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Economic Impacts of Integrated Pest Management (IPM) Farmer Field Schools (FFS): Evidence from Onion Farmers in the Philippines

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ABSTRACT

This article comprehensively examines the impact of IPM-FFS on yield, insecticide expenditures, labor expenditures, herbicide expenditures, fertilizer expenditures, and profit, based on data from onion producers in the Philippines. Propensity score matching (PSM) and regression-based approaches that account for 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 and the other inputs. 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 Impacts of Integrated Pest Management (IPM) Farmer Field Schools (FFS): Evidence from Onion Farmers in the Philippines

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 short-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.

2. Empirical Setting and Data

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)¹ in collaboration with the University of the Philippines, Los Baños (UPLB) and three other US Universities (see Norton et. al., 1999). 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.² 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

¹ 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.

² As noted by one referee, the IPM-CRSP also focused on developing IPM practices for eggplants (in addition to onions) in this region of the Philippines.

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 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 after transplanting with participants having standing onion crops. The curriculum is generally focused on IPM methodologies that farmers can learn. The IPM methods are typically biological and cultural practices that can be effectively used as substitutes to chemical pesticides for control of pests and diseases. Some of the IPM techniques taught include: (a) use of biological control for soil-borne diseases (e.g., *Trichoderma*, *Vesicular Arbuscular Mycorrhiza* (VAM)), (b) use of viral insecticides to control armyworms (e.g., Nucleopolyhedrovirus (NPV)), (c) use of yellow sticky traps to control leafminers, thrips, and aphids, and (d) use of rice straw and stale seedbed techniques for better weed management and for increasing natural enemies of onion insect pests (e.g., spiders).

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 (i.e., the techniques discussed above). 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 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 terms of reducing insecticide use (expenditures), increasing yield, and subsequently enhancing farmers' income. If there is statistical evidence that training from IPM-FFS reduces 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. Traditional t-tests and Ordinary Least Squares (OLS) approaches may provide misleading results because of selection bias.

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.³ 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

³ One referee pointed out that IPM experiments were conducted in selected farmers' fields in these areas even prior to the formal IPM-FFS trainings in 2004.

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.⁴ 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, 11 farmers 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 Ex post power tests were conducted to show that the sample size used have enough power (i.e., high enough probability of correctly rejecting the null hypothesis when the null hypothesis is truly false) with respect to the major inferences emphasized in the study. However, it should be noted that non-significance of IPM-FFS on some outcomes of interest may be due to the relatively small sample size. Detailed results of all power tests are available from the authors upon request.

3. Empirical Approach and Estimation Procedures

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:

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

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:

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

But in reality, we cannot observe the outcome of IPM-FFS farmers had they not adopted, $E(Y^0 \mid D = 1)$. We only observe the non-IPM-FFS outcome from non-IPM-FFS farmers, $E(Y^0 \mid D = 0)$. 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)):

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

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

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

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):

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

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) :

$$(5) \quad (Y^1, Y^0 \perp D) | X$$

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):

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

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 , $P(X) \equiv \Pr(D = 1 | X)$, called the propensity score, where

$$(7) \quad 0 < P(X) < 1$$

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

$$(8) \quad D \perp X | P(X)$$

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:

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

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

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

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.⁵ 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

⁵ 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.

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:⁶

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

The odds ratio that individual i receive treatment is:

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

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

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

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 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.

3.2. The Regression-based Method

As a robustness check to the PSM approach, 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:

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

⁶ Equation (12) is based on the assumption that $F(\cdot)$ follows the logistic distribution.

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

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:

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

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:

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

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:

$$(17) \quad \hat{ATE}(X) = E(Y^1 - Y^0 | X) = \hat{\alpha} + (X - \bar{X})\hat{\gamma}$$

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):

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

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 case⁷. Based on equation (16), the procedure to see the impact of the “selection on unobservables” bias relies on the condition:

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

⁷ 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 index⁸. 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:

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

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 $[E(\varepsilon | D = 1) - E(\varepsilon | D = 0)]$ 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:

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

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 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

⁸ 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.

adopt the IPM-FFS, \hat{D} , as an instrument for the actual D dummy variable in estimating equation (16) as follows:

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

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

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

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. Results

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 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 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 and fertilizer expenditures 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.

PSM Results

The first stage probit estimates for the probability of IPM-FFS adoption to be used in the PSM are presented in Table 2. The balancing property is satisfied for this probit specification (See Appendix 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.^{9,10} 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 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, and profit are presented in Table 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). These magnitudes are lower than the study of Yorobe et. al. (2011), where they found the reduction in insecticide expenditures to be around PhP 5,500.¹¹

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,

⁹ For the bandwidth value at 0.06, we followed Silverman's (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.

¹⁰ 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 authors upon request.

¹¹ However, the study of Yorobe et. al. (2011) only give the *ATE* (not the *ATT*) impacts of IPM-FFS on the insecticide expenditures.

the difference are statistically insignificant.¹² For yields, labor expenditures, herbicide expenditures, and fertilizer expenditures, the results show that IPM-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. One likely reason is that the use of the other inputs increased for IPM-FFS participants (even though insecticide use decreased) and yields were also not substantially different. Another reason may be that insecticide expenditures tend to be proportionally smaller than the other input expenditures in our sample of farmers (i.e., labor and fertilizer).

4.2. 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)¹³. 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 Panel B), therefore we only use 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 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, 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

¹² 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.

¹³ We used the command “rbounds” in STATA to conduct the “Rosenbaum bounds” analysis.

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.

4.3. 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 same observed characteristics. The results from these regression-based methods are presented in Table 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). Note that the parameter estimates for the IPM-FFS variable in Table 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 6 and then calculated the *ATT* impacts of IPM-FFS on the interested outcomes using equation (18). The results are presented in Table 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.

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 7). The estimated ratios, τ , related to the significant IPM-FFS impacts on insecticide expenditures and profit are presented in Table 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 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 evidence of IPM-FFS impacts from the regression-based method on insecticide expenditures and profit are not strong.

4.4. 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 the PSM approach are also utilized here. The first stage probit estimates for the probability of IPM-FFS adoption are presented in Table 9 and the results from the regression-based method using the IV technique are presented in Table 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 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 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).

5. Conclusion

This study empirically examines the impacts of IPM-FFS on yields, insecticide expenditure, labor expenditure, herbicide expenditure, fertilizer expenditure, and profit 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 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 expenditure, herbicide expenditure, and fertilizer expenditure. Because the magnitude of expenditures on other inputs aside from insecticides increases with IPM-FFS and the impacts of IPM-FFS on yield 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. Without these direct economic 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, data on the health status of farmers needs to be 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 clinically 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 assess the impact of IPM-FFS on the environment. Data on environmental variables within the farm (i.e., no. of beneficial insects, biodiversity) 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.

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Table 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)	8.98	7.12	9.92	7.99	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
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 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 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 (<i>n=197: IPM-FFS = 69, Non-IPM-FFS = 128</i>)			
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 (<i>n=124: IPM-FFS = 62, Non-IPM-FFS = 62</i>)			
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 (<i>n=188: IPM-FFS = 62, Non-IPM-FFS = 126</i>)			
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

Continued....

Table 3. Continued...

D. Kernel Matched Sample			
<i>(n=190: IPM-FFS = 62, Non-IPM-FFS = 128)</i>			
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. 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
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
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
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

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

Table 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 6. Parameter Estimates from the Regression-based Method

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

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

Table 7. The *ATT* impacts of IPM-FFS: Regression-based Method.

Outcomes	<i>ATT</i> 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

Table 8. Assessment of “Selection on unobservables”: Altonji et al. (2005) Procedure.

Outcome	Ratio
Insecticide Expenditures	0.772
Profit	0.433

Table 9. First Stage Probit Result for 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 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
Farmer Characteristics						
IPM-FFS	-3.060	-5.932***	-6.072	1.444	-10.114	-19.241
Sex	3.149	-3.070	-4.301	1.629	0.587	112.702
Age of Farmers	-0.087	0.041	-0.266	-0.029	0.169	-1.335
Farm Area	0.171	-0.294	0.370	-0.124	-2.653	40.711
Onion farming Experiences	0.017	0.045	0.508**	0.074	-0.469**	-1.264
Income other than Onion Farming	-0.001	0.020	0.100	-0.011	0.055	0.213
Degree of Pest Infestation	-0.072	-0.023	-0.015	0.001	-0.062	-1.265
Town	-4.178	-4.110**	-4.719	-0.585	1.100	-48.988
Interaction term: IPM-FFS x de-meaned Farmer Characteristics						
Sex	-1.230	8.380	12.992	-5.929	1.317	-163.574
Age of Farmers	0.191	-0.128	0.519	0.199	-0.799*	-1.344
Farm Area	-2.469	0.303	-4.292	0.032	0.582	-139.749*
Onion farming Experiences	-0.003	-0.168	-1.228**	-0.331**	1.002*	4.286
Income other than Onion Farming	0.114	-0.078	-0.338	0.056	0.004	4.004
Degree of Pest Infestation	0.079	0.086	0.104	-0.054	0.181	1.138
Town	12.233	2.995	6.865	0.702	-6.482	111.989
Constant	14.542**	8.675**	28.372***	2.006	26.943**	139.001

Table 11. The *ATT* impacts of IPM-FFS: Regression-based Method using the Instrumental Variables (IV) technique.

Outcomes	<i>ATT</i> 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

Appendix 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.