Which Farmers Benefit the Most from *Bt* Corn Adoption in the Philippines? Estimating Heterogeneity Effects

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Selected Poster prepared for presentation at the International Association of Agricultural Economists (IAAE) Triennial Conference, Foz do Iguaçu, Brazil, 18-24 August, 2012.

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ABSTRACT

The potential contributions of new biotechnologies to sustainable food and income security have been the subject of widespread discussions around the turn of the twenty-first century. But distributional issues of which segments of GMO adopters benefit the most have not been given ample attention. Using propensity scores, we apply the (a) stratification-multilevel method of estimating heterogeneous treatment effects (SM-HTE); and the (b) matching-smoothing method of estimating heterogeneous treatment effects (MS-HTE) proposed by Xi, Brand, and Jann (2011). We find that the incidence of higher yields, lower insecticide use and reduced seed utilization in the Philippines diminishes progressively as a farmer's propensity to adopt *Bt* corn increases. Farmers with a low propensity to adopt *Bt* are those who farm smaller, non-irrigated farms located farther from seed suppliers and farmers without previous training on pest identification. In most cases, while these farmers are typically poorer farmers in smaller parcels, cannot afford irrigation and are situated in remote areas away from easily accessible seed suppliers, there is no evidence, however, that profits differ across farmers with varying propensities to adopt the *Bt* variety.

1. Introduction

The potential contributions of new biotechnologies to sustainable food and income security have been the subject of widespread discussions around the turn of the twenty-first century. More narrowly, the influence of genetically modified crops in enhancing developing country agriculture has been trumpeted into the poverty literature as pro-poor (Glover, 2009). The evidence, by far, has been mixed. Most importantly, distributional issues of which segments of GMO adopters benefit the most have not been given ample attention. Using propensity scores, we apply the (a) stratification-multilevel method of estimating heterogeneous treatment effects (SM-HTE); and the (b) matching-smoothing method of estimating heterogeneous treatment effects (MS-HTE) proposed by Xi, Brand, and Jann (2011). We find that the incidence of higher yields, lower insecticide use and reduced seed utilization in the Philippines diminishes progressively as a farmer's propensity to adopt *Bt* corn increases. And since farmers with larger, irrigated farms situated closer to seed suppliers and farmers who have previously been trained at pest identification are more likely to adopt *Bt* corn, then *Bt* technology benefits the most, farmers whose propensity to adopt *Bt* is lower. These farmers are those who farm smaller, non-irrigated farms located farther from seed supplier and farmers who have not received any training on pest identification. In most cases, while these farmers are typically poorer farmers who farm smaller parcels, cannot afford irrigation and are situated in remote areas away from easily accessible seed suppliers, there is no evidence, however, that there is a difference in profits enjoyed by farmers across varying levels of propensities to adopt the *Bt* variety.

2. Adoption of *Bt* Corn in the Philippines

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. Most of the yellow corn produced in the Philippines is sold to the livestock and poultry feed mill industries, although some small farmers keep some proportion of output to be consumed as food especially in times of poor harvest (Gerpacio et al., 2004).

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 arm size ranging from less than a hectare to about 4 hectares (Mendoza and Rosegrant, 1995; Gerpacio et al., 2004). Corn producing households are also typically headed by men, although it is becoming increasingly common to see both husband and wife equally making farm decisions. These corn producing households usually grow other cash crops in a small percentage of their cultivated area and some engage in small-scale (backyard) poultry and livestock production to augment income and supply home needs (Mendoza and Rosegrant, 1995; Gerpacio et al., 2004).

Land preparation for corn cultivation in the Philippines usually consists of one or two plowing operations, harrowing to level the field and reduce the size of soil clods, and furrowing. These land preparation activities are often done with the use of water buffalos, but may be mechanized on level terrain, especially if sufficient capital is available to pay for tractor rental. Furrowing is immediately followed by sowing and basal fertilizer application. Producers in major yellow corn producing areas historically plant the higher yielding hybrid varieties as opposed to the local/traditional open pollinated variety (OPV), although there are some farmers in these areas who still plant OPVs primarily for home consumption. Chemical fertilizers are generally applied 25-30 days after planting. Off-barring, hilling-up, and manual/hand weeding are the common cultural practices to control weeds. In some cases, herbicides are used.

Harvesting, dehusking, and sometimes shelling are done manually with both family and hired labor. Corn is sun-dried immediately after harvest, usually on drying pavements at home or in common areas in the community. Dried ears to be sold to the feed industry are then typically shelled using mechanical shellers contracted through cooperatives or individual entrepreneurs in the area (although some still manually shell the ears). Dried and shelled corn is immediately sold, making storage unimportant. Farmers usually sell their corn products directly in public markets or to feed millers, where prices are often higher. Corn farmers with loans from trader-financiers oftentimes have to sell their grain to these same trader-financiers even at lower prices. These trader-financiers loan out agricultural inputs (i.e. fertilizers, insecticides) to farmers at higher than market value, and deduct the value of agricultural inputs (plus interest) from the harvest sold back to them. Farmers who lack sufficient capital to fund their farm operations usually borrow from these trader-financiers since it is more convenient (i.e. no collateral required, easily accessible) than formal credit channels such as cooperatives and commercial rural banks (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 and sometimes loan arrangements with trader-financiers impose constraints on the availability of insecticides when it is really needed (i.e. priority given to paying customers).

With the Asian corn borer as a major insect pest for corn in the country, the agricultural sector was arguably interested in *Bt* corn technology as a means of control. In addition, this technology was seen as having the potential to improve corn productivity in the country since yields have been low (~2 metric tons/ha) and corn imports have increased over time. *Bt* corn was first introduced in the Philippines in 1996 on a limited trial basis. Greenhouse evaluations were done in local and international plant breeding laboratories based in the country, in collaboration with Monsanto Philippines, Inc. Between 1999 and 2002, after approval from the National Committee on Biosafety in the Philippines (NCBP), field trials of *Bt* corn were conducted in the major corn-producing areas of the country. Finally, in December 2002, 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 (including that combined with herbicide tolerance) 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) currently sell *Bt* corn seeds in the Philippines. In addition to hybrid seeds, these companies have extensive operations in the marketing of agricultural chemicals (Cabanilla, 2007).

3. Estimation Methods and Data

Evaluation problem, matching and heterogeneity of effects

The estimation of causal effects is inherently a comparison of potential outcomes. In particular, the causal effect for farmer *i* is the comparison of farmer *i*'s outcome if farmer *i* adopts the new technology (potential outcome under *Bt* or when treatment, $T = 1$), Y_i^1, and farmer *i*'s outcome if farmer *i* does not adopt the new technology (potential outcome under non-*Bt* or when treatment, $T = 0$), Y_i^0. The fundamental problem of causal inference is that for each farmer, we can observe only one of these potential outcomes at a particular point in time because each farmer will either plant *Bt* corn ($T = 1$) or non-*Bt* corn ($T = 0$), but not both. As such, the estimation of the causal effect of *Bt* is associated with the problem of predicting unobserved outcomes. In particular, we come across the issue of predicting potential outcomes for *Bt* farmers had they not adopted *Bt*; at the same, we also run into problem of predicting potential outcomes for non-*Bt* farmers had they adopted *Bt*.

For efficient causal inference and estimation of potential outcomes, we would like to compare *Bt* and non-*Bt* groups of farmers that are similar as possible. If the groups are very different, the prediction Y^1 for the non-*Bt* farmers will be made using information from farmers who look very different from themselves, the same thing occurs for the prediction of Y^0 for the *Bt* farmers.

A solution to this is the assumption of "strongly ignorable treatment assignment" which implies that (a) the treatment assignment (*T*) (*Bt* adoption in this case) is independent of the potential outcomes (Y^0, Y^1) given the covariates (*X*): $T \perp (Y^0, Y^1) \mid X$, and (b) there is a positive probability of receiving each treatment for all values of $X : 0 < P(T = 1 \mid X) < 1$ for all *X*. The first part of the definition is oftentimes referred to as "unconfoundedness", "ignorability" or "selection on observables". Hence, after conditioning on a set of observable farm/farmer characteristics, outcomes are conditionally mean independent of *Bt* adoption.

The ignorability assumption makes sense in that matching on or controlling for the observed covariates also matches on or controls for the unobserved covariates inasmuch as these unobserved covariates are related to those that are observed (Stuart, 2010). However, conditioning on X can be difficult due to the "curse of dimensionality." In other words, as the number of characteristics used in matching *Bt* and non-*Bt* farmers increases, the chances of finding an exact match are reduced; oftentimes, including even a relatively small number of characteristics can quickly result in some *Bt* farmers remaining unmatched. To tackle this issue, Rosenbaum and Rubin (1983) suggest matching treated and untreated individuals solely on their 'propensity score' – the estimated probability of being treated given observable characteristics

(X): $T \perp (Y^0, Y^1) \mid P(T = 1 \mid X)$. This reduces the matching from a multi-dimensional problem (where the number of dimensions depends on the number of available variables) to a one-dimensional problem. In our case, each *Bt* farmer is matched to the non-*Bt* farmer who is most similar in terms of probability of adopting *Bt*, where this probability is calculated on the basis of individual characteristics. Once the two groups are formed, the average effect is estimated for each outcome by simply computing the difference in means between the two groups.

However, to the extent that farmers can self-select into *Bt* adoption based on their anticipated benefits and costs of the adoption, and for reasons unknown to the evaluator, there is no guarantee that treatment effects will remain unbiased. Self-selection in most empirical work is circumvented with the use of instrumental variables (IV). When farmers self-select into the *Bt* adoption decision, for instance, based on their "ability," then a regression of potential outcomes of interest, Y_i, (such as yield, profits, and input demands) on the *Bt* adoption variable (D_i) and other independent variables leaves an error term, e_i, that includes the unobservable characteristic "ability", A, that influences the *Bt* adoption decision ($e_i = A_i'\gamma + v_i$). This results in omitted variables bias in estimating the coefficient on D_i. If one has access to a variable (instrument called Z_i) that satisfies the exclusion restriction in that it is correlated with D_i and uncorrelated with any other determinants of the dependent variables, (uncorrelated with A_i and v_i) then the omitted variables bias is avoided.

However, potential problems with the use of IV can arise. First, problems of estimation and inference surface in the presence of "weak instruments." Weak instruments are those that do not have a high degree of explanatory power for the endogenous independent variables, or when the number of instruments becomes large. In a situation of weak instruments, the danger is that the instrumental variables test will fail to discern a problem of endogenous explanatory variables, even when significant (finite sample) bias is present, because the estimated standard errors are not very accurate (Hausman, 2001). Second, access to IVs that satisfy the exclusion principle is not available.

In using IVs to estimate heterogenous treatment effects, Imbens and Angrist (1994) demonstrate that the linear IV estimate can be interpreted under weak conditions as a weighted average of local average treatment effects (LATE), where the weights depend on the elasticity of the endogenous regressor to changes in the IVs. This means that the effect of a variable is only pronounced for segments of the population affected by the observed changes in the IVs, and that those segments which respond most to changes in the instruments will have the largest effects on the magnitude of the IV estimate.

Given the practical difficulty of accessing IVs when estimating heterogenous treatment effects, Xie, Brand and Jann (2011) propose two methods hinged on the ignorability assumption: the (a) stratification-multilevel method of estimating heterogeneous treatment effects (SM-HTE); and the (b) matching-smoothing method of estimating heterogenous treatment effects (MS-HTE).   SM-HTE estimates propensity scores for the probability of treatment given a set of observed covariates for each unit in the initial step then constructs balanced propensity score strata (ranges of propensity score) in the subsequent step. Average treatment effects are estimated for each strata by directly comparing outcomes between the treated and untreated groups within the strata or by applying OLS within each strata. A linear trend is then evaluated across the strata by using variance-weighted least squares regression of strata-specific treatment effects on strata ranges of propensity scores.

MS-HTE overcomes two of the weaknesses of the SM-HTE: the assumption of homogeneity within strata such that both all treated (and untreated) observations are considered interchangeable within a strata; and, the assumption of a linear trend in the pattern of treatment heterogeneity. In MS-HTE, the treated units are matched to untreated units based on estimated propensity scores. The data is then transformed into treated-untreated comparisons. Treatment effects are then estimated as a function of the propensity score by fitting a non-parametric model as a smoothing device.

Data and definition of variables

The data used in this study is from the International Food Policy Research Institute (IFPRI). Field work was conducted in the Province of Isabela in Northern Luzon and the Province of South Cotabato in Mindanao from July 2007 to April 2008 (Figure 1). Based on secondary data and interviews with key informants, these sites were known to have both adopters and non-adopters of *Bt* maize. 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).

Focus group discussions were undertaken to draw out qualitative information about knowledge-building processes, intergenerational transfers of knowledge, farming skills, and the capacity of farmers to choose between *Bt* and non-*Bt* maize. The outcomes of these discussions also helped shape the survey instruments used to interview individuals. Sampled farmers were interviewed face to face with pre-tested questionnaires and visual aids. Key informant interviews were used to compile information about seed supply channels. A total of 466 small-scale growers of *Bt* (254) and non-*Bt* (212) maize were randomly selected in 16 villages. Non-*Bt* farmers in the 2007/2008 survey were restricted to hybrid corn users (specifically Monsanto's *Dekalb818 and*

Dekalb9051 Isohybrid) and excluded users of traditional varieties. This narrows the analysis to the performance difference between *Bt* corn relative to a more homogenous population of non-*Bt* farmers (i.e. hybrid corn users only). Table 1 presents summary statistics for all variables used in the empirical analysis.

4. Empirical results

Propensity score estimation

Table 1 provides results for the propensity score probit estimation for predicting the likelihood of *Bt* adoption. The estimation results suggest that farmers that had previously attended training on pest identification are likely to adopt the *Bt* variety. Also, farmers who farm larger corn areas and at the same time, irrigated parcels, are most likely to embrace the *Bt* technology. Table 1 also suggests that farmers within shorter distance from seed suppliers are likely to adopt the *Bt* variety.

Homogenous effects estimation

A rather naïve approach to estimating homogenous effects is to regress particular outcome variables such as profit, yield, and input (i.e. insecticide, seed, labor, fertilizer, herbicides) use on *Bt* and take the parameter estimate on *Bt* as the effect. Another naïve approach would be to control for propensity scores across farmers. Table 2 presents the estimated average effects of *Bt* adoption on various outcome variables. Overall, the results suggest that controlling for factors that might have induced self-selection or have predisposed farmers (pre-adoption heterogeneity bias) to adopt *Bt* through the propensity score results in lower effects of *Bt* across all outcome variables. But because these average effects obscure the heterogeneity in the effects of *Bt* due to inherent differences in *Bt* adopters, we need to evaluate possible heterogeneous effects.

Heterogeneous effects estimation across strata

We evaluate heterogeneous effects following the SME-HTE methodology by Xie, Brand and Jann (2011). In Level-1, propensity score stratum-specific *Bt* effects on outcome variables are estimated by OLS:

(1) $$Y_{i\,j} = \alpha_j + \gamma_j Bt_i$$

where Y_{ij} is the conditional expected value for a particular outcome variable, Y, for the ith farmer in the jth propensity score stratum and *Bt* is an indicator variable for *Bt* corn adoption. The estimated slopes from (1) are then used as observations in a Level-2 model that summarizes the pattern of heterogeneous *Bt* effects across propensity-score strata:

(2) $$\gamma_j = \mu_0 + \delta_j + \varepsilon_j$$

where γ_j are the estimated Level-1 slopes, μ_0 is the Level-2 intercept, δ_j is the Level-2 slope and an error term, ε_j , assumed to be Normally distributed.

Table 3 and Figure 2 report the results of the SM-HTE approach. Only about a third of the Level-1 slopes in Table 3 are statistically significant. Interestingly, Level-2 slopes are statistically significant only for yield and seed use. In Table 3, the yield-increasing effect of *Bt* diminishes at PhP 328.43 for every unit change in propensity score rank. Interestingly, the seed-reducing effect of the *Bt* variety is implied only in the upper strata (3 through 5) and that this effect declines by 1.15 bags/ha for every unit change in propensity rank. It is surprising, however, that no statistically significant insecticide use-reducing effect of *Bt* is found when others did (Mutuc, Rejesus and Yorobe, 2011). The limited number of Level-1 slopes that are estimated in the stratification step subsequently limits the identification of higher order functions; we address this by using the MS-HTE by Xie, Brand, and Jann (2011).

Heterogeneous effects estimation from matching/smoothing method

Following the estimation of propensity scores for *Bt* adoption, adopter and non-adopters of *Bt* are then matched according to these propensity scores and the differences between them with respect to yield, profit and input use are generated using the kernel matching method. These differences are plotted over the range of propensity scores and a smoothed curve is The results of this non-parametric approach are depicted in Figure 2. Compared to Figure 1, we now have a continuous representation of the propensity scores.

While the insecticide-reducing effect of *Bt* was not apparent under the SM-HTE approach in Figure 1, it becomes evident in Figure 2 above propensity scores of 2 but that this insecticide-reducing effect of *Bt* diminishes as we move to higher propensity scores. As such, farmers that benefit the most from this effect are those whose propensity to plant *Bt* are somewhat on the lower end. Consistent with the results under the SM-THE model, farmers progressively benefit from reduced use of seeds as their propensity to adopt *Bt* increases. In Figure 2, we also observe the yield-increasing effects of *Bt* to decrease as farmers' propensity to adopt *Bt* increases. In short, farmers who benefit the most from increased yield due to the *Bt* variety are the least likely to adopt the technology.

5. Conclusions and Policy Implications

The incidence of higher yields, lower insecticide use and reduced seed utilization in the Philippines diminishes progressively as a farmer's propensity to adopt *Bt* corn increases. And since farmers with larger, irrigated farms situated closer to seed suppliers and farmers who have previously been trained at pest identification are more likely to adopt *Bt* corn, then *Bt* technology benefits the most, farmers whose propensity to adopt *Bt* is lower. These farmers are those who farm smaller, non-irrigated farms located farther from seed supplier and farmers who have not received any training on pest identification. In most cases, while these farmers are typically poorer farmers who smaller parcels, cannot afford irrigation and are situated in remote areas away from easily accessible seed suppliers, there is no evidence, however, that there is a difference in profits enjoyed by farmers across varying levels of propensities to adopt the *Bt* variety. There is, however, an important caveat that needs to be taken into account. The survey crop year 2007/2008 was a year of bad weather in the major corn-producing areas (i.e., extreme dry spell in Isabela province and unusually heavy rains in South Cotabato province (Yumul, Jr., Cruz, Dimalanta, Servando, & Hilario, 2010). Thus, the results of this study are for an atypical year. It would be more substantial if several surveys can be analyzed in a similar context to see if results widely vary or remain the same. This study is the first to evaluate heterogeneity effects of *Bt* corn adoption and there is a wide latitude for similar studies better assess whether *Bt* adoption resonates well with the claim that genetically modified crops are indeed pro-poor.

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Table 1. Propensity Score Probit Regression Models Predicting *Bt* Adoption

Bt Adoption	Coefficient	p-value
Farm experience	-0.0045	0.554
Age	0.0079	0.296
Education	0.0016	0.878
Household size	-0.0264	0.527
Pest identification training (Attended = 1)	0.6766	0.000*
Ownership (Owner = 1)	-0.2829	0.392
Borrowing (Borrowed money = 1)	0.0013	0.994
Distance to seed supplier	0.0162	0.044**
Infestation relative to last year (Less severe = 1)	-0.1399	0.324
Corn area	0.2721	0.007*
Scouting (Scouting for pests = 1)	-0.0854	0.663
Irrigation (Irrigated = 1)	0.9816	0.000*
Location dummy (Isabela = 1, South Cotabato = 0)	0.4165	0.165
Constant	-1.2481	0.030**
LR χ^2	101.69	
Prob > χ^2	(0.000)	

Table 2. Homogenous Effects of *Bt* Adoption on Select Variables

	$Y_i = \alpha + \gamma Bt$		$Y_i = \alpha + \gamma Bt + \lambda pscore$		
	Bt	Constant	*Bt*	Prop Score	Constant
Profit (PhP/ha)	15368.85 (0.128)	19639.81* (0.009)	10574.75 (0.397)	26898.88 (0.314)	8598.27 (0.542)
Yield (kg/ha)	950.63* (0.000)	3731.31* (0.000)	548.55* (0.002)	1883.35* (0.000)	2993.26* (0.000)
Insecticide (kg/ha)	-0.73* (0.000)	0.98* (0.000)	-0.64* (0.000)	-0.62** (0.047)	1.28* (0.000)
Fertilizer (50-kg bags/ha)	1.64* (0.000)	7.86* (0.000)	1.06* (0.010)	2.43* (0.005)	6.92* (0.000)
Seed (kg/ha)	-1.06** (0.011)	19.41* (0.000)	-0.95** (0.043)	-0.19 (0.848)	19.38* (0.000)
Herbicide (L/ha)	0.76* (0.003)	1.03* (0.000)	0.34 (0.276)	2.05* (0.002)	0.23 (0.500)
Labor (man-days/ha)	4.45*** (0.077)	49.49* (0.000)	5.04*** (0.091)	1.20 (0.850)	49.55* (0.000)

Notes: P-values in parentheses. *,**,*** correspond to 1%, 5%, and 10% levels of significance.

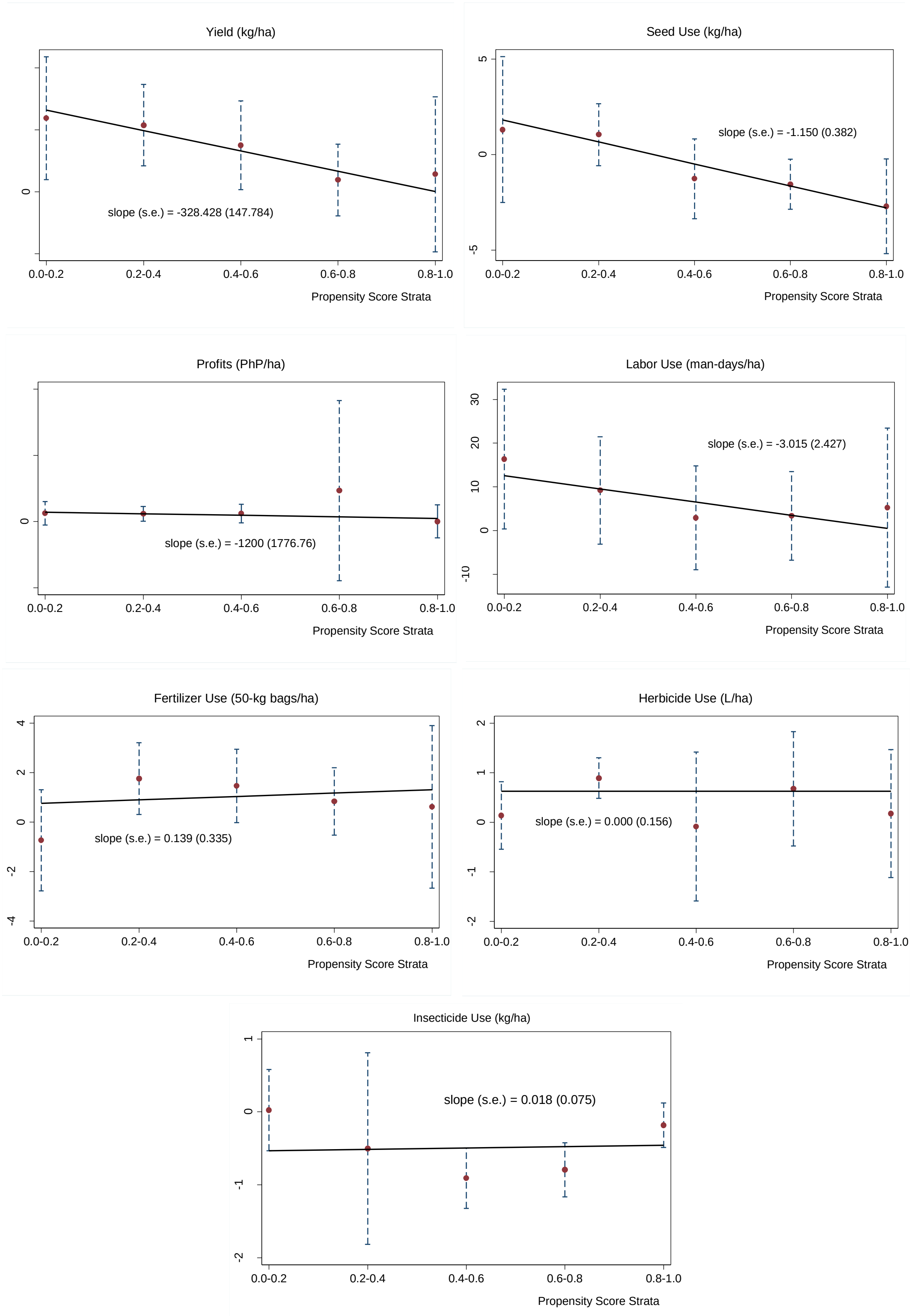
Table 3. Treatment Effects by Strata: Profit, Yield, Inputs on *Bt*

Level-1 Slopes	Profit (PhP/ha)	Yield (kg/ha)	Insecticide (kg/ha)	Fertilizer (50-kg bags/ha)	Seed (kg/ha)	Herbicide (L/ha)	Labor (man-days/ha)
1 [0.0-0.2)	6221.11	1186.08**	0.02	-0.73	1.30	0.13	16.36**
	(0.166)	(0.019)	(0.933)	(0.482)	(0.503)	(0.693)	(0.045)
2 [0.2-0.4)	5766.36**	1075.37	-0.50	1.75**	1.04	0.89*	9.19
	(0.042)	(0.001)*	(0.453)	(0.018)	(0.207)	(0.000)	(0.141)
3 [0.4-0.6)	5961.75***	749.89	-0.90*	1.46***	-1.27	-0.08	2.94
	(0.095)	(0.040)**	(0.000)	(0.053)	(0.235)	(0.910)	(0.627)
4 [0.6-0.8)	23345.02	189.90	-0.79*	0.84	-1.56***	0.67	3.37
	(0.501)	(0.521)	(0.000)	(0.227)	(0.020)	(0.250)	(0.513)
5 [0.8-0.1]	182.5392	281.55	-0.18	0.62	-2.71***	0.17	5.26
	(0.977)	(0.659)	(0.242)	(0.711)	(0.032)	(0.789)	(0.570)
Level-2 Slope	-1150.31	-328.43***	0.01	0.13	-1.15*	0.00	-3.01
	(0.517)	(0.026)	(0.806)	(0.680)	(0.003)	(1.000)	(0.214)

Notes: P-values in parentheses. *,**,*** correspond to 1%, 5%, and 10% levels of significance.

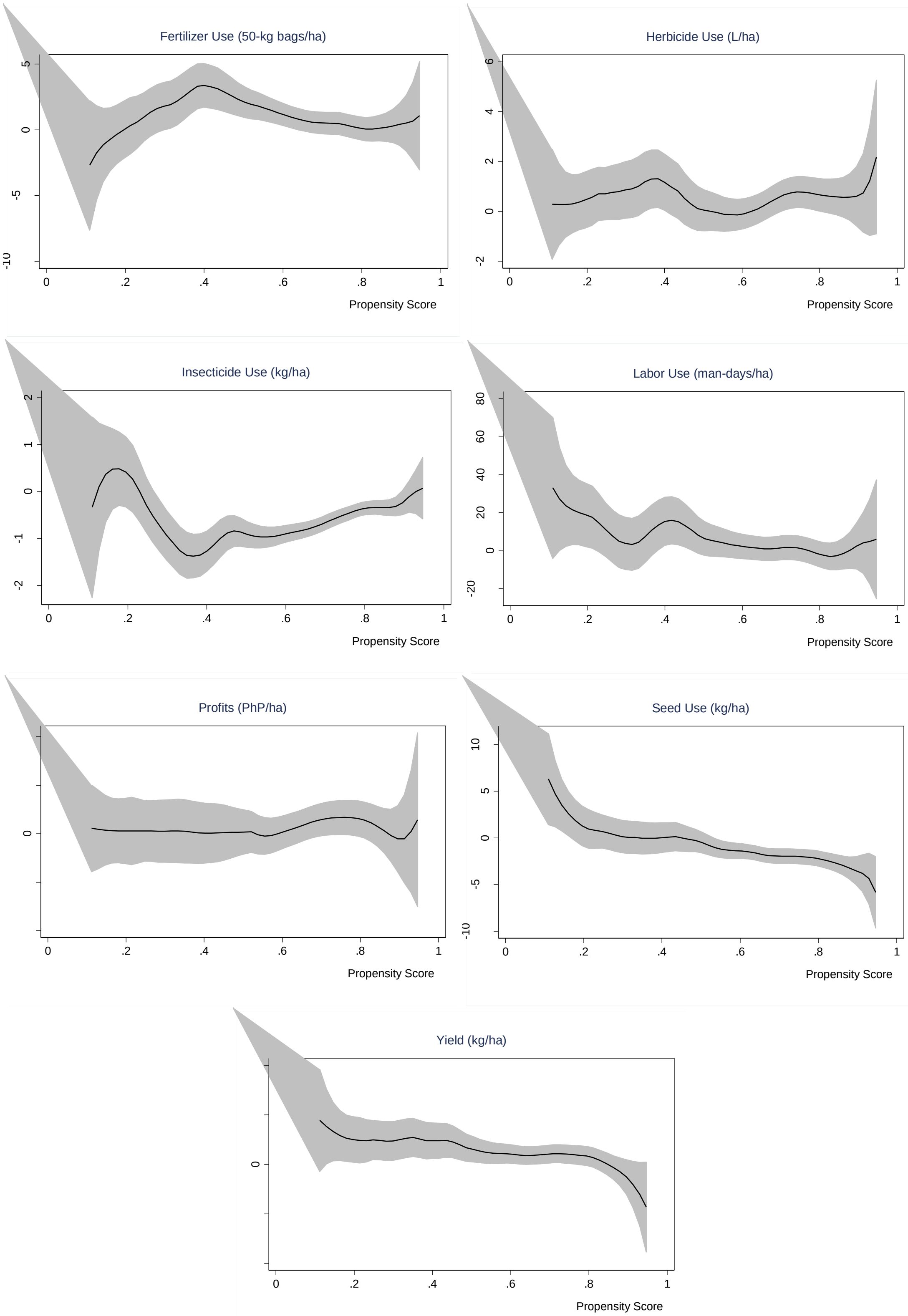
Figure 1. Survey Areas: Isabela and South Cotabato Provinces, Philippines

Figure 2. Stratified *Bt* Effects on Profit, Yield and Input Use



Notes: Red dots refer to treatment effects within strata with 95% confidence intervals represented by dashed lines. Black line is the linear trend line.

Figure 3. Matched Differences in *Bt* Effects



Notes: Local polynomial smoothing (kernel matching), degree (2) and bandwidth (0.1). Shaded bands pertain to 95% confidence interval.