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Article

Adoption and Impacts of Integrated Pest Management in Bangladesh: Evidence from Smallholder Bitter Gourd Growers

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Received: 26 January 2019; Accepted: 12 April 2019; Published: 17 April 2019

Abstract: Determinants of integrated pest management (IPM) adoption, productivity and efficiency of bitter gourd (*Momordica charantia* L.) growers in Bangladesh were jointly measured using propensity score matching (PSM), sample selection stochastic frontier production function (SFPF) and inverse probability weighted regression adjustment (IPWRA) techniques. The significant value ($P < 0.05$) of the selectivity variable ($\rho_{(w,v)}$) coefficient justifies the use of the sample selection SFPF. The decision to adopt IPM was positively influenced by the training and other farmers' decisions to adopt. Mean technical efficiency (MTE) was found to be significantly higher for adopters (0.59) compared to non-adopters (0.40). The MTE analysis suggests that arranging more training sessions and making farmers more familiar with the IPM practices would improve the technical efficiency of the growers. Adoption of IPM practices significantly reduced the number pesticide applications, which imply environmental benefits from their adoption.

Keywords: adoption; impact evaluation; pesticide applications; productivity; sample selection stochastic production frontier; technical efficiency

1. Introduction

Pesticide use in Bangladesh increased in the early 1970sdue to government's support for chemical control measures to prevent crop losses and increase production [1–5]. Inappropriate use of pesticides has caused harmful effects on farmers' health [6–9], while farmers' good health has a positive effect on production efficiency [10,11]. Pesticide use in Bangladesh is particularly high in vegetables, which has caused other countries to consider restricting vegetable imports from Bangladesh [12]. To reduce the negative impacts of pesticides, the Government of Bangladesh has emphasized the use of integrated pest management (IPM) and declared a national IPM policy with the goal of ensuring healthy crop production and increasing the income of the farmers on a sustainable basis [13].

IPM integrates different pest management practices to minimize pesticide use and ensure favourable economic and ecological consequences [14–17]. The vegetable IPM programme in Bangladesh gained momentum with the introduction of the Integrated Pest Management Innovation Lab (IPM IL), which is a global research support programme funded by the United States Agency for International Development (USAID) that began working in Bangladesh in 1998. The present study uses the data from a subproject of the IPM IL that involved IPM technology transfer through a three-year training programme in selected areas of Bangladesh for several vegetables. This study focuses on the bitter gourd (*Momordica charantia* L.), which is grown extensively during the summer season and is one of the most popular cucurbitaceous vegetables in Bangladesh. IPM practices for bitter gourd are among the most promising in Bangladesh.

Bitter gourd production is hindered by several insect pests such as cucurbit fruit fly, aphids, and spider mites. To combat these pests, a combination of different IPM practices have been recommended: these include the use of pheromone and mashed sweet gourd traps to manage fruit fly infestations, collection and destruction of affected fruits with larvae, yellow sticky traps for aphids, and poultry refuse for soil amendment, larval or egg parasitoids [18,19]. Technology transfer methods—such as short-term farmer training, small group discussions and IPM field days—were conducted by the IPM IL in the study areas. The objective was to increase knowledge and adoption of IPM practices while improving production efficiency of the growers [20]. Farm-level adoption of these practices has had a wide range of impacts on productivity and efficiency that need to be evaluated. Rigorous impact studies of the bitter gourd IPM adoption are limited in Bangladesh. Studies [4,21] have mainly concentrated on the pest management and pesticide risk issue ignoring the production efficiency of the growers. A few other studies [22–24] have estimated the productivity impacts of IPM, but they have not considered the selection bias problem that arises when the sample of farmers analyzed is non-random. To fulfill these gaps, the present study was undertaken to determine the farm-level productivity and efficiency impacts of bitter gourd IPM in Bangladesh.

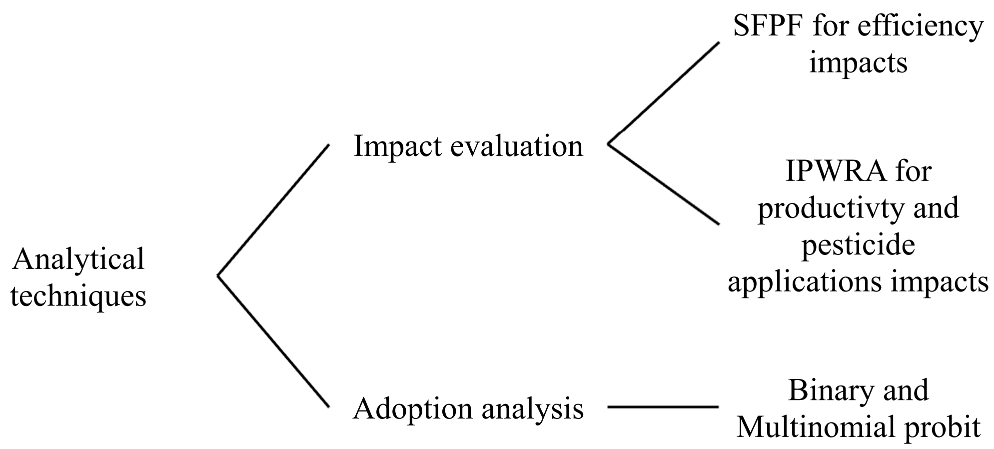
2. Materials and Methods

2.1. Data Sources and Sample Size

This study used the data of a sub-project of IPM IL, which was initiated in Jessore and Barisal region of Bangladesh during 2013 to disseminate the above mentioned IPM practices through a three-year training programme. A total of 838 farmers were selected by IPM IL from 104 randomly selected villages. Face-to-face interviews were conducted in the selected villages during 2015. Out of 838 farmers, 168 farmers cultivated bitter gourd during 2015. All of those bitter gourd growers were included in the analysis to achieve the objectives. Among the recommended practices, bitter gourd growers' adopted only three practices: sex pheromone trap, yellow stick trap and poultry refuse for soil amendment. Thus, in this study bitter gourd growers were considered to be an IPM adopter if he or she adopted any one of the three IPM practices. Out of 168 farmers, 81 farmers were considered as IPM adopters, of which 66 farmers adopted one practice and 15 adopted two practices.

2.2. Analytical Technique

Descriptive statistics and econometric modeling were used to achieve the objectives. Major analytical techniques that were used are as follows.



2.2.1. Adoption Analysis

Both binary and multinomial probit regression were used to identify the factors affecting adoption of bitter gourd IPM practices [25,26]. For the binary probit model, a farmer is considered to be an adopter if they adopted any one of the recommended IPM practices, in which case they are given a score of one, and if otherwise are given 0.

$$Y_i{}^* = Y_{ia} - Y_{ina} > 0 = a + zX_i + u_i, \text{ where } u_i \sim N(0,1), i = 1 \ldots n \quad (1)$$

$$Y = 1 \textit{ if } Y^* > 0, \text{Otherwise } 0 \quad (2)$$

where, $Y_i{}^*$ is the latent variable representing the probability of farmers deciding to adopt IPM. Y_{ia} and Y_{ina} represents IPM adopters and non-adopters, respectively. X_i represents the socio-economic and technological factors affecting the adoption decision, and z is the vector of parameters to be estimated.

Since the dependent variable "adoption of IPM" takes more than one value, a multinomial probit regression was used, which is an extension of binary model in the case where the dependent variable can take more than two values [26].

$$Pr(Y = j|\, X_i) = a + zX_i + u_i \quad (3)$$

where, Y taking on the values (0,1,2).

2.2.2. Impact Evaluation

To measure the productivity and efficiency impacts of IPM, both a conventional stochastic frontier production function (SFPF) and a multi stage sample selection stochastic frontier production function approach were used. First, all available data were used to estimate a pooled as well as separate SFPF models for adopters and non-adopters, ignoring any biases [24,27–31]. Second, to control for biases from observed characteristics, propensity score matching (PSM) was implemented using the whole sample. Finally, two separate SFPFs, one for adopters and one for non-adopters, were estimated using the matched sample obtained from the PSM to correct for selectivity bias from unobserved characteristics [32–35]. Thus, the models incorporate corrections for both sources of bias. The study also employed inverse probability weighted regression adjustment (IPWRA) to measure the impacts of IPM adoption on productivity and pesticide applications.

The stochastic frontier production function (SFPF) is appropriate for assessing technical efficiency (TE), when the data are repeatedly inclined by measurement errors and other stochastic factors [30,36]. To measure the technical efficiency (ability of a farm producing maximum output from the minimum quantity of inputs) of a farm producing bitter gourd, a production function was specified as follows;

$$Y_i = f\,(X_i, \beta_i) + \varepsilon_i \quad (4)$$

where, Y_i is the crop output of the ith farm, X_i represents explanatory variables, and ε_i represents the error terms. The model postulates that the error term ε_i is made of the following two independent components [37]:

$$\varepsilon_i = (v_i - u_i) \quad (5)$$

Therefore, the production frontiers was written as:

$$Y_i = f\,(X_i; \beta) + (v_i - u_\mathrm{i}) \quad (6)$$

v_i is independently and identically distributed random errors, having $N(0, \sigma_v{}^2)$ distribution and capture the effects of random shocks outside the farmer's control, measurement errors and other statistical noise. u_i are non-negative ($u \geq 0$) one sided random variables that capture the effects of technical inefficiency, which is assumed to be independently distributed with a half normal distribution (U $\sim|N(0, \sigma_u{}^2)|$).

The model above ignores the selectivity biases that may arise from observed and unobserved sources. To overcome the limitation of the above specification of SFPF, the present study followed a multi stage procedure. First, PSM was used to alleviate biases from observables. Using observed characteristics of the sample, PSM constructs a statistical comparison group that is based on a model of the probability of participating in the treatment [38]. The reliability of PSM depends on conditional independence assumption (CIA) and sizable common support. We used a binary probit model to produce a propensity score for each respondent. Second, using the sample under the common support region from PSM, a stochastic production frontier corrected for sample selection bias [39] was estimated which is internally consistent to mitigate the biases from unobservable factors [40,41]:

Sample selection:

$$d_i = 1[\alpha^* z_i + w_i > 0],\ w_i \sim N(0,1) \tag{7}$$

Stochastic frontier:

$$y_i = \beta^* x_i + \varepsilon_i \tag{8}$$

(y_i, x_i) is observed only when $d_i = 1$.
Error structure:

$$\varepsilon_i = v_i - u_i \tag{9}$$

$$u_i = |\sigma_u U_i| = \sigma_u |U_i|\ where\ U_i \sim N(0,1) \tag{10}$$

$$v_i = \sigma_v V_i\ where\ V_i \sim N(0,1) \tag{11}$$

$$(w_i, v_i) \sim bivariatenormalwith\left[(0,1),\ (1,\ \rho\sigma_v,\ \sigma_v^2)\right] \tag{12}$$

The model assumes that the unobserved characteristics (w_i) in the sample selection model are correlated with the noise term (v_i) in the stochastic frontier function. d is equal to one for IPM adopters and zero for non-adopters. z indicates explanatory variables included in the sample selection model. w_i is the unobservable error term. y is output (yield in this study). x is a vector of explanatory variables included in the stochastic frontier function. v is the two-sided random error, independent of the u, that permits for random variations in output due to factors such as omitted explanatory variables, measurement error in y and other exogenous shocks, and u is the one sided non-negative error term (farm specific technical inefficiency). A statistically significant value of ρ indicates that selectivity bias in unobservable is present. Details of this model are available in [32,39].

To check for robustness of the SFPF approach, IPWRA was used: it is a doubly robust technique that provides a consistent estimation of average treatment effect on the treated (ATT) in the presence of misspecification in the treatment or outcome model [42]. The ATT was calculated in two steps: first, we used multinomial logistic regression, which allows for more than two values of the dependent variable, to calculate propensity scores.

$$Pr\ (T_i = 0, 1, 2) = f\ (z_i b) + e_i \tag{13}$$

where, z_i is a set of covariates explaining treatment assignment T, and b is unknown parameter to be estimated.

Second, a linear regression model was run using the inverse of the calculated propensity scores as weights to capture the effect of IPM adoption on the outcome variables [43].

$$Yi = h\ (A_i \beta) + w_i \tag{14}$$

where, A is a vector of covariates that influence the outcome Y.

3. Results and Discussion

3.1. Descriptive Statistics

Descriptive statistics of the variables used in the SFPF, probit and multinomial probit models are presented in Table 1. Some differences in selected characteristics (seed, fertilizers, distance to market, education, experience, training and FAI) were significant between adopters and non-adopters, while other characteristics were not. These differences indicate that the two groups are not directly comparable and thus justify the use of sample selection framework.

Table 1. Descriptive statistics of the variables.

Variables [z]	Adopters		Non-Adopters		Mean Difference [y]
	Mean	Standard Deviation	Mean	Standard Deviation	
Human labour (man-day/ha)	388	191	373	177	15
Seed (kg/ha)	1790	1283	2513	1488	−723 ***
Chemical fertilizers (kg/ha)	865	432	1038	544	−173 **
Organic fertilizers (kg/ha)	8603	9093	9622	10,004	−1019
Material cost (Tk/ha)	81,871	38,684	79,337	26,294	2534
Yield (kg/ha)	22,714	12,542	20,569	11,388	2144
Distance to market (km)	1.28	1.07	1.73	1.57	−0.45 **
No. of active member	3.27	1.55	3.17	1.30	0.09
Schooling years	7.63	4.33	6.23	4.32	1.39 **
Farming experience (years)	17.62	10.15	21.06	11.41	−3.44 **
Farm size (ha)	1.11	1.06	0.96	0.79	0.14
IPM training (yes/no)	0.41	0.49	0.07	0.25	0.33 ***
Extension contact (yes/no)	0.81	0.39	0.79	0.41	0.02
Credit access (yes/no)	0.55	0.50	0.59	0.49	0.04
Contact with neighbours (yes/no)	0.70	0.41	0.79	0.40	0.09
FAI (No.)	2.84	3.51	0.39	1.12	2.44 ***
Sample size	81		87		

[z] FAI indicates number of other farmers adopting IPM near the primary farmer's field; Tk. indicates Bangladeshi currency; USD 1 = Approx. Tk. 80 (at the time of analysis). [y] ** and *** indicate significant at $P \leq 0.05$, and 0.01, respectively. A *t*-test was used to assess the mean difference.

3.2. Determinants of IPM Adoption

The significant chi-square values and fairly low Pseudo R^2 indicates good fit of the models. IPM training plays a significant role in the decision to adopt IPM. The farmers with IPM training in the previous year were likely to adopt more. This result is supported by other studies [44,45], which found that farmers who received training adopted more. Training provides opportunities to meet with experts of the relevant field which may increase the likelihood of an adoption decision. Adoption by other farmers (FAI) also significantly influenced the adoption decision of the primary farmer, which may indicate the need of additional field demonstrations to enhance the adoption process. Multinomial probit regression also exhibits similar findings. In the case of the binary model, negative and significant coefficient of distance to market (DM) indicates that DM is inversely related to adoption [46]. The farmers who live near the market adopted more may be due to fact that they can communicate with local extension agents more frequently in the market compared to the farmers who live far away from the market. However, this factor becomes insignificant if the farmers adopted more than one IPM practice, which indicates that the initial adoption decision may be influenced by the distance to a market, while extent of adoption may depend on other factors such as training and demonstration (Table 2).

Table 2. Factors affecting the adoption of IPM.

Variables	Binary Probit		Multinomial Probit			
			1 Practice		2 Practices	
	Co-Effi. [z]	SE [y]	Co-Effi.	SE	Co-Effi.	SE
Constant	−0.184	0.549	−0.136	0.770	−3.366	1.466
Distance to market (km)	−0.191 *x	0.099	−0.268 *	0.143	−0.276	0.230
No. of active member	0.038	0.082	0.070	0.116	−0.062	0.181
Farming experience (years)	−0.009	0.011	−0.015	0.015	−0.029	0.028
Schooling years	0.018	0.027	0.017	0.039	0.091	0.060
Farm size (ha)	0.015	0.135	−0.059	0.198	0.308	0.248
Credit access (yes/no)	0.004	0.237	−0.084	0.333	0.544	0.519
Extension contact (yes/no)	−0.046	0.294	−0.102	0.412	0.975	0.970
Contact with neighbours (yes/no)	−0.253	0.271	−0.344	0.381	−0.409	0.577
IPM training (yes/no)	1.037 ***	0.325	1.146 **	0.457	2.084 ***	0.564
FAI (No.)	0.282 ***	0.071	0.381 ***	0.097	0.376 ***	0.116
Log-likelihood	−83.68		−114.33			
χ^2	65.31 ***		50.44 ***			
Pseudo R^2	0.28		–			
No. of obs.	168		168			

[z] Co-effi. indicates estimated coefficient of the explanatory variables. [y] SE indicates standard error. [x] *, **, and *** indicate significant at $P \leq 0.1$, 0.05, and 0.01 respectively.

3.3. Test of Different Parameters for the Selection of Model

The functional form of the SFPF was determined by testing the competence of the Cobb–Douglas relative to the less restrictive translog. Results of the hypothesis test indicate that Cobb–Douglas type production function is appropriate (Table 3). Rejection of the null hypothesis 'no inefficiency component' justify the use of a stochastic frontier framework (Table 3).

Table 3. Selection of different parameters of the SFPF.

Hypothesis	LR Test Statistics/z Value	Degree of Freedom	χ^2/*p*-Value	Outcome
a. Functional form test				
H_0: Cobb-Douglas H_1: Translog	24.68	15	37	Cobb-Douglas
b. Frontier test				
H_0: No inefficiency component	−2.22	–	0.013	Frontier

3.4. Parameter Estimates of Conventional and Sample Selection SFPF

The empirical results of the pooled model under the conventional SFPF framework indicate that coefficients of chemical and organic fertilizers are positive and significant, at 1% and 10% levels respectively, while that of seedling and human labour are positive but not significant (Table 4). A 1% increase in the use of chemical and organic fertilizers, keeping other things constant, would increase the yield of bitter gourd by 0.354 and 0.024 percent, respectively. To estimate the effect of IPM adoption on the yield, we included 'adoption status' as a dummy variable in the pooled model. The results revealed that IPM adoption has a positive and significant ($P < 0.01$) effect on the yield of bitter gourd, which is consistent with the findings of [24].

Table 4. Estimated coefficients of the conventional and sample selection stochastic frontier production function. Dependent variable = Yield (kg/ha).

Variables	Conventional SFPF			Sample Selection SFPF	
	Pooled	**Adopters**	**Non-Adopters**	**Adopters**	**Non-Adopters**
Constant	7.438 ***z (1.516)	9.708 *** (2.135)	6.303 ** (2.608)	9.338 *** (3.253)	6.438 *** (0.236)
Seed	0.093 (0.073)	0.153 * (0.090)	0.012 (0.122)	0.217 (0.160)	−0.178 *** (0.008)
Human labour	0.038 (0.093)	−0.019 (0.135)	−0.010 (0.126)	−0.036 (0.166)	−0.045 *** (0.012)
Chemical fertilizer	0.354 *** (0.080)	0.335 *** (0.104)	0.417 *** (0.145)	0.334 *** (0.127)	0.315 *** (0.010)
Organic fertilizers	0.024 * (0.014)	−0.007 (0.024)	0.033 ** (0.016)	−0.008 (0.034)	0.025 *** (0.002)
Material cost	−0.056 (0.133)	−0.244 (0.188)	0.103 (0.163)	−0.225 (0.278)	0.331 *** (0.020)
Adoption status	0.245 *** (0.089)	–	–	–	–
Model Diagnostics					
Log likelihood	−161.29	−70.23	−84.16	−125.30	−119.51
$\sigma_{(u)}$	–	–	–	0.704 *** (0.259)	1.134 *** (0.008)
$\sigma_{(v)}$	–	–	–	0.464 *** (0.123)	0.026 *** (0.010)
$\rho_{(w,v)}$	–	–	–	0.776** (0.350)	−0.438 (1.005)
Sample size	168	81	87	81	77

z ***, ** and * indicate significant at $P \leq 0.1$, 0.05, and 0.01, respectively. Values in the parentheses indicate standard error.

Estimation of the sample selection SFPF shows that the coefficient of the selectivity variable ($\rho_{(w,v)}$) is significantly different from zero for adopters ($P < 0.05$), which confirms the presence of selection bias (Table 4). The presence of selectivity bias imply that the efficiency estimates from conventional models are biased [32,47]. The empirical results of the sample selection framework revealed that most of the variables selected for SFPF are significant. For adopters, the coefficient of chemical fertilizers was found positive and significant at the 1% level (Table 4), which implies that 1% increase in the use of chemical fertilizers, keeping other things constant, would increase the yield of bitter gourd by 0.334 percent. For non-adopters, the coefficient of chemical fertilizers, organic fertilizers and material cost have positive and significant effects on the yield of bitter gourd. The negative and significant coefficient of seed ($P < 0.01$) is unexpected but might be due to farmers using more seed than the recommended dose. Non-adopters may also experience more seed related diseases causing low germination and thus planted more seed.

3.5. Technical Efficiency Distribution

The TE distribution under both conventional and sample selection approaches exhibited wide variation which is similar to the findings of other studies [24,48]. Under the conventional SFPF model, the mean technical efficiency (MTE) was similar for both groups of farmers (Figure 1). When we used sample selection SFPF, the MTE of both adopters and non-adopters reduced compared to the conventional model, which indicates that the conventional model overestimated the technical efficiency score due to selectivity bias. The finding also indicates that IPM adopters in the study areas were technically more efficient compared to non-adopters and the difference was significant at 1% level. The MTE analysis of adopters implies that production of bitter gourd could be increased by 56% if technical efficiency was improved. Additional field days and small group discussion with farmers are warranted as they can play a crucial role in increasing the TE of the growers.

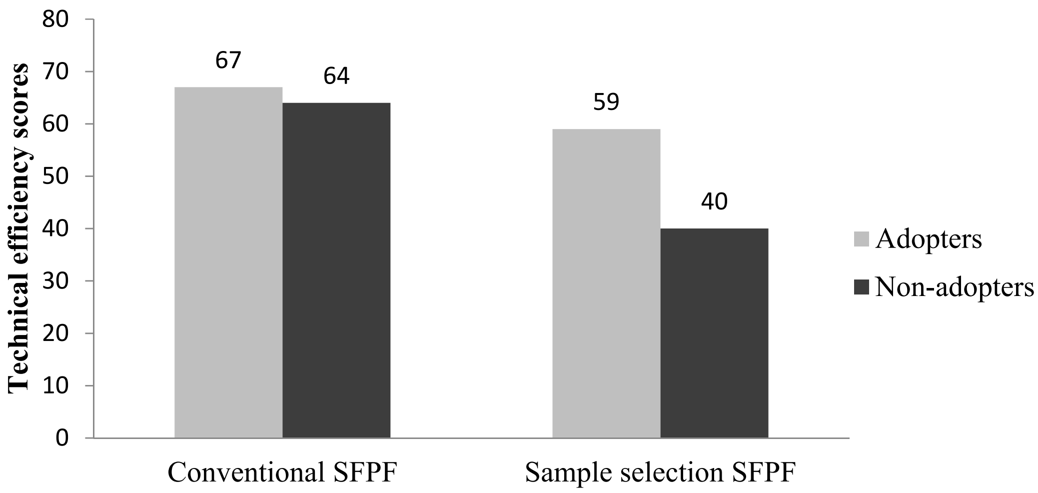


Figure 1. Technical efficiency estimates of adopters and non-adopters.

3.6. Impacts of IPM Adoption on Productivity and Pesticide Applications

Adopters of IPM were categorized based on the number of IPM practices adopted (0, 1, or 2) to compare with non-adopters (Table 5). The findings indicate that the productivity impact of IPM is not robust. The farmers who adopted one IPM practice were statistically similar in terms of yield per hectare. The farmers who adopted two IPM practices received marginally higher yield compared to non-adopters. Other studies [21,44,49] have also found that IPM is not always effective in increasing the productivity. This may be due to the fact that farmers were found to be unenthusiastic when it came to adopt the full package of IPM and that yield is driven by factors other than IPM. However, farmers who adopted IPM practices performed better in terms of reducing pesticide applications as compared to the farmers who did not adopt IPM, thus reducing potential negative impacts of pesticide use on health and environment. Findings also indicate that the farmers who adopt two IPM practices significantly reduce pesticide applications compared to those who adopt one IPM practice. Additional awareness-building programmes and training sessions should enhance the level of adoption and reduce the negative effects of pesticide applications on environment.

Table 5. Impact on yield and number of pesticide applications.

Outcome Variable	Number of IPM Practices Adopted		ATT ^{z}	SE ^{y}
Yield	1	0	3514	2816
	2	0	8109 *^{x}	4331
	2	1	4988	4122
Number of pesticide applications	1	0	−2.80 *	1.66
	2	0	−7.37 ***	1.55
	2	1	−2.81 **	1.22

^{z} ATT indicates average treatment effect on the treated. ^{y} SE indicates standard error. ^{x} *, ** and *** indicate significance at $P \leq 0.1$, 0.05, and 0.01, respectively.

4. Conclusions

The study jointly analyzed the determinants of IPM adoption as well as productivity and efficiency impacts of IPM adoption on the bitter gourd growers in Bangladesh. Model diagnostics indicate the existence of sample selection bias, which implies that estimation using previous approaches may have led to biased results regarding productivity and technical efficiency. Findings indicate that IPM training and other farmers decisions to adopt can significantly influence the adoption decision of the primary farmers. Additional awareness-building programmes and field visits to disseminate information about bitter gourd IPM practices should increase adoption. Technical efficiency analysis suggests that there is an ample scope to improve technical efficiency level of the bitter gourd growers. Additional training sessions and field demonstrations are warranted to increase the efficiency level of the adopters. The findings also reveal that IPM adoption reduced the pesticide applications, which may result in environmental benefits. IPM adopters received marginally higher yield than non-adopters, which may have a positive effect on the income of the growers. Hence, there is a scope for raising the role of vegetable IPM in anti-poverty programmes in Bangladesh.

Author Contributions: Conceptualization, M.S.R and G.W.N.; methodology, M.S.R.; investigation, M.S.R.; statistical analysis, M.S.R.; writing—original draft preparation, M.S.R.; writing—review and editing, M.S.R. and G.W.N.; supervision, G.W.N.

Funding: This research was funded by United States Agency for International Development (USAID) grant number AID-OAA-L-15-00001.

Acknowledgments: The authors express thanks to IPM IL for providing the financial support to complete this study. The authors are also thankful to the farmers and enumerators for their co-operation and help.

Conflicts of Interest: The authors declare no conflict of interest.

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