for the 2003/2004 crop year (101 Bt adopters and 306 non-Bt adopters).

The 2007/2008 survey was confined to the provinces of Isabela and South Cotabato since both are major corn producing provinces in the country where a high number of the Bt adopters reside. An important difference between the 2007/2008 data and the 2003/2004 data is that the non-Bt farmers in the 2007/2008 data are strictly hybrid corn users. There are no non-Bt farmers that used traditional varieties in the 2007/2008 data, while in the 2003/2004 data the non-Bt farmers are a mixture of farmers that used hybrid and traditional varieties. The IFPRI administrators of the 2007/2008 survey restricted the non-Bt farmers in 2007/2008 to only be hybrid users to be able to meaningfully see the performance difference between Bt corn relative to a more homogenous population of non-Bt farmers (i.e. hybrid corn users only). Unfortunately we could not reliably delineate the proportion of traditional and hybrid variety users in the data we received. Seventeen top corn producing barangays from four towns were selected from these

[8] The sampling procedure for non-Bt respondents was designed as such to reduce potential selection problems. This sampling approach reduces “placement bias” that is related to the promotion programs of seed companies that are only focused in certain locations. Also, “placement bias” is not a critical issue given that seed companies’ promotion efforts were uniformly performed in the major corn growing provinces included in the survey (based on our consultation with Philippine social scientists working in those areas).

two sites. The farmers interviewed were randomly chosen from lists of all yellow corn growers in each barangay. As above, after removing observations with incomplete information and missing data, 466 observations (out of 468) are used in the analysis for the 2007/2008 crop year (254 Bt adopters and 212 non-Bt adopters). Note that the crop year 2007/2008 was considered a bad weather year for corn due to an extreme dry spell in Isabela province and unusually heavy rains in South Cotabato province (Yumul et al., 2010).

Estimation Procedures and Empirical Specification

In our analysis, the input variables, *x*, included in the stochastic production functions include four input variables (seed (in kg/ha), fertilizer (in kg/ha), insecticide (in li/ha), and labor (in mandays/ha)), as well as a Bt dummy variable (=1 if Bt adopter; =0 otherwise).[9] The dependent variable *y* is corn yield (in tons/ha).

For Di Falco and Chavas (2006) production function, we use the approach described in Di Falco and Chavas (2006) (which is also described in Just and Pope, 1979 and Antle, 1983) to estimate the parameters β_1, β_2, and β_3. First, we estimate the following "mean" regression model (equation (6a)) using nonlinear least squares (NLS): $y = f_1(x, \beta_1) + e$, resulting in a consistent first round estimate $\hat{\beta}_1$ and $\hat{e} = y - f_1(x, \hat{\beta}_1)$. Second, the parameters of the variance and skewness equations (β_2 and β_3 in (6b) and (6c)) are estimated by using the following specification: $\hat{e}^i = f_i(x, \beta_i) + \varepsilon_i$ for i = 2, 3. But note that the variance of *e* is $f_2\left(x, \beta_2\right)$ and the variance of ε_i is $\left[f_{2i}(x, \hat{\beta}_i) - \left(f_i(x, \hat{\beta}_i) \right)^2 \right]$. It follows that the regression models to be estimated in the first,

[9] We recognize that there may be other observable farm-level variables (i.e., farming experience, education, etc.) that can affect yield. As explained below, we control for these issues using propensity score matching (PSM). This allows us to have a parsimonious production function specification that eases convergence problems especially in the estimation of the extended Saha et al. (1997) model. The parsimonious specification here is consistent with the specification in Shankar et al. (2007).

second, and third steps above exhibit heteroskedasticity and this is accounted by using weighted NLS and/or White's heteroskedasticity robust standard errors.

Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were the specification tests undertaken to determine which functional forms would best fit in $f_i(x, \beta_i)$ for i = 1, 2, 3 (equations (6a) to (6c)). Based on Specification tests, we use the Cobb-Douglas functional form for the mean and variance, and use the linear functional form for the skewness.

For the extended Saha et al. (1997) model in equations (7) – (9), the parameters (β, α, μ, ρ) are estimated directly using maximum likelihood estimation. From equation (8), the log-likelihood function of equation (7) can be represented as follows:

$$(10) \qquad LLF\left(\beta,\alpha,\mu,\rho\right)=\frac{n}{2}\ln(2\pi)-\frac{1}{2}\sum_i\left\{B_i\left(\cdot\right)+\frac{\left[\ln y_i-\ln f_i\left(\cdot\right)+\mu A_i\left(\cdot\right)\right]}{B_i\left(\cdot\right)}\right\},$$

where i indexes the observations in this case. Specification tests were again used to determine the functional form for $f\left(\cdot\right)$ and $A\left(\cdot\right)$. As with the Di Falco and Chavas (2006, 2009) mean and variance specification above, the Cobb-Douglas functional form was found to best fit $f\left(\cdot\right)$ and $A\left(\cdot\right)$, and this functional form is used in the estimation for the extended Saha et al. (1997) model.

One issue that needs to be dealt with at this point is the possibility of selection problems due to the non-random selection of Bt adopters. Since the adoption of Bt is not randomly assigned it is possible that there are unobservable variables (not included in the production function specification) that affect both the outcome variable y and the decision to adopt Bt. For example, it is likely that farmers who adopt Bt are those with better management ability (or are more efficient) than the non-Bt adopters. Since management ability is unobserved and not included in the stochastic production function specification, it can be that the observed difference between the yields (or risks) of Bt and non-Bt adopters is due to the systematic difference in management abilities between the two groups (i.e., not due to the Bt technology per se).

We account for this selection problem by using propensity score matching (PSM). Ideally, the best "control" group for which to compare the performance of the Bt adopters is the Bt adopters themselves had they not adopted Bt (i.e., the so-called counterfactual). However, this is unobservable since Bt adopters cannot be non-adopters at the same time. Hence, non-adopters are typically used as the "proxy" counterfactual. But as mentioned above, the problem with this is that there may be variables (i.e. management ability) that systematically determine whether or not a farmer adopts Bt and these variables also affect the yields (or risks) of the producers. In our PSM, logit models of Bt adoption is first estimated to generate propensity scores for Bt and non-Bt adopters. Using the estimated propensity scores, the PSM approach enables us to find matching non-Bt adopters that are "similar" to the Bt-adopters so that valid yield (or risk) impacts of Bt technology can be estimated. We include a number of independent variables in the logit adoption model so as to cover all possible variables that could determine adoption and yields are accounted for.[10] Then one-to-one matching without replacement is used to match non-Bt adopters with similar propensity scores with Bt-adopters. Selection and endogeneity tests are conducted on this matched sample to determine whether the selection/endogeneity issues are accounted for through PSM.

Once the parameters of the production functions are estimated using the matched sample, the welfare implications of Bt adoption is assessed using the risk premium (R) and certainty equivalent (CE) measures defined in equations (4) and (2), respectively. To calculate these two

[10] The summary statistics of the variables included in the logit estimation model for 2003/2004 and 2007/2008 are in Appendix Table 2. Note that in the spirit of conciseness, we did not thoroughly discuss the PSM procedure here. But the interested reader is referred to Wooldridge (2002), Godtland et al. (2004), and Rodriguez et al. (2007) for a more detailed description of the PSM approach.

welfare measures, we assume that the farmer's utility is represented by a constant relative risk aversion (CRRA) utility function: $U(\pi) = -\pi^{1-r}$, where $r > 1$ is the coefficient of relative risk aversion. We use $r = 2$ where $U(\pi) = -1/\pi$ in our analysis.[11] This characterization of the utility function was chosen because it reflects risk aversion and DARA behavior (see footnote 2). The "approximate" risk premium (as defined in equation (4)) is then calculated so that the variance effect and the skewness effect of Bt can be assessed separately. The *CE* measure is calculated next using equation (2) where p is the average output price gathered from the survey and $c(x)$ is a vector of average input costs also calculated based on the survey data.[12]

Another welfare measure considered in this study is the Lower Partial Moment (LPM) measure (see Berg and Strap, 2006; Unser, 2006). This measure only considers the lower part of the profit distribution as follow:

$$LPM_m^{\pi_0} = \int_{-\infty}^{\pi_0} (\pi_0 - \pi)^m f(\pi) d\pi \tag{11}$$

where π_0 is the farmer's profit target, π is the farmer's profit, $f(\pi)$ is the profit distribution, and m is the order of LPM (i.e., the weight placed on negative deviation from π_0). We set the farmer's profit target as zero and use $m = 0$, which is essentially the probability of a profit loss from growing Bt or non-Bt corn.[13] To calculate equation (11), we used both the estimates from the Di Falco and Chavas (2006, 2009) and the extended Saha et al. (1997) production function. This allows us to simulate a profit distribution (at the mean values of all inputs, output price, and costs) and then calculate the LPM in (11).

[11] The coefficient of relative risk aversion between 2 and 2.5 is typically considered as a sign of moderate risk aversion (Di Falco and Chavas, 2009), which is why we chose r=2 in our analysis. We also analyze the case of r=3 and the results of this analysis are similar to r=2. These results are available from the authors upon request.

[12] To assure the existence of $U(.)$ and facilitate the computation of R and CE, we added a fixed, positive wealth level (W) such that $(\pi + W) > 0$.

[13] The other most frequently used orders of LPM are when k=1 and 2 which refer to the profit loss expectation and the profit loss variance respectively.

Results

Descriptive Statistics and Propensity Score Matching (PSM) Results

The summary statistics for the variables used in the stochastic production function estimation are presented in Table 1. In both crop years, the mean yields of Bt farmers tend to be larger than those for the non-Bt farmers. Average fertilizer application in both years also tends to be larger for Bt farmers than for non-Bt farmers.

PSM was undertaken in this study to account for possible selection issues with regards to Bt adoption. This sub-sample of matched Bt and non-Bt farmers are used to then estimate the stochastic production function.[14] Based on our PSM runs, there are 91 matched Bt and non-Bt observations for 2003/2004 and 147 matched Bt and non-Bt observations for 2007/2008.[15] The summary statistics for the matched sample are presented in Table 2. Similar to the full sample, the mean yields of Bt farmers tend to be larger than those for the non-Bt farmers.

Stochastic Production Function Results: Di Falco and Chavas (2006, 2009)

The parameter estimates of the stochastic production function based on the Di Falco and Chavas (2006, 2009) specification (using the matched sample) are presented in Table 3. For the mean function (Panel A), Bt technology has a statistically significant positive effect on mean corn yields at the 1% level in both 2003/2004 and 2007/2008. This suggests that Bt corn does have a strong statistically significant mean yield increasing effect in the Philippines for both years under consideration. In 2003/2004, insecticide and fertilizer inputs have statistically significant positive effects on mean yields (as expected), while labor unexpectedly has a negative effect on mean

[14] The first stage logit estimates for the PSM, comparison of means of the observable characteristics for the matched and unmatched data are in Appendix Tables 2and 3.

[15] Common support restrictions were imposed that resulted in the reduction of the number of Bt farmers in the matched sample. The matched sample also passed the balancing test (i.e., at different strata the equality of means of observed characteristics are satisfied). Selection and endogeneity tests also indicate that none of these issues were present after matching. Results of these tests and the common support restrictions are available from the authors upon request.

yields. In 2007/2008, only fertilizer and labor have statistically significant positive effects on mean yields, while the seed and insecticide effects are statistically insignificant.

Based on the estimated variance and skewness functions (Panel B and C), our results suggest that Bt has no statistically significant effect on the variance and skewness of corn yields.[16] This result indicates that Bt corn does not provide strong risk reducing effects (i.e., no evidence of variance reduction and/or downside risk reduction). No inputs seem to have a statistically significant effect on variance and skewness of output in both crop years for the Di Falco and Chavas (2006, 2009) specification.

To ascertain the magnitude of the impact of Bt, we calculate the marginal effects of Bt on the mean, variance, and skewness of yields and present it in Table 5 (Panel A).[17] Because the Bt variable is binary, the marginal effects are calculated as follows $\left(E(y)\big|_{\text{Bt}} - E(y)\big|_{\text{Non-Bt}}\right)$, $\left(V(y)\big|_{\text{Bt}} - V(y)\big|_{\text{Non-Bt}}\right)$, and $\left(S(y)\big|_{\text{Bt}} - S(y)\big|_{\text{Non-Bt}}\right)$, with all other variables held fixed at their mean values. The marginal effect results again suggest that Bt has a statistically significant mean increasing effect, but there is no statistical evidence of any risk effects (i.e., no significant yield variance or skewness effect).

Stochastic Production Function Results: Extended Saha et al. (1997)

In Table 4, the parameter estimates of the extended Saha et al. (1997) model are presented. The results for crop year 2007/2008 suggests that the 'conventional' (non-damage abating) inputs –

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[16] We also estimated the coefficient of variation (CV) function by estimating $|\hat{e}| / f_1(x, \hat{\beta}_1) = CV(x, \beta_{cv}) + \varepsilon_{cv}$ where $\hat{e}^2$ is the residual from estimated mean function $f_1(x, \hat{\beta}_1)$ and $CV(\cdot)$ is the CV function. The results from this specification also suggest that Bt has no effect on CV. These results guard against the criticism that the variances tend to increase along with increases in the mean. The coefficient of variation (CV) is an alternative measure of risk when comparing two groups (Bt and non-Bt in our case) that have different means.

[17] Since the functional form of the mean and variance functions are Cobb-Douglas, the marginal effects of Bt are not equal to estimated parameters associated with the Bt variable in Panels A and B of Table 3 (which is why the marginal effects of Bt on the mean and the variance has to be separately calculated). But the marginal effect of Bt on skewness is indeed the parameter estimate from the skewness function since this is specified as a linear function.

fertilizer and labor– have a statistically significant positive effect on mean yields, which we expected a priori. In 2003/2004, the only conventional input that has a statistically significant effect on mean yields is fertilizer.[18] These inferences are consistent with the parameter estimates from the Di Falco and Chavas (2006, 2009) specification seen in Table 3.

Similar to the Di Falco and Chavas (2006, 2009) approach above, the marginal effect of Bt on the mean, variance, and skewness of yields are calculated as $\left(E(y)\big|_{\text{Bt}} - E(y)\big|_{\text{Non-Bt}}\right)$, $\left(V(y)\big|_{\text{Bt}} - V(y)\big|_{\text{Non-Bt}}\right)$, and $\left(S(y)\big|_{\text{Bt}} - S(y)\big|_{\text{Non-Bt}}\right)$, with all other variables held fixed at their mean values using the parameter estimates in Table 4. The marginal effects again suggest that Bt has a strongly significant positive effect on mean yields. Note that the magnitudes of these mean effects are also fairly similar to the ones estimated for the Di Falco and Chavas (2006, 2009) model. In 2007/2008, the results from Table 5 also suggest (as in the Di Falco and Chavas, (2006, 2009) approach) that Bt does not have a statistically significant effect on the variance and skewness of yields (i.e., no significant risk effects). But in 2003/2004, the results from Table 5 suggest that Bt has a statistically significant variance and skewness increasing effects on output.

Welfare Effects: Risk Premium, CE estimates, and the Probability of Profit Loss

Since most of the cases show the insignificant effect of Bt on production risk (e.g., variance and skewness of yields), there would have been no statistical difference between the risk premiums of Bt farmers and non-Bt farmers, except for the case of the extended Saha et al. (1997) model for crop year 2003/2004. Thus, it would be straightforward to infer that the strong positive mean yield effect of Bt will result in a higher *CE* welfare measure for Bt farmers relative

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[18] Another important parameter in Table 4 is ρ, which represents the covariance of the error terms e and ε in equation 7. As explained in Shankar (2007), the strongly significant ρ suggests that the Saha et al (1997) model is preferred over the standard damage abatement specification where the correlation of these terms is zero. In the context of this study, a positive ρ also implies that the higher unobserved pest densties are higher when unobserved growth conditions are better (i.e., adequate rainfall).

to the non-Bt farmers (i.e., based on *CE*, Bt will be preferred). However, it would also be interesting to see whether the CE of Bt farmers would have still been larger than the *CE* of non-Bt farmers had the estimates of the variance and skewness effects of Bt were statistically significant. From Table 5, the parameter estimates from the Di Falco and Chavas (2006, 2009) models suggest that Bt is variance reducing (i.e. decreases risk) and skewness reducing (i.e., increases downside risk), while the parameter estimates from the extended Saha et al. (1997) model indicates that Bt is variance increasing (i.e., increases risk) and skewness increasing (i.e., reduces downside risk). Will the mean yield effect of Bt corn still overwhelm the risk effects of Bt had the risk effects actually been significant in the estimation? Would the *CE* estimate still be higher for Bt farmers in this case?

To answer these questions, we use the parameter estimates in the variance and skewness functions (in Tables 3 and 4) to calculate the second and third moments (variance and skewness) of profits and then we computed the risk premium (*R*) associated with Bt and non-Bt corn.[19] The *CE* can then be calculated directly using *R* and the mean expected profit (see equation (2) above). The variance and skewness components of the risk premium, the total risk premium (*R*), and the *CE* for Bt and non-Bt corn are presented in Table 6.

For the Di Falco and Chavas (2006, 2009) model, Bt production resulted in lower *R* in both crop years, which means that the variance reduction from Bt dominates the downside risk increasing effect of Bt. In contrast, the results for the extended Saha et al. (1997) model reveals that *R* is higher for Bt and, in this case, the downside risk increasing effect dominates the variance reduction effect of Bt.

[19] We calculate the approximate risk premium based on equation (4) where there is a variance component and a skewness component. The second and third moment of the profit distribution are calculated at the means of the input variables, mean corn price, and mean input costs (based on the survey data).

In 2003/2004, the *CE* for Bt farmers is statistically significantly higher than for the non-Bt farmers. Thus, even with the increasing risk premium in the extended Saha et al. (1997) model in this crop year, Bt corn technology is still preferred. In 2007/2008 crop year, the risk premium (*R*) is also higher for Bt corn farmers compared to the non-Bt farmers using the parameters from the extended Saha et al. (1997) model. Although the *CE* for Bt corn farmers is higher than the *CE* of non-Bt farmers in this case, the differences are insignificant in 2007/2008. We posit that these welfare results may be due to the type of non-Bt farmer in the 2003/2004 and 2007/2008 sample. Recall that in 2003/2004 the non-Bt farmers are composed of producers that utilize both traditional and hybrid varieties, while in 2007/2008 the non-Bt sample is strictly farmers that use hybrid varieties. Given this feature of the two data sets, it seems plausible that the statistically significant *CE* difference would be observed in 2003/2004 (i.e. more pronounced difference between Bt and non-Bt since non-Bt includes the typically lower yielding traditional varieties), but the statistically significant difference is not observed in 2007/2008.

For the LPM measure or the probability of profit loss from growing Bt compared to non-Bt, we simulated profit distributions based on equation (5) and (7) using the parameter estimates from Table 3 and 4 at mean values of all inputs, output price, and costs (i.e. these means are based on the survey data). The simulated profit distributions of Bt and non-Bt farmers for both the Di Falco and Chavas (2006, 2009) and the extended Saha et al. (1997) production functions are presented in Figure 1 and 2 respectively. The area under the profit distribution curve to the left of zero profit is the probability of profit loss. For the Di Falco and Chavas (2006, 2009) model, these areas are smaller for the Bt farmers (area under the curve of 0.014 for crop year 2003/2004 and 0.089 for crop year 2007/2008) as compared to the non-Bt farmers (area under the curve of 0.072 for crop year 2003/2004 and 0.125 for crop year 2007/2008) as shown in

Figures 1A and 1B. This implies that Bt corn has a reduced probability of profit loss. For the extended Saha et al. (1997) model, the area under the profit distribution curve to the left of zero profit for crop year 2003/2004 is equal to 0.047 for Bt farmers which is smaller as compared to the area of 0.091 for non-Bt farmers. But for crop year 2007/2008, these areas are very close (0.119 for Bt and 0.125 for non-Bt) and we cannot definitively conclude that Bt corn has a lower probability of profit loss compare to non-Bt farmers that use hybrid corn in this case. We also formally tested for the equality of the areas under the profit distribution curve to the left of zero for the Bt farmers versus the non-Bt farmers. The results are consistent to what we see from the graphs in that we reject the null hypothesis of equality of the probability of profit loss between Bt and non-Bt farmers, except for the extended Saha et al. (1997) model using the 2007/2008 data (i.e., there is no significant difference in the probability of profit loss for Bt and non-Bt farmers in this case).

Another profit/welfare oriented issue that would be informative here is to determine whether the observed benefits from the mean yield effects of Bt corn compensate for the increased cost of using the Bt seed technology. This is important because it is possible that Bt increases mean yields but the cost could have been prohibitive such that the higher Bt seed costs negate the benefits from the yield increase. Based on the yield effects estimated in Table 5, as well as corn prices and seed costs from the data, we find that the estimated revenue benefits of Bt more than compensates for the increased cost of the Bt seed (See Table 7). However, the net revenue above seed cost for Bt farmers is only statistically significant in the 2003/2004 crop year and not in 2007/2008. This is fairly consistent with the simulation results from the LPM analysis above (See Figures 1 and 2).

Conclusions

This paper investigates the impact of Bt corn technology on production risk and farmer welfare within a developing country environment. We used two separate farm-level survey data of corn production collected in the Philippines for the 2003/2004 and 2007/2008 crop years to conduct our analysis.

Two stochastic production functions are estimated to evaluate the mean, variance, and skewness effects of Bt technology on corn yields. Propensity score matching was used to account for potential selection bias due to the non-random placement of Bt "treatment". Results from the stochastic production function estimates indicate that Bt corn has a strong statistically significant mean yield increasing effect, but there seems to be no overwhelming evidence that Bt technology significantly reduces production risk (i.e., in majority of the cases examined, Bt has no significant variance/risk and skewness/downside risk effect). Hence, these results imply that we cannot strongly attribute production risk reduction as a characteristic of single-trait Bt corn technology in the Philippines. Based on our results, one can only say that single-trait Bt corn technology (that primarily controls for a single lepidopteran pest such as Asian corn borer) tend to increase mean yields but there is no strong evidence to suggest that this technology reduces production risk.

This result is somewhat expected based on the study of the National Research Council (2010, p. 144-145) where agronomic risk reduction is predominantly observed for Bt crops that control for corn rootworm (rather than or in addition to lepidopteran pests). This study explains that corn rootworm protection from Bt may allow for a denser root system that tends to reduce risk from extreme bad events. In fact, the crop insurance premium discount for Bt corn in the US was only applicable to the "triple-stack" (or three-trait) Bt corn variety where there are Bt toxins controlling for both corn borer and corn rootworm, as well as having herbicide resistance. The yield risk reduction that prompted the premium rate discount in the US is not applicable for single-trait Bt corn varieties that only control for corn borer. This is consistent with our results where we find that single trait Bt corn that only controls for corn borer does not have statistically significant yield risk reducing effect.

In terms of the welfare effects of Bt corn, the strong mean yield increasing effect of Bt corn in the Philippines and the mostly statistically insignificant risk effects theoretically implies that the certainty equivalent measures for Bt farmers should be higher than those for non-Bt farmers. Even if the estimated risk effects are assumed to be significant in all cases we examined, our analysis still shows the that the mean yield increasing effect of Bt corn tend to dominate the risk effects such that the magnitude of the overall welfare measure (i.e., the certainty equivalent) for Bt farmers is larger than those of non-Bt farmers. However, the higher certainty equivalents for Bt farmers over non-Bt farmers are only statistically significant for the 2003/2004 data and not for the 2007/2008 data. This may be due to the feature of the two data sets where the non-Bt producers in 2003/2004 are a mixture of traditional and hybrid users, while the non-Bt producers in 2007/2008 are only hybrid users.

Consistent with the certainty equivalent welfare results above, we find that the probability of suffering a profit loss is lower for Bt farmers than for non-Bt farmers. This statistically lower probability of loss for Bt farmers was strongly observed for the 2003/2004 data, but not in the 2007/2008 data (especially using the extended Saha et al. (1997) model). Again, this may be due to the fact that the non-Bt farmers in 2003/2004 data are a mixture of traditional and hybrid users, while the non-Bt producers in 2007/2008 are only hybrid users. This implies that there may not be much difference in the probability of profit loss between farmers who use hybrid corn and those who use Bt corn.

Although this paper provides important insights to the risk effects of Bt corn, it is important to keep in mind the limitations of our analysis. First, this study only uses data from two separate cross-sectional data sets, rather than a panel data set. Using a panel data set in the future would enable one to better account for individual farmer heterogeneity and selection issues. A panel data analysis with more than two years of data would also provide more insights into the dynamics and evolution of production risk over time. Second, we only focus on a particular "single-trait" Bt corn variety for a specific developing country. As multi-trait Bt corn varieties become more widely available across the globe, it would be interesting to see whether the risk reduction observed for triple-stack varieties in the US can also be observed in other parts of the world -- particularly in a developing country context where smallholder farmers typically have limited options to manage risk. If these triple-stack varieties improve yields and reduces risk in developing countries, then small subsistence farmers would likely benefit more from this multi-trait Bt technology. Third, the results of our study are greatly dependent on the crop growth conditions during the survey years. We observe that the mean yield increasing impact of Bt technology is more effective in the year with good weather (i.e., the crop year 2003/2004) compared to the year with poor weather (i.e., the crop year 2007/2008). This may be due to the fact that pest infestation tend to be high in good weather and Bt technology provides a larger yield advantage under conditions of high pest infestation (Ma and Subedi, 2005; Shankar et al., 2007). However, this result is opposite to the observation in Mutuc et al. (2011) where the mean yield effect of Bt tends to be stronger under poor weather conditions rather than good weather conditions. But note that the Mutuc et al. (2011) study did not account for the potential variance and skewness effects of Bt, which may account for the difference in results. Future work should focus on carefully examining the role of weather conditions on the yield impacts of Bt technology.

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Table 1. Summary Statistics for the Full Data Set in 2003/2004 and 2007/2008.

Variable	--- Crop Year 2003/2004 ---				--- Crop Year 2007/2008 ---			
	Bt (n=101)		Non-Bt (n=306)		Bt (n=254)		Non-Bt (n=212)	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Yield (tons/ha)	4.85	0.16	3.60	0.08	4.68	0.11	3.73	0.12
Seed (kg/ha)	19.13	0.50	18.43	0.24	18.35	0.24	19.42	0.36
Insecticide (li/ha)	0.26	0.05	0.77	0.10	0.25	0.05	0.99	0.12
Fertilizer (kg/ha)	452.02	17.98	400.65	9.84	475.13	13.00	391.60	10.65
Labor (man-days/ha)	54.19	2.51	56.64	1.92	53.94	1.89	49.80	1.57

Table 2 Summary Statistics for the Matched Data Set in 2003/2004 and 2007/2008.

Variable	--- Crop Year 2003/2004 ---				--- Crop Year 2007/2008 ---			
	Bt (n=91)		Non-Bt (n=91)		Bt (n=147)		Non-Bt (n=147)	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Yield (tons/ha)	4.83	1.61	4.01	1.51	4.57	1.46	4.06	1.70
Seed (kg/ha)	19.22	5.23	18.27	3.24	18.25	3.61	19.64	5.09
Insecticide (li/ha)	0.23	0.50	0.89	2.02	0.22	0.61	1.10	1.74
Fertilizer (kg/ha)	454.81	180.33	394.01	145.41	476.17	212.26	425.02	166.25
Labor (man-days/ha)	54.47	24.62	51.16	24.32	51.12	27.37	51.27	22.21

Table 3. Parameter estimates for the Di Falco and Chavas (2006, 2009) stochastic production function: Bt corn.

Equation/Variable	Crop Year 2003/2004		Crop Year 2007/2008	
	Estimate	p-value	Estimate	p-value
A. Mean function				
Constant	1.830	0.03	0.694	0.01
Seed	0.114	0.31	-0.097	0.34
Insecticide	0.016	0.04	-0.006	0.39
Fertilizer	0.156	0.02	0.220	<0.01
Labor	-0.112	0.04	0.186	<0.01
Bt	0.216	<0.01	0.080	0.08
B. Variance function				
Constant	7.531	0.78	0.230	0.53
Seed	-0.841	0.49	0.193	0.62
Insecticide	-0.045	0.17	0.016	0.46
Fertilizer	-0.033	0.89	0.367	0.15
Labor	0.323	0.44	-0.110	0.46
Bt	-0.070	0.80	-0.210	0.20
C. Skewness function				
Constant	-6.211	0.39	-0.094	0.97
Seed	0.191	0.65	0.096	0.51
Insecticide	0.067	0.87	-0.363	0.46
Fertilizer	0.012	0.18	-0.003	0.51
Labor	-0.017	0.83	0.020	0.44
Bt	-0.558	0.83	-1.104	0.38

Table 4. Parameter estimates for the extended Saha et al. (1997) stochastic production function: Bt corn.

Parameter	Crop Year 2003/2004		Crop Year 2007/2008	
	Estimate	p-value	Estimate	p-value
Constant	13.140	0.08	1.416	0.83
Seed	0.118	0.42	-0.089	0.45
Fertilizer	0.104	0.04	0.296	<0.01
Labor	-0.130	0.08	0.234	<0.01
Insecticide	-0.013	0.30	0.007	0.40
Bt	-0.132	0.21	-0.066	0.36
ρ	0.919	<0.01	0.922	<0.01
μ	1.637	0.25	1.475	0.32

Table 5. Estimated mean, variance, and skewness effects of Bt corn

	Mean effect $\left(E(y)\big\|_{\text{Bt}} - E(y)\big\|_{\text{Non-Bt}}\right)$	Variance effect $\left(V(y)\big\|_{\text{Bt}} - V(y)\big\|_{\text{Non-Bt}}\right)$	Skewness effect $\left(S(y)\big\|_{\text{Bt}} - S(y)\big\|_{\text{Non-Bt}}\right)$
A. Parameters from Di Falco and Chavas (2006,2009)			
Crop year 2003/2004	1.009	-0.131	-0.558
	(<0.01)	(0.80)	(0.83)
Crop year 2007/2008	0.346	-0.466	-1.104
	(0.08)	(0.19)	(0.38)
B. Parameters from extended Saha et al. (1997)			
Crop year 2003/2004	0.958	1.417	5.364
	(<0.01)	(0.02)	(0.05)
Crop year 2007/2008	0.397	0.446	1.360
	(0.07)	(0.15)	(0.20)

Note: Values in parentheses are the p-values

Table 6 Welfare effects of Bt corn: variance effect on risk premium, skewness effect on risk premium, total risk premium (*R*), and certainty equivalent (CE)

Model/Technology	--- Crop Year 2003/2004 ---				--- Crop Year 2007/2008 ---			
	Variance Part of R	Skewness Part of R	*R*	CE	Variance Part R	Skewness Part of R	*R*	CE
A. Parameters from Di Falco and Chavas (2006,2009)								
Non-Bt	3,914.14	-835.91	3,078.23	13,100	6,733.35	-917.87	5,815.47	11,834
Bt	3,084.29	-406.07	2,678.25	20,124	5,309.71	-97.01	5,212.70	13,490
p-value for equality in CE				(<0.01)				(0.47)
B. Parameters from extended Saha et al. (1997)								
Non-Bt	6,495.81	-3,621.13	2,874.68	14,563	7,907.70	-4,708.96	3,198.74	14,258
Bt	7,956.80	-4,437.46	3,519.34	20,098	8,767.49	-5,271.90	3,495.59	15,533
p-value for equality in CE				(0.04)				(0.55)

Table 7 Assessment of whether the mean yield increasing benefit from Bt corn compensates the higher cost associated with the Bt seed technology

	Yield *(tons/ha)*	Corn Price *(PhP. /Kg)*	Revenue *(PhP./ha)*	Seed Price *(PhP. /Kg)*	Seed Cost *(PhP./ha)*	Total Cost *(PhP./ha)*	Net Benefit *(PhP./ha)*
A. Parameters from Di Falco and Chavas (2006,2009)							
Crop year 2003/2004							
Non-Bt	4.177	8.56	35,766	116.86	2,190	19,588	16,178
Bt	5.187	8.56	44,408	224.55	4,209	21,606	22,802
							(<0.01)
Crop year 2007/2008							
Non-Bt	4.162	10.15	42,253	180.00	3,410	24,604	17,649
Bt	4.508	10.15	45,766	309.79	5,869	27,063	18,703
							(0.60)
B. Parameters from extended Saha et al. (1997)							
Crop year 2003/2004							
Non-Bt	4.324	8.56	37,025	116.86	2,190	19,588	17,437
Bt	5.282	8.56	45,223	224.55	4,209	21,606	23,617
							(0.03)
Crop year 2007/2008							
Non-Bt	4.143	10.15	42,061	180.00	3,410	24,604	17,457
Bt	4.540	10.15	46,091	309.79	5,869	27,063	19,028
							(0.70)

*Note: (1) Corn price, seed price, and seed costs are averages based on the data collected. All other costs are assumed equal between Bt and non-Bt farmers (only seed cost differ). (2) Values in parentheses are p-values that test equality in the net benefit levels of Bt versus non-Bt farmers.

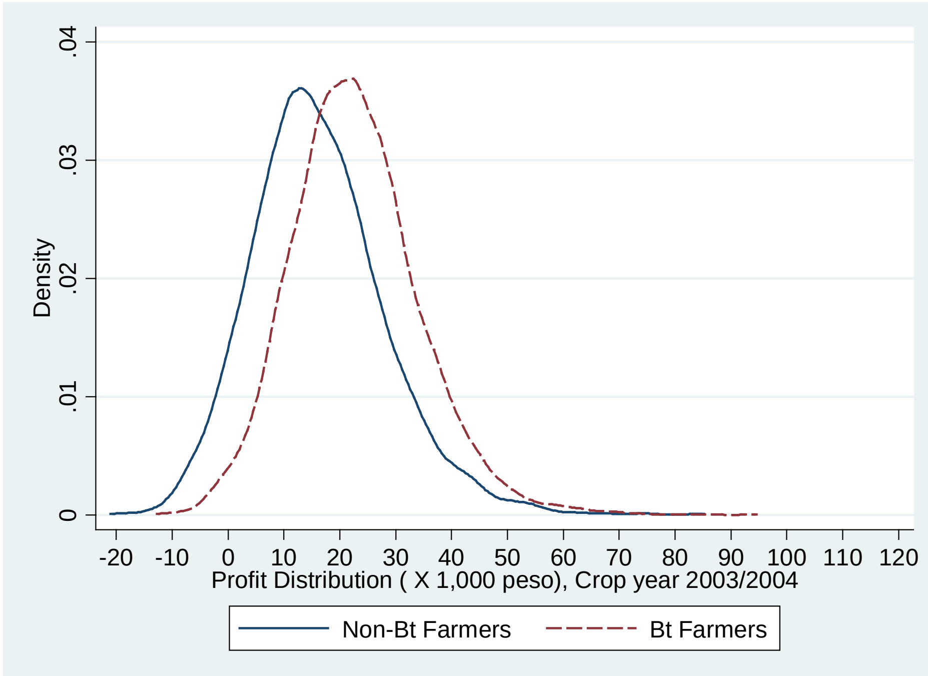

Figure 1A

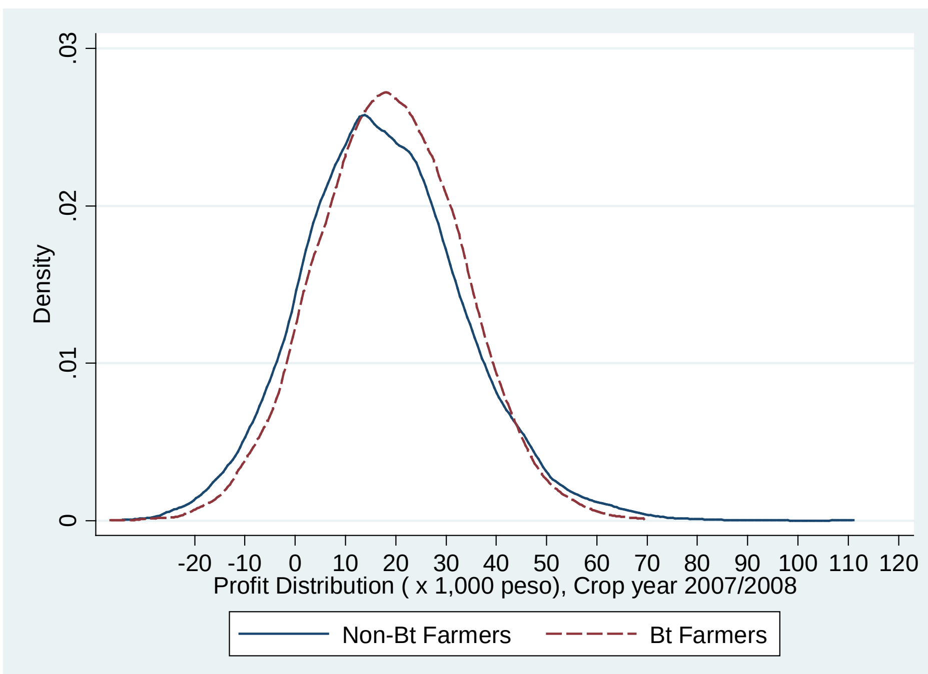

Figure 1B

Figure 1 Simulated profit distribution from Di Falco and Chavas (2006, 2009) production function for Crop Years 2003/2004 (1A) and 2007/2008 (1B)

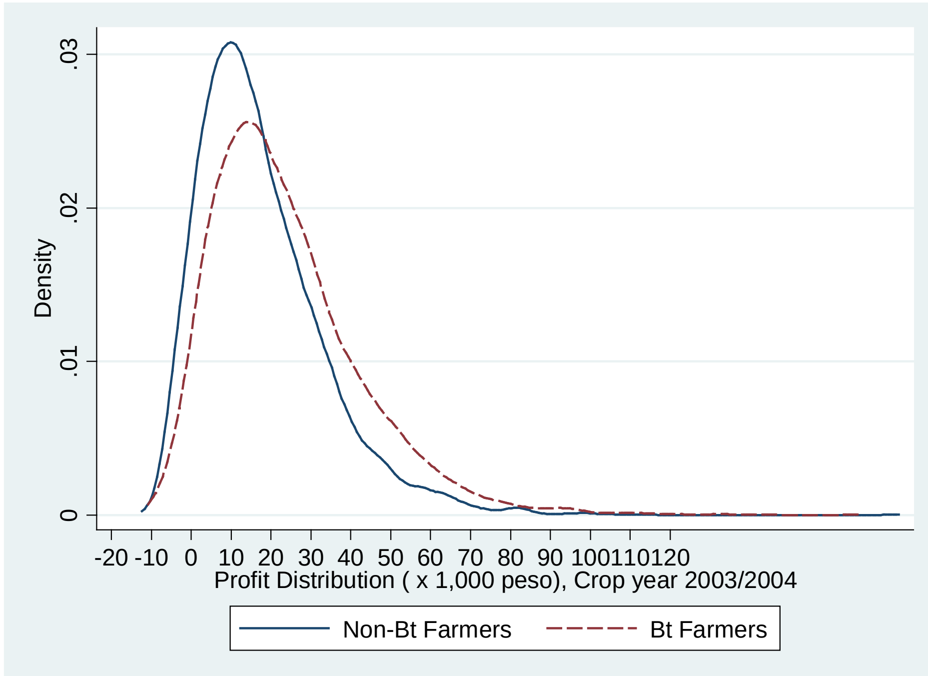

Figure 2A

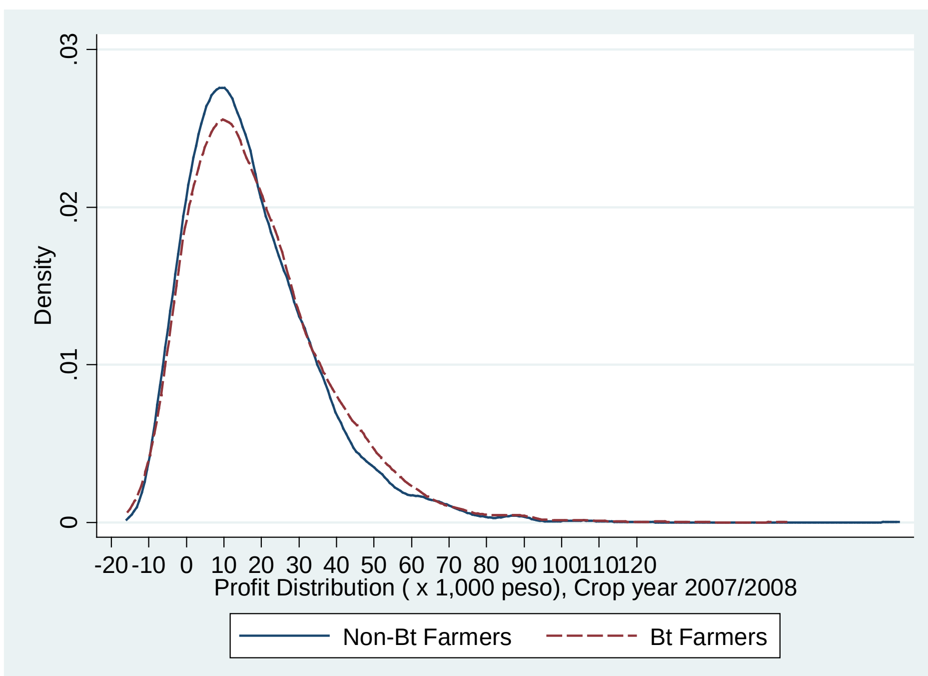

Figure 2B

Figure 2 Simulated profit distribution from Saha et al. (1997) production function for Crop Years 2003/2004 (2A) and 2007/2008 (2B)

Appendix

Derivation of the moment conditions to extend the Saha et al. (1997) model

Consider a random variable, Y, whose logarithm is normally distributed

(A1) $$\ln Y \sim N(\mu, \sigma^2)$$

The probability density function (pdf) of this distribution is

(A2) $$f_Y(Y; \mu, \sigma^2) = \frac{1}{Y \cdot \sigma\sqrt{2\pi}} \cdot e^{-(\ln(y)-\mu)^2/2\sigma^2}$$

And the moments of this distribution is

(A3) $$EY^n = e^{n\mu + n^2\sigma^2/2}$$

From equation (A3), it is readily verified that the mean of the distribution is

(A4) $$EY = e^{\mu + \sigma^2/2}$$

For the second central moment (the variance),

$$V(Y) = E(Y - EY)^2$$
$$V(Y) = EY^2 - (EY)^2$$

and based on equation (A3) the following equations hold

$$V(Y) = e^{2\mu + \frac{4\sigma^2}{2}} - (e^{\mu + \sigma^2/2})^2$$
$$V(Y) = e^{2\mu + 2\sigma^2} - e^{2\mu + \sigma^2}$$
$$V(Y) = (e^{2\mu + \sigma^2}) \cdot (e^{\sigma^2} - 1)$$

(A5) $$V(Y) = (EY)^2 \cdot (e^{\sigma^2} - 1).$$

For the third central moment,

$$S(Y) = E(Y - EY)^3$$
$$S(Y) = E(Y^3 - 3Y^2(EY) + 3Y(EY)^2 - (EY)^3)$$
$$S(Y) = EY^3 - 3(EY^2)(EY) + 2(EY)^3$$

and based on equation (A3) :

$$S(Y) = e^{3\mu + \frac{9\sigma^2}{2}} - 3(e^{2\mu + 2\sigma^2})(e^{\mu + \frac{\sigma^2}{2}}) + 2e^{3\mu + \frac{3\sigma^2}{2}}$$
$$S(Y) = e^{3\mu + \frac{3\sigma^2}{2}} \cdot (e^{3\sigma^2} - 3e^{\sigma^2} + 2)$$

(A6) $$S(Y) = (EY)^3 \cdot (e^{\sigma^2} - 1)^2 (e^{\sigma^2} + 2)$$

Let the natural logarithm of output have a normal distribution as in equation (9):

$$\ln(y) \sim N(\ln f(\cdot) - \mu A(\cdot), B(\cdot)),$$

where *A(·)* is a continuous and differentiable function appear in the damage abatement function and $B(\cdot) = [1 + A(\cdot)^2 - 2A(\cdot)\rho]$ which have been defined earlier. After substituting

$\ln f(\cdot) - \mu A(\cdot)$

for μ and *B(·)* for σ^2 in equation (A4), (A5), and (A6), the mean, variance and the third central moment of output become:

(A7) $$E(y) = \bar{y} = f(\cdot) \cdot e^{\frac{B(\cdot)}{2} - \mu A(\cdot)}$$

(A8) $$V(Y) = \bar{y}^2 \cdot e^{B(\cdot) - 1}$$

(A9) $$S(Y) = \bar{y}^3 \cdot (e^{B(\cdot)} + 2) \cdot (e^{B(\cdot)} - 1)^2$$

For damage control inputs, they only appear in function *A(·)* of the damage abatement function, not in the function *f(·)*. Therefore the effects of damage control input, z_k, on the mean, variance, and the third moment can be computed directly by differentiation of equation (A7), (A8), and (A9) with respect to z_k, after some simplification:

(A10) $$\frac{\partial E(y)}{\partial z_k} = \bar{y} \cdot (A(\cdot) - \rho - \mu) \cdot \frac{\partial A(\cdot)}{\partial z_k}$$

(A11) $$\frac{\partial V(y)}{\partial z_k} = 2\bar{y}^2[e^{B(\cdot)} \cdot (2A(\cdot) - 2\rho - \mu) - (A(\cdot) - \rho - \mu)] \cdot \frac{\partial A(\cdot)}{\partial z_k}$$

(A12) $$\frac{\partial S(y)}{\partial z_k} = 3\bar{y}^3(e^{B(\cdot)} - 1)[((e^{B(\cdot)})^2 + e^{B(\cdot)})(3A(\cdot) - 3\rho - \mu) - (2(A(\cdot) - \rho - \mu)] \cdot \frac{\partial A(\cdot)}{\partial z_k}.$$

Appendix Table 1. Summary Statistics of the variables used in PSM

Crop Year/ Variable	Bt		Non-Bt	
	Mean	St. Dev.	Mean	St. Dev.
A. Crop Year 2003/2004 (Bt: n= 101; Non-Bt: n=306)				
Farming experience (no. of years)	15.49	10.74	16.68	11.37
Education (no. of years)	9.72	3.51	7.97	3.18
Planted corn area (ha)	2.39	3.35	1.93	3.04
Training (=1 if farmer has attended an ag. training, zero otherwise)	0.47	0.50	0.42	0.49
Electricity (=1 if farmer has access to electricity, zero otherwise)	0.93	0.27	0.83	0.37
Borrow (=1 if borrowed capital, zero otherwise)	0.56	0.50	0.48	0.50
Topography (=1 if plain/flat, zero otherwise)	0.66	0.47	0.59	0.49
Extension (=1 if there is an extension worker in the area, zero otherwise)	0.61	0.49	0.64	0.48
Bukidnon (=1 if located in Bukidnon, zero otherwise; Bicol omitted)	0.13	0.34	0.35	0.48
Socsargen (=1 if located in Socsargen, zero otherwise; Bicol omitted)	0.38	0.49	0.31	0.46
Isabela (=1 if located in Isabela, zero otherwise; Bicol omitted)	0.48	0.50	0.18	0.38
B. Crop Year 2007/2008 (Bt: n= 254; Non-Bt: n=212)				
Farming experience (no. of years)	17.80	11.23	16.05	12.45
Education (no. of years)	7.65	3.30	7.45	6.25
Household size (no. of persons)	4.41	1.55	4.63	1.68
Distance to seed supplier (km)	7.59	14.71	3.58	5.23
Training (=1 if has training, zero otherwise)	0.37	0.48	0.34	0.47
Government seed source (=1 if bought seed from government, zero otherwise)	0.06	0.24	0.02	0.15
Company seed source (=1 if bought seed from company, zero otherwise)	0.62	0.49	0.68	0.47
Cooperative seed source (=1 if bought seed from cooperative, zero otherwise)	0.12	0.32	0.09	0.29
Borrow (=1 if borrowed capital, zero otherwise)	0.73	0.44	0.67	0.47
Isabela (=1 if located in Isabela, zero otherwise; South Cotabato omitted)	0.72	0.45	0.43	0.50

Appendix Table 2. First Stage Logit Results for the PSM

Crop Year/Variable	Parameter Estimate	P-value
A. Crop Year 2003/2004 (Bt: n= 101; Non-Bt: n=306)		
Farming experience	-0.016	0.223
Education	0.170	0.000
Planted corn area	0.041	0.280
Training	0.366	0.186
Electricity	0.593	0.209
Borrow	-0.142	0.637
Topography	0.765	0.028
Extension	0.346	0.227
Bukidnon	1.194	0.140
Socsargen	2.142	0.006
Isabela	3.915	0.000
Intercept	-6.129	0.000
Log-Likelihood		-174.110
Pseudo-R-squared		0.217
B. Crop Year 2007/2008 (Bt: n= 254; Non-Bt: n=212)		
Farming experience	0.013	0.135
Education	0.008	0.591
Household size	-0.041	0.534
Distance to seed supplier	0.028	0.049
Training	0.776	0.002
Government seed source	2.664	0.000
Company seed source	0.214	0.442
Cooperative seed source	0.304	0.430
Borrow	0.059	0.821
Isabela	1.557	0.000
Intercept	-1.562	0.004
Log-Likelihood		-276.485
Pseudo-R-squared		0.120

Appendix Table 3. Comparison of Means of the observable characteristics for the Unmatched and Matched Data.

Observable Variables	Unmatched Data			Matched Data		
	Bt	Non-Bt	p-value of difference	Bt	Non-Bt	p-value of difference
A. Crop Year 2003/2004						
Farming experience	15.05	16.68	0.20	14.97	14.08	0.53
Education	9.81	7.95	<0.01	9.71	9.77	0.91
Planted corn area	2.42	1.93	0.18	2.40	2.17	0.69
Training	0.48	0.42	0.29	0.47	0.45	0.77
Electricity	0.93	0.83	0.02	0.92	0.90	0.60
Borrow	0.56	0.48	0.15	0.56	0.52	0.55
Topography	0.65	0.59	0.28	0.64	0.67	0.64
Extension	0.61	0.64	0.56	0.61	0.60	0.88
Bukidnon	0.13	0.35	<0.01	0.14	0.11	0.51
Socsargen	0.37	0.31	0.26	0.38	0.46	0.30
Isabela	0.48	0.17	<0.01	0.45	0.43	0.77
B. Crop Year 2007/2008						
Farming experience	17.88	16.00	0.09	16.07	17.47	0.30
Education	7.62	8.21	0.38	8.09	8.12	0.96
Household size	4.43	4.62	0.21	4.66	4.59	0.71
Distance to seed supplier	7.59	3.58	<0.01	3.67	4.31	0.35
Training	0.36	0.33	0.41	0.31	0.35	0.39
Government seed source	0.06	0.01	0.02	0.01	0.02	0.31
Company seed source	0.62	0.69	0.10	0.65	0.67	0.71
Cooperative seed source	0.12	0.09	0.33	0.12	0.12	1.00
Borrow	0.74	0.67	0.09	0.72	0.69	0.61
Isabela	0.73	0.44	<0.01	0.63	0.61	0.72