ABSTRACT

SANGLESTSAWAI, SANTI. Economic and Risk effects of Bt Corn and Integrated Pest Management Farmer Field Schools: A Developing Country Perspective. (Under the direction of Roderick M. Rejesus).

This study consists of three essays focusing on the impacts of agricultural technologies that have been developed to reduce pesticide use in developing countries. The first essay explores the production risk effects of Bt corn in the Philippines. To analyze the risk effects of Bt corn, we first use the model developed by Di Falco and Chavas (2006, 2009) to examine the impacts of Bt corn on the mean, variance, and skewness of yields. We also extend Saha et al.'s (1997) model to study the downside risk (i.e., skewness) effects of Bt corn within a damage abatement specification. Our results indicate that single-trait Bt corn do not have a statistically significant risk reducing or downside risk reducing effect, the main benefit is through its mean yield increasing effect.

The second essay analyzes the possible heterogeneous effects of Bt crop adoption at different points of the yield distribution. To achieve this objective, we apply the instrumental variable quantile regression (IVQR) approach that has recently been developed to account for endogeneity problems specifically in quantile regression analysis. We find that the effect of Bt corn on yields is generally more strongly felt by producers at the lower end of the yield distribution, which are typically poor smallholders. Hence, this is evidence that poor farmers may benefit more from the Bt corn technology.

The third essay focuses on the impacts of Integrated Pest Management Farmer Field Schools (IPM-FFS) on input use, yield, and farmers' self-reported health status, in the context of an onion-based production system in the Philippines. Propensity score matching (PSM) and regression-based approaches that account for the potential bias due to selection

problems from observable variables are used to achieve the objective of the study. Sensitivity of our IPM-FFS impact results to potential bias due to "selection on unobservables" was also assessed. We find that farmers who participate in the IPM-FFS training program have statistically lower insecticide expenditures than the non-IPM-FFS farmers. But we do not find any evidence that the IPM-FFS training program significantly affects yield, farmers' self-reported health status, and other inputs use (i.e., labor). There is some evidence indicating that IPM-FFS farmers may have statistically higher profit levels than non-IPM-FFS producers, but these results are sensitive to and may still be invalidated by bias due to unobservable variables.

Economic and Risk effects of Bt Corn and Integrated Pest Management Farmer Field Schools: A Developing Country Perspective

by
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DEDICATION

To my family, my teachers, and my friends

BIOGRAPHY

Santi Sanglestsawai was born in 1975 in Kanchanaburi, Thailand. He received his undergraduate degree in Civil Engineering from Chulalongkorn University in Bangkok in 1997. After working as a civil engineer at the Office of Accelerated Rural Development for two years, he received a scholarship from the Dutch government (Nuffic) to pursue his study in sanitary engineering at UNESCO-IHE Institute for Water Education in Delft, The Netherlands. After he earned a Masters degree in sanitary engineering in 2002, he came back to Thailand and worked at the Department of Water Resources. While he was working at the Department of Water Resources, he realized that he wanted to learn about Agricultural Economics. He attended the Masters Program in Agricutural Economics at Kasetsart University while still working on his job at the same time. After completing his Masters degree in Agricultural Economics in 2006, he received a scholarship from the Thai government to join the Ph.D. program in Economics at North Carolina State University, with a primary field in Agricultural Economics.

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Chapter 1

Introduction

In order to feed the growing world's population (especially in developing countries), a series of research, development, and technology transfer activities spurred the so-called "green revolution" that started in the late 1960s and continues to this day. As part of this "green revolution", farmers in developing countries learned to apply high levels of chemical pesticides to control agricultural pests. Although there are a number of benefits from pesticide use (i.e., direct prevention of crop losses and increasing agricultural production), the negative impacts on farmers' and consumers' health and the environment are now also widely recognized. Due to serious concerns about the hazards of chemical pesticides, there are many efforts to reduce excessive use of insecticides in developing countries. Genetically-Modified (GM) crops and Integrated Pest Management (IPM) are among various options that have been developed to reduce pesticide use and potentially increase yield at the same time.

This dissertation is comprised of three essays analyzing the impacts of a GM crop (Bt corn) and IPM-Farmer Field School (IPM-FFS, onion), from a developing country perspective (the Philippines). The first essay (Chapter 2) analyzes the production risk effects of Bt corn. Specifically, this essay extends previous studies about production risk effects of Bt (which only considered the mean yield and yield variance impact of Bt technology) by including the effects of Bt on the skewness of yields within a damage abatement

While most of the previous studies have provided empirical evidence on the yield increasing and pesticide reducing effects of Bt crops based on the analysis at the mean (i.e., the effect of Bt technology on the mean yield and mean pesticide use), another important question is how does Bt technology affect yields at different points of the yield distribution. Knowing the effects of Bt technology at different points of the yield distribution gives a more complete picture of the economic impacts of Bt crops. The second essay (Chapter 3) aims to fill this gap in the literature by investigating the effect of Bt corn adoption at different points of the yield distribution and determining whether lower yielding farmers benefit from this technology the same way the "average" yielding farmer does.

The third essay (Chapter 4) focuses on another pesticide reducing concept -- the IPM-FFS. This essay aims to comprehensively examine the impact of IPM-FFS on yield, insecticide expenditures, labor expenditures, herbicide expenditures, fertilizer expenditures, profit, and farmer's self-reported health status. This study also addresses potential endogeneity and self-selection bias that may affect inferences from the estimation. Two econometric methods that account for these issues are used in this study: (1) a propensity score matching (PSM) method that creates a valid comparison group (the counterfactual) from the non-IPM-FFS farmers, and (2) a regression-based approach. Since these approaches mainly account for potential bias due to observable variables, the sensitivity of the impact results to potential selection bias due to unobservable variables is also evaluated.

Chapter 2

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

2.1 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 are now being 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 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).

[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)

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

[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

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 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

(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.

[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).

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.

2.2 Conceptual Framework

Assume that a particular farm produces output y using a vector of inputs x according to the stochastic production function: $y = g(x, v)$, where v is a vector of unobserved factors not under the control of the producer (i.e., unobserved weather variables, production or pest conditions). At planting, the vector v is perceived as a random vector with a particular subjective distribution. Given the stochastic production function above, the farm generates net income as follows: $\pi = p \cdot g(x, v) - c(x)$, where $p > 0$ is the output price and $c(x)$ is the cost of inputs x. Further, assume that the utility of the farmer depends on net income (e.g., $U(\pi)$) and is characterized by a von Neumann-Morgenstern utility function. Expected utility of the farmer can then be defined as:

(1) $$EU(\pi) = EU[p \cdot g(x, v) - c(x)],$$

where E is the expectation operator applied over the subjective probability distribution of the unobserved random vector faced by the producer. Following Pratt (1964), equation (1) can alternatively be expressed as follows:

(2) $$EU(\pi) = U\left[E(\pi) - R\right],$$

where $E(\pi)$ is expected net income and R is the risk premium that measures the cost of private risk bearing. The risk premium R measures the decision-maker's willingness-to-pay for a scheme (i.e., insurance) that would eliminate the risk exposure (from v) by replacing the random net income (π) with its expected value $E(\pi)$.

From (2), a certainty equivalent (CE) welfare measure can then be defined as the sure amount of net income that the farmer would be willing to receive that would give the same utility as the expected value of the random income:

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

Assuming that $\partial U / \partial \pi > 0$, a producer's risk preference could then be defined as risk averse, risk neutral, or risk loving if $R > 0$, $R = 0$, or $R < 0$, respectively, and then correspondingly: $\partial^2 U / \partial \pi^2 < 0$, $\partial^2 U / \partial \pi^2 = 0$, or $\partial^2 U / \partial \pi^2 > 0$ (Pratt, 1964). In general, under risk aversion, increasing risk exposure tends to lower the CE (since R increases with increasing risk) and makes the decision-maker worse-off.

Risk preferences can be represented by the Arrow-Pratt risk aversion coefficient $r_2 \equiv -\left(\partial^2 U / \partial \pi^2\right) / \left(\partial U / \partial \pi\right)$, where risk aversion corresponds to $r_2 > 0$ (and $\partial^2 U / \partial \pi^2 < 0$, $R > 0$). Given the definitions above, it is clear that R and CE are partly determined by the risk preference of a particular producer. Moreover, Pratt (1964) also defined decreasing absolute risk aversion

(DARA) as situations where increasing mean income tends to reduce the risk premium *R*, and showed that $\partial r_2 / \partial \pi < 0$ under DARA. As mentioned above (see footnote 2), assuming DARA preferences for farmer-decision makers is reasonable given the empirical evidence to date supporting this behavior.

Assuming DARA preferences, equations (2) and (3) implies that *R* and *CE* depend on the relevant moments of the profit distribution. Since $\pi = p \cdot g(x,v) - c(x)$ and $p > 0$, the moments of the profit distribution is, in general, closely related to the moments of the production function $g(x, v)$. For the specific case where *p* is known, each moment of the profit function is proportional to the moments of production and the effect of production risk (i.e., from the moments of $g(x, v)$), the risk premium and certainty equivalent can be assessed. Specifically, the effects on *R* of changes in the variance and skewness of the profit (or production) distribution can be determined by taking a Taylor series approximation on both sides of (2) evaluated at the point $E(\pi)$ (See Di Falco and Chavas, 2006, 2009):[5]

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

From (4), the risk premium *R* can be approximated as follows:

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

where $M_i = E\left[\pi - E\left(\pi\right)\right]^i$ is the ith 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

[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.

$r_3 = -\left(\partial^3 U / \partial \pi^3\right) / \left(\partial U / \partial \pi\right)$, all evaluated at E($\pi$). Equation (4) and (5) allows us to decompose the effect of variance and skewness on the risk premium of the producer. If M_3=0, then equation (5) reduces to the standard Arrow-Pratt approximation where the risk premium is proportional to the variance of the profit distribution. This gives the intuitive result that increasing profit variance would result in higher risk premium (or higher cost of private risk bearing), under risk aversion behavior (i.e., when $\partial^2 U / \partial \pi^2 < 0$ and $r_2 > 0$). Equation (5) extends this result by allowing one to see 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 $r_3 < 0$). This suggests that a reduction in downside risk exposure (as implied by an increase in skewness) would tend to reduce the private cost of risk bearing.

Given the conceptual relationship between the first three moments of the profit distribution and the producer's risk premium, we can empirically estimate the effect of Bt corn on risk premiums (and *CE*) 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 $g(x, v)$:

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

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 (6) is a more general expression that expands the traditional Just-Pope production function (Just and Pope, 1978, 1979) to also account for skewness. From (6), it follows that the mean, variance, and skewness of $g(x,v)$ can be represented as:

(7a) $$E\left[g\left(x,v\right)\right] = f_1\left(x,\beta_1\right)$$

(7b) $$E\left[\left(g\left(x,v\right) - f_1\left(x,\beta_1\right)\right)^2\right] = f_2\left(x,\beta_2\right)$$

(7c) $$E\left[\left(g\left(x,v\right) - f_1\left(x,\beta_1\right)\right)^3\right] = f_3\left(x,\beta_3\right).$$

Equations (7a) - (7c) provide a flexible representation of the effects of inputs (including the Bt corn technology) on the distribution of output under uncertainty. Hence, this goes beyond previous studies (Hurley et al., 2004; Crost and Shankar, 2008; Shankar et al., 2007, 2008) that only investigated the effect Bt technology on the mean and variance of output.

We generally expect that the mean function in (7a) 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 ith 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 (6) 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:

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

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 $h(\cdot)$, 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 (8) 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:

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

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 (9) 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]

(10a) $$E(y)=f(\cdot)\times\left[\exp\left(\tfrac{B(\cdot)}{2}-\mu A(\cdot)\right)\right]$$

(10b) $$V(y)=E\left[y-E(y)\right]^2=\left(E(y)\right)^2\times\left[\exp\left(B(\cdot)\right)-1\right]$$

(10c) $$S(y)=E\left[y-E(y)\right]^3=\left(E(y)\right)^3\times\left[\exp\left(B(\cdot)\right)+1\right]\times\left[\exp\left(B(\cdot)\right)-1\right]^2.$$

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 2.A.

The set of equations in (7a) – (7c) and (10a) – (10c) allows us to examine the effect of Bt on the mean, variance, and skewness of output, and then determine the effects of these changes in the output distribution on the risk premium and CE of corn producers.

2.3 Empirical Setting and Data

2.3.1 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

[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).

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 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). The two cross-section data sets serves as the basis for estimating equations (7a) – (7c) and (10a) – (10c) in two separate crop years. Table 2.1

reports the summary statistics for the yield and key input variables used in the stochastic production function estimation in both crop years.

2.3.2 Estimation Procedures and Empirical Specification

Our analysis relies on: (i) the stochastic production function developed by Di Falco and Chavas (2006, 2009) that allows us to estimate equations (7a) – (7c), and (ii) the stochastic production function with damage abatement specification by Saha et al. (1997) which we extended to be able to estimate equations (10a) – (10c). To have a parsimonious specification, the *x* variables 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).

To estimate the parameters β_1, β_2, and β_3 from equations (7a) to (7c), we use the approach described in Di Falco and Chavas (2006) (which is also described in Just and Pope, 1979 and Antle, 1983). First, we estimate the following "mean" regression model (equation (7a) 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 (7b) and (7c)) are estimated by using the following specification:

[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).

$\hat{e}^i = f_i(x, \beta_i) + \varepsilon_i$ 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, second, and third steps above exhibit heteroskedasticity and this is accounted by using weighted NLS and/or White's heteroskedasticity robust standard errors.

Specification tests were undertaken to determine which functional form to use in $f_i(x, \beta_i)$ for $i = 1, 2, 3$ (equations (7a) to (7c)). Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) were used to determine which among the following functional forms would best fit the mean and variance function. Cobb-Douglas, linear-log, and quadratic were used to test for mean function, while Cobb-Douglas, linear, and quadratic were used to test for variance function. Based on the specification tests the Cobb-Douglas functional form fits the data best for equations (7a) to (7b) and this is the form we use for the mean and variance. For the skewness equation, a quadratic and a linear specification were the two forms tested to allow for both positive and negative values for $\hat{e}^3$. Specification tests indicate that the linear form is best for the skewness equation and this is the form we use in the analysis.

For the extended Saha et al. (1997) model in equations (8) – (10), the parameters (β, α, μ, ρ) are estimated directly using maximum likelihood estimation. From equation (9), the log-likelihood function of equation (8) can be represented as follows:

$$LLF\left(\beta, \alpha, \mu, \rho\right) = \frac{n}{2}\ln(2\pi) - \frac{1}{2}\sum_i \left\{ B_i\left(\cdot\right) + \frac{\left[\ln y_i - \ln f_i\left(\cdot\right) + \mu A_i\left(\cdot\right)\right]}{B_i\left(\cdot\right)} \right\}, \tag{11}$$

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

To give more insight as to what stochastic production function specification empirically fits our data best (i.e., the Di Falco and Chavas (2006, 2009) or the extended Saha et al (1997) model), we utilize the Vuong closessness test that is a type of likelihood ratio test for non-nested models (Vuong, 1989). We also examined the AIC and BIC statistics to further compare the fit of the Di Falco and Chavas (2006, 2009) specification with 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. For example, we include education and years of farming to account for unobserved management ability as a potential source of selection bias.[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. [11]

[10] The summary statistics of the variables included in the logit estimation model for 2003/2004 and 2007/2008 are in Appendix 2.B. 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.

[11] The final specification of variables used in the logit model for each crop year was selected mainly by looking at these selection and endogeneity tests. That is, the selected specification is where the eventual matched sample did not produce any statistical evidence of selection and endogeneity issues in the stochastic production function estimation. The results of these tests are available from the authors upon request.

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 (5) and (3), respectively. To calculate these two 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.[12] 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 (5)) 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 (3) 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.[13]

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:

$$LPM_m^{\pi_0} = \int_{-\infty}^{\pi_0} (\pi_0 - \pi)^m f(\pi) d\pi \tag{12}$$

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

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

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.[14] To calculate equation (12), 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 (12).

For the Di Falco and Chavas (2006) production function, the distribution of corn yield in equation (6) was simulated by using the parameter estimates of $f_1(x,\beta_1), f_2(x,\beta_2)$ and $f_3(x,\beta_3)$, at the mean values of all inputs from the survey data. We followed Di Falco and Chavas (2006) by assuming $k = 2$, setting e_2 as a standard normal distribution with mean 0 and variance 1, and setting $e_3 \equiv [v - E(v)] / \left[E(v - E(v))^2\right]^{\frac{1}{2}}$ -- where v follows a gamma distribution with mean 1, variance 1 and skewness 2 -- to generate 10,000 random numbers. This simulated corn yield distribution was used to generate the profit distribution at the mean values of output price and at the mean values of costs based on the survey data.

For the extended Saha et al. (1997) production function, the log of corn yield follows the normal distribution as discussed in equation (9) above. We used the parameter estimates β, α, μ, and ρ to calculate the mean and variance of the log of corn yield distribution at the mean values of all inputs from the survey data. We then generated 10,000 random numbers of corn yield. Similar to the Di Falco and Chavas (2006) production function, we generated the profit distribution at the mean values of output price and at the mean values of costs based on the survey data.

[14] 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.

2.4 Results

2.4.1 Descriptive Statistics and Stochastic Dominance Analysis

The summary statistics for the variables used in the stochastic production function estimation are presented in Table 2.1. 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.

To further visualize the difference in yields of Bt and non-Bt producers, we used kernel density estimation to graph the yield distribution of Bt and non-Bt farmers in both crop years based on the full data set (See Figures 2.1A and 2.1B).The yield distribution of Bt farmers is to the right of the non-Bt farmers, but the shape of the distribution for Bt and non-Bt farmers are very similar. This implies that mean yields for Bt farmers tend to be higher than those for non-Bt farmers (i.e., the right shift of the Bt yield distribution), but the variance and skewness of the yield distribution tends to not differ between the Bt and non-Bt farmers.

Stochastic dominance analysis was also undertaken to gain some insight into the risk benefits of Bt technology vis-à-vis non-Bt (See, for example, Shankar et al., 2007). This technique provides a method for comparing risky technologies when risk preferences of producers are unknown. In brief, stochastic dominance analysis relies on direct comparisons and rankings of distributions of outcomes for risky alternatives (See Hardaker et al., 1997, Chavas, 2004). Conclusions regarding dominance of any particular alternative depend on the restrictions one places on the utility function that underlies the analysis.

First-degree stochastic dominance (FSD) is the most general approach, requiring the weakest assumptions. The only assumption made under FSD is that the decision-makers prefer more to less (i.e., positive marginal utility). In our case, this means preferring higher yields to less, which is a generally acceptable assumption. Graphically, if the cumulative density function (CDF) of yields for Bt lies to the right of the non-Bt alternative for any given probability level, then the Bt technology is preferred to the non-Bt alternative under FSD. If the CDFs cross, then outcomes cannot be ordered using FSD and an additional (or stronger) assumption is needed for the risky alternatives to be ordered.

If ordering by FSD is not possible, then the less-general second-degree stochastic dominance (SSD) test may be used. SSD adds the assumption that the decision-maker is risk averse, in addition to the FSD assumption of preferring more to less. Risk aversion is a generally acceptable behavioral assumption for farmers in the Philippines, which allows us to use SSD. Graphically, if the area accumulated under a CDF of yields for Bt is always less than the area accumulated under a CDF of yields for non-Bt, then Bt is preferred to non-Bt under SSD.

The CDFs for the yields of Bt and non-Bt farmers for the 2003/2004 and 2007/2008 crop years are presented in Figure 2.2A and 2.2B. Although the Bt CDF is to the right of the non-Bt CDF at most yield levels (suggestive of FSD for Bt), there are slight crossings at the lower and upper ends of the yield CDF for both crop years (i.e. at yields less than 1 ton/ha and above 8 tons/ha). Hence, FSD cannot be directly used in this case. However, a ranking based on SSD could be used and, in this case, the Bt technology second-degree stochastically dominates the non-Bt technology in both years. In 2003/2004, the approximate area under the

Bt CDF is 7.42 while the area under the non-BT CDF is 8.42. In 2007/2008, the approximate area under the Bt CDF is 6.37 while the area under the non-Bt CDF is 7.35.[15]

Although stochastic dominance distinguishes Bt as the dominant strategy, it is important to point out its limitations in ranking risky alternatives. Specifically, stochastic dominance assumes that the observed differences between CDFs are solely due to the alternatives being compared (e.g., the Bt technology in this case). However, in a non-experimental setting like this study, we know that other observable factors, such as input levels and farmer characteristics, could influence the yield CDFs of the two technologies being compared. This is the reason why we also use stochastic production function regression methods (described above) that allows one to control for other observable factors that affects the yield outcomes. Stochastic dominance analysis serves to complement the stochastic production function results presented below.

2.4.2 Controlling for Selection Issues: Propensity Score Matching (PSM) Results

PSM was undertaken in this study to account for possible selection issues with regards to Bt adoption. The first stage logit estimates for the PSM are presented in Table 2.2. In both crop years, it can be seen that there are several observable characteristics that significantly determine Bt adoption (e.g., education in 2003/2004, training in 2007/2008,

[15] Note that we also used two other dominance criteria – stochastic dominance with respect to a function and stochastic efficiency with respect to a function. In these two dominance techniques, constant absolute risk aversion is an additional assumption. Results from this additional analysis suggest that Bt is preferred to non-Bt at all reasonable absolute risk aversion coefficients (i.e., 0.000004 - 0.35; See Babcock et al., 1993 for justification of this range). Results of this analysis are available from the authors upon request.

etc.). Since these are not included in the production function specification, these variables could cause selection bias in the stochastic production function estimation. Hence, PSM is an appropriate approach to control for these characteristics that determine Bt adoption.

Based on the predicted propensity scores from the first stage logit model, one-to-one matching of the Bt group to the non-Bt group resulted in a matched sample with 91 Bt and non-Bt observations for 2003/2004 and 147 Bt and non-Bt observations for 2007/2008 (See Table 2.3).[16] Comparison of means of the observable characteristics in the matched data set (See Table 2.4) indicates that the matching procedure resulted in valid counterfactuals (i.e., the means of the observable characteristics of the Bt observations do not statistically differ from the means of the non-Bt observations). Further, the matched sample did not exhibit any selection and endogeneity issues (see footnote 9).

2.4.3 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 2.5. 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

[16] 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 stratums 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.

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 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.[17] 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 2.7 (Panel A).[18] 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

[17] 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 result 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.

[18] 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 2.5 (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.

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).

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

In Table 2.6, 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 –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.[19] These inferences are consistent with the Di Falco and Chavas (2006, 2009) parameter estimates from Table 2.5.

Note that for the extended Saha et al. (1997) damage abatement production function, the parameter estimates associated with insecticide and Bt are not directly interpretable. Marginal effects have to be calculated to discern the magnitude of the effects of these damage abating inputs, as well as the statistical significance of these effects. 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

[19] Another important parameter in Table 2.6 is ρ, which represents the covariance of the error terms e and ε in equation 8. 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).

mean values. But in particular, the marginal effects are calculated based on equations (10a) to (10c) using the parameter estimates in Table 2.6 and evaluated at the means of the variables (other than the Bt dummy). 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 2.7 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 2.7 suggest that Bt has a statistically significant variance and skewness increasing effects on output.

In light of the slightly different results between the Di Falco and Chavas (2006, 2009) model and the extended Saha et al. (1997) model, it is important to determine which model empirically fits the data better using the Vuong closeness test. Since this test relies on a likelihood value, an alternative to the NLS approach to estimating Di Falco and Chavas (2006, 2009) need to be used because the NLS approach does not provide a likelihood measure that can be used in the Vuong test. A maximum likelihood procedure is used estimate the Di Falco and Chavas (2006, 2009) model to compute a likelihood measure, but unfortunately we encountered convergence issues with this approach. Given this situation, we opted to estimate the standard Just-Pope specification (i.e. with only the mean and variance) to obtain a likelihood value that would allow us to compare the fit of this model versus the traditional Saha et al. (1997) model (with only the mean and variance components as well). The null hypothesis of the Vuong test is that the standard Just-Pope specification

(model 1) and the Saha et al. (1997) specification (model 2) are equally close to the actual model. The Vuong test statistics for crop year 2003/2004 and 2007/2008 are -2.929 (p-value < 0.01) and -3.982 (p-value < 0.01) respectively. The negative test statistics of this Vuong test suggest the damage abatement specification empirically fits our data better. AIC and BIC measures also support this result. For crop year 2003/2004, AIC and BIC of the standard Just-Pope specification are 687.65 and 726.09, which is larger than the values of 203.50 and 229.14 for the Saha et al. (1997) specification. And for crop year 2007/2008, the AIC and BIC of the standard Just-Pope specification are 1,072.44 and 1,116.64, which is also larger than the values of 295.02 and 324.49 for the Saha et al. (1997) specification. Based on these tests, the result from the extended Saha et al (1997) model may be more meaningful than the Di Falco and Chavas (2006,2009) specification in the context of our data.

2.4.5 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 (where there is a statistically different variance and skewness effects). 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 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 2.7, 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 2.5 and 2.6) 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.[20] The *CE* can then be calculated directly using *R* and the mean expected profit (see equation (3) 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 2.8.

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

[20] We calculate the approximate risk premium based on equation (5) 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).

reveals that *R* is higher for Bt and, in this case, the downside risk increasing effect dominates the variance reduction effect of Bt.

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 (6) and (8) using the parameter estimates from Table 2.5 and 2.6 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 2.3 and 2.4 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 Figure 2.3 A and 2.3 B. 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 2.7, 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 2.9). 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 2.3 and 2.4).

2.5 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. We first compared the yield distribution of Bt and non-Bt corn through stochastic dominance analysis and found that Bt corn second-degree stochastically dominates non-Bt corn. This suggests that between these two risky alternatives (Bt vs. non-Bt), risk-averse farmers would be better off adopting Bt corn technology.

Two stochastic production functions are then 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 higher in good weather and Bt technology provide a higher 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.

Table 2.1. 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 2.2. First Stage Logit Results for the PSM Approach.

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

Table 2.3. 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 2.4. PSM Results: Equality of Means 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

Table 2.5. 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 2.6. 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 2.7. 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 2.8.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 2.9. 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.

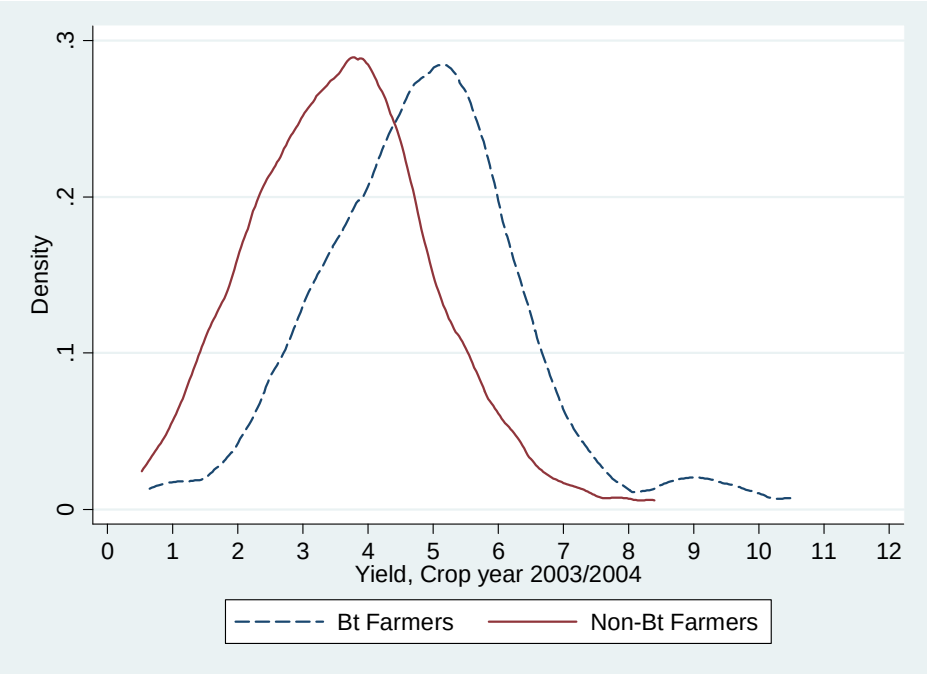

Figure 2.1A

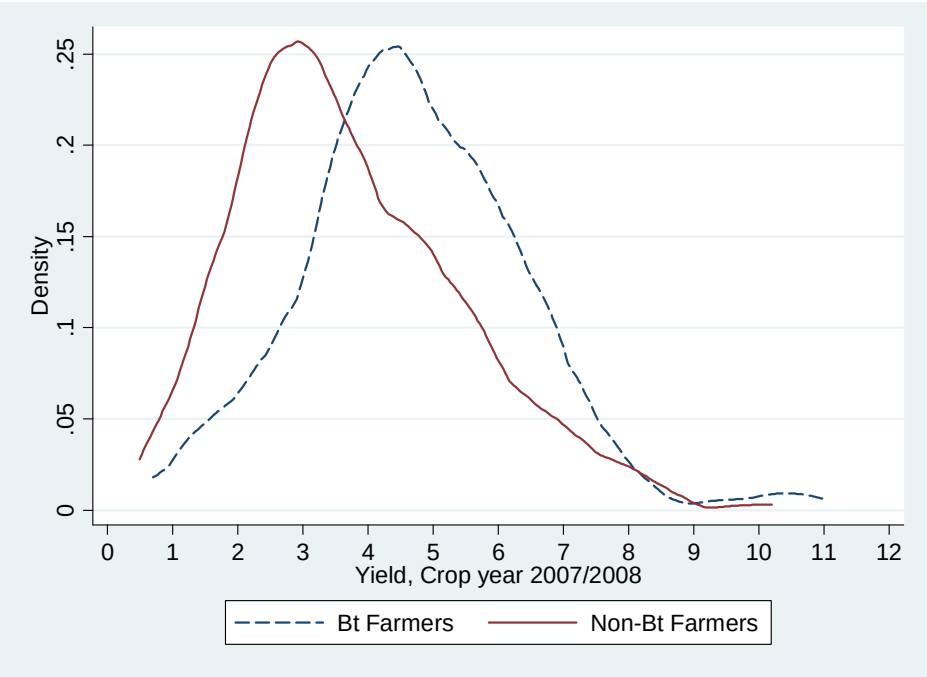

Figure 2.1B

Figure 2.1: Kernel yield density estimates for Bt and non-Bt farmers in Crop Years 2003/2004 (2.1A) and 2007/2008 (2.1B).

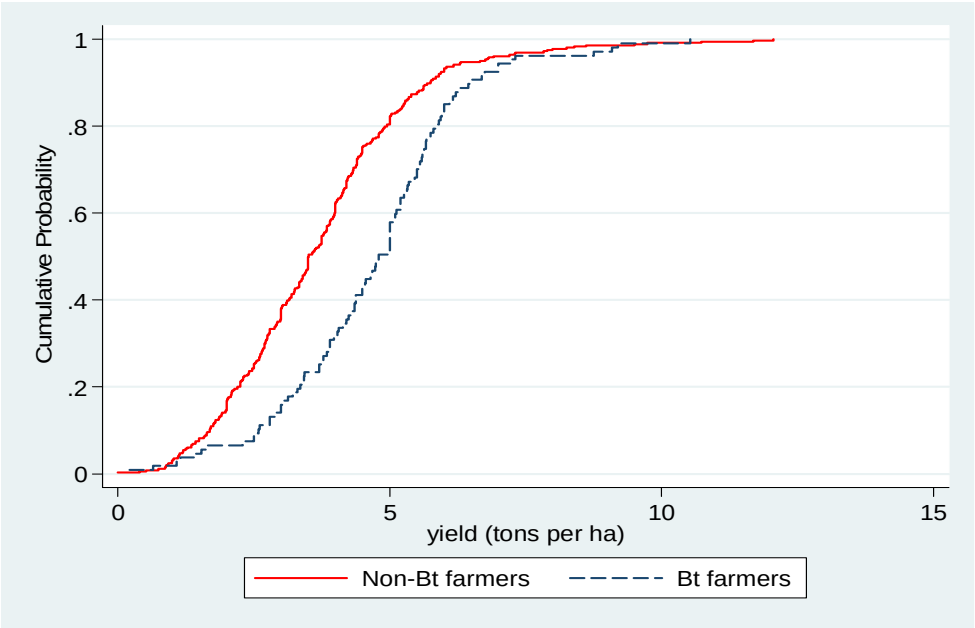

Figure 2.2A

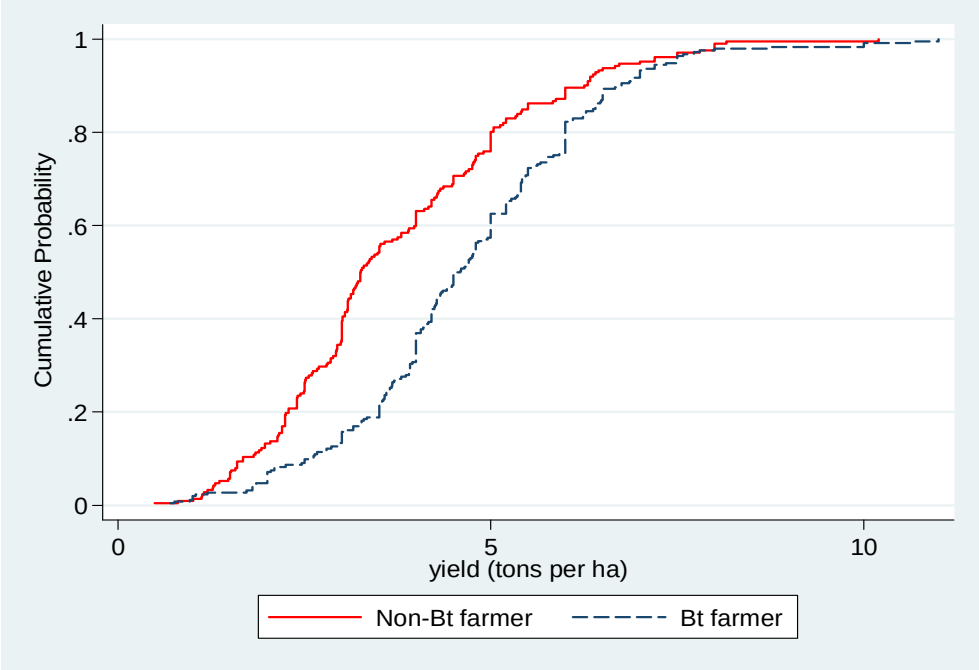

Figure 2.2B

Figure 2.2. Cumulative Distribution of Yields for Bt and non-Bt farmers in Crop Years 2003/2004 (2.2A) and 2007/2008 (2.2B)

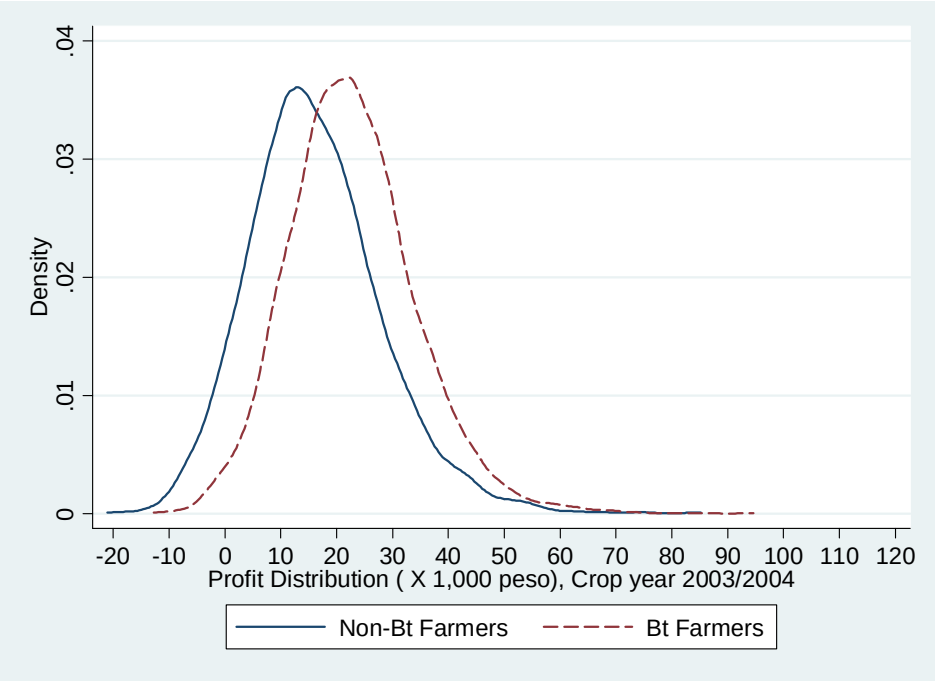

Figure 2.3 A

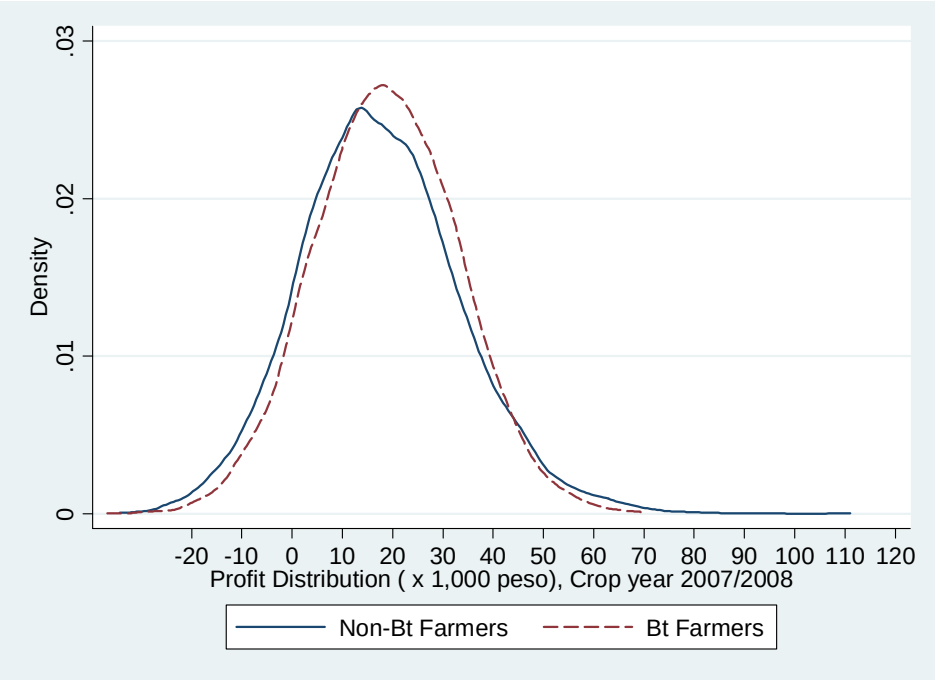

Figure 2.3 B

Figure 2.3 Simulated profit distribution from Di Falco and Chavas (2006, 2009) production function for Crop Years 2003/2004 (2.3 A) and 2007/2008 (2.3 B)

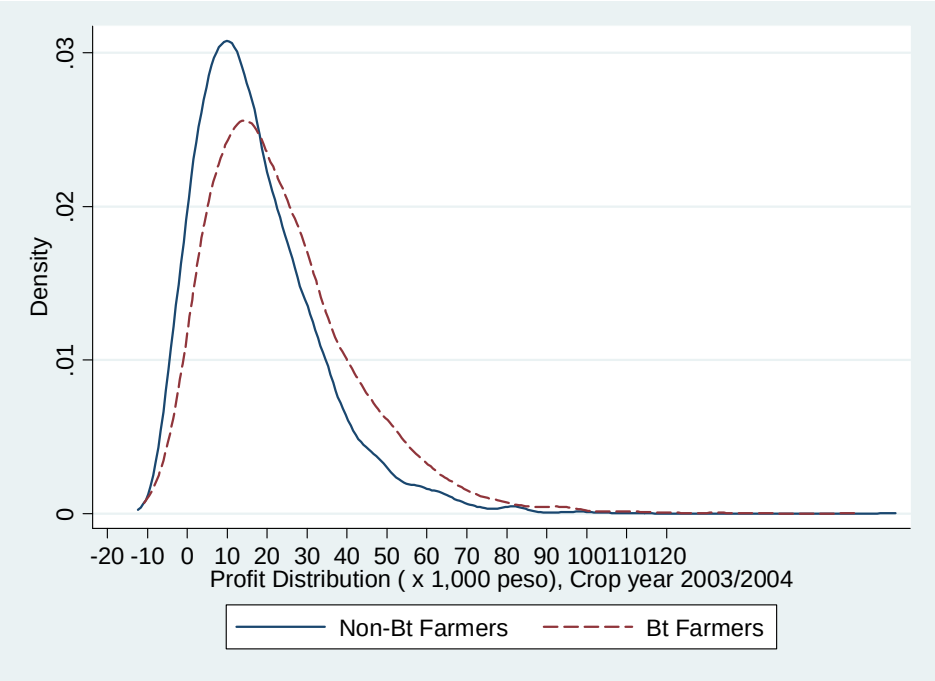

Figure 2.4 A

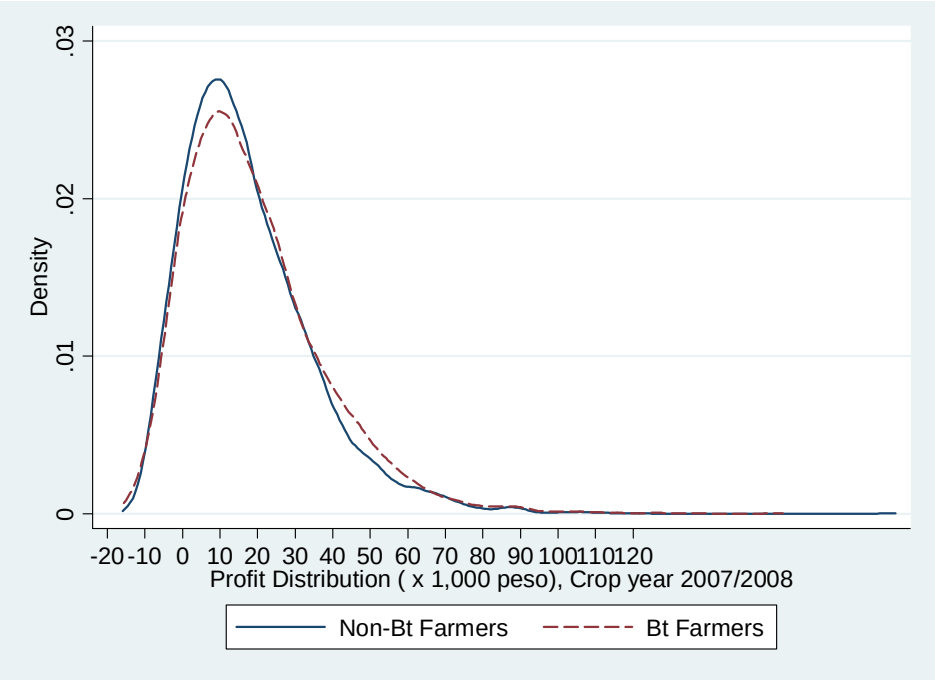

Figure 2.4 B

Figure 2.4 Simulated profit distribution from Saha et al. (1997) production function for Crop Years 2003/2004 (2.4 A) and 2007/2008 (2.4 B)

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Chapter 3

Do Lower Yielding Farmers Benefit from Bt? Evidence from Instrumental Variable Quantile Regressions

3.1 Introduction

Genetically-Modified (GM) crops have been recognized as a technology that can potentially provide higher yields and reduce pesticide use for farmers. These are some of the reasons why the cultivation of GM crops have continued to increase worldwide since its first introduction in 1996 (FAO, 2004; James, 2008). In particular, insect-resistant crops that have a gene from the soil bacterium *Bacillus thuringensis* (Bt) is now one of the most widely adopted GM crop variety in the world.

There have been a number of studies that have provided empirical evidence on the yield increasing and pesticide reducing effects of Bt crops (See Smale et al., 2007 and Qaim, 2009 for a comprehensive review of this literature). 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 (rather than Bt cotton), the existing literature also show similar yield-increasing and insecticide-reducing effects for Bt corn, albeit with a smaller magnitude (Brookes and Barfoot, 2005, Gouse et al., 2006; Fernandez Cornejo and Li, 2005; Yorobe and Quicoy, 2006; Qaim, 2009).

Based on these previous studies, it seems that (on the surface) both lower yielding and higher yielding farmers in developing countries equally benefit from using Bt crops. Given that developing county farmers at the lower end of the yield distribution tend to be poorer farmers and those at the upper end are wealthier farmers[21], these previous studies also seem to imply that the benefits of Bt crops would be felt by all types of farmers regardless of whether they are poor smallholders or larger commercial producers. However, most of these studies only investigate the effect of Bt technology on *mean* yield and *mean* pesticide use.[22] This general result only imply that Bt corn tends to have a statistically significant positive effect on the yields of the "average" (or the mean yielding) farmer. This finding does not give specific information on whether (and how much) Bt affects yields at the lower or upper end of the yield distribution. It is possible that Bt corn has a heterogeneous impact on yields at different points of the distribution.

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[21] The data used in this study also show that farmers at the lower end of the yield distribution have lower income than the farmers in the upper end of the yield distribution as shown in Appendix 3.A.

[22] One study that is somewhat of an exception is Qaim and De Janvry (2005) where they separately examined the effect of Bt cotton for small-scale producers (i.e., farms with less than 90 hectares) and large-scale producers (i.e., farms with more than 90 hectares). They found that the yield and pesticide use effects of Bt are more largely felt by the small-scale producers in Argentina. Note, however, that this study does not specifically investigate the impact of Bt on farmers at different points of the yield distribution.

In general, policy makers in developing countries would be more interested in supporting increased adoption of Bt crops if there is empirical evidence that the lower yielding farmers (who are typically poor smallholders) specifically benefit from Bt crops. Knowing the effects of Bt technology at different points of the yield distribution gives a more complete picture of the economic impacts of Bt crops. For example, if Bt crops only have a statistically significant effect at the higher end of the yield distribution, while there is no (or there is a negative) Bt impact for lower yielding smallholder farmers, then promoting Bt crops would not be a good policy option to improve the welfare of poor smallholders and improve farm productivity. On the other hand, if Bt crops have a significant yield effect in the lower tail of the cross-sectional yield distribution, then advocating the use of Bt crops to poor farmers may be a viable approach to increase poor smallholders' income, improve agricultural productivity, and enhance overall welfare.

One way to capture the effects of Bt crops at different points of the yield distribution is to use quantile regression techniques introduced by Koenker and Basset (1978). The main difference between quantile regression and other regression approaches like ordinary least squares (OLS) is that it allows for estimating various quantile functions at various percentiles of the outcome distribution (i.e., the dependent variable distribution) instead of just one function at the mean. This technique has been used in various studies in applied economics to study effects of regressors at different points of a particular outcome distribution, mostly in studying wage distribution or trade effects (See Bishop et al., 2005; Falaris, 2008; Yasar et al., 2006 for example).

However, if there are endogeneity or self-selection problems, the coefficient estimates from standard quantile regression techniques may be biased (Melly, 2006; Wehby et al., 2009; Chernozhukov and Hansen, 2004). Moreover, the standard instrumental variable (IV) or two stage least squares (2SLS) approach in ordinary least squares (OLS) regression is not directly applicable in a quantile regression context. Chen and Portnoy (1996) actually developed a quantile regression analogue to the standard 2SLS approach called a two stage quantile regression (2SQR), but Chernozhukov and Hansen (2004) show that 2SQR is not consistent when the quantile treatment effect differ across quantiles, which is the main purpose for using quantile regression. To address this problem, Chernozhukov and Hansen (2004, 2005, 2006) developed an IV technique that is applicable for quantile regressions (called the instrumental variable quantile regression or IVQR) and they have shown that the estimated coefficients in this approach are unbiased.[23] Note that there are only a few studies that have applied IVQR in empirical settings (See Atella et al., 2008; Wehby et al.,2009 for example)

To the best of our knowledge, there has been no study that has investigated the possible heterogeneous effects of Bt crop adoption on different points of the yield distribution, especially in the presence of self-selection (i.e., non-random selection of Bt adopters; see Shankar et al., 2008 and Crost and Shankar, 2008 for the importance of accounting for self-selection). This study aims to fill this gap in the literature and specifically determine the effect of Bt corn adoption at different points of the yield distribution. To

[23] There are other "IV" type approaches applicable to quantile regressions (See, for example, Abadie, Angrist and Imbens, 2002). One of the advantage of the Chernozhukov and Hansen (2004) approach is that it is applicable to different types of endogenous/self-selected variables (i.e., binary, discrete, continuous). Most of the other approaches only apply to binary endogenous variables (i.e., quantile treatment effects).

achieve this objective, we apply the IVQR approach of Chernozhukov and Hansen (2004, 2005, 2006) to two separate farm level data sets collected from Bt and non-Bt corn farmers in the Philippines during the 2003/2004 and 2007/2008 crop years. As a robustness check, we also use conventional quantile regression techniques where the selection issues are addressed through propensity score matching (PSM) rather than IV.

3.2 Empirical Setting and Data Description

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.[24] After removing observations due to incomplete

[24] 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

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 (where we could not reliably delineate the proportion of farmers who used traditional versus hybrid 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 more meaningfully see the performance difference between Bt corn relative to a more homogenous population of non-Bt farmers (i.e. hybrid corn users only). Seventeen top corn producing barangays from four towns were selected from these 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).

The two cross-sectional data sets described above are used for estimating the empirical model of interest for two separate years via IVQR and quantile regression with

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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).

PSM. Table 2.1 reports the summary statistics for the yield and key input variables used in the estimation for both crop years.

3.3 Econometric Framework

Our analysis primarily relies on the IVQR technique developed by Chernozhukov and Hansen (2004), but we also use standard quantile regression with propensity score matching (PSM) as a robustness check. The following Cobb-Douglas production function specification is estimated in this study:

(1) $\ln(y_i) = \beta_0 + \beta_{seed} \ln(seed_i) + \beta_{fert} \ln(fert_i) + \beta_{insec} \ln(insec_i) + \beta_{labor} \ln(labor_i) + \beta_{Bt} Bt_i + u_i$

where y is corn yield (in tons/ha), *seed*, *fert*, *insec*, and *labor* represent four input quantity variables: seed (in kg/ha), fertilizer (in kg/ha), insecticide (in li/ha), and labor (in man-days/ha)), *Bt* is a dummy variable (=1 if *Bt* adopter; =0 otherwise), and u is the residual. Note that in using a Cobb-Douglas specification in equation (1), we implicitly impose positive skewness due to the log transformations. This restriction is reasonable for our study since the raw yield data do indeed exihibit positive skewness (See Figure 3.1). In the next sub-sections, we first discuss the basics of quantile regression, then describe the IVQR approach, and, lastly, describe the quantile regression approach with propensity score matching (PSM).

3.3.1 The Quantile Regression

The corn production function in equation (1) can be written in the context of quantile regression (Koenker and Basset, 1978; Buchinsky, 1998) as follows:

(2) $$\ln y_i = X_i'\beta_\tau + u_{\tau i} \quad \text{with} \quad Q_\tau(\ln y_i \mid X_i) = X_i'\beta_\tau$$

where ln y is a vector of log corn yield, X is a matrix that is comprised of a vector of one, log of input variables including the Bt dummy variable indicated in equation (1), β_τ is the vector of parameters to be estimated, and $u_{\tau i}$ is a vector of residuals. $Q_\tau(\ln y_i|X_i)$ denoted the τth conditional quantile of ln y_i given X_i. The τth sample quantile, $0 < \tau < 1$, is defined as any solution to the minimization problem:

(3) $$\min_{\beta \in R^k}\Big[\sum_{i \in \{i:\ln y_i \geq X_i'\beta\}} \tau \mid \ln y_i - X_i'\beta_\tau \mid + \sum_{i \in \{i:\ln y_i < X_i'\beta\}} (1-\tau) \mid \ln y_i - X_i'\beta_\tau \mid\Big].$$

This is normally written in compact form as:

(4) $$\min_{\beta \in R^k} \sum_{i=1}^{n} \rho_\tau(u_{\tau i})$$

where $\rho_\tau(\cdot)$ is the *check function* defined as :

(5) $$\rho_\tau(\lambda) = \begin{Bmatrix} \tau\lambda & if\ \lambda \geq 0 \\ (\tau-1)\lambda & if\ \lambda < 0 \end{Bmatrix}.$$

In contrast to OLS estimation, problem (3) or (4) cannot be solved by differentiation techniques since it is not differentiable. However, it can be shown to have a linear programming (LP) representation and its solution is obtained in a finite number of simplex iterations. The solution to problem (3) and (4) is the vector of parameters, β_τ, that minimize the sum of weighted absolute deviations. Changing τ continuously from zero to one, we can find the effects of the inputs, X, at different parts of the corn yield distribution. Hence, in our study context, we would be able ascertain the effect of the Bt variable at different points of the corn yield distribution.

Quantile regression allows the coefficient estimate, β_τ, to be different at different quantile functions. These coefficient estimates are the marginal change in the log of corn yield due to a marginal change in log of inputs. In the case of the *Bt* variable, the coefficient can be used to calculate the percentage change in corn yield when farmers switch from conventional or hybrid seed to Bt seed technology as follows:

(6) $$\%\nabla y = 100(e^{\beta_{Bt}} - 1)$$

Quantile regressions are more robust to the presence of outliers in the data compared to the least squares estimator, because it places less weight to the residuals associated with these outliers (i.e., the residuals to be minimized are in absolute terms rather than squared terms). Previous studies also indicate that quantile regression outperforms the least square estimator in the case of non-Gaussian error distributions (Koenker and Basset, 1978; Buchinsky, 1998).

3.3.2 The Instrumental Variable Quantile Regression (IVQR)

As mentioned in previous studies of Bt technology (Shankar et al., 2008; Crost and Shankar, 2008), non-random selection of Bt adopters (i.e., the so-called selection problem) is an important issue to address when assessing the impact of Bt. 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 production function specification, it can be that the observed difference between the yields 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). Similar to the least squares estimator, using conventional quantile regression in the presence of self-selection to adopt Bt corn may give biased estimates of Bt impact on corn yield at different quantiles.

Following Chernozhukov and Hansen (2004, 2005, 2006), the conventional quantile model for corn yield can be written as:

(7) $$\ln y = X'\beta(U^*), \qquad U^* \mid X \sim Uniform(0,1)$$

where $\ln y$ and X are the same as defined in equation (2), $\tau \mapsto X'\beta(\tau)$ is strictly increasing and continuous in τ, the disturbance U^* is the unobserved farmer management ability. We could estimate $\beta(\tau)$ at quantile index $\tau \in (0,1)$ by the quantile regression discussed above.

In the case where Bt adoption is endogenous or self-selected, the *Bt* variable is correlated with U^*. Equation (6) is slightly modified to deal with the endogeneity problem as follows:

(8.1) $$\ln y = Bt \cdot \beta_{Bt}(U) + X'\beta(U) \qquad U \mid X, Z \sim Uniform(0,1)$$

(8.2) $$Bt = \delta(X, Z, V),$$ (where V is statistically dependent on U)

(8.3) $$\tau \mapsto Bt \cdot \beta_{Bt}(\tau) + X'\beta(\tau)$$ (where this is strictly increasing in τ),

The variable *Bt* is an endogenous binary variable for Bt corn adopters determined by equation (8.2). The vector V is comprised of unobserved random variables correlated with U,

and Z is a vector of instrumental variables that are independent of U but correlated with Bt adoption. From equation (8.1) and (8.3), it can be implied that

(9) $$\Pr(\ln y \le Bt \cdot \beta_{Bt}(\tau) + X'\beta(\tau) \mid X, Z) = \tau$$

Equation (9) provides that 0 is the τth quantile of random variable, $\ln y - (Bt \cdot \beta_{Bt}(\tau) + X'\beta(\tau))$, conditional on ($X,Z$). To solve equation (9) is to find a solution to the quantile regression of $\ln y - (Bt \cdot \beta_{Bt}(\tau) + X'\beta(\tau))$ on (X,Z) which is equivalent to:

(10) $$Q_\tau(\ln y - Bt \cdot \beta_{Bt}(\tau) \mid X, Z) = X'\beta(\tau) + Z' \cdot \gamma(\tau)$$

If we know the true value of $\beta_{Bt}(\tau)$, we could estimate the coefficients $\beta(\tau)$ and $\gamma(\tau)$ by

(11) $$\min_{\beta,\gamma \in R^k} \sum_{i=1}^{n} \rho_\tau(\ln y_i - Bt \cdot \beta_{Bt}(\tau) - X_i'\beta(\tau) - Z'\gamma(\tau))$$

But we do not know the value of $\beta_{Bt}(\tau)$. However, we know that the true value of $\beta_{Bt}(\tau)$ is the only one for which the coefficients on Z (the instrumental variables), $\gamma(\tau)$, are zero. Thus in practice, we try different values for $\beta_{Bt}(\tau)$ and solve the minimization problem (11) and look for a value that makes $\gamma(\tau)$ as close to zero as possible.

In this study, the vector of instrumental variables, Z, used for the two separate cross-sectional data are different. Recall from our discussion above that the data used in this study come from two different 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. Based on the available variables in our data set for crop year 2003/2004, we use seed price (Philippines peso/kg) as an instrumental variable for Bt

adoption. This is a reasonable IV since this variable is expected to influence the decision to adopt Bt technology but not affect the unobservable variables that influence the corn production function (e.g., unobserved management ability) as specified in equation 8.1. We argue that relative seed prices influence whether or not a corn producer adopt Bt, but these seed prices are competitively determined in the market such that no single farmer can affect it (i.e., the unobservable ability of an individual farmer cannot influence market price).

On the other hand, the IVs we use for the IFPRI data for 2007/2008 are the aforementioned seed price variable and a distance variable that shows the distance of the farm to the seed source/seller or market (in km). The distance variable is also a reasonable IV since Bt adoption is likely correlated with distance to seed source but distance to seed source is probably not correlated to unobserved characteristics that influence corn production (i.e., management ability). Normally one would expect that distance of the farm to seed source would be negatively related to the likelihood of Bt adoption (i.e., farmers that are farther away from the seed store are less likely to buy Bt seed). However, we argue that a positive relationship is also possible in the Philippines because of the existence of free delivery services made available by Monsanto (the main company that supplies Bt corn in the Philippines). With the availability of this free service, farmers that are farther away tend to utilize delivery and are the ones more likely adopt Bt. We posit that these farmers are likely to adopt Bt because if they do not adopt Bt they will have to incur the transport cost of buying insecticides once there is an infestation in their non-Bt crop.

3.3.3 Robustness Check: Quantile Regression with Propensity Score Matching

We already account for self-selection bias in estimating the yield impact of Bt corn by using the IVQR method described above. However, the standard quantile regression could also be used to estimate the impact of Bt on corn yield at different quantiles if we can eliminate the self-selection problem from our data set directly. Propensity score matching (PSM) technique developed by Rosenbaum and Rubin (1983) is commonly used to control for self-selection bias. The idea of this method is that the Bt adoption becomes quasi-randomly assigned (no self-selection problem due to observable variables) after matching non-Bt adopters that have similar probability to adoption with Bt-adopters (i.e., similar propensity scores). We employ the PSM technique to create a subset of corn farmers that are quasi-randomly assigned to Bt or non-Bt adoption from the full data set. The standard quantile regression is then used to estimate the impact of Bt on corn yield at different quantiles from this subset of corn farmers. This approach serves as a robustness check for the IVQR technique.

In the process of estimating the probability to adopt Bt (i.e., the propensity scores), we include a number of independent variables in the logit adoption model so as to cover all possible observable variables that could determine adoption and yields. Therefore, the PSM approach only addresses selection problems due to selection on "observables" (i.e., the independent variables in the logit regression are observable characteristics). But even though PSM actually just accounts for selection on "observables", selection problems due to

“unobservable” variables (like unobserved management ability) may sometimes still be swept away especially if the “unobservables” determining adoption are highly correlated with the “observables.”

To confirm that the self-selection problem (due to both observable and unobservable variables) is removed from our subset of corn farmers, we follow common practice to check for the existence of this problem by using a Hausman test (See Hausman, 1978 for details). This test is based on comparing the parameters estimates from the OLS regression and the 2SLS or IV regression where the null hypothesis for no self-selection is the parameters estimates from both regressions are not different. Once we determine that the subset of corn farmers (i.e., the matched sample) has no self-selection problems, the standard quantile regression method using the matched sample allows us to check the robustness of the results from the IVQR.

3.4 Results

3.4.1 Descriptive Statistics and Simple Percentile Comparison Results

The summary statistics for the yield, key input variables, and instrumental variables used in this study are presented in Table 3.1. The yield levels at different percentiles are presented in Table 3.2. In both crop years, yields of Bt farmers tend to be uniformly higher than non-Bt farmers. But it seems like Bt technology equally benefits all farmers in the whole distribution except for the tails. To further visualize the difference in yields of Bt and non-Bt producers, we used kernel density estimation to graph the yield distribution of Bt and non-Bt

farmers in both crop years (See Figures 3.1A and 3.1B).The yield distribution of Bt farmers is to the right of the non-Bt farmers, but the shape of the distribution for Bt and non-Bt farmers are very similar. This is a visual confirmation of the seemingly homogenous impact of Bt at different points on the yield distributions. However, we cannot make this conclusion based only on this simple visual comparison since there are other observable factors (such as input levels and farmer characteristics) that could influence yields.

3.4.2 The Instrumental Variable Quantile Regression (IVQR) Results

The parameter estimates of the IVQR based on the Cobb-Douglas production specification in equation (1) are presented in Table 3.3. For crop year 2003/2004 (Panel A), Bt has a statistically significant positive impact in all yield quantiles. Based on the parameter estimates, we calculate the percentage change in corn yield (due to Bt) using equation (6) and then find the absolute yield change (tons/ha) at different percentiles based on information from Table 3.2 (see Table 3.4). The results suggest that the magnitude of the percentage increases in yield due to Bt technology are more largely felt in the lower quantiles. However the absolute yield changes are not much different across quantiles ranging from 0.98 tons/ha to 1.37 tons/ha. These percentage effects of Bt technology on corn yields at different percentiles for crop year 2003/2004 are graphically presented in Figure 3.2A.[25] In general, the results from the IVQR using 2003/2004 data shows that the yield increasing effects of Bt tend to be more strongly felt in the lower yield quantiles.

[25] The graphs presenting the absolute effects with 95% confidence bands and the graphs that show only significantly effects in both percentage and absolute terms are presented in Appendix 3.E.

For crop year 2007/2008 (Panel B), Bt generally also has a statistically significant positive impact on yields in almost all quantiles (i.e., except for the 0.1 and 0.9 quantiles where the effect of Bt is insignificant). The percentage and absolute impact of Bt on corn yield at different percentiles for crop year 2007/2008 are presented in Table 3.4 (right-most panel). The percentage effects of Bt on corn yields at different percentiles for crop year 2007/2008 are also graphically presented in Figure 3.2B. Based only on the cases where Bt has a statistically significant yield effect (as seen in Figure 3.2B), we find that the effect of Bt on yields at the lower quantiles (e.g., 0.3 and 0.4) tend to have a larger magnitude compared to the quantiles at 0.5 or above (e.g., 0.5, 0.6, 0.7, and 0.8). The only exception is at the 0.2 quantile where the effect of Bt on yield seem to be smaller than the effect observed at most of the upper quantiles (i.e., 0.5 to 0.7). Nevertheless the general pattern of these results still suggest that yield enhancing effects of Bt is more strongly felt by farmers having yields at the 50th percentile or lower (i.e., higher yield increasing effect in percentage terms are observed for farmers in the lower part of the distribution).[26]

[26] We also estimated the OLS, 2SLS, and the standard quantile regressions for comparison. The results of these regressions are presented in Appendix 3.B. The effect of Bt on crop yield based on the OLS and the 2SLS estimations for crop year 2003/2004 are very close to the median (50th quantile) IVQR estimation. For crop year 2007/2008, the OLS, 2SLS, and the median IVQR all show different effect of Bt on crop yield with the median IVQR estimation giving the highest effect. The pattern of the impact of Bt on yields from the standard quantile regression are similar to the results from IVQR. The exceptions are that the standard quantile regression gives smaller effect of Bt on yield for crop year 2007/2008 and the effect of Bt on yield at the upper and lower quantiles are closer for crop year 2003/2004 (i.e., the IVQR show higher benefit for the lower quantile).

3.4.3 Robustness Check: Quantile Regression with Propensity Score Matching Results

As a robustness check for IVQR, we also utilized standard quantile regression and applied it to a matched sample of Bt and non-Bt adopters produced through PSM techniques. PSM was undertaken to create a subset of corn farmers where selection issues are accounted for. This sub-sample of matched Bt and non-Bt farmers are used to then estimate standard quantile regression models that would allow us to assess the impact of Bt on corn yield at different quantiles. 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.[27] The yield levels at different percentiles for this matched samples are presented in Table 3.5.Similar to the full sample results in Table 3.2, the Bt producers tend to have uniformly higher yields relative to the non-Bt producers across all quantiles. Although the difference between Bt and non-Bt yields tend to be more "variable" or "heterogeneous" as compared to the results from the full sample (Table 3.2).

The parameter estimates from the quantile regression with PSM for the Cobb-Douglas production specification in equation (1) are presented in Table 3.6. For crop year 2003/2004 (Panel A), Bt has statistically significant positive impacts on all yield quantiles

[27] The first stage logit estimates for the PSM and comparison of means of the observable characteristics for the matched and unmatched data set are presented in Appendix 3.C. We followed the Hausman test to check for the existence of the self-selection problem in the matched samples, the result suggest that there is no self-selection problem in our matched data set thus we can use the standard quantile regression to check the robustness of the results from the IVQR. The results of the Hausman test are presented in Appendix 3.D.

except for both the lower and upper tails of the distribution (0.1 and 0.9, respectively). Similar to IVQR, we calculate the percentage change in corn yield using equation (6) and the absolute yield change at different percentiles based on the parameter estimates from Table 3.5 and present it in Table 3.7. In crop year 2003/2004, the pattern of the impact of Bt on yield distribution are similar to the results from IVQR in that the percentage increases in yield due to Bt technology tend to be more pronounced at the lower quantiles (see "% Impact"column in the left panel of Table 3.7). This general pattern is evident in Figure 3.3A.

For crop year 2007/2008 (Panel B), the impact of Bt on yields are insignificant for upper part of the distribution (0.5 and above), as well as the left-most tail (0.1) (See bottom panel of Table 3.6). For the lower part of the yield distribution (from 0.2 to 0.4), we find that Bt has a positive significant impact. Based on only these quantiles that have statistically significant Bt effect on yield for the 2007/2008 data, we still find a pattern where the Bt effect on yield is more strongly observed in the lower quantiles (i.e., estimated Bt effect on yield is higher at 0.2 compared to 0.4). This is again graphically observed in Figure 3.3B. But even if we consider all quantiles (i.e., even if some of the Bt effects are insignificant in the quantiles other than 0.2 to 0.3 or 0.4), we see in Table 3.7 that, in general, the magnitudes of the Bt effects tend to be more strongly felt in the lower quantiles (see "% Impact" column in the right panel of Table 3.7).

Overall, the standard quantile regression results using the matched sample still support the observation in the IVQR results that the effect of Bt on yields tends to be more pronounced for farmers at the lower end of the yield distribution (i.e., specifically, those

farmers with yields below the 50th percentile). The same inference being made from two quantile regression approaches point to the robustness of the result above.

3.5 Conclusion

This study more carefully examines the effect of Bt corn on yields by examining whether this technology has heterogeneous yield effects at different points in the yield distribution. Specifically, this study moves beyond the previous literature to determine if the effect of Bt is different for lower yielding farmers vis-à-vis the higher-yielding farmers. Most previous Bt studies that utilize ordinary least square (OLS) techniques typically provides information only on how Bt affects the "mean" (or average) yielding farmer and this type of approach do not provide evidence on the potential differential effect of Bt on lower yielding farmers, who are typically the poor smallholders in the Philippines (See Appendix Table 1).

Using farm-level survey data from the Philippines and quantile regression techniques that control for selection problems, we find that the effect Bt corn on yields is generally more strongly felt by producers at the lower end of the yield distribution. If we subscribe to the typical belief that lower-yielding producers are mostly poor smallholders (i.e., subsistence farmers), then the results from our analysis provides some evidence that Bt corn technology has benefited poor corn farmers in the Philippines through higher relative yield effects as compared to the more commercial producers at the upper end of the yield distribution. It is likely that the proportionately higher yield effect observed for poor smallholders is made possible by the damage abating property being "embedded" within the Bt technology. The

effectiveness of the technology does not really depend on whether the farmer has higher education or managerial ability (i.e., learning curve is minimal for the smallholders).

With higher yields (and assuming costs of adopting Bt do not negate the yield benefits), it is reasonable to surmise that income of poor producers has the potential to be enhanced by the Bt technology. But it must be noted that higher yields from Bt do not necessarily imply that poor farmers' incomes and their welfare would necessarily be improved (i.e., the yield benefits should still be weighed against the costs of using Bt) (See Glover, 2009). Nevertheless, the strong positive Bt effect on yields observed for lower yielding producers gives some indication that Bt technology do provide relatively more benefits to poor farmers. This insight can be used by policy makers to justify policies that encourage (or subsidize) the use of Bt technology among poor smallholders. As Glover (2009) have indicated, one potential barrier for Bt to successfully help poor farmers is the higher cost of this technology such that poorer farmers cannot effectively access the technology. With institutional subsidy policies in place to help poor farmers and together with the technology's potential yield increasing effects, Bt technology is one among several possible tools that can help increase poor farmers' income, improve agricultural productivity, and enhance overall farmer welfare in the Philippines.

In spite of this paper's contribution to our understanding of the potential heterogeneity of the yield impacts of Bt in the Philippines, it is important to take note of the limitations of the study. 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. Second, we only

examine the potential heterogeneous effect of Bt on yields and not on other outcome variables like insecticide use, labor, and profits/income. Future work should investigate whether the effects of Bt on these other outcome variables is different for lower-yielding farmers and higher-yielding farmers.

Table 3.1 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
Seed Price (PhP./kg)	224.84	34.43	116.50	27.80	310.10	55.54	176.18	39.07
Distance to Seed Suplier (km)	-	-	-	-	7.59	14.71	3.58	5.23

Table 3.2 Yield at Different Percentiles in 2003/2004 and 2007/2008.

Percentile of Yield	--- Crop Year 2003/2004 ---				--- Crop Year 2007/2008 ---			
	Bt (n=101) (tons/ha)	Non-Bt (n=306) (tons/ha)	difference (tons/ha)	p-value	Bt (n=254) (tons/ha)	Non-Bt (n=212) (tons/ha)	difference (tons/ha)	p-value
10%	3.00	1.87	1.13	<0.01	2.56	1.68	0.88	<0.01
20%	3.70	2.42	1.28	<0.01	3.50	2.29	1.21	<0.01
30%	4.06	2.80	1.26	<0.01	3.92	2.80	1.12	<0.01
40%	4.50	3.24	1.26	<0.01	4.20	3.00	1.20	<0.01
50%	5.00	3.54	1.46	<0.01	4.59	3.26	1.33	<0.01
60%	5.20	3.97	1.23	<0.01	5.00	4.00	1.00	<0.01
70%	5.53	4.23	1.30	<0.01	5.42	4.50	0.92	<0.01
80%	5.90	4.67	1.23	<0.01	6.00	5.00	1.00	<0.01
90%	6.48	5.33	1.15	<0.01	6.75	6.25	0.50	0.09

Table 3.3 Parameter Estimates for the Cobb-Douglas production function using IVQR.

Crop Year/Variable	IVQR estimates								
	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
A. Crop Year 2003/2004 (Bt: n= 101; Non-Bt: n=305)									
Constant	-0.861	-1.424	-0.946	-0.531	-0.017	0.248	0.769	1.201	1.556
	(0.11)	(<0.01)	(0.02)	(0.17)	(0.96)	(0.52)	(0.06)	(<0.01)	(<0.01)
ln(seed)	0.440	0.476	0.421	0.380	0.247	0.162	0.144	0.126	0.033
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.03)	(0.17)	(0.24)	(0.34)	(0.84)
ln(pesticide)	0.025	0.023	0.012	0.009	0.007	0.009	0.003	0.010	0.008
	(0.02)	(<0.01)	(0.12)	(0.25)	(0.33)	(0.23)	(0.71)	(0.27)	(0.43)
ln(fertilizer)	0.097	0.184	0.181	0.156	0.159	0.161	0.074	0.046	0.070
	(0.10)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.10)	(0.35)	(0.24)
ln(labor)	-0.067	-0.019	-0.060	-0.079	-0.089	-0.072	-0.044	-0.064	-0.088
	(0.41)	(0.78)	(0.33)	(0.18)	(0.13)	(0.22)	(0.47)	(0.34)	(0.28)
Bt	0.550	0.410	0.317	0.315	0.278	0.239	0.249	0.217	0.169
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
B. Crop Year 2007/2008 (Bt: n= 249; Non-Bt: n=207)									
Constant	-2.782	-1.396	-1.228	-0.863	-1.182	-1.494	-1.241	-0.593	-0.573
	(<0.01)	(0.01)	(0.02)	(0.09)	(0.02)	(<0.01)	(0.02)	(0.29)	(0.40)
ln(seed)	-0.220	-0.261	-0.139	-0.115	-0.051	-0.001	0.008	0.026	0.139
	(0.24)	(0.08)	(0.33)	(0.40)	(0.70)	(0.99)	(0.96)	(0.87)	(0.45)
ln(pesticide)	-0.013	-0.001	0.005	0.001	0.001	-0.007	-0.001	0.004	0.011
	(0.29)	(0.90)	(0.58)	(0.95)	(0.87)	(0.43)	(0.92)	(0.72)	(0.34)
ln(fertilizer)	0.416	0.355	0.314	0.245	0.310	0.336	0.344	0.299	0.233
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.01)
ln(labor)	0.443	0.246	0.220	0.212	0.174	0.192	0.150	0.075	0.152
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.23)	(0.04)
Bt	-0.025	0.275	0.422	0.400	0.342	0.343	0.319	0.242	0.136
	(0.81)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.20)

Note: Values in parentheses are the p-values

Table 3.4 Percentage and Absolute Yield Impact of Bt in 2003/2004 and 2007/2008 based on IVQR.

Percentile of Yield	--- Crop Year 2003/2004 ---			--- Crop Year 2007/2008 ---		
	Non-Bt Yield (tons/ha)	% Impact	Absolute Impact (tons/ha)	Non-Bt Yield (tons/ha)	% Impact	Absolute Impact (tons/ha)
10%	1.87	73.40	1.37	1.68	-2.45	-0.04
20%	2.42	50.73	1.23	2.29	31.71	0.73
30%	2.80	37.29	1.04	2.80	52.53	1.47
40%	3.24	37.06	1.20	3.00	49.20	1.48
50%	3.54	32.11	1.14	3.25	40.72	1.32
60%	3.97	27.03	1.07	4.00	40.87	1.63
70%	4.23	28.34	1.20	4.50	37.55	1.69
80%	4.67	24.28	1.13	5.00	27.32	1.37
90%	5.33	18.40	0.98	6.25	14.51	0.91

Table 3.5. Yield at Different Percentiles from the Matched Sample in 2003/2004 and 2007/2008.

Percentile of Yield	--- Crop Year 2003/2004 ---				--- Crop Year 2007/2008 ---			
	Bt (n=91) (tons/ha)	Non-Bt (n=91) (tons/ha)	difference (tons/ha)	p-value	Bt (n=147) (tons/ha)	Non-Bt (n=147) (tons/ha)	difference (tons/ha)	p-value
10%	3.00	2.31	0.69	0.17	2.64	1.92	0.72	0.02
20%	3.70	2.72	0.98	<0.01	3.50	2.50	1.00	<0.01
30%	4.04	3.00	1.04	<0.01	3.92	3.00	0.92	<0.01
40%	4.50	3.58	0.92	<0.01	4.13	3.26	0.87	<0.01
50%	5.00	4.00	1.00	<0.01	4.50	4.00	0.50	0.07
60%	5.20	4.33	0.87	<0.01	5.00	4.50	0.50	0.05
70%	5.56	4.75	0.81	<0.01	5.28	5.00	0.28	0.19
80%	5.90	5.28	0.62	0.06	6.00	5.42	0.58	0.10
90%	6.48	5.85	0.63	0.32	6.50	6.38	0.12	0.77

Table 3.6. Parameter Estimates for the Cobb-Douglas production function using Quantile Regression with PSM.

Crop Year/Variable	Quantile Regression estimates								
	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
A. Crop Year 2003/2004 (Bt: n= 91; Non-Bt: n=91)									
Constant	-1.461	0.048	-0.334	0.284	1.796	1.124	1.529	1.696	1.680
	(0.35)	(0.93)	(0.54)	(0.60)	(<0.01)	(0.04)	(<0.01)	(<0.01)	(<0.01)
ln(seed)	0.188	0.008	0.289	0.302	-0.071	0.115	0.056	-0.009	-0.037
	(0.67)	(0.97)	(0.11)	(0.08)	(0.70)	(0.52)	(0.76)	(0.94)	(0.87)
ln(pesticide)	0.046	0.022	0.016	0.017	0.011	0.006	0.009	0.008	0.011
	(0.13)	(0.04)	(0.13)	(0.13)	(0.35)	(0.54)	(0.34)	(0.11)	(0.61)
ln(fertilizer)	0.463	0.212	0.213	0.126	0.023	0.029	0.052	0.071	0.078
	(<0.01)	(<0.01)	(<0.01)	(0.02)	(0.55)	(0.40)	(0.09)	(<0.01)	(0.17)
ln(labor)	-0.226	-0.055	-0.159	-0.163	-0.084	-0.038	-0.101	-0.095	-0.067
	(0.37)	(0.54)	(0.06)	(0.05)	(0.34)	(0.64)	(0.19)	(<0.01)	(0.56)
Bt	0.284	0.258	0.297	0.283	0.211	0.189	0.165	0.076	0.142
	(0.18)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.01)	(0.03)	(0.27)
B. Crop Year 2007/2008 (Bt: n= 147; Non-Bt: n=147)									
Constant	-2.035	-1.172	-0.709	-1.083	-0.960	-0.982	-0.147	0.099	0.120
	(0.09)	(0.25)	(0.33)	(0.01)	(0.18)	(0.07)	(0.79)	(0.85)	(0.77)
ln(seed)	-0.226	-0.220	-0.165	-0.109	-0.148	-0.090	-0.179	0.058	0.050
	(0.41)	(0.39)	(0.36)	(0.33)	(0.43)	(0.51)	(0.20)	(0.66)	(0.67)
ln(pesticide)	-0.023	-0.008	0.015	-0.009	-0.008	-0.007	-0.008	-0.008	0.003
	(0.13)	(0.59)	(0.16)	(0.19)	(0.47)	(0.43)	(0.38)	(0.34)	(0.70)
ln(fertilizer)	0.325	0.282	0.217	0.295	0.341	0.359	0.300	0.164	0.147
	(0.05)	(0.05)	(0.03)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.03)	(0.02)
ln(labor)	0.394	0.276	0.249	0.221	0.168	0.132	0.109	0.105	0.185
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.03)	(0.02)	(0.08)	(0.04)	(<0.01)
Bt	0.069	0.208	0.178	0.126	0.127	0.098	-0.009	0.061	0.012
	(0.49)	(0.03)	(0.02)	(<0.01)	(0.12)	(0.11)	(0.89)	(0.29)	(0.83)

Note: Values in parentheses are the p-values

Table 3.7 Percentage and Absolute Yield Impact of Bt in 2003/2004 and 2007/2008 based on Quantile Regression with PSM.

Percentile of Yield	--- Crop Year 2003/2004 ---			--- Crop Year 2007/2008 ---		
	Non-Bt Yield (tons/ha)	% Impact	Absolute Impact (tons/ha)	Non-Bt Yield (tons/ha)	% Impact	Absolute Impact (tons/ha)
10%	2.31	32.84	0.76	1.92	7.18	0.14
20%	2.72	29.45	0.80	2.50	23.07	0.58
30%	3.30	34.61	1.14	3.00	19.44	0.58
40%	3.58	32.74	1.17	3.26	13.46	0.44
50%	4.00	23.50	0.94	4.00	13.52	0.54
60%	4.33	20.76	0.90	4.50	10.35	0.47
70%	4.75	17.88	0.85	5.00	-0.90	-0.04
80%	5.28	7.88	0.42	5.42	6.27	0.34
90%	5.85	15.25	0.89	6.38	1.17	0.07

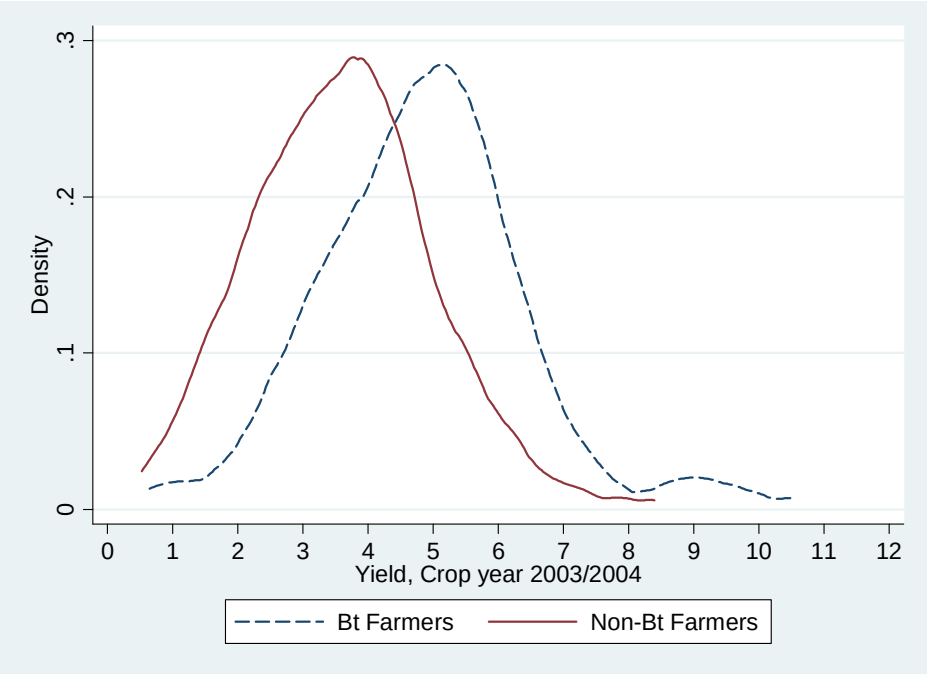

Figure 3.1A

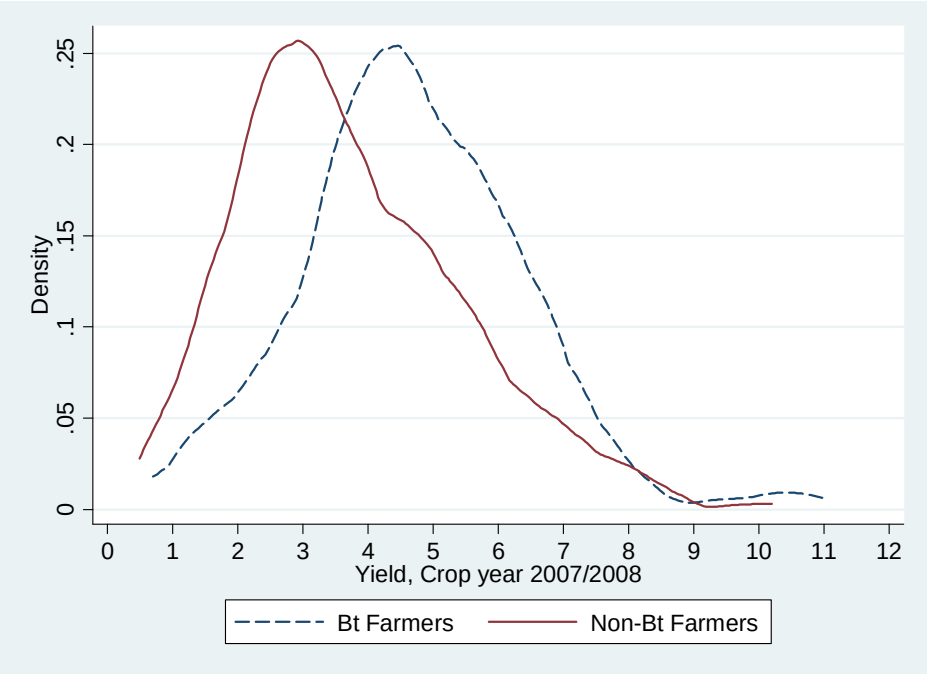

Figure 3.1B

Figure 3.1: Kernel yield density estimates for Bt and non-Bt farmers in Crop Years 2003/2004 (3.1A) and 2007/2008 (3.1B).

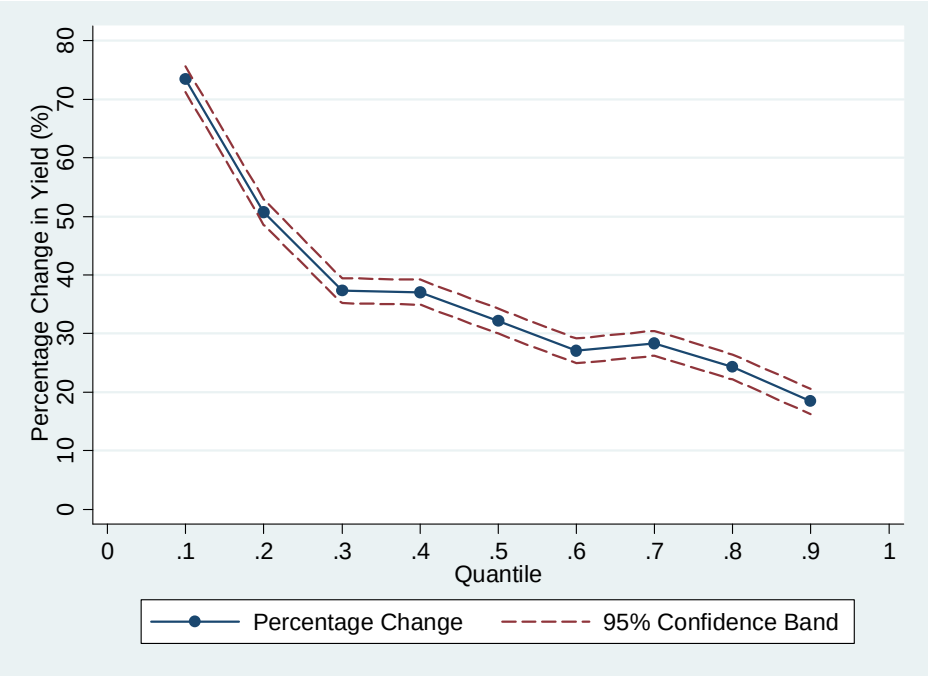

Figure 3.2A

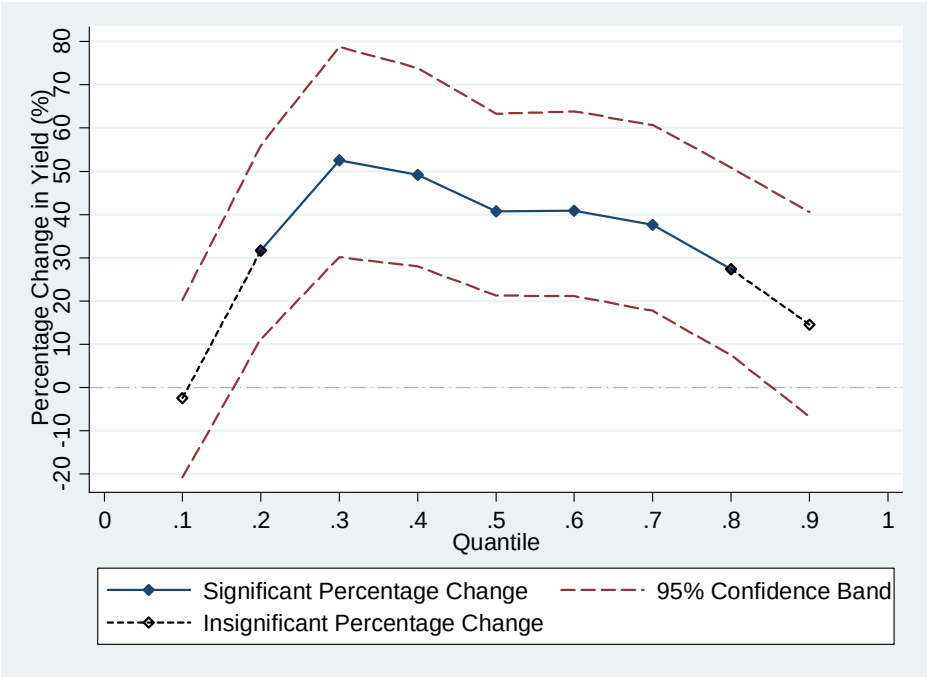

Figure 3.2B

Figure 3.2: Percentage Yield Impact of Bt using IVQR for Crop Year 2003/2004 (3.2A) and Crop Year 2007/2008 (3.2B)

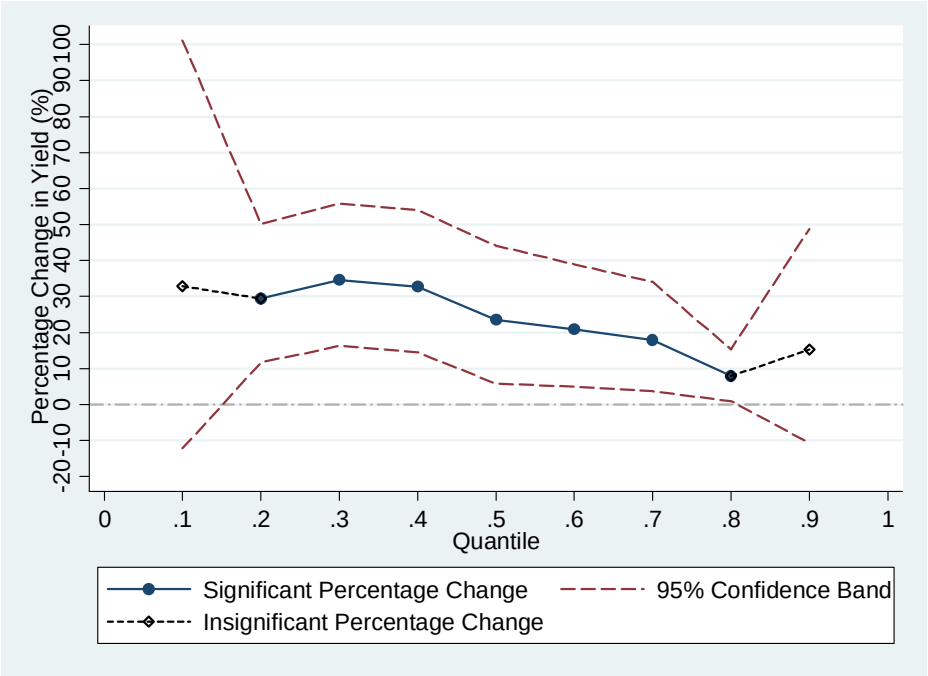

Figure 3.3A

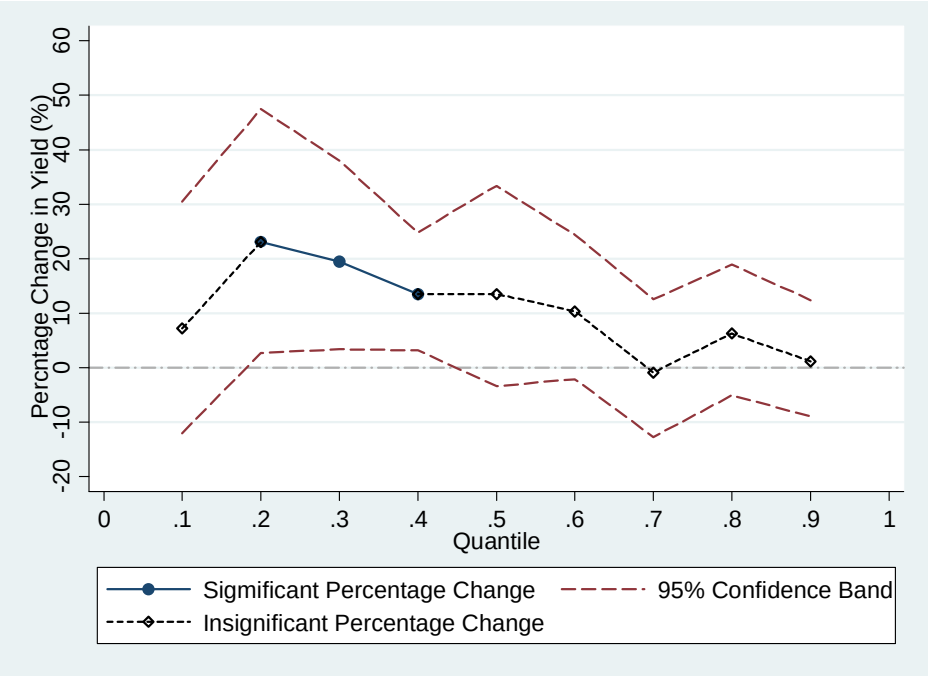

Figure 3.3B

Figure 3.3: Percentage Yield Impact of Bt using Quantile Regression with PSM for Crop Year 2003/2004 (3.3A) and Crop Year 2007/2008 (3.3B)

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Chapter 4

The Impacts of Integrated Pest Management (IPM) Farmer Field Schools (FFS) on Inputs and Output: Evidence from Onion Farmers in the Philippines

4.1 Introduction

Chemical pesticides have been used extensively for pest control by farmers in developing countries such as the Philippines. About 70% of farmers in the Philippines use chemicals as their main crop protection practice and some of them even utilize chemical pesticides that are restricted and/or banned (i.e., categories I and II) (Javier, et.al, 2005). The use (and misuse) of chemical pesticides have caused serious problems to ecosystem and human health (Rola and Pingali, 1993; Pingali and Roger, 1985; Antle and Pingali, 1994; and Tjornhom et.al, 1997). Chemical pesticide misuse is even more evident in vegetable crop production (relative to traditional grain crops) because of its vulnerability to a wider range of pest and diseases (Tjornhom et.al, 1997).

With increasing concerns about the adverse effects of chemical pesticide use, there have been many efforts to reduce excessive use of insecticides in developing countries.

Integrated pest management (IPM) that involves the use of cultural, biological, and chemical techniques to control pest populations has been developed and promoted as an alternative option for farmers in developing countries (Norton et.al, 1999). IPM in the Philippines was initiated by the Food and Agriculture Organization (FAO) in the late 1970s. Extension and training programs were also developed during this period to teach farmers the IPM method (Pontius et. al., 2002).

Conventional extension approaches, such as mass media, bulletins or extension agent visits, have been used to convey research findings as a technological package in the past, although these approaches were viewed to have limited success. These methods are seen as less effective for improving knowledge when compared to more participatory approaches like Farmer Field Schools (FFS) (Feder et.al, 2004; Rola et.al, 2002; Rola and Pingali, 1993). With its first introduction in East Asia in the late eighties for rice-based systems, the IPM-FFS model has spread significantly in Asia, Africa, and Latin America and has evolved to include a broader coverage of other farm relevant topics in the curriculum and to varieties of crops (Feder et.al, 2004; Godtland et.al, 2004). The FFS has also been regarded as the best suited approach for introducing knowledge-intensive technologies (like IPM) in the Philippines, although there has been limited success in spreading the technology through spill-over to non-FFS farmers (Rola et.al, 2002).

Initial assessments of the IPM-FFS approach and early impact studies have documented strong impacts on yield and pesticide use. However, these early studies did not address potential endogeneity and self-selection bias that may have affected the results. More recently, there have been econometric studies that analyzed the impact of IPM-FFS while

controlling for selection and endogeneity issues. However, evidence across countries suggests conflicting results. Feder et. al. (2004) used a difference-in-difference (DID) model with panel data from Indonesia and found no significant difference between FFS participants and non-participants in terms of pesticide use and yield outcomes. However, using the same panel data used by Feder et. al. (2004) in Indonesia, Yamazaki and Resodarmo (2008) found that FFS participants significantly increased yield and reduced pesticide use in the shorter-term. In the medium term, however, no significant difference in performance between FFS participants and non-participants was observed. Rejesus et. al. (2011) also used a DID approach to investigate the impacts of IPM-FFS on Vietnamese farmers' IPM knowledge, yield, and pesticide use. They did not find statistically significant impacts of IPM-FFS on yield, but there is some evidence that IPM-FFS improve farmers' knowledge about IPM concepts (at least initially). Rejesus et. al. (2011) also found that IPM-FFS reduce overall pesticide use, but IPM-FFS did not have statistically significant impacts on insecticide use when broken down into different periods after sowing. In contrast, Godtland et. al. (2004), while controlling for selection using propensity score matching techniques, revealed that participants in Peru knew more about IPM and have significantly higher yields than their non-participant counterparts. Rejesus et. al. (2009) combined the instrumental variables (IV) approach with the inverse mills ratio technique to control for endogeneity and selection problems in evaluating the impact of IPM-FFS on pesticide use in Vietnam and found that IPM-FFS participants significantly reduced the amount of pesticide use. Yorobe et. al. (2011) also used the IV approach to examine the insecticide use impact of IPM-FFS in the

Philippines and found that the IPM-FFS farmers tend to have lower insecticide expenditures as compared to non-IPM-FFS farmers.

The Philippines has had eighteen years of participatory IPM-FFS experience in rice and vegetables, but most of the impact evaluations in this country to date merely depend on before-and-after or with-and-without approaches. More sophisticated econometric estimation that controls for endogeneity and/or selection biases have not yet been done so far for the IPM-FFS experience in the Philippines (except for Yorobe et. al., 2011). Such documentation is necessary to aid decision makers in planning for a more effective national IPM dissemination strategy.

The purpose of this study is to comprehensively examine the impact of IPM-FFS on yields, insecticide expenditures, labor expenditures, herbicide expenditures, fertilizer expenditures, profit, and farmer's self-reported health status. The study particularly focuses on onion production in the Philippines considering the length of IPM-FFS experience for this crop in the country and onion's vulnerability to a wide range of pests. Two methods used in the analysis to account for the selection bias problems include: (1) propensity score matching (PSM) methods that create a comparison group (i.e., the counterfactual) from non-IPM farmers, and (2) a regression-based approach described in Wooldridge (2002) and Godtland et al. (2004). A farm survey of onion growers in Nueva Ecija, Philippines where FFS trainings have been conducted provides the data for the evaluation.

4.2 Empirical Setting and Data

4.2.1 Background: Onion Production and FFS in the Philippines

The first IPM-FFS program was initiated in Central Luzon, Philippines in 1994 under the auspices of the IPM-CRSP Southeast Asia Regional program of USAID. From 1994-2008, Phase 1, 2, and 3 of the IPM CRSP project in Southeast Asia focused on the research, development, and outreach of IPM practices for rice-vegetable cropping systems in the province of Nueva Ecija, Philippines. It was mainly conducted by the Philippine Rice Research Institute (PhilRice)[28] in collaboration with the University of the Philippines, Los Baños (UPLB) and three other US Universities (see Norton et. al., 1999). Instead of other vegetables that are grown after rice in Nueva Ecija (like tomatoes and eggplant), the program concentrated on onion since it provides the highest income to farmers after the wet season rice crop and it is popularly grown by farmers in the area. The preliminary survey also showed that pesticide use was quite intensive for this crop. Ten years after the implementation of the IPM-CRSP in the area, several mature IPM technologies were eventually developed for onions and were ready to be transferred to farmers.

In 2004, the IPM-FFS training was initiated in five barangays (villages) in Nueva Ecija as part of the program's technology promotion and transfer activities. This was followed-up in one barangay in 2007, two barangays in 2008 and one barangay in 2009. Site selection was primarily based on several criteria: ease of access, peace and order, onion

[28] Philippine Rice Research Institute (PhilRice) is a government corporate entity attached to the Department of Agriculture to help develop high-yielding and cost-reducing rice technologies so farmers can produce enough rice for all Filipinos.

planted area, support from local agricultural extension office, and farmer's receptivity. A total of 91 onion growers participated in the first training program in 2004 and 132 growers in the period 2007-2009. As in any FFS training, the conduct of the program was participatory and experiential and all learning activities are conducted in the field. Hence, the training commences at the start of the planting season with participants having standing onion crops. The curriculum is generally focused on IPM methodologies that farmers can learn. For the whole growing season, participants visit their onion fields weekly and congregate thereafter to discuss field activities/observations particularly with respect to insects and pests. In the classroom, farmers are then taught by pest experts on how to manage these insects and pests the IPM way. This includes biological and cultural practices that can be effectively used as substitutes to chemical pesticides for control of pests and diseases. This knowledge is then applied by the participant in their fields under the guidance of the trainers. Post-evaluation of the method is also undertaken weekly to inform other farmers on the method and its effectiveness. The training lasts until the end of the harvest season. Aside from experiential learning, the program also uses pamphlets and brochures in addition to the lectures. Samples of the materials needed for biological control are also distributed so that participants can study and test it in their fields.

After IPM-FFS training was launched for onion farmers in Nueva Ecija area in 2004, there are now concerns about how successful the IPM-FFS is in term of reducing insecticide use (expenditures), increasing yield, and subsequently enhancing farmers' income. If there is statistical evidence that training from IPM-FFS reduce insecticide use and improves farm income, then this is justification for policymakers to maintain funding for this program and

possibly expand it in other parts of the country to cover more crops. However, since the participation in IPM-FFS program is voluntary and the sites for which the IPM-FFS trainings were conducted were not randomly chosen, farmers' decision to attend the IPM-FFS may depend on various factors including unobserved management abilities and observed personal characteristics like sex, age of farmers, experience, distance to extension office, income from other sources, etc. This non-random nature of IPM-FFS participation makes it difficult to evaluate the impacts of the IPM-FFS training program based on direct comparison of the mean outcomes between IPM-FFS participants and non-participants. The traditional t-tests and Ordinary Least Squares (OLS) approach may be provide misleading results because of self-selection bias. To overcome this self-selection problem in evaluating the impacts of the IPM-FFS training program, we employ two econometric methods: (1) PSM methods, and (2) a regression-based approach described in Wooldridge (2002) and Godtland et. al. (2004), which are discussed in more detail in section 4.3 below.

4.2.2 Sampling and Data Description

The data used in this study came from a face-to-face farm-level survey of onion growers in two areas of Nueva Ecija province, Philippines on October 2009. A three stage sampling framework was followed for this study. The town of Talavera and San Jose City were immediately selected for this study since the IPM-FFS trainings in 2004 and 2007-2009 were conducted in barangays within these sites. Majority of farmers participating in FFS in the province also came from these two locations and onion remains a primary vegetable crop

in these areas after rice. Farmers in these areas practice an intensive rice-onion cropping system.

In the second stage, eight major onion growing barangays (i.e, the smallest political unit in the Philippines) within Talavera and San Jose City were selected, four where FFS training has been conducted (FFS-barangays) and four where FFS training was not conducted (non-FFS barangays). The non-FFS barangays were chosen based on their distance from the FFS barangays and the importance of onion as a second crop to rice. Distance was a major factor in order to assure that spill-over effects from FFS to non-FFS farmers are minimized. However, it is important to note that an earlier study in the Philippines have already indicated that spill-over from FFS-trained farmers to other non-trained farmers tends to be insignificant (Rola et al., 2002). In addition, we chose the non-FFS barangays so that the socio-economic, climatic, and topographic characteristics are similar to the FFS-barangays (for comparability). The FFS barangays chosen include Caaninaplahan and Pag-Asa in Talavera and San Agustin and Kita-kita in San Jose. Of the nine barangays with FFS training in Nueva Ecija, more than 50 percent were residents of these four selected barangays. The non-FFS barangays chosen were Cabubulaonan and Caputikan in Talavera and Tayabo and Tabulac in San Jose. These non-FFS barangays were at least 5 kilometers away from the nearest FFS barangay. Cabubulaonan is adjacent to Caputikan but, Tayabo and Tabulac are quite distant from each other.

A total of 200 onion growers were selected randomly from the eight barangays. For the FFS participants, the complete list was provided by the Philippine Rice Research Institute (PhilRice), while for the non-participants, the list of onion growers was secured from village

heads. The selection of the barangays and the onion growers was carefully validated with the agricultural extension workers in the area and with experts from PhilRice. Only farmers who planted onions in the 2008 cropping season were included in the sampling frame. Based on our data, there were 7 farmers who attended IPM-FFS in 2004, 11farmers in 2007, 27 farmers in 2008, and 24 farmers attended in 2009 (i.e., total of 69 IPM-FFS farmers). Although we have data on when farmers attended the IPM-FFS training, we do not control for the effect of IPM-FFS timing in our study (See Yamazaki and Resodarmo, 2008 and Rejesus et al., 2011). This can be a topic for future work.

Enumerators, using a pre-tested questionnaire, surveyed the randomly selected onion farmers and asked information about several outcome variables of interest that may be affected by the IPM-FFS program including yield, profit, health status, and various input expenditures (e.g., insecticide, herbicide, fertilizer, and labor). Since direct comparison of mean outcomes between IPM-FFS adopters and non-adopters may give biased results due to self-selection (as mentioned earlier), additional data on socio-economic characteristics that may affect farmers' decision to attend the IPM-FFS program were also collected. These characteristics were collected to be able to find non-participants that are as similar as possible to the IPM-FFS adopters. The following socio-economic characteristics are the observable variables used in the PSM and regression-based methods: sex, age of farmers, experience, income from other sources, distance to extension office, distance to pesticide suppliers, degree of pest infestation, and location. After removing observations due to incomplete information and missing data issues, 197 observations (69 IPM-FFS farmers and 128 non-IPM farmers) are used in this study.

4.3 Empirical Approach and Estimation Procedures

4.3.1 Selection Bias and Propensity Score Matching Method

Let Y^1 be an outcome of interest when a farmer participates in IPM-FFS (treated state), Y^0 be the outcome when a farmer did not participate in IPM-FFS (untreated state), and D is a dummy variable indicating IPM-FFS participation. The observed outcome is:

(1) $$Y = DY^1 + (1-D)Y^0$$

To accurately estimate the impact of IPM-FFS on outcomes of interest, we need to look at the difference between the outcomes from the IPM-FFS farmers and the outcomes from the same farmers had they not participated in the IPM-FFS (i.e., the counterfactual). This impact is known as the average treatment effect on the treated (*ATT*) which is defined as:

(2) $$ATT = E(Y^1 - Y^0 \mid D=1) = E(Y^1 \mid D=1) - E(Y^0 \mid D=1)$$

But in reality, we cannot observe the outcome of IPM-FFS farmers had they not adopted, $E(Y^0|D=1)$. We only observe the non-IPM-FFS outcome from non-IPM-FFS farmers, $E(Y^0|D=0)$. If adoption of IPM-FFS is randomly assigned, the adoption dummy variable D would be statistically independent of outcome (Y^1, Y^0). Then *ATT* is identical to the expected impact of IPM-FFS on a randomly drawn farmer (known as the average treatment effect (*ATE*)):

(3.1) $$E(Y^1 - Y^0 \mid D=1) = E(Y^1 - Y^0) = E(Y^1) - E(Y^0) = ATE$$

(3.2) $$E(Y \mid D=1) = E(Y^1 \mid D=1) = E(Y^1)$$

(3.3) $$E(Y \mid D=0) = E(Y^0 \mid D=0) = E(Y^0).$$

In the case that the treatment indicator D and outcome Y are independent and using equations (3.1) to (3.3), we can estimate the ATT as (Wooldridge, 2002):

(4) $$ATT = E(Y^1 \mid D = 1) - E(Y^0 \mid D = 0)$$

However, this randomization of IPM-FFS adoption is not met in our case since there are both observed and unobserved characteristics of farmers that influence the IPM-FFS adoption and the outcome of interests. Given non-random adoption of IPM-FFS, using equation (4) in estimating the impacts of IPM-FFS would yield biased estimators (i.e., due to selection bias).

There are two main sources of selection bias when directly comparing outcomes from IPM-FFS adopters and non-adopters: (1) selection on observables and (2) selection on unobservables. The "selection on observables" bias is likely to arise since the distribution of some observed characteristics of the IPM-FFS adopters differ from their non-adopter counterparts. These observed characteristics would have impacts on the outcome of interests even without the IPM-FFS adoption. Another possible source of the bias from "selection on observables" is that the locations for IPM-FFS trainings are not randomly selected. One way to control the differences in observed characteristics between IPM-FFS farmers and non-IPM-FFS farmers is to find non IPM-FFS farmers that have a set of observed characteristics, X, similar to IPM-FFS farmers to serve as valid surrogates for the missing counterfactuals. This method is based on the conditional independence (CI) assumption which states that the distributions of Y^1 and Y^0 should be independent of treatment assignment, D, conditional on a set of observables, X (Rubin, 1977; Rosenbaum and Rubin , 1983) :

(5) $$(Y^1, Y^0 \perp D) \mid X \; .$$

For *ATT*, we are interested in the outcome of IPM-FFS farmers had they not adopted, $E(Y^0|D=1)$. That is, we only need independence between Y^0 and D. Then the CI assumption condition can be weakened to the conditional mean independence (CMI) assumption (Heckman, Ichimura, and Todd, 1998):

(6) $$E(Y^0 \mid X, D=1) = E(Y^0 \mid X, D=0)$$

However, matching directly on all characteristics in X becomes infeasible when the dimension of X is large. Rosenbaum and Rubin (1983) proposed propensity score matching (PSM) techniques to solve this problem by matching treated and control groups (IPM-FFS and non-IPM-FFS farmers in our case) based on the probability of treatment (probability of participating in IPM-FFS) given X, $P(X) \equiv \Pr(D=1 \mid X)$, called the propensity score, where

(7) $$0 < P(X) < 1.$$

Matching by $P(X)$ instead of the whole set of X needs "the balancing property" of pre-treatment variables, given $P(X)$, to hold:

(8) $$D \perp X \mid P(X)$$

Another basic criterion in the PSM method is that the matching should be done on "the common support" region. This common support region are observations with propensity scores belonging to the intersection of propensity scores for the treated and controls (Becker and Ichino, 2002; Caliendo and Kopeinig, 2008). Rosenbaum and Rubin (1983) show that given condition (5), (7), and (8) (plus the common support criterion), condition (6) becomes:

(9) $$E(Y^0 \mid P(X), D=1) = E(Y^0 \mid P(X), D=0)$$

and the average treatment effect on the treated is calculated by:

(10) $$ATT = E(Y^1 \mid D = 1, P(X)) - E(Y^0 \mid D = 0, P(X)).$$

In this study, we follow common steps in implementing the PSM method (see Sianesi, 2001; Becker and Ichino, 2002; Caliendo and Kopeinig, 2008). The first step is the estimation of propensity score, *P(X)*, using a parametric binary response model (logit or probit model) and "testing for the balancing property". The second step is selecting the matching methods and then matching IPM-FFS farmers with non-IPM-FFS farmers. Following standard practice in the PSM literature, nearest neighbor matching (NNM) and kernel-based matching (KM) methods are employed in this study. A common support constraint is also imposed where the observations to be matched are dropped from the sample when their estimated propensity score is either above the maximum or below the minimum propensity score of the opposite group. The next step is checking the matching quality to see whether the mean of all variables in *X* are statistically the same between the matched treated and control groups. If the matching quality is satisfactory, we can estimate the *ATT* using equation (10). But if the equality of means of any variables between two groups is rejected, we have to go back to the first step to re-estimate the propensity score using a different set of conditional variables until we find the proper set. However, if the matching quality is still not acceptable after trying with different sets of variables, other approaches should be considered.

The PSM method is an effective semi-parametric tool to control for selection bias that is specifically due to observable variables ("selection on observables"), however if there are unobserved variables which affect assignment into treatment and the outcome variable simultaneously, a "hidden bias" or "selection on unobservables" bias might arise and the

PSM estimator may no longer be consistent.[29] Therefore, given this limitation of PSM, the last step is to test the sensitivity of the results to see how strong the influence of unobserved variables would have to be in order to undermine the implications of the PSM analysis. We use the "Rosenbaum bounds" method proposed by Rosenbaum (2002) to assess the impact of unobserved variables on the PSM results (See Gangl and DiPrete, 2004; Watson, 2005 for more details).

The "Rosenbaum bounds" method relies on the assumption that the probability of treatment for individual *i* is determined by both observable and unobservable variables: [30]

(11) $$P(D_i = 1 \mid X_i, u_i) = F(\beta X_i + \gamma u_i)$$

The odds ratio that individual *i* receive treatment is:

(12) $$\frac{P_i}{1-P_i} = e^{(\beta X_i + \gamma u_i)}$$

For two matched individuals (*i* and *j*) with identical observed variables, the ratio of the odds between these two individuals is:

(13) $$\frac{\frac{P_i}{1-P_i}}{\frac{P_j}{1-P_j}} = \frac{e^{\beta X_i + \gamma u_i}}{e^{\beta X_j + \gamma u_j}} = e^{\gamma(u_i - u_j)}$$

If there are either no "selection on unobservable" bias or no differences on unobserved variables, $\gamma(u_i - u_j)$ is equal to zero and the ratio in equation (13) is one. If there is an

[29] In this case, instrumental variable (IV) methods or panel DID methods are usually used to account for unobservable variables driving selection. However, it should be noted that although IV and DID approaches are typically used to control for "selection on unobservables", these methods are not without its own limitations. Studies by Imbens and Angrist (1994) argue that IV methods with binary endogenous variables only have a "local" interpretation (i.e. the local average treatment effect). On the other hand, DID methods rely on the existence of a baseline survey data prior to treatment.

[30] Equation (12) is based on the assumption that $F(\cdot)$ follows the logistic distribution.

unmeasured variable that affects the probability of treatment, this ratio is no longer equal to one. For simplicity, Aakvik (2001) assume that $u \in \{0,1\}$. We can assess the sensitivity of the outcomes with respect to the "selection on unobservables" bias by varying the value of e^{γ} and looking for the value that eliminate the impact of the treatment. The result is said to be sensitive to unobserved variables if this value is close to one. In this case, we should interpret the result with caution and/or consider other evaluation approaches like instrumental variable (IV) methods or panel data difference-in-difference (DID) estimators as a robustness check.

4.3.2 The Regression-based Method

As a robustness check to the PSM approach used to assess the impact of IPM-FFS on our outcomes of interest, we also employ the regression-based approach described in Godtland et al. (2004) (see also Wooldridge, 2002, pp. 611-613). This method is also based on the conditional independence (CI) assumption (condition (5) above) which can be rewritten in parametric form as follows:

(14.1) $$E(Y^0 \mid X) = \alpha_0 + (X - \bar{X})\beta_0$$

(14.2) $$E(Y^1 \mid X) = \alpha_1 + (X - \bar{X})\beta_1$$

where X is the vector of observable variables with average value $\bar{X}$. Then we can write the expected outcome Y conditional on a set of observed variables as:

(15) $$E(Y \mid X, D) = \delta + \alpha D + X\beta + D(X - \bar{X})\gamma$$

The parameters δ, α, β, and γ can be estimated by using ordinary least square (OLS) method to regress Y on D, X, and $D(X - \bar{X})$ from:

(16) $$Y = \delta + \alpha D + X\beta + D(X - \bar{X})\gamma + \varepsilon$$

If there are no unobserved variables that determine *Y*, the parameter estimates from the OLS regression are consistent and we can derive the average treatment effect given *X* as:

(17) $$A\hat{T}E(X) = E(Y^1 - Y^0 \mid X) = \hat{\alpha} + (X - \bar{X})\hat{\gamma}$$

We can average this equation over any groups of population to obtain the impact of treatment on the outcomes of those groups. Averaging equation (17) over the whole sample gives us the *ATE*, which is equal to $\hat{\alpha}$. To estimate *ATT*, which is of more interest in this study, we average equation (17) over the treated group (the IPM-FFS farmers in our case):

(18) $$ATT = E(\hat{\alpha} + (X - \bar{X})\hat{\gamma} \mid D = 1) = \hat{\alpha} + \left(\sum_{i=1}^{N} D_i\right)^{-1} \left[\sum_{i=1}^{N} D_i (X_i - \bar{X})\hat{\gamma}\right]$$

Similar to the *PSM* method, the regression from equation (16) only allows us to account for bias due to "selection on observables". In case there are unobserved variables (in the error component, ε) that determine the outcome and treatment decision simultaneously, the parameters estimates are no longer consistent. However, we can assess the magnitude of the potential "selection on unobservable" bias that would eliminate the impacts of treatment on the outcomes. We follow the procedure by Altonji et al. (2005) that use the information about "selection on observables" to guide whether bias due "selection on unobservables" are problematic in this case[31]. Based on equation (16), the procedure to see the impact of the "selection on unobservables" bias relies on the condition:

(19) $$\frac{E(\varepsilon \mid D = 1) - E(\varepsilon \mid D = 0)}{Var(\varepsilon)} = \frac{E(X\beta \mid D = 1) - E(X\beta \mid D = 0)}{Var(X\beta)}$$

[31] This method has been applied in Rejesus et al. (2011) and Godtland et al. (2004)

This condition states that the relationship between D and the variance-adjusted mean of the distribution of the index of unobservable that determine outcomes is the same as the relationship between D and the variance-adjusted mean of the observable index[32]. To measure the impact of "selection on unobservables" bias, we would like to know how large this bias have to be to account for the entire estimate of α under the null hypothesis that there is no impact from treatment ($\alpha = 0$ and $\gamma = 0$). We regress D on X so that $D = X\theta + \tilde{D}$ where $X\theta$ is the predicted value and $\tilde{D}$ is residuals. Altonji et al. (2005) show that the bias from unobservables on the parameter estimate for $D, \hat{\alpha}$, from equation (16) is:

(20) $$bias(\hat{\alpha}) = \frac{Var(D)}{Var(\tilde{D})}\left[E(\varepsilon \mid D = 1) - E(\varepsilon \mid D = 0)\right]$$

Under the null hypothesis that there is no impact from treatment, we regress equation (16) by imposing $\alpha = 0$ and $\gamma = 0$ and calculate the right hand side of equation (19). The $bias(\hat{\alpha})$ can be estimated from equation (20) using $\left[E(\varepsilon \mid D = 1) - E(\varepsilon \mid D = 0)\right]$ from equation (19). The ratio of the shift in the distribution of unobservable that is required to explain away the entire observed treatment effect based on observable variables is:

(21) $$\tau = \frac{\hat{\alpha}}{bias(\hat{\alpha})}$$

If τ is substantially higher than 1, then shift in unobservable has to be substantially larger than shift in the observables to invalidate the measured treatment impact and the "selection on unobservable" may not be a big issue in this case. On the other hand, if this

[32] The assumptions for this condition are (1) the variables X are chosen at random from the full set of variables (observed and unobserved) that determine the outcome and (2) the number of variables X are large and none of them dominates the distribution of D or the outcome.

ratio is close to or less than 1, it means that the same or smaller shift in unobservable can eliminate the treatment impact. Similar to the PSM method, we should interpret the regression-based result with caution and/or consider other evaluation approaches as a robustness check when τ is close to or less than one. In the cases where our outcome variables of interest are sensitive to unobservable variables, the IV technique is typically used (especially for cross-sectional data). The application of the IV technique with the regression-based method above is done by using the predicted probability to adopt the IPM-FFS, $\hat{D}$, as an instrument for the actual D dummy variable in estimating equation (16) as follows:

(22) $$Y = \delta + \alpha \hat{D} + X\beta + \hat{D}(X - \bar{X})\gamma + \varepsilon$$

and the probability to adopt the IPM-FFS, $\hat{D}$, is estimated by probit or logit model:

(23) $$D = c + W\theta + \nu$$

where W is a vector of instrumental variables that affect IPM-FFS adoption, c and θ are the parameters to be estimated, and ν is the random error term. Note that the vector of instruments has to include an "exclusion" restriction where at least one variable only affects the IPM-FFS decision but not the outcome variables (e.g., yield, profit, and input expenditures). Similar to the OLS regression-based method, the parameter estimates from equation (22) give the *ATE* equal to $\hat{\alpha}$ while the *ATT* can be calculated using equation (18).

4.4 Results

4.4.1 Descriptive Statistics

Summary statistics for the variables used in the regression-based estimation and the probit model for the PSM method are presented in Table 4.1. The set of observable variables, *X*, used in this study are consistent with previous empirical studies of IPM-FFS impact (See Feder et al., 2004; Rejesus et al., 2009; Yorobe et al., 2011). Based on Table 4.1, the mean yield, herbicide expenditures, and profits are higher for IPM-FFS farmers compared to non-IPM-FFS farmers, while insecticide expenditures are lower for IPM-FFS farmers relative to non-IPM-FFS farmers. The mean labor expenditures, fertilizer expenditures, and farmer's self-reported health score do not seem to statistically differ between IPM-FFS adopters and non-adopters. However, we cannot make a conclusion based on these simple mean comparisons because of bias from "selection on observables" and "selection on unobservables", as mentioned above.

4.4.2 PSM Results

The first stage probit estimates for the probability of IPM-FFS adoption to be used in the PSM are presented in Table 4.2. The balancing property is satisfied for this probit specification (See Appendix 4.A.). The probit results suggest that farms that are closer to the extension office and pesticide suppliers are more likely to adopt IPM-FFS. Hence, these are the main observable variables that seem to drive participation in IPM-FFS. The next step is to match IPM-FFS farmers with non-IPM-FFS farmers using the propensity scores estimated

from the probit model. We implement two matching methods; the nearest neighbor matching and the kernel-based matching methods. We used one-to-one and ten-to-one matching for the nearest neighbor matching (NNM) method and we used the Epanechnikov kernel matching (KM) with a bandwidth at 0.06 for the kernel matching.[33,34] The comparison of means of the observable variables between the treated and control groups for the unmatched sample and the matched samples (from the different matching approaches) are presented in Table 4.3. The mean comparison results suggest that the matched non-IPM-FFS observations are not significantly different from the matched IPM-FFS observations in their observable characteristics and we can estimate the IPM-FFS impacts based on the matched samples.

The impacts of IPM-FFS on yields, insecticide expenditures, labor expenditures, herbicide expenditures, fertilizer expenditures, profit, and farmer's self-reported health status are presented in Table 4.4. The results from the matched samples show that insecticide expenditures are smaller for the IPM-FFS farmers relative to the non-IPM-FFS farmers. This is as expected since the main objective of introducing IPM-FFS is to reduce the excessive use of insecticides. The reduction in insecticide expenditures for IPM-FFS farmers from different matching methods ranges from PhP1,638 to PhP2,037(See Table 4.4). These magnitudes are lower than the study of Yorobe et. al. (2011), where they found the reduction in insecticide

[33] For the bandwidth value at 0.06, we followed Silverman (1986) recommendation in selecting the bandwidth value for kernel matching; the value is $h = 1.06\sigma n^{-1/5}$, where h is the bandwidth, σ is the standard deviation of outcome of interest, and n is the number of observation in the sample.

[34] We also used different numbers (i.e., 5, 15, and 20) in the nearest matching method and we also used different bandwidths (i.e. 0.05 and 0.1) for the kernel matching method. The results of these alternative matching schemes are not substantially different from the results reported here and are available from the author upon request.

expenditures are around PhP 5,500.[35] Based on these reductions in insecticide use, we expected improvement in farmer's health due to IPM-FFS adoption. However the impact of IPM-FFS on farmer's health is insignificant. The possible explanation is that we do not have accurate information on actual farmer's health condition (i.e., from a doctor's diagnosis) since the health status variable used in this study are self-reported[36]. Hence, there may be measurement errors. Different farmers have different perspective on their health condition relative to the true state of their health. As mentioned in a number of health studies, individuals with the same true health status may have different levels against which they judge their health and may not accord with the appraisal of medical experts (See Groot, 2000; Sen, 2002; Jurges, 2007). For example, a farmer who writes down a lower health score may actually be healthier than a farmer who puts a higher score in the survey. This may have led to our inconsistent results that reduction in insecticide use does not come with better health conditions.

For the impact of IPM-FFS on profit, only the result from 1-to-1 NNM method indicates that IPM-FFS farmers receive higher profit (about PhP49,559 higher) than their non-IPM-FFS counterparts at 10% significant level. Although the results based on other matching procedures show that the profit magnitudes for IPM-FFS farmers are higher than the non-IPM-FFS farmers, the difference are statistically insignificant.[37] For yields, labor expenditures, herbicide expenditures, and fertilizer expenditures, the results show that IPM-

[35] However, the study of Yorobe et. al. (2011) only give the *ATE* (not the *ATT*) impacts of IPM-FFS on the insecticide expenditures.
[36] In the questionnaire, farmers were asked to rate their general health and well-being relative to their farmer neighbors from 1(poor health) to 5 (good health).
[37] All the results of alternative matching schemes that are not reported here also suggest insignificant impact of IPM-FFS on profit. Results from these runs are available from the authors upon request.

FFS do not have a statistically significant impact on these variables across all matching methods used. In general, our results suggest that the statistically significant reduction in insecticide expenditures due to IPM-FFS did not result in a statistically significant increase in profits. This may be because insecticide expenditures tend to be proportionally smaller than the other input expenditures in our sample of farmers (i.e., labor and fertilizer).

4.4.3 The Impact of Unobservable Variables on PSM Results

The sensitivity of the results from PSM to unobservable variables can be done by using the "Rosenbaum bounds" method mentioned above. But the available tool to conduct the "Rosenbaum bounds" analysis can only be implemented for 1-to-1 NNM method (Kassie et al., 2010)[38]. Based on 1-to-1 NNM sample, the statistically significant ATT estimates from IPM -FFS are only for the insecticide expenditures and profit outcomes (Table 4.4 Panel B), therefore we only us the "Rosenbaum bounds" to test the impact of bias due to "selection on unobservables" for these two ATT estimates and omit all other insignificant ATT estimates (See Ali and Abdulai, 2010). The results of this analysis are presented in Table 4.5.

The results from the "Rosenbaum bounds" analysis suggest that in order to eliminate the estimated insecticide expenditures reduction impact of IPM-FFS, the unobservable variables would have to increase the ratio of the odds by more than 50 percent ($e^{\gamma} = 1.50$). On the other hand, the positive impact of IPM-FFS on profits could be eliminated if unobservables can increase the ratio of the odds by only 20 percent or less. These numbers of e^{γ} are similar to many other studies in social sciences (See Kumar, 2009; Swain and Floro,

[38] We used the command "rbounds" in STATA to conduct the "Rosenbaum bounds" analysis.

2009; Lee, 2010; Anderson, 2011; Sen et.al, 2011; Clement, 2012). Aakvik (2001) considered the value of 2.0 as very large and stated that this sensitivity analysis only shows how hidden biases might alter the inferences, but it does not indicate if these biases exist or what magnitudes are plausible. Similar to Aakvik (2001), Gangl and Diprete (2004) referred to the "Rosenbaum bounds" as the worse-case scenario. Many studies that utilized PSM claimed that the most important observed variables are already included in their studies and concluded the value of 1.5 and higher to be not sensitive to unobservable variables (See Aakvik , 2001; Gangl and Diprete, 2004). Similar to other studies in PSM, we already included important observed variables that affect the IPM-FFS adoption. Therefore, based on the results above, we are quite confident that participation in IPM-FFS statistically reduces the insecticide expenditures by farmers. But we still cannot definitively conclude that the IPM-FFS significantly increases profit, since this outcome is sensitive to unobservable variables and the results from other matching method on profit are insignificant.

4.4.4 The Regression-based Method Results

As a robustness check to the PSM results, we implement the regression-based method based on equation (16) to assess the impact of IPM-FFS on our outcomes of interest. The observable variables used in this regression are the same as the variables used in the first stage probit model for the PSM method, thus we can compare the impact of IPM-FFS adoption on the outcome variables conditional on the on the same observed characteristics accounted for. The results from these regression-based methods are presented in Table 4.6. The parameter estimate for IPM-FFS adoption is only statistically significant for insecticide

expenditure outcome (at the 1% level) and profit (at the 10% level). Although we have no evidence that IPM-FFS improve farmer's health, we find that the younger farmers tend to be healthier than the elder farmers as can be seen from the last column of table 4.6. However the parameter estimates for the IPM-FFS variable in Table 4.6 are the *ATE* impacts of IPM-FFS on the outcome variables.

In order to get the *ATT* impacts, we used the parameter estimates from Table 4.6 and then calculated the *ATT* impacts of IPM-FFS on the interested outcomes using equation (18). The results are presented in Table 4.7. These results are consistent with the results from PSM analysis where we found statistically strong evidence that IPM-FFS tend to reduce the insecticide expenditures of farmers who adopted IPM-FFS (statistically significant at 1% level). The insecticide expenditures reduction magnitude of PhP1,854 from this regression-based method is consistent with the results from the PSM approach. However, as with the PSM analysis, the impact of IPM-FFS on profit is weaker (but still statistically significant at 5% level). The profit increasing impact of IPM-FFS from this regression-based analysis is not much different from the magnitude of the 1-to-1 NNM of PSM analysis (about PhP55,194 compare to PhP49,559). The impacts of IPM-FFS on other outcomes are also insignificant in the regression-based approach.

4.4.5 The Impact of Unobservable Variables on the Regression-Based Results

We assess the sensitivity of the regression-based results to unobservable variables by using the procedure of Altonji et al. (2005). This analysis is based on calculating the ratio of the shift in the distribution of unobservable that is required to explain away the entire observed treatment effect. Similar to the PSM method, we only test the impact of unobservable variables for insecticide expenditures and profit outcomes, since these are the outcomes that are statistically significantly affected by IPM-FFS (Table 4.7). The estimated ratios, τ, related to the significant IPM-FFS impacts on insecticide expenditures and profit are presented in Table 4.8.

The τ ratios are less than 1 for both insecticide expenditures (0.772) and profit (0.433). Thus, the normalized shift in the distribution of unobservables would have to be only 77% and 43% as large as the shift in observables to explain away the impact of IPM-FFS on insecticide expenditures and profit respectively. These results are consistent with the "Rosenbaum bounds" analysis for PSM that the impact of IPM-FFS on insecticide expenditures is more robust to the presence of unobservable variables than the impact of IPM-FFS on profit. Since a small shift (less than 1) in distribution of unobservables can invalidate the *ATT* estimates from the regression-based method, therefore the evidences of IPM-FFS impacts from the regression-based method on insecticide expenditures and profit are not strong.

4.4.6 The IV with the Regression-Based Method Results

Since the impact of IPM-FFS on insecticide expenditures and profit are sensitive to unobservable variables, we then used the instrumental variable (IV) technique in estimating the regression-based method to control for "selection on unobservables" and to see whether the results change. In this case, we proposed distance to extension office and distance to pesticide suppliers as instrumental variables in estimating the first stage probit model for IPM-FFS adoption. Except for these two variables, the rest of observable variables used in section 4.4.4 are used with the predicted values of IPM-FFS adoption in estimating equation (22). The first stage probit estimates for the probability of IPM-FFS adoption are presented in Table 4.9 and the results from the regression-based method using the IV technique are presented in Table 4.10.

These results confirm the statistically significant insecticide expenditures reduction impact of IPM-FFS from the previous sections. However, the insecticide expenditures reduction magnitude is much higher at PhP 5,812 which is very close to the *ATE* magnitudes from the study of Yorobe et. al. (2011), this shows that the unobservable factors can alter the magnitude of the impact. The impacts of IPM-FFS on other outcomes including profit are insignificant. The insignificant impact of IPM-FFS on profit from the regression-based method using IV technique provide an evidence that there are other unobservable factors that can invalidate the results from PSM with 1-to-1 NNM and the regression-based method methods in previous sections. For the impacts of IPM-FFS on other outcomes, this method also provides similar results with the PSM and the regression-based method (i.e., the impacts of IPM-FFS on other outcomes are insignificant).

4.5 Conclusion

This study empirically examines the impacts of IPM-FFS on yields, insecticide expenditures, labor expenditures, herbicide expenditures, fertilizer expenditures, profit, and farmer's self-reported health status using data from onion farmers in the Philippines. We control for "selection on observables" by using the PSM method, but a regression-based method described in Godtland et al. (2004) is also employed as a robustness check. As these methods only control for "selection on observables", we also analyze the sensitivities of our IPM-FFS impact results to bias due to "selection on unobservables". We find evidence that IPM-FFS farmers tend to spend less for insecticides as indicated by the results from all analyses in this study. However, the results from regression-based methods still suggest that the IPM-FFS impact on insecticide expenditures may be sensitive to unobservable variables. The result from the application of an instrumental variable (IV) technique with the regression-based methods to control for "selection on unobservables" also confirms that IPM-FFS have statistically significant reduction impact on insecticide expenditures (even though the magnitude of the effect using this approach is higher than in the PSM).

In general, we can conclude that the IPM-FFS training program is quite successful in terms of reducing excessive insecticide use. With lower insecticides use, it is reasonable to expect that IPM-FFS would improve farmers' health because reduction in pesticide use is usually associated with better health outcomes (see Rola and Pingali, 1993; Pingali et. al., 1994; and Antle and Pingali, 1994). However, we do not find strong evidence that IPM-FFS has a statistically significant effect on farmers' health. But note that this result may be due to

the fact that health status is self-reported in our survey and measurement errors may be an issue in the estimation.

With respect to the impact of IPM-FFS on profit, we also do not find strong evidence that IPM-FFS farmers receive higher profits than non-IPM-FFS farmers. Although one matching result (1-to-1 NNM) and the regression-based method result show a profit increasing effect of IPM-FFS, these results are highly sensitive to bias due to unobservable variables. There is no evidence that IPM-FFS training significantly affects yields, labor expenditures, herbicide expenditures, and fertilizer expenditures. Because the insecticide expenditures are only a small portion of input expenditures (as can be seen from Table 4.4.) and the impacts of IPM-FFS on yield and other input expenditures are insignificant, the strong reduction in insecticide expenditures due to IPM-FFS do not necessarily translate to statistically higher profits.

In summary, our study suggests that the IPM-FFS significantly reduces the level of insecticide use of participating farmers, but we do not have evidence that IPM-FFS significantly impacts the other outcome variables of interest (e.g., yield, profit, and other input expenditures). Thus, it is difficult to claim that the IPM-FFS program is an unequivocal success in terms of bringing direct economic benefits to farmers since we do not find strong evidence that IPM-FFS improves income and farmer health. Without these direct benefits, farmers may lose motivation to attend this program if no structural changes to this IPM dissemination method are made. Perhaps policy makers and extension educators can adjust the IPM-FFS program to further emphasize (or include) other agronomic practices that not only reduce insecticide expenditures, but also optimize (or reduce) the use of other inputs

like fertilizer and herbicides. The more efficient use of all inputs would likely reduce total expenditures and eventually translate to higher incomes.

Even though the empirical findings from this study provide interesting results, there are still opportunities for future research in this area that can potentially improve our understanding of the economic effects of IPM-FFS. First, a better measure of health status needs to be more objectively collected in future investigations in order to more accurately quantify the impact of IPM-FFS on farmer's health. This may be done by collecting more specific information regarding farmer's health status (i.e., frequency of health symptoms, the expenditure to treatment the illness, etc.) as a proxy for health status. For example, Pingali et. al.(1994) collaborated with a medical doctor to better assess farmers' health as it is related to chemical exposure. Huang et al.(2008) measured farmer's health status based on the reported number of pesticide-generated illnesses from the following symptoms: headaches, nausea, skin irritation, digestive discomfort, or other problems. Second, more work should be done to more directly assess the impact of IPM-FFS on the environment. Data on environmental variables within the farm (i.e., no. of beneficial insects) or in nearby water sources (i.e., nitrate levels in nearby rivers/streams) needs to be collected over time (together with the other variables collected in this study) to accurately assess the environmental effect of IPM-FFS. Assessment of the environmental impact of IPM-FFS would provide a better picture of the total benefits of this training program to include the positive environmental externality from lower insecticide use. Similar to assessing the impact of IPM-FFS on farmer's health, researchers may need to collaborate with environmental scientists to collect appropriate measures of environmental conditions. Lastly, once the benefits of IPM-FFS are better

understood (including the non-monetary health and environmental benefits), then a benefit-cost analysis should be undertaken to determine whether the cost of funding the IPM-FFS dissemination approach is worth it. As mentioned in previous literature (see Feder et al., 2004; Yorobe et al. 2011), FFS tend to be more expensive than other modes of IPM information dissemination (i.e., field days). Hence, if the net benefits derived from IPM-FFS are similar to other dissemination methods, then resources may be better spent on these alternative IPM dissemination methods rather than IPM-FFS. The role of alternative IPM dissemination methods as a substitute or complement to IPM-FFS would be better understood if these types of benefit-cost studies can be conducted.

Table 4.1. Summary Statistics

Variables	Full Sample (n=197)		IPM-FFS farmers (n=69)		Non IPM-FFS farmers (n=128)	
	Mean	St. Dev	Mean	St. Dev	Mean	St. Dev
Yield (tons/ha)	8.88	6.72	9.64	6.94	8.47	6.59
Insecticide Expenditures (x 1,000 PhP)	4.253	4.079	3.058	2.830	4.897	4.494
Labor Expenditures (x 1,000 PhP)	19.006	10.673	18.343	9.618	19.363	11.220
Herbicide Expenditures (x 1,000 PhP)	3.307	3.381	3.817	4.800	3.032	2.254
Fertilizer Expenditures (x 1,000 PhP)	20.441	11.680	20.622	12.764	20.343	11.103
Profit (x 1,000 Php)	145.959	153.815	178.603	183.046	128.361	132.974
Farmers General Health (0-5)	4.25	0.89	4.20	0.87	4.27	0.90
IPM-FFS adoption	0.35	0.48	-	-	-	-
Sex (Male = 1, Female = 0)	0.82	0.38	0.86	0.35	0.80	0.40
Age of Farmers (years)	47.20	12.11	47.04	10.95	47.28	12.74
Farm Area (ha)	1.22	1.00	1.17	0.77	1.24	1.11
Onion farming Experiences (years)	19.07	10.88	17.74	8.96	19.79	11.77
Income other than Onion Farming (x 1,000 Php/month)	15.792	16.665	18.303	18.431	14.438	15.539
Distance to Pesticide Suppliers (km)	8.05	4.35	6.49	4.01	8.90	4.30
Distance to Nearest Extension Office (km)	7.81	6.31	5.46	5.50	9.07	6.38
Degree of Pest Infestation (% of whole crop)	12.06	17.63	12.78	17.87	11.66	17.55
Town (Talavera = 1, Other = 0)	0.53	0.50	0.45	0.50	0.58	0.50

Table 4.2. First Stage Probit Result for the PSM Approach.

Variable	Parameter Estimate	P-value
Sex	0.271	0.324
Age of Farmers	0.005	0.634
Farm Area	-0.056	0.581
Onion farming Experiences	-0.009	0.389
Income other than Onion Farming	0.007	0.210
Distance to Pesticide Suppliers	-0.074	0.009
Distance to Nearest Extension Office	-0.047	0.006
Degree of Pest Infestation	0.003	0.607
Town	0.014	0.954
Intercept	0.168	0.767
Log-Likelihood		-113.341
Pseudo-R-squared		0.112

Table 4.3. Comparison of means of the observable variables between IPM-FFS and Non-IPM-FFS farmers

Variables	IPM-FFS	Non-IPM-FFS	P-value
A. Unmatched Sample			
(*n=197: IPM-FFS = 69, Non-IPM-FFS = 128*)			
Sex	0.855	0.805	0.380
Age of Farmers	47.043	47.281	0.896
Farm Area	1.173	1.243	0.638
Onion farming Experiences	17.739	19.789	0.208
Income other than Onion Farming	18.302	14.438	0.121
Distance to Pesticide Suppliers	6.486	8.898	<0.001
Distance to Nearest Extension Office	5.462	9.071	<0.001
Degree of Pest Infestation	12.783	11.664	0.672
Town	0.449	0.578	0.085
B. 1-to-1 Nearest Neighbor Matched Sample			
(*n=124: IPM-FFS = 62, Non-IPM-FFS = 62*)			
Sex	0.855	0.855	1.000
Age of Farmers	47.323	45.065	0.292
Farm Area	1.163	1.182	0.911
Onion farming Experiences	17.903	18.258	0.854
Income other than Onion Farming	14.973	16.867	0.523
Distance to Pesticide Suppliers	6.968	7.210	0.729
Distance to Nearest Extension Office	5.910	6.502	0.537
Degree of Pest Infestation	11.403	13.129	0.596
Town	0.435	0.419	0.857
C. 10-to-1 Nearest Neighbor Matched Sample			
(*n=188: IPM-FFS = 62, Non-IPM-FFS = 126*)			
Sex	0.855	0.874	0.756
Age of Farmers	47.323	47.115	0.921
Farm Area	1.163	1.159	0.978
Onion farming Experiences	17.903	18.753	0.658
Income other than Onion Farming	14.973	18.774	0.291
Distance to Pesticide Suppliers	6.968	7.263	0.677
Distance to Nearest Extension Office	5.910	6.559	0.504
Degree of Pest Infestation	11.403	12.373	0.758
Town	0.435	0.431	0.957
D. Kernel Matched Sample			
(*n=190: IPM-FFS = 62, Non-IPM-FFS = 128*)			
Sex	0.855	0.872	0.783
Age of Farmers	47.323	46.748	0.782
Farm Area	1.163	1.148	0.928
Onion farming Experiences	17.903	17.776	0.946
Income other than Onion Farming	14.973	16.977	0.478
Distance to Pesticide Suppliers	6.968	7.122	0.827
Distance to Nearest Extension Office	5.910	6.316	0.680
Degree of Pest Infestation	11.403	11.828	0.888
Town	0.435	0.437	0.990

Note: The means of the matched non-IPM-FFS in 10-to-1 nearest neighbor matched sample and kernel matched sample are the weighted-average based on the weights produced in the matching procedures.

Table 4.4. The impacts of IPM-FFS on yields, insecticide expenditures, labor expenditures, herbicide expenditures, fertilizer expenditures, profit, and farmer's self-reported health status: PSM Approach

Variables	IPM –FFS mean	Non-IPM-FFS mean	Difference	p-value
A. Unmatched Sample				
Yield	9.927	8.470	1.457	0.172
Insecticide Expenditures	3.058	4.897	-1.839	0.002
Labor Expenditures	18.343	19.363	-1.020	0.524
Herbicide Expenditures	3.817	3.032	0.785	0.120
Fertilizer Expenditures	20.622	20.343	0.279	0.873
Profit	178.603	128.361	50.242	0.028
Farmer's health	4.203	4.266	-0.063	0.637
B. 1-to-1 Nearest Neighbor Matched Sample				
Yield	9.564	7.960	1.605	0.174
Insecticide Expenditures	3.184	4.822	-1.638	0.017
Labor Expenditures	18.623	19.354	-0.732	0.672
Herbicide Expenditures	3.732	3.278	0.454	0.539
Fertilizer Expenditures	21.111	20.754	0.357	0.881
Profit	170.843	121.284	49.559	0.078
Farmer's health	4.194	4.323	-0.129	0.434
C. 10-to-1 Nearest Neighbor Matched Sample				
Yield	9.564	8.706	0.858	0.493
Insecticide Expenditures	3.184	5.221	-2.037	0.005
Labor Expenditures	18.623	20.292	-1.669	0.363
Herbicide Expenditures	3.732	3.331	0.400	0.582
Fertilizer Expenditures	21.111	21.004	0.107	0.962
Profit	170.843	129.914	40.929	0.156
Farmer's health	4.194	4.268	-0.074	0.638
D. Kernel Matched Sample				
Yield	9.564	8.427	1.137	0.360
Insecticide Expenditures	3.184	5.020	-1.834	0.005
Labor Expenditures	18.623	19.046	-0.424	0.807
Herbicide Expenditures	3.732	3.284	0.448	0.545
Fertilizer Expenditures	21.111	20.320	0.791	0.704
Profit	170.843	126.600	44.242	0.128
Farmer's health	4.194	4.267	-0.073	0.626

Note: P-values for the matched sample are calculated from bootstrapped standard errors at 200 replications.

Table 4.5. The "Rosenbaum bounds" Analysis for "Selection on unobservables"

e^{γ} value	p-value
A. Insecticide expenditures	
1.00	0.004
1.05	0.006
1.10	0.010
1.15	0.014
1.20	0.020
1.25	0.028
1.30	0.037
1.35	0.049
1.40	0.062
1.45	0.077
1.50	0.094
1.55	0.113
1.60	0.133
B. Profit	
1.00	0.034
1.05	0.048
1.10	0.067
1.15	0.088
1.20	0.113
1.25	0.142
1.30	0.173

Table 4.6. Parameter Estimates from the Regression-based Method

Variables	Yield	Insecticide Expenditures	Labor Expenditures	Herbicide Expenditures	Fertilizer Expenditures	Profit	Farmers' Health
Farmer Characteristics							
IPM-FFS	1.619	-1.711***	-0.653	0.604	1.274	40.518*	-0.009
Sex	2.933*	0.796	0.920	0.517	1.305	52.467	-0.148
Age of Farmers	-0.034	-0.027	-0.127	0.012	-0.070	-0.857	-0.014*
Farm Area	-0.279	-0.348	-1.162	-0.005	-2.668***	2.192	0.032
Onion farming Experiences	0.024	-0.008	0.105	-0.019	-0.119	0.308	0.004
Income other than Onion Farming	0.013	0.006	-0.023	-0.001	0.069	0.473	0.002
Distance to Pesticide Suppliers	-0.033	0.111	0.158	-0.029	0.310	3.294	-0.008
Distance to Nearest Extension Office	0.105	0.080	0.032	0.035	-0.059	0.982	-0.021
Degree of Pest Infestation	-0.048	0.017	-0.020	-0.010	0.040	-1.116	0.000
Town	-0.021	3.441***	-2.387	-0.518	1.009	-30.275	0.169
Interaction term: IPM-FFS x de-meaned Farmer Characteristics							
Sex	-2.359	-2.425	-4.047	-3.560**	-0.065	-28.698	0.157
Age of Farmers	-0.029	0.007	0.042	0.084	-0.146	-3.562	-0.003
Farm Area	-1.829	0.785	-1.743	-0.497	0.314	-53.531*	0.061
Onion farming Experiences	-0.030	0.074	-0.085	-0.058	0.100	-2.817	-0.003
Income other than Onion Farming	0.066	-0.029	0.026	0.033	-0.029	2.699*	-0.014
Distance to Pesticide Suppliers	0.222	-0.062	0.085	0.125	0.085	3.498	0.036
Distance to Nearest Extension Office	-0.105	-0.114	-0.035	-0.141	0.560*	-3.157	0.007
Degree of Pest Infestation	0.003	-0.023	0.065	-0.044	-0.053	0.656	0.000
Town	1.257	2.413	1.492	0.425	-6.655	3.798	0.234
Constant	7.345**	6.145***	24.260***	2.802*	24.002***	103.323	5.048***

Note: *,**, and *** show the significant level at 10%, 5%, and 1% respectively.

Table 4.7. The *ATT* impacts of IPM-FFS: Regression-based Method.

Outcomes	*ATT* impacts of IPM-FFS	P-value
Yield	1.632	0.174
Insecticide Expenditures	-1.854	0.005
Labor Expenditures	-0.663	0.716
Herbicide Expenditures	0.727	0.185
Fertilizer Expenditures	0.120	0.950
Profit	55.194	0.025
Farmer's health	-0.128	0.386

Table 4.8. Assessment of "Selection on unobservables": Altonji et al. (2005) Procedure.

Outcome	Ratio
Insecticide Expenditures	0.772
Peofit	0.433

Table 4.9. First Stage Probit Result for the the Regression-based Method using the Instrumental Variables (IV) technique.

Variable	Parameter Estimate	P-value
Distance to Pesticide Suppliers	-0.069	0.003
Distance to Nearest Extension Office	-0.052	0.002
Intercept	0.529	0.100
Log-Likelihood		-115.326
Pseudo-R-squared		0.096

Table 4.10. Parameter Estimates from the Regression-based Method using the Instrumental Variables (IV) technique

Variables	Yield	Insecticide Expenditures	Labor Expenditures	Herbicide Expenditures	Fertilizer Expenditures	Profit	Farmers' Health
Farmer Characteristics							
IPM-FFS	-3.060	-5.932***	-6.072	1.444	-10.114	-19.241	0.375
Sex	3.149	-3.070	-4.301	1.629	0.587	112.702	0.086
Age of Farmers	-0.087	0.041	-0.266	-0.029	0.169	-1.335	-0.005
Farm Area	0.171	-0.294	0.370	-0.124	-2.653	40.711	-0.110
Onion farming Experiences	0.017	0.045	0.508**	0.074	-0.469**	-1.264	-0.009
Income other than Onion Farming	-0.001	0.020	0.100	-0.011	0.055	0.213	0.008
Degree of Pest Infestation	-0.072	-0.023	-0.015	0.001	-0.062	-1.265	0.003
Town	-4.178	-4.110**	-4.719	-0.585	1.100	-48.988	0.074
Interaction term: IPM-FFS x de-meaned Farmer Characteristics							
Sex	-1.230	8.380	12.992	-5.929	1.317	-163.574	-0.618
Age of Farmers	0.191	-0.128	0.519	0.199	-0.799*	-1.344	-0.030
Farm Area	-2.469	0.303	-4.292	0.032	0.582	-139.749*	0.437
Onion farming Experiences	-0.003	-0.168	-1.228**	-0.331**	1.002*	4.286	0.032
Income other than Onion Farming	0.114	-0.078	-0.338	0.056	0.004	4.004	-0.034
Degree of Pest Infestation	0.079	0.086	0.104	-0.054	0.181	1.138	-0.008
Town	12.233	2.995	6.865	0.702	-6.482	111.989	0.586
Constant	14.542**	8.675**	28.372***	2.006	26.943**	139.001	4.392***

Table 4.11. The *ATT* impacts of IPM-FFS: Regression-based Method using the Instrumental Variables (IV) technique.

Outcomes	*ATT* impacts of IPM-FFS	P-value
Yield	-3.692	0.375
Insecticide Expenditures	-5.812	0.012
Labor Expenditures	-5.243	0.396
Herbicide Expenditures	1.701	0.380
Fertilizer Expenditures	-10.625	0.110
Profit	-22.169	0.801
Farmer's health	0.158	0.760

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Chapter 5

Conclusions

This dissertation includes three essays analyzing the impacts of agricultural technologies – a Genetically-Modified (GM) crop and Integrated Pest Management (IPM) – which have been developed to reduce excessive insecticides use. We analyze this issue from a developing country perspective (the Philippines). The first and second essays focus on single-trait Bt corn, one of the most widely adopted GM crop variety, and the third essay focuses on the impacts of IPM Farmer Field Schools (FFS), an intensive IPM information dissemination method, on onion production.

The first essay analyzes the production risk effects of Bt corn in the Philippines by examining the impacts of Bt corn on the mean, variance, and skewness of yields, and then evaluating its welfare implications. Our results indicate that Bt corn do not have a statistically significant risk reducing or downside risk reducing 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. Overall, we can conclude that Bt corn farmers in the Philippines is better off (in welfare terms) relative to non-Bt farmers given the Bt corn's dominant yield increasing effect and lower probability of profit loss.

The second essay extends the literature that examines the yield impacts of Bt by determining how Bt corn technology affects yield at different points of the yield distribution

(i.e., are there heterogeneous yield impacts?). We find that the effect of Bt corn on yields is generally more strongly felt by farmers at the lower end of the yield distribution as compared to the farmers at the upper end of the yield distribution. The strong positive Bt effect on yields observed for lower yielding farmers gives some indication that Bt technology do provide benefits to poor farmers since low-yielding farmers tend to be poor smallholders in the Philippines.

The first and second essays together provide a more comprehensive picture of the impacts of Bt corn on yields and farmer welfare in developing country context. The findings in these two essays are useful information for policy makers to develop strategies that can help encourage the use of Bt technology, especially for poor smallholders. However, one potential barrier for Bt to successfully help poor farmers is the higher cost of this technology such that poorer farmers cannot effectively access the technology. If an institutional subsidy policy is put in place to help poor farmers and together with the technology's potential yield increasing effects, Bt technology is one possible tool that can help increase poor farmers' income, improve agricultural productivity, and enhance overall farmer welfare.

The third essay focuses on the impacts of the IPM-FFS on yields, insecticide expenditures, labor expenditures, herbicide expenditures, fertilizer expenditures, profit, and farmer's self-reported health status based on data from onion producers in the Philippines. We find evidence that farmers who participate in the IPM-FFS training program have statistically lower insecticide expenditures than the non-IPM-FFS farmers. However, there is no evidence that the IPM-FFS training program significantly affects yields, farmers' self-reported health, and other inputs used. The insignificant effect of IPM-FFS on farmers'

health result may be due to the fact that health status is self-reported in our survey and measurement errors may be an issue in the estimation. Although we find some evidence that IPM-FFS farmers receive higher profit than non-IPM-FFS farmers, the results are highly sensitive to potential bias from unobservable variables. Hence, we cannot strongly conclude that IPM-FFS improves farmer profits. We posit that because insecticide expenditures are only a small portion of total input expenditures, the reduction in insecticide expenditures due to IPM-FFS did not necessarily translate to higher profits. Since IPM-FFS seem to only significantly reduce insecticide use, policy makers and extension educators may need to adjust the IPM-FFS curriculum to further emphasize (or include) other agronomic practices that also optimize (or reduce) the use of other inputs like labor, fertilizer, and herbicides. The more efficient use of all inputs would likely reduce total expenditures and eventually translate to higher incomes.

Although this dissertation contributes to our understanding of the impacts of Bt technology and IPM-FFS, there are still other interesting issues that need to be explored in future research. To help policy makers judge the true value of Bt corn and IPM-FFS, a comprehensive benefit-cost analysis is needed. To conduct a benefit-cost analysis for the IPM-FFS, future research needs to more accurately ascertain the effects of IPM-FFS on farmers' health and its impact on environmental outcomes. For the Bt technology, the effect of Bt on other outcome variables (i.e., profits, farmer income, health, and environment) also needs to be studied in the future. The results of these types of benefit-cost comparisons would allow policy makers and other stakeholders to develop strategies and programs that can improve agricultural productivity and overall farmer welfare.

APPENDICES

Appendix 2.A.

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

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

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

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

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

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

Appendix 2.B.

Summary Statistics of the variables used in PSM in Chapter 2.

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 3.A.

Profit of corn farmers at different percentiles of yield distribution in 2003/2004 and 2007/2008.

Percentile of Yield	--- Crop Year 2003/2004 ---		--- Crop Year 2007/2008 ---	
	Mean yield (tons/ha)	Mean profit (x 1,000 PhP)	Mean yield (tons/ha)	Mean profit (x 1,000 PhP)
0% - 10%	1.37	-3.70	1.34	-5.92
10% - 20%	2.14	6.12	2.10	12.04
20% - 30%	2.65	8.22	2.50	14.86
30% - 40%	3.04	29.24	2.96	14.50
40% - 50%	3.42	16.75	3.13	19.75
50% - 60%	3.78	34.61	3.55	19.71
60% - 70%	4.10	20.60	4.22	20.35
70% - 80%	4.43	32.19	4.87	26.87
80% - 90%	4.98	41.65	5.56	26.16
90% - 100%	6.17	74.57	7.19	40.48

Note: the result is based on the data of non-Bt farmers

Appendix 3.B.

Parameter estimates for the OLS and the two stage least squares (2SLS) approaches

Equation/Variable	Crop Year 2003/2004		Crop Year 2007/2008	
	Estimate	p-value	Estimate	p-value
A. OLS Approach				
Constant	-0.058	0.85	-1.623	<0.01
ln(seed)	0.301	<0.01	-0.050	0.61
ln(pesticide)	0.013	0.03	-0.008	0.20
ln(fertilizer)	0.126	<0.01	0.369	<0.01
ln(labor)	-0.077	0.10	0.204	<0.01
Bt	0.296	<0.01	0.147	<0.01
B. 2SLS Approach				
-First Stage (probit) Result				
Constant	-7.027	<0.01	-4.996	<0.01
Seed Price	0.040	<0.01	0.021	<0.01
Distance	-	-	0.023	0.07
-Second Stage Result				
Constant	-0.222	0.47	-1.679	<0.01
ln(seed)	0.361	<0.01	0.008	0.94
ln(pesticide)	0.012	0.05	-0.005	0.45
ln(fertilizer)	0.128	<0.01	0.349	<0.01
ln(labor)	-0.083	0.08	0.201	<0.01
Bt	0.289	<0.01	0.234	<0.01

Parameter Estimates for the Cobb-Douglas production function for the Quantile Regression.

Crop Year/Variable	Quantile Regression estimates								
	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90
A. Crop Year 2003/2004 (Bt: n= 101; Non-Bt: n=306)									
Constant	-1.012	-1.595	-1.041	-0.534	0.032	0.236	0.754	1.128	1.451
	(0.36)	(0.01)	(<0.01)	(0.19)	(0.90)	(0.43)	(0.01)	(<0.01)	(<0.01)
ln(seed)	0.476	0.503	0.404	0.370	0.229	0.142	0.148	0.097	0.046
	(0.21)	(0.01)	(<0.01)	(<0.01)	(<0.01)	(0.12)	(0.10)	(0.40)	(0.75)
ln(pesticide)	0.019	0.023	0.012	0.009	0.007	0.010	0.003	0.009	0.010
	(0.24)	(0.04)	(0.08)	(0.29)	(0.20)	(0.08)	(0.57)	(0.19)	(0.17)
ln(fertilizer)	0.112	0.195	0.202	0.167	0.159	0.171	0.079	0.065	0.066
	(0.11)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.02)	(0.18)	(<0.01)
ln(labor)	-0.075	-0.004	-0.054	-0.087	-0.089	-0.069	-0.051	-0.055	-0.069
	(0.54)	(0.96)	(0.30)	(0.16)	(0.03)	(0.13)	(0.26)	(0.33)	(0.09)
Bt	0.333	0.357	0.291	0.303	0.291	0.266	0.267	0.227	0.208
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
B. Crop Year 2007/2008 (Bt: n= 254; Non-Bt: n=212)									
Constant	-2.988	-1.794	-1.511	-1.257	-1.425	-1.553	-1.323	-0.483	-0.331
	(0.02)	(0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.04)	(0.18)	(0.39)
ln(seed)	-0.200	-0.156	-0.076	-0.175	-0.037	0.004	-0.028	-0.053	0.058
	(0.49)	(0.39)	(0.50)	(0.08)	(0.67)	(0.96)	(0.86)	(0.56)	(0.55)
ln(pesticide)	-0.005	-0.010	-0.005	-0.010	-0.017	-0.015	-0.012	-0.008	0.005
	(0.77)	(0.35)	(0.45)	(0.12)	(<0.01)	(<0.01)	(0.27)	(0.17)	(0.49)
ln(fertilizer)	0.475	0.385	0.305	0.368	0.338	0.394	0.384	0.304	0.233
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)
ln(labor)	0.389	0.231	0.245	0.188	0.187	0.126	0.139	0.105	0.152
	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.07)	(0.02)	(<0.01)
Bt	0.026	0.162	0.224	0.174	0.175	0.178	0.153	0.116	0.073
	(0.81)	(0.02)	(<0.01)	(<0.01)	(<0.01)	(<0.01)	(0.05)	(<0.01)	(0.14)

Note: Values in parentheses are the p-values

Appendix 3.C.

First Stage Logit Results for the PSM in Chapter 3.

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

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

Appendix 3.D.

Hausman test: Parameter estimates for the OLS and 2SLS approaches from Matched Data used in the Quantile Regression in Chapter 3.

Equation/Variable	Crop Year 2003/2004		Crop Year 2007/2008	
	Estimate	p-value	Estimate	p-value
A. OLS Approach				
Constant	0.933	0.12	-1.139	0.02
ln(seed)	0.102	0.56	-0.087	0.44
ln(pesticide)	0.019	0.03	-0.010	0.17
ln(fertilizer)	0.102	0.12	0.298	<0.01
ln(labor)	-0.119	0.11	0.233	<0.01
Bt	0.221	<0.01	0.093	0.06
B. 2SLS Approach				
Constant	0.709	0.27	-1.181	0.01
ln(seed)	0.172	0.36	-0.061	0.59
ln(pesticide)	0.018	0.04	-0.009	0.19
ln(fertilizer)	0.106	0.13	0.291	<0.01
ln(labor)	-0.120	0.11	0.230	<0.01
Bt-hat	0.221	<0.01	0.135	0.03

Note: The covariates used in *Bt-hat* estimation are the instrumental variables used in the IVQR estimation.

Hausman test: p-values for equality of parameter estimates between OLS and 2SLS.

Variables	p-values	
	Crop Year 2003/2004	Crop Year 2007/2008
ln(seed)	0.13	0.14
ln(pesticide)	0.31	0.67
ln(fertilizer)	0.51	0.34
ln(labor)	0.87	0.45
Bt vs Bt-hat	0.99	0.20

Appendix 3.E.

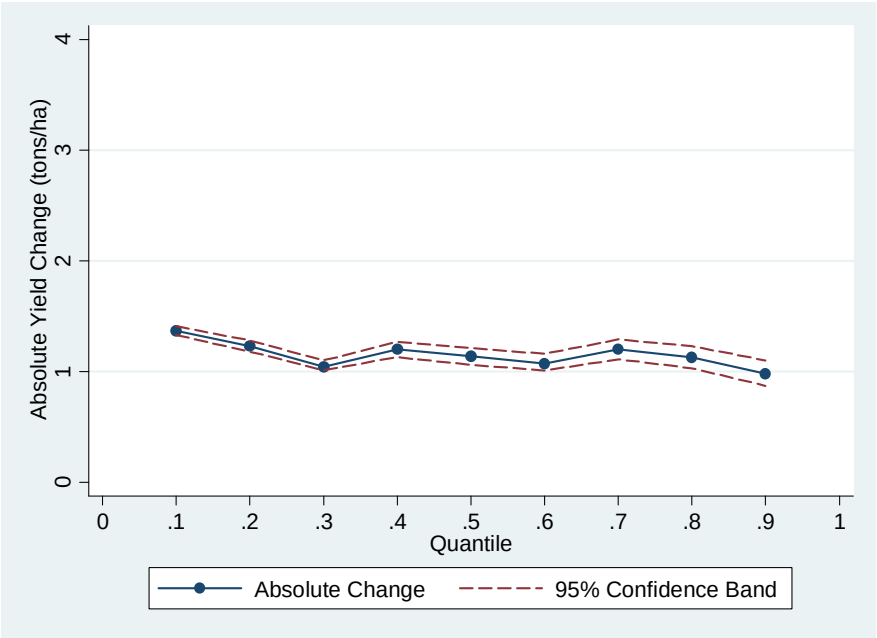

Figure A3.1.1

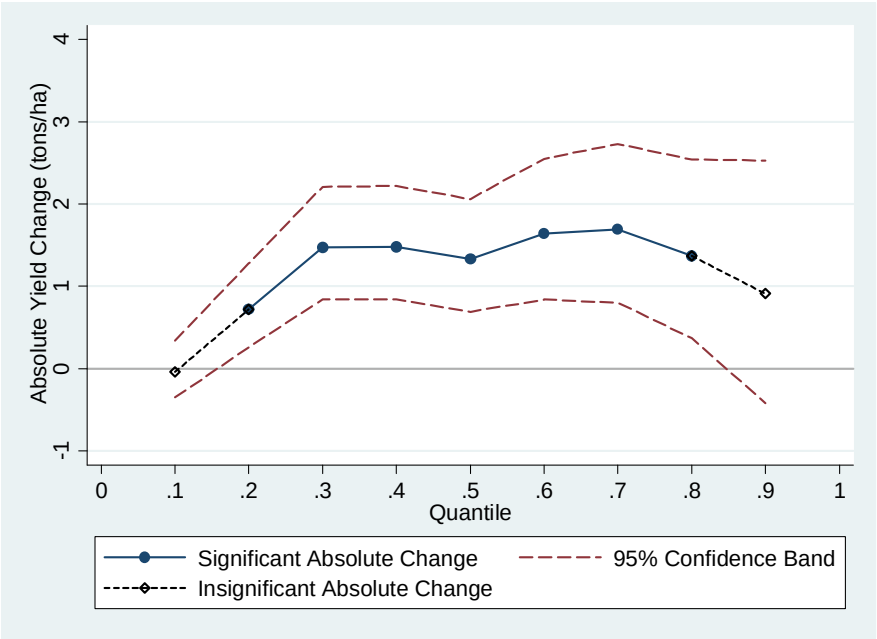

Figure A3.1.2

Figure A3.1: Absolute Yield Impact of Bt using IVQR for Crop Year 2003/2004 (A3.1.1) and Crop Year 2007/2008 (A3.1.2)

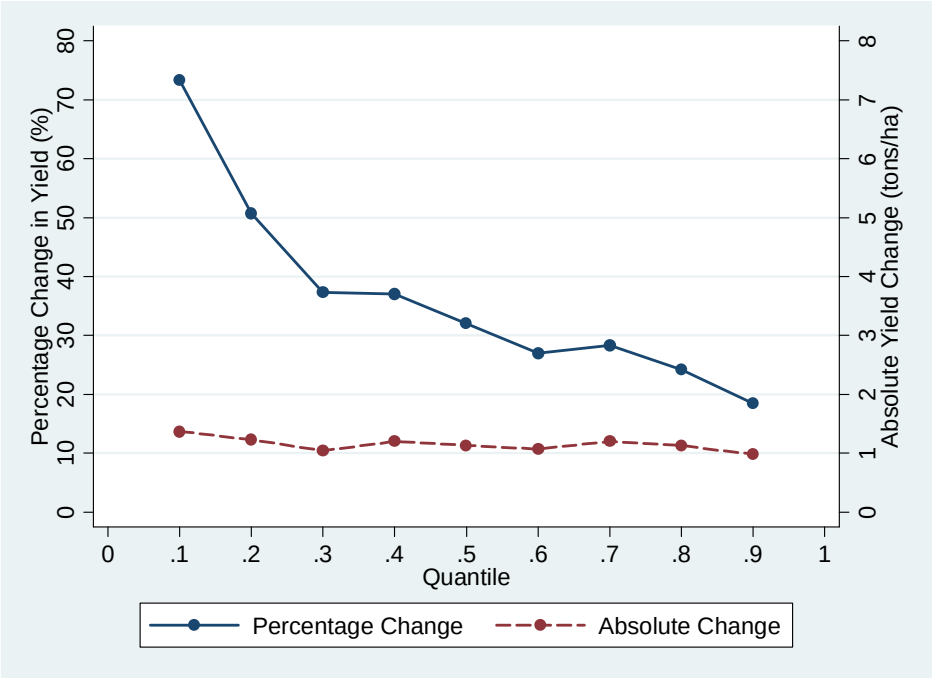

Figure A3.2.1

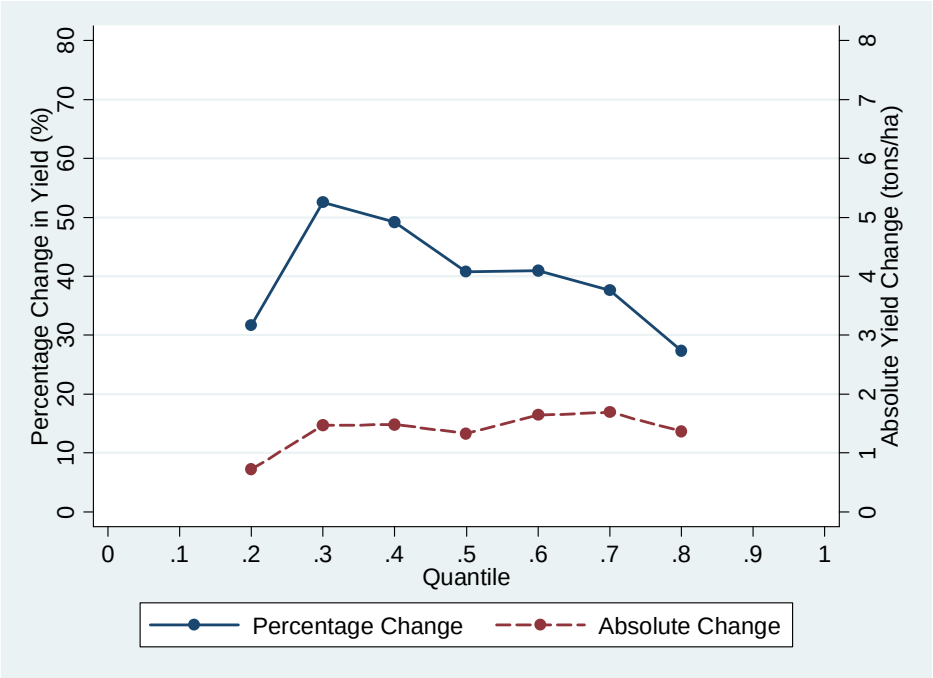

Figure A3.2.2

Figure A3.2: Significant Percentage and Absolute Yield Impact of Bt using IVQR for Crop Year 2003/2004 (A3.2.1) and Crop Year 2007/2008 (A3.2.2)

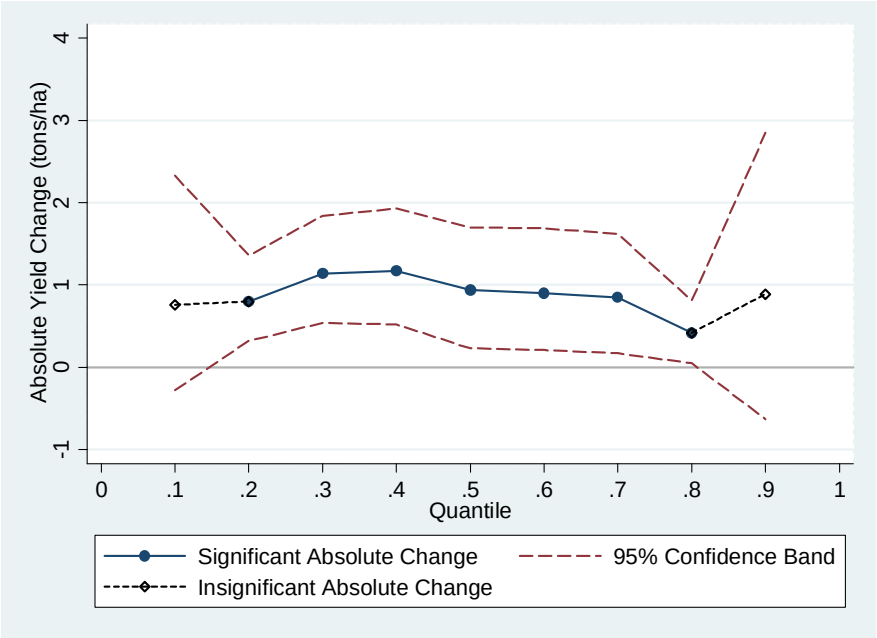

Figure A3.3.1

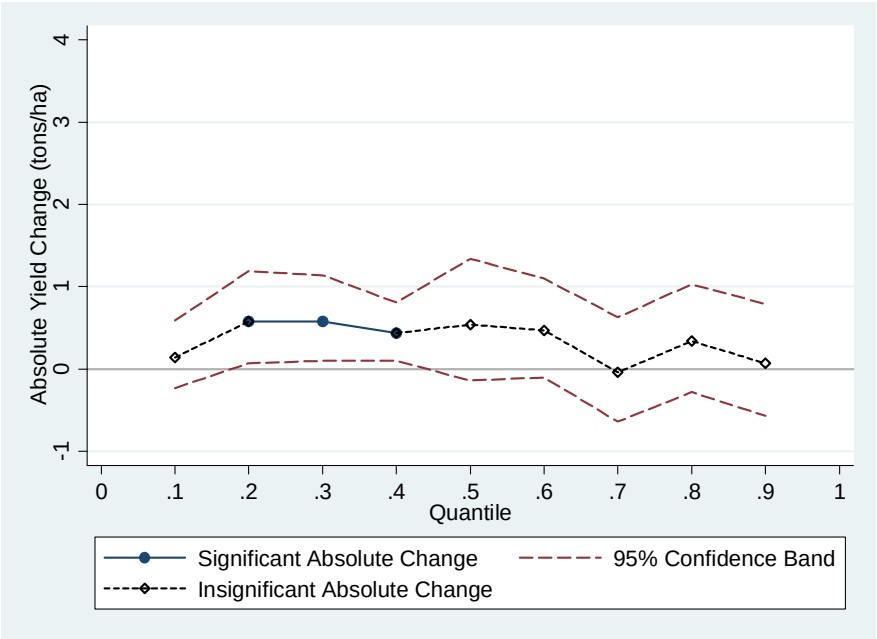

Figure A3.3.2

Figure A3.3: Absolute Yield Impact of Bt using Quantile Regression with PSM for Crop Year 2003/2004 (A3.3.1) and Crop Year 2007/2008 (A3.3.2)

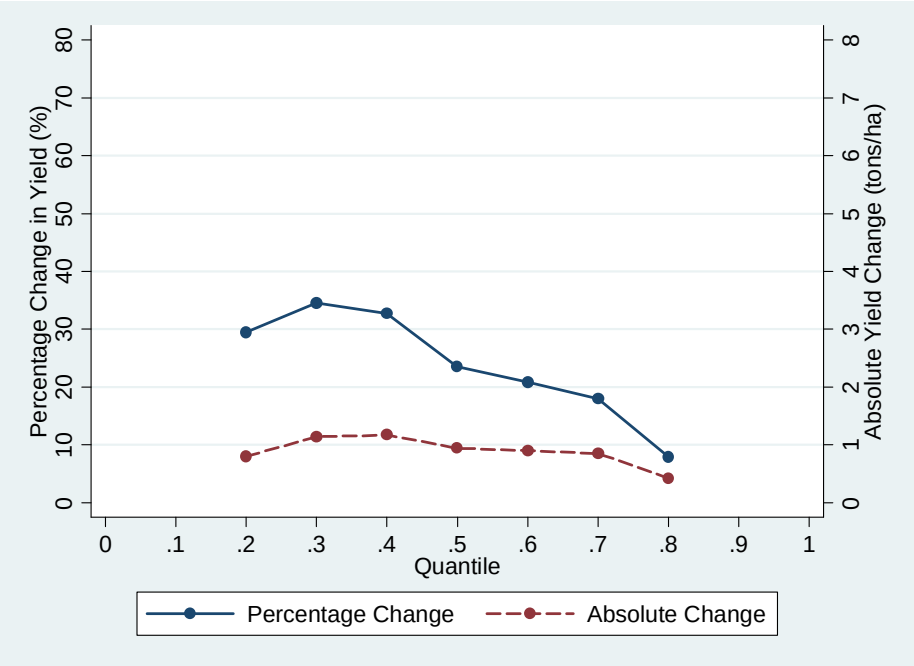

Figure A3.4.1

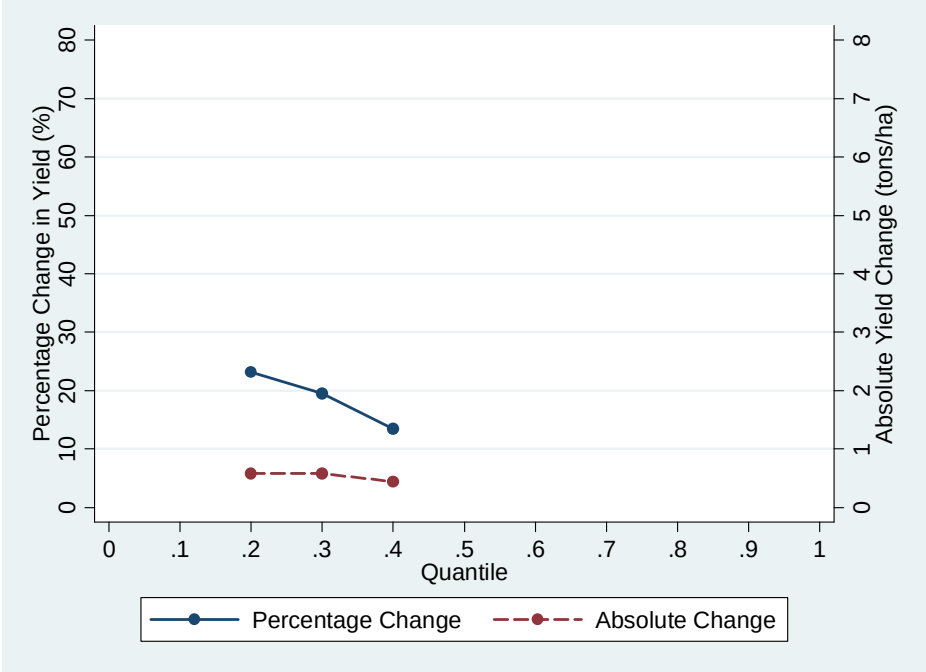

Figure A3.4.2

Figure A3.4: Significant Percentage and Absolute Yield Impact of Bt using Quantile Regression with PSM for Crop Year 2003/2004 (A3.4.1) and Crop Year 2007/2008 (A3.4.2)

Appendix 4.A.

Balancing test results: p-values for equality of means of observable characteristics between IPM –FFS and Non-IPM-FFS farmers.

Variables	Stratum1	Stratum 2	Stratum 3	Stratum 4
Farmer Characteristics				
Sex	0.05	0.78	0.36	0.50
Age of Farmers	0.34	0.75	0.50	0.65
Farm Area	0.48	0.66	0.47	0.13
Onion farming Experiences	0.49	0.43	0.28	0.67
Income other than Onion Farming	0.42	0.94	0.24	0.31
Distance to Pesticide Suppliers	0.98	0.70	0.98	0.42
Distance to Nearest Extension Office	0.68	0.76	0.01	0.37
Degree of Pest Infestation	0.74	0.79	0.68	0.40
Town	1.00	0.20	0.88	0.34
Number of Observations	40	74	57	21

Note: Balancing is satisfied as long as the p-values in each stratum is not less than 0.01.