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Economic impacts of integrated pest management on vegetables production in Bangladesh

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ABSTRACT

Impacts of integrated pest management (IPM) were assessed for six vegetables: eggplant (*Solanum melongena* L.), bitter gourd (*Momordica charantia* L.), tomato (*Solanum lycopersicum* L.), cabbage (*Brassica oleracea* L. *var capitata*), cucumber (*Cucumis sativus* L.), and country bean (*Lablab purpureus* L.) in Bangladesh. Propensity score matching (PSM), inverse probability weighting (IPW), and inverse probability weighted regression adjustment (IPWRA) were used to assess farm level impacts of IPM. Economic surplus analysis was employed to estimate market level benefits. IPM adoption significantly reduced the number of pesticide applications and pesticide costs for eggplant, bitter gourd, and tomato. For all vegetables together, pesticide costs per hectare were Tk. 1990.42 ($24.88 USD), Tk. 2039.63 ($25.50 USD), and Tk. 2017.53 ($ 25.21 USD) less for adopters than for non-adopters based on nearest neighbor, kernel and radius matching, respectively. IPW and IPWRA also exhibited similar type of findings. The highest market level benefits were obtained for eggplant IPM research and training. IRR was also highest for eggplant IPM research (42%) followed by tomato (39%). Policy implication included measures for more extension efforts and increased investment in IPM research and development.

1. Introduction

The crop sector in Bangladesh is dominated by rice, but vegetable production and consumer demand for vegetables have grown in recent years, raising farm incomes and improving diets. Unfortunately, vegetables are attacked by numerous pests, and farmers rely heavily on synthetic chemicals to control them (Hossain et al., 2000; Ahmed et al., 2005; Muriithi et al., 2016). Pesticide use in Bangladesh is six times higher in vegetables (1.12 kg/ha) than in rice (0.20 kg/ha) (Alam, 2013). Excess use of pesticides raises the cost of production and causes harmful effects on health and the environment (Kouser and Qaim, 2013; Muriithi et al., 2016). Integrated pest management (IPM) can potentially play an important role in reducing the reliance on pesticides.

IPM integrates biological, cultural, and chemical pest practices to enhance productivity and minimize pesticide use (Greene et al., 1985; Norton et al., 1999; Harris et al., 2013; Kabir and Rainis, 2015a). The Government of Bangladesh, with assistance of the Food and Agriculture Organization (FAO), introduced vegetable IPM in Bangladesh in 1996 (Kabir and Rainis, 2015b). Since then, various national and international organizations have implemented vegetable IPM programs in Bangladesh. The Integrated Pest Management Innovation Lab (IPM IL) funded by United States Agency for International Development (USAID) began a vegetable IPM program in Bangladesh in 1998 with goals of reducing losses due to pests, raising farmer incomes, and reducing pesticide use (Akter, 2004). In collaboration with the Bangladesh Agricultural Research Institute (BARI), the program has developed and promoted several vegetable IPM technologies such as pheromone traps, grafting, soil amendments, pest-resistant varieties, bio-pesticides, and beneficial insects (Mian et al., 2016).

The present study uses data from a sub-project of the IPM IL that involved IPM technology transfer for six vegetables: eggplant (*Solanum melongena* L.), bitter gourd (*Momordica charantia* L.), tomato (*Solanum lycopersicum* L.), cabbage (*Brassica oleracea* L. *var capitata*), cucumber (*Cucumis sativus* L.), and country bean (*Lablab purpureus* L.) in four districts[1] of the country. Due to various initiatives, including IPM research, development, and training, synthetic pesticide use has declined in Bangladesh since 2012. The coverage area of pheromone and bio-control agents has increased substantially in recent years (Alam, 2013). Farm-level adoption of IPM technologies has resulted in a wide range of

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[1] Geographical region in Bangladesh used for administrative purpose.

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impacts that need to be evaluated to understand the causal contributions of IPM research, development, and training. However, rigorous impact evaluations of vegetable IPM technology adoption have been relatively scarce in Bangladesh. One study conducted by Gautam et al. (2017) in Bangladesh found that IPM adopters reduced the quantity of pesticides used and increased eggplant yields. Another by Ahsanuzzaman (2015) found that IPM adopters had higher sweet gourd (*Cucurbita maxima* Duchesne) yield compared to non-adopters. Other studies (Karim, 2004; Dasgupta et al., 2005; Akter et al., 2016) estimated the farm-level impact of IPM adoption, but appear to have used non-random sampling of households in their analyses, leading to potential bias in results.

Few studies have examined societal or market-level economic impacts of IPM on vegetables in Bangladesh. Akter (2004) conducted a study to estimate the market-level economic impacts of IPM in Bangladesh and found that IRR (Internal Rate of Return) of eggplant IPM research was 26%. Rakshit et al. (2011) estimated the market-level impact of using pheromone traps for mass trapping in sweet gourd production and estimated a rate of return on investment in pheromone research of 140–165%. No recent studies have been conducted to estimate the market level impacts of IPM research for different vegetables in Bangladesh. The causal effect of IPM adoption on pesticide use is yet to be studied empirically in Bangladesh. The current study was undertaken to assess impacts of IPM adoption on yields, number of pesticide applications, and pesticide costs for specific vegetables in Bangladesh. It also estimates the economic returns on investment in IPM research and development on the selected vegetables in the study areas.

2. Data and methods

2.1. Study areas

A total of 104 villages were selected randomly from 1963 villages in four districts: Jessore, Magura, Barisal, and Jhalokati. These districts are located in the south-western part of Bangladesh. These districts had been chosen by the IPM IL project for IPM technology transfer efforts to correspond with USAID “Feed-the-Future” (FtF) program districts. Vegetable production is more intensive in Jessore and Magura than in Barisal and Jhalokati where high levels of poverty and malnutrition are prevalent. Agriculture is the primary source of income in all four districts.

2.2. Data sources and sample size

To assess the impacts of IPM technologies on yield, pesticide applications, and pesticide cost, data were generated in three rounds of interviews with farmers in 2013, 2014, and 2015. The villages were divided into treatment and control groups for the survey, with 52 villages in each group. From each village, a complete list of vegetable farmers was collected and eight or nine farmers were randomly selected to interview, resulting in 838 farmers interviewed in 2013. The intent was to conduct a randomized control trial (RCT). Unfortunately, due to miscommunication with those conducting the training, IPM training was later conducted in some of the control villages and not in some of the treatment villages, eliminating the possibility of RCT analysis. To overcome this problem, one year of cross section data were used to achieve the objectives of the study. Using data from the 2015 survey, the sample was divided into two groups: IPM adopters and non-adopters. Farmers who adopted any one of several IPM practices were considered to be IPM adopters and the other farmers to be non-adopters; these IPM practices included: i) grafting (grafting a local varieties of eggplant onto a wild relative resistant to bacterial wilt, *Ralstonia solanacearum*), ii) yellow sticky traps (sticky cards to monitor insect infestations), iii) pheromone traps (for mass trapping of male moths), iv) tricho-compost (trichoderma laced compost to manage soil diseases), v) tricho-leachate (liquid obtained during production of tricho-compost and used as fungicide), vi) soil amendment with poultry refuse (poultry litter to vegetable fields to manage soil diseases and provide fertilizer), vii) larval or egg parasitoids (beneficial organism for insect pest management), viii) predatory ladybird beetles (predatory insects for aphids and mites), and ix) pest resistant varieties (varieties that are resistant to pest attack). A total of 751 farmers were interviewed in 2015, a smaller number than in 2013 because a few farmers had migrated to other villages and some were not interested in being interviewed. Of those 751 farmers, 112 farmers did not cultivate any of the six selected vegetables during 2015 and were dropped from the sample, leaving 639 farmers for the analysis. The distribution of farmers by vegetable and location is presented in Table 1.

Table 1
Distribution of farmers interviewed in the study areas in 2015.

Vegetables	Farmer group	Locations				Total
		Jessore	Magura	Barisal	Jhalokati	
Eggplant	IPM adopters	38	16	26	18	98
	Non-adopters	38	87	29	31	185
Bitter gourd	IPM adopters	19	03	44	15	81
	Non-adopters	18	19	21	29	87
Tomato	IPM adopters	11	2	41	31	85
	Non-adopters	22	14	60	54	150
Cucumber	IPM adopters	01	03	16	18	38
	Non-adopters	21	17	15	28	81
Cabbage	IPM adopters	01	01	09	09	20
	Non-adopters	12	16	19	32	79
Country bean	IPM adopters	05	00	11	06	22
	Non-adopters	15	26	12	30	83
All vegetables	IPM adopters	66	21	93	56	236
	Non-adopters	93	135	75	100	403

To calculate the market-level benefits, an economic surplus model was used with data on IPM adoption, yields, and costs from the survey conducted in 2015. Secondary sources of information such as research reports and agricultural statistics from the Bangladesh Bureau of Statistics (BBS) were used to collect data on yearly district level production, prices, and elasticities (responsiveness of supply and demand to prices).

2.3. Methods for assessing farm-level impacts of IPM

An instrumental variable (IV) approach is often used to solve the selection bias problem that can arise when farmers who receive interventions (treatments) are not chosen (selected) randomly (Abadie, 2003; Heckman and Salvador, 2003; Yen et al., 2008). Finding a credible instrument is, however, difficult (Imbens and Woolridge, 2009). Moreover, the IV approach does not rely on exogeneity assumptions, and thus violates the overlap assumption (Imbens, 2004). Therefore, the present study employed propensity score matching (PSM) to assist in drawing causal inferences from the data (Gautam et al., 2017; Schreinemachers et al., 2016; Gitonga et al., 2013; Khan et al., 2012; Abebaw et al., 2010). PSM matches adopter households with non-adopter households that have similar likelihoods of adopting the technology based on the observed characteristics. The major difficulty with PSM is in comparing the outcome for the group exposed to the technology to what the outcome for that exact same group would have been had the technology transfer not happened (Khandker et al., 2010; Winters et al., 2010). Matching methods help create a counterfactual from the control group, but the validity depends on two conditions: a conditional independence assumption (CIA) and sizable common support or overlap in propensity scores across the adopters and non-adopters. Failing to achieve CIA would mean that there are unobserved factors that affect the outcome and lead to a hidden bias (Caliendo and Kopeinig, 2008). Under the CIA, the average treatment effect on the treated (ATT) can be computed as:

$$ATT = E(Y_1 - Y_0|X, T = 1) = E(Y_1|X, T = 1) - E(Y_0|X, T = 1)$$

Where, T indicates whether a farmer adopted IPM or not (adopter = 1, otherwise = 0), X is observed characteristics, $E(Y_1|X, T = 1)$ is the mean outcome of the adopters conditioned on X in the treated situation and $E(Y_0|X, T = 1)$ is the mean outcome of the non-adopters conditioned on X in the treated situation.

To estimate ATT, the study followed three steps: first, propensity scores were estimated by using the following probit model:

$$Y_i^* = \beta X_i + u_i, \text{ where } u_i \sim N(0, 1), i = 1 \ldots .n$$

$$Y = 1_{\{Y^* > 0\}} = 1 \text{ if } Y^* > 0, \text{ Otherwise } 0,$$

Here, X_i = observed characteristics of the farmers, Y = farmers adopting IPM technologies (adopter = 1, otherwise = 0).

If any farmer adopted one of the IPM technologies mentioned earlier, he or she was considered an IPM adopter and given a score of one, otherwise given 0. In the second step, the region of common support was selected and a balancing test was performed. The third and final step was to match adopters and non-adopters by the estimated propensity scores and the mean difference of outcome in these two matched groups was considered as the impact of the IPM technology adoption. Three matching algorithms (nearest neighbor (NN) matching, radius matching and kernel matching) were used to estimate the treatment effect. Separate analyses were conducted to measure the impacts of IPM technologies on yield, number of pesticide applications, and pesticide cost for eggplant, bitter gourd, and tomato. Due to the small sample size, cabbage, cucumber, and country bean were not considered independently in the analysis. To include them, vegetables as a whole were considered in an analysis in which all the selected six vegetables were grouped together.

To check the robustness of the PSM analysis, we also used inverse probability weighting (IPW) and a doubly robust estimator known as inverse-probability-weighted- regression adjustment (IPWRA). IPW uses the inverse of the propensity score as weights in calculating the average value of the outcome variable (Imbens, 2004; Wooldridge, 2007). Farmers with low predicted probability of adoption of IPM received a lower weight while farmers with a high predicted probability of adoption received a higher weight. IPWRA is consistent in the presence of misspecification in the treatment or outcome model (Wooldridge, 2010). IPWRA models estimate the ATT in two steps (Imbens and Woolridge, 2009): first, propensity scores were calculated using multinomial logistic regression, which allows for more than two categories of the dependent variable. In the second step, the inverse of the estimated propensity scores were used as weights to run the linear outcome model.

2.3.1. Outcome variables

The farm level impacts of IPM technologies were assessed using the following outcome indicators:

Yield (kg/ha): Production of the specific vegetable during the season divided by the farmer's total cultivated area (in hectares) of that vegetable. In the case of all vegetables combined, the production was averaged across vegetables and weighted by the production area of each vegetable on the farm.

Pesticide application (number): Total number of pesticide applications made by the farmer per season on the vegetable. In the model with all vegetables combined, the number of applications was averaged across vegetables for the farmer, with the applications weighted by the production area of each vegetable on the farm.

Pesticide cost (Tk., Bangladeshi currency): Per hectare expenditures on pesticides per season by the farmer for the vegetable. For vegetables as a group, the cost of pesticides was averaged across vegetables and weighted by the production area of each vegetable.

2.4. Assessing market-level economic impact

An *ex-post* economic evaluation of IPM was conducted using an economic surplus analysis to assess benefits. Those benefits were combined with IPM IL costs in a benefit cost analysis to estimate the internal rate of return (IRR) and net present value (NPV) of the investment on IPM technology research and training for various vegetables in the four selected districts. Calculating the change in economic surplus is one of the most common methods for estimating research returns in a partial equilibrium framework (Alston et al., 1995). In this study, the analysis was completed under a closed economy assumption because only small quantities of the vegetables produced in Bangladesh are exported or imported. Following Alston et al. (1995), the changes in total economic surplus (ΔTS), consumer's surplus (ΔCS), and producer's surplus (ΔPS) in a closed economy with linear demand and supply and a parallel research-induced supply shift were calculated as:

$$\Delta TS = \Delta CS + \Delta PS = P_o Q_o K (1 + 0.5Z\eta)$$

$$\Delta CS = P_o Q_o Z (1 + 0.5Z\eta)$$

$$\Delta PS = P_o Q_o (K - Z) (1 + 0.5Z\eta)$$

Where P_0 and Q_0 are the initial price and quantity before the research, η is the absolute value of the elasticity of demand, and ε is elasticity of supply.

$Z = K\varepsilon/(\varepsilon + \eta)$, where Z is the price reduction due to the supply shift. K represents the vertical shift of the supply function expressed as a portion of the initial price. The value of K was calculated as:

$$K = \left(\frac{E(Y)}{\varepsilon}\right) - \left(\frac{E(C)}{1 + E(Y)}\right) A$$

where E(Y) is the expected proportionate yield increase per hectare after adoption of the new technology, E(C) is the expected proportionate change in variable input cost per hectare, and A is the adoption rate for the technology.

The change in economic surplus (benefits) was calculated for each year, and the costs were the expenditures related to the development and dissemination of IPM packages for the selected vegetables. Net benefits were discounted at 5%, which is assumed to be the real rate of return on alternative public investments. NPV was calculated over an 18-year period beginning from 1998, the first year that IPM IL costs were incurred. The NPV of the discounted benefits and cost was calculated as:

$$NPV = \sum_{t=1}^{n} \frac{R_t - C_t}{(1 + i)^t}$$

Where, R_t = benefits in year t, C_t = cost in the year t, and i = discount rate.

The IRR is the interest rate that makes the net present value equal to zero. It was calculated as:

$$NPV = 0 = \sum_{t=1}^{n} \frac{R_t - C_t}{(1 + IRR)^t}$$

2.4.1. Data and assumptions for economics surplus analysis

2.4.1.1. Elasticities of demand and supply. Few estimates (Awal et al., 2008; Murshid et al., 2008; Huq and Arshad, 2010) of the own price elasticity of demand (responsiveness of quantity demanded due to a change in price) for vegetables in Bangladesh are available in the literature. The present study used a relatively inelastic value of −0.50, which is approximately the average of the price elasticities of demand for vegetables in Bangladesh in the literature. For the supply elasticity (responsiveness of quantity supplied due to a change in price), a study conducted by Rahman (1986) estimated the supply elasticity for vegetables at 0.20 in Bangladesh. A more recent study is not

Table 2
Key parameters and initial assumptions for the economic surplus analysis.

Parameters	Vegetables					
	Eggplant	Bitter gourd	Tomato	Cabbage	Cucumber	Country beans
Supply elasticity	1.00	1.00	1.00	1.00	1.00	1.00
Demand elasticity	0.50	0.50	0.50	0.50	0.50	0.50
Per hectare yield change (%)	38.4	8.4	2.6	45.6	33.9	25
Per hectare cost change (%)	−5	−16	−11.6	−6.2	−88	−4.9
Max. adoption rate (%)	0.35	0.48	0.36	0.20	0.31	0.20
Base price (Tk./MT)	27070	32523	43736	16380	20203	30240
Base quantity (MT)	21017	3740	8600	14854	3740	10818

Note: Approximately Tk. 80 = 1 US$ (at the time of the analysis), MT = Metric ton.

available of the supply elasticity for vegetables in Bangladesh. Alston et al. (1995) recommend using a supply elasticity of one when a reliable estimate is not available. The present study used one due to the lack of a recent estimate (Table 2).

2.4.1.2. Adoption rate. The present study used the 2015 survey data to measure the adoption rate of IPM technologies. The IPM IL project developed IPM packages for the vegetables, which were disseminated through the Department of Agricultural Extension (DAE) and Non-Government Organization (NGO) partners. However, they also disseminated the technologies directly to farmers through a three-year training program that was initiated in 2013 in the fours districts that are the focus of this study. The present study assumed that adoption of IPM only occurred in 2015 as a result of the training program in the selected four districts. The estimated maximum adoption rates of the IPM technologies in the study areas for the six vegetables were 0.35, 0.48, 0.36, 0.20, 0.31 and 0.20 for eggplant, bitter gourd, tomato, cabbage, cucumber and country bean, respectively (Table 2).

2.4.1.3. Changes in yield and production cost. The proportionate changes in yields for all vegetables were estimated using the 2015 survey data. The proportionate change in production cost for eggplant was also estimated using the 2015 survey data. The proportionate change in production costs for tomato and cucumber were estimated using survey data conducted by BARI in 2011 (Islam et al., 2011), while the change in production costs for cabbage and country bean were calculated by Akter (2004) and Karim et al. (2013), respectively (Table 2).

2.4.1.4. Prices and quantities. The initial prices and quantities of the vegetables were obtained from the Bangladesh Bureau of Statistics (BBS, 2015). A three-year average of harvest time market prices (2012–2014) was used to control for annual variation. National prices were used because prices were not available for the selected districts, but differences are expected to be small. To reduce the effects of annual variation due to weather and other factors, a three-year average of district-level production data for the vegetables was used in the model (BBS, 2014; BBS, 2015).

3. Results and discussion

3.1. Basic household characteristics of the survey respondents

A comparison of characteristics of adopters and non-adopters from the 2015 survey is presented in Table 3. Differences in age, education, farming experience, family size, and societal membership status were significant. These differences indicate that use of propensity score matching is warranted.

Table 3
Characteristics of the adopters and non-adopters.

Characteristic	Adopters	Non-adopters	Mean diff.	t-values or χ^2
Sample size	236	403	–	–
Age (years)	43.16	46.53	−3.37***	−3.30
Education (years of schooling)	6.57	5.73	0.84**	2.32
Vegetable farming experience (years)	17.69	20.78	−3.09***	−3.50
Family size (Nos.)	4.77	4.42	0.35***	2.77
Active members (Nos.)	3.06	3.04	0.02^{ns}	0.13
Farm size (hectare)	0.89	0.94	-0.05^{ns}	−0.63
Extension contact (% of farmers)	79.66	77.92	1.74^{ns}	0.26
Societal Membership (% of farmers)	40.67	31.26	9.41**	5.81
IPM training received (% of farmers)	40.25	11.41	28.84***	71.98
Access to credit (% of farmers)	52.11	49.87	2.24^{ns}	0.29

Note: ** and *** denote significance of mean difference at 5% and 1% level respectively; ns = not significance; Active members defined as 16–60 years old. Differences in means of extension contact, societal membership, IPM training and access to credit were tested using χ^2, with t-tests used for all other comparisons.

3.2. Adoption of IPM practices

Among the 10 IPM practices suggested by IPM IL, farmers adopted pheromone traps the most, followed by poultry refuse for soil amendment (Table 4). Only a few farmers used yellow sticky traps and tricho-compost. Other recommended IPM practices were not adopted by the farmers.

3.3. Impact of IPM on the yield, pesticide applications, and pesticide costs

Findings indicate that adoption of IPM practices had a non-significant effect on the yield of eggplant and bitter gourd, but a significant impact on tomato yield (Appendix Table A1). Pesticide application costs were significantly lower for adopters than for non-adopters. Depending on the matching technique, IPM adopters had savings in pesticide costs of Tk. 15700–30100 ($196 - $376 USD), Tk. 11400–14300 ($142 - $179 USD), and Tk. 13300–17600 ($166 - $220 USD) for eggplant, bitter gourd, and tomato respectively. IPW also exhibited similar findings, confirming their robustness (Appendix Table A1).

Probit and multinomial logistic regression results for vegetables as a whole and "region of common support" are presented in Appendix Tables B1 and B2. The results indicated that distance to market (DM) and experience had negative effects on IPM adoption, while IPM training and number of other farmers adopting IPM near the respondent farmer's field (FAI) positively influenced adoption. Fairly low pseudo R^2

Table 4
Percentage of farmers adopting different IPM practices in study areas based on field survey in 2015.

IPM practices	Vegetables					
	Eggplant	Bitter gourd	Tomato	Cucumber	Cabbage	Country bean
Sex pheromone trap	28	38	21	21	7	10
Yellow sticky trap	1	1	3	–	–	1
Poultry refuse	12	17	24	17	13	14
Tricho-compost	2	1	1	2	–	1

Table 5
Impact of IPM practices on yield, pesticide applications and pesticide costs for the selected vegetables as a group.

Outcome variable	Number of samples		Average treatment effect on treated (ATT)	S.E	t-value
	Adopters	Non-adopters			
Yield					
NN matching	236	121	234.50	506.32	0.46
Kernel matching	236	400	255.93	288.46	0.88
Radius matching	236	400	64.11	291.71	0.22
IPW	236	400	386.62	240.13	1.61
Number of pesticide application					
NN matching	236	121	−3.94	3.43	−1.15
Kernel matching	236	400	−4.42*	2.50	−1.76
Radius matching	236	400	−5.75***	2.17	−2.64
IPW	236	400	−20.07**	9.51	−2.11
Pesticide cost					
NN matching	236	121	−1990.42***	824.66	−2.41
Kernel matching	236	400	−2039.63***	650.92	−3.13
Radius matching	236	400	−2017.53***	456.98	−4.41
IPW	236	400	−5473.18***	2065.95	−2.65

Note: *, ** and *** indicates significance at 10%, 5% and 1% level respectively.

values indicated that the allocation of the farmers in the control group was fairly random, allowing for a good match between treatment and control households (Pradhan and Rawlings, 2002). Nearest neighbor, kernel matching, and radius matching identified 121, 400, and 400 households as non-adopters (control), respectively. Pesticide applications were reduced significantly through adoption of IPM technologies based on results from applying kernel, radius, and IPW techniques (Table 5). IPM adopters used sex pheromone traps and soil amendments to manage insects and soil borne diseases and reduced the number of pesticide applications. Due to fewer pesticide applications in vegetable fields, pesticide costs were significantly lower for IPM adopters. For vegetables as a group, pesticide costs decreased by Tk. 1990.42 ($24.88 USD), Tk. 2039.63 ($25.50 USD), Tk. 2017.53 ($25.21 USD) and Tk. 5473.18 ($68.41 USD) based on the nearest neighbor, kernel matching, radius matching and IPW, respectively. Overall findings of the study suggest that IPM adopters have cost advantages over non-adopters. This result is consistent with findings in other studies conducted in Bangladesh and elsewhere (Karim et al., 2013; Pretty and Bharucha, 2015; Gautam et al., 2017), indicating that IPM technology is helpful in reducing frequency of pesticide applications and pesticide costs.

To check the robustness of our findings, we categorized the adopters based on the number (0, 1, or 2) of IPM practices adopted and used IPWRA technique to compare the results with non-adopters (Table 6). The results indicate that the farmers who are adopting more IPM practices were showing better performance in terms of reducing pesticide applications and costs compared to the farmers who did not adopt IPM.

3.4. Market-level economic impacts

Benefits to IPM research and training were assessed by calculating changes in consumer and producer surplus from a rightward shift in the supply curve induced by adoption of IPM practices in the four districts. Total undiscounted changes in producer and consumer surplus for the period 1998–2015 were estimated at Tk. 23.46 and 46.92 million ($293,250 and $586,500 USD), respectively for eggplant IPM research and training in the selected districts. The estimated total net benefits from IPM research and training on eggplant was Tk. 68.93 million ($861,625 USD) for the period 1998 to 2015 in the four selected districts (Table 7). Consumer surplus was higher than producer surplus due to the inelastic demand for all the six vegetables in the closed economy model. The estimated net benefits to society from IPM research and training by the IPM IL for the other five vegetables were Tk 18.27, 3.27, 18.51, 22.53 and 16.24 million ($228375, 40827, 231375, 281625 and 203000 USD) for tomato, bitter gourd, cabbage, cucumber and country bean, respectively for the period 1998 to 2015 (Table 7). Our findings confirm those of other studies (Akter, 2004; Sparger et al., 2011; Myrick et al., 2014) that aggregate benefits of vegetable IPM research and training exceed their costs.

Table 6
Impact of IPM practices on yield, number of pesticide applications and pesticide costs for the selected vegetables as a group.

Outcome variable	Number of IPM practices adopted		ATT	SE
	Adopters	Non-adopters		
Yield	1	0	457.87*	276.25
	2	0	526.61	430.77
Number of pesticide applications	1	0	−12.86*	7.05
	2	0	−25.06***	6.95
Pesticide costs	1	0	−4107.46***	1536.09
	2	0	−5476.91***	1559.28

Note: *, ** and *** indicates significance at 10%, 5% and 1% levels respectively; 0 = no IPM practice adopted; 1 = adoption of any one of the IPM practices described in Table 4; 2 = adoption of any two IPM practices described in Table 4.

The estimated net present values (NPV's) (total discounted values

Table 7
Undiscounted economic benefits from IPM research and training (Million Tk.) in four districts of Bangladesh for the period 1998–2015.

Vegetables	Change in Total producer surplus	Change in Total consumer surplus	Change in Total surplus	Total research cost	Net benefit
Eggplant	23.46	46.92	70.38	1.45	68.93
Tomato	6.33	12.66	18.99	0.72	18.27
Bitter gourd	1.78	3.55	5.33	2.06	3.27
Cabbage	6.80	13.60	20.40	1.89	18.51
Cucumber	8.18	16.36	24.54	2.01	22.53
Country beans	6.37	12.74	19.11	2.87	16.24

Table 8
Estimated rates of returns to IPM research and training in four districts of Bangladesh.

Vegetables	NPV (Million Tk.)	IRR (%)
Eggplant	29.30	42
Tomato	7.79	39
Bitter gourd	1.10	13
Cabbage	7.67	29
Cucumber	9.05	30
Country beans	6.58	24

over the period 1998–2015) were Tk. 29.30, 7.79, 1.10, 7.67, 9.05 and 6.58 million ($366250, 97375, 13750, 95875 and 82250 USD) for eggplant, tomato, bitter gourd, cabbage, cucumber and country bean, respectively, in the four districts of Bangladesh. These positive values indicate that society benefited from its investments in vegetable IPM research and training. The estimated internal rates of return on investment (IRRs) were 42% for eggplant, 39% for tomato, 13% for bitter gourd, 29% for cabbage, 30% for cucumber, and 24% for country bean. These IRR values imply that on average, each taka invested in IPM research and training returned 42, 39, 13, 29, 30, and 24% annually from the date of the initial investment for eggplant, tomato, bitter gourd, cabbage, cucumber, and country bean, respectively (Table 8). These rates indicate that the investment in IPM research and training by the IPM IL in the study areas is profitable and beneficial to society.

4. Conclusions

The findings of this study indicate that IPM has reduced the number of pesticide applications and pesticide costs for each of the selected vegetables in four districts in Bangladesh which may indicate that IPM adopters are increasing their returns by reducing their cost of production. These increased returns may help reduce poverty and malnutrition in rural areas of Bangladesh. The estimated reduction in pesticide applications and expenditures may also imply environmental and health benefits from IPM adoption. The Government might want to provide incentives to public and private agricultural institutions to increase IPM research and training. Findings also indicate that investment in vegetable IPM research and training provides sizable benefits to the society as a whole. In this regard, an increase in investment in IPM research and extension may be warranted by both Government and donor agencies.

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Appendix A

Table A.1
Impact of IPM technologies on yield, number of pesticide application and pesticide cost for different vegetables

Outcome variable	Eggplant			Bitter gourd			Tomato		
	ATT	S.E	t-value	ATT	S.E	t-value	ATT	S.E	t-value
Yield									
NN matching	768	5216	0.14	1674	3747	0.44	9162**	3673	2.49
Kernel matching	1041	2898	0.35	2588	2202	1.12	6867***	2552	2.69
Radius matching	861	2934	0.29	1567	2121	0.73	5804**	2720	2.13
IPW	3650	4302	0.85	2349	2033	1.16	6213**	2618	2.37
Number of pesticide application									
NN matching	−5.78	7.81	−0.74	−1.41	3.41	−0.41	−2.32	2.97	−0.78
Kernel matching	−5.58	4.19	−1.33	−2.62	2.05	−1.27	−2.75	2.91	−0.94
Radius matching	−7.21*	4.31	−1.67	−5.41***	1.80	−3.0	−2.44	2.16	−1.13
IPW	−7.31*	4.35	−1.68	−2.88*	1.61	−1.79	−3.01	2.27	−1.33
Pesticide cost									
NN matching	−30100*	16221	−1.85	−6408	6699	−0.95	−17600***	5515	−3.19
Kernel matching	−28800**	14129	−2.03	−11400**	5483	−2.07	−16100***	6329	−2.68
Radius matching	−15700**	7518	−2.08	−14300***	3381	−4.24	−13300***	3170	−4.18
IPW	−33130***	12584	−2.63	−11679**	4566	−2.56	−14877***	4162	−3.57

Note: *, ** and *** indicates significance at 10%, 5% and 1% level respectively.

Appendix B

Table B.1

Probit and multinomial logistic regression results for adoption of IPM technologies

Variables	Binary probit		Multinomial logistic			
			Adopted any 1 IPM practices		Adopted any 2 IPM practices	
	Co-efficient	S.E	Co-efficient	S.E	Co-efficient	S.E
Constant	−0.1960	0.251	−0.2696	0.444	−3.898	0.932
DM (km)	−0.1093***	0.042	−0.2129***	0.079	−0.0527	0.130
Active member (No.)	0.0546	0.046	0.0718	0.081	0.1592	0.151
Experience (yrs)	−0.0154***	0.006	−0.0079***	0.023	0.0222	0.045
Education (yrs)	−0.0003	0.013	−0.0269	0.010	−0.0262	0.021
Farm size (Hec.)	−0.0450	0.066	−0.1365	0.127	0.1455	0.165
Loan (Tk)	0.1369	0.111	0.1911	0.195	0.5526	0.381
Ett (yes/no)	0.0641	0.140	0.1296	0.249	0.4326	0.521
Ntt (yes/no)	−0.3509**	0.145	−0.5282***	0.254	−0.6799	0.449
IPM training (No.)	0.7921***	0.139	1.1170***	0.244	2.1406***	0.408
FAI (No.)	0.1510***	0.024	0.2816***	0.050	0.3457***	0.062
Log likelihood	−350.65		−440.60			
LR $chi^2(10)$	140.38		160.21			
Prob > chi^2	0.000		0.000			
Pseudo R^2	0.17		0.15			
Number of obs.	639		634			

Note:DM = distance to market; Ett = extension contact; Ntt = contact with neighbor; FAI = number farmers adopting IPM near the respondent farmer's field.

Table B.2
Description of the estimated propensity score in region of common support.

Percentiles		Smallest		
1%	0.0863984	0.06906		
5%	0.1288453	0.075677		
10%	0.1562165	0.079354	Obs	636
25%	0.2073558	0.083584	Sum of Wgt.	636
50%	0.2937427	Largest	Mean	0.368454
75%	0.4922062	0.99088	Std. Dev.	0.215123
90%	0.6949868	0.997307	Variance	0.046278
95%	0.8257425	0.997607	Skewness	1.05628
99%	0.9683808	0.999912	Kurtosis	3.31256

Step 1: Identification of the optimal number of blocks.

The final number of blocks is 5.
This number of blocks ensures that the mean propensity score is not different for treated and controls in each block.

Step 2: Test of balancing property of the propensity score

The balancing property is satisfied.

Table B.3
The inferior bound, the number of treated and controls for each block

Inferior of block of propensity score	Adoption		Total
	0	1	
0.06906	120	21	141
0.2	207	71	278
0.4	48	62	110
0.6	18	51	69

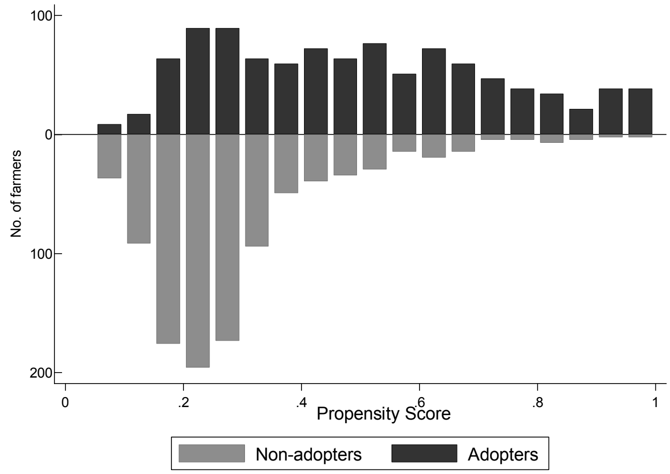

Fig. B.1. Propensity score matching of matches by IPM technology adoption for all the selected vegetables.

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