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IMPACT ON AGRICULTURAL PRODUCTIVITY AND INCOME DUE TO USE OF PESTICIDES IN OFF-SEASON VEGETABLE IN ODISHA

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ABSTRACT

The cultivation of crops outside the regular cropping calendar when supply is low and prices are high can give farmers better profits and consumers more choice. However, off-season production may increase pesticide risk if crops are more affected by pests and diseases and farmers do not handle pesticides correctly. This study quantified the effect of training in off-season tomato production on the income and pesticide use of smallholder vegetable farmers in Odisha, India. The study uses farm level data from 94 trained and 160 non-trained farm households and applies propensity score matching and inverse probability weighting to correct for selection bias. For the average smallholder vegetable farmer, training increased net household income by about 48%. We found that 31% of the trained farm households who had initially adopted the technology continued its use in the second year, but farm households who discontinued using the technology also experienced significant income gains from the training. There was a significant increase in pesticide use (+56%) and although there was an improvement in pesticide handling practices, trained farmers may have been more exposed to pesticide health risk. The policy implication is that while off-season vegetable production can create dramatic income improvements, it is important to emphasize safe and sustainable pest management methods as part of policies promoting it.

INTRODUCTION

Fruit and vegetables taste best when eaten in season. This is also when they are cheapest. This is good for consumers, but a problem for farmers, who would prefer producing and selling vegetables in the off-season—if they could. Modern technologies such as protected cultivation and specially bred varieties increasingly allow farmers to do this. These technologies can make an important contribution to the year-round availability of nutrient rich food to consumers, and to the income of farmers. Yet high production costs and increased risk make income gains uncertain, while intensive pesticide use may pose a risk to farmers and consumers alike.

This paper explores the effect of off-season cultivation of tomatoes (Solanum lycopersicum) in central Odisha, India. Off- season (also called counter-season) vegetable cultivation is the growing of vegetables under adverse climatic or economic conditions. The agricultural cropping season in South Asia is generally divided into two main seasons as determined by the South Asian monsoon. The kharif season—often referred to as spring, summer, rainy or simply monsoon season—is characterized by high temperatures, high rainfall and high humidity. Over 85% of the annual rainfall typically falls in this period, which generally lasts from May to November. Typical summer crops are rice, soybean, mungbean, and summer vegetables such as okra, amaranth, Indian spinach and gourds. The rabi season also referred to as autumn or winter has much cooler and drier conditions and lasts from November to March. Typical rabi crops are wheat, maize, potatoes, mustard, and winter vegetables such as cabbage, eggplant, and tomato.

Previous studies have suggested that farmers growing tomatoes during the kharif season have received high profits. Zaman et al. (2006) analysed on station data from experimental plots and showed that every dollar (USD) invested in off-season tomato production gave revenues of 3.3 dollars (benefit cost ratio). In comparison, growing tomatoes in the rabi season gave only a benefit cost ratio of 1.7 (Zaman et al., 2010). Karim et al. (2009) estimated the benefit cost ratio for off-season tomato production from on-farm data in Jessore district and estimated it to be 4.2. These estimates are based on data from experimental plots or from adopting farmers only, and thus are probably not representative for the average vegetable farmer. Furthermore, these studies did not estimate the profitability of a similar group of non-adopting farmers. To our knowledge, there has been no ex-post evaluation of off-season tomato production in Odisha, or elsewhere, that uses a valid counterfactual. In fact, few studies have been conducted on the impact of off-season vegetable production on incomes and pesticide use in developing countries, despite the rapid spread of these technologies (Kang et al., 2013; Nair and Barche, 2014). To address this gap, this study aims to quantify the effect of training in off-season cultivation of tomatoes on the income of smallholder farmers and the intensity of pesticide use in Odisha. It also identifies challenges to off-season tomato production.

The paper starts by describing the intervention that is being evaluated. It then describes how data were collected and how the evaluation design minimized the confounding effects of selection bias and technology spill overs. After presenting the results, we discuss the limitations of the study as well as the implications of the findings for research and development of off-season vegetable production in Odisha and elsewhere.

Sampling site

Fig.1. Map of Odisha state.

Fig. 2: Map of Odisha in India.

2. Background

Agricultural production in Odisha is changing from a single focus on rice for food security to diversification with higher-value crops (FAO, 2011). According to Rahman (2009), crop diversification is the desired strategy for agricultural growth in Odisha. Many international donors have invested in crop diversification programs. Vegetables play a key role in these efforts, particularly for smallholder farmers, as average farm size has declined over time and higher returns per hectare are needed to improve the living standards of a growing population. Previous studies have shown that the adoption of improved vegetable technologies can lead to dramatic improvements in economic well-being (e.g. Weinberger and Genova II, 2005). Yet, Mahmoud and Shively (2004) noted that some have questioned the promotion of vegetables because of the environmental and health effects of high pesticide use. Tomatoes are the most important vegetable in India after eggplant and potato (which is considered a vegetable in Odisha).

Most tomato varieties are not well adapted to hot and humid tropical conditions that characterize the kharif season. Flowers tend to drop under heat stress, thereby reducing fruit set and yield. High humidity and heavy rainfall can lead to more problems with pests and diseases, particularly fungal diseases and physiological disorders.

Since the early 1990s, the Bangladesh Agricultural Research Institute (BARI) in collaboration with AVRDC – The World Vegetable Centre developed a technology package that includes heat tolerant tomato varieties (BARI Hybrid Tomato-4 being the most popular one), raised planting beds, low-cost rain shelters, hormone sprays to improve fruit set, and integrated crop management (pruning, staking, field sanitation, disease and pest management).1 Unfortunately, BARI Hybrid Tomato-4 is susceptible to the whitefly-transmitted tomato yellow leaf curl virus. Farmers apply insecticides frequently in often-futile attempts to kill whiteflies and reduce tomato yellow leaf curl incidence. Various other insect pests are also abundant during the kharif season and motivate farmers to spray In 2012, AVRDC selected 104 farmers (50 from Angul district and 54 from Sambalpur district) and gave them two days of intensive training in off-season tomato production. Off-season tomato production is a complicated innovation because it requires a range of parallel changes to farmers' usual practices. The project implementers therefore targeted relatively progressive farmers who already had experience planting vegetables and an interest in off- season tomato, but who had not grown it before. It was expected that other farmers could observe and learn from them and adopt later on. The project targeted smallholder farmers with less than 2.5 acres (1 ha) of farmland.

Training topics included healthy seedling production (preparation of potting mixtures for raising seedlings, double transplanting, and use of plastic plug trays), cultivation techniques (field prepara tion, rain shelter construction and crop management), and pest and disease management through integrated pest management (IPM). Nearly all topics included hands-on practice sessions. Trainees visited existing off-season tomato farmers and tomato nurseries. After the training, farmers received 3 g of quality seed (BARI Hybrid Tomato-4) and partial input support for the purchase of plastic sheets, bamboo, jute and nylon ropes, plant growth regulators (hormones), nets, fertilizers and pesticides to an equivalent of 10,000 Taka (USD 130). These inputs were enough for growing 2 decimals (81 m2) of off-season tomato, though farmers were free to plant a larger acreage if they wanted. Farmers received no regular support in the second year; data from that year were therefore used for this study.

After the training, project staff visited most farmers nearly every week during the kharif season to provide technical assistance. When farmers had problems with pests and diseases, the project staff would come and advise them how to deal with it. Most farmers had cell phones and could easily contact project staff for advice. Trained farmers were encouraged to share their knowledge and skills with their peers.

3. MATERIAL AND METHODS

3.1. Selection bias

This study evaluates impact using observational data for trained and non-trained farmers. Selection bias is the main concern when using observational data. There are two sources of selection bias. The first is self-selection bias, which occurs when farmers with favourable characteristics self-select into the training program. This was not an issue in our study because the project implementers, not the individual farmers, decided whom to invite for the training. The second source of selection bias is program placement bias. This is a potential source of bias in our study because project implementers purposively selected relatively progressive farmers with experience in planting vegetables and an interest in off-season tomato. Farmers selected for the training are therefore likely to have characteristics that could allow them to be more successful in using the technology than the average vegetable farmer. It would therefore be incorrect to directly compare trained farmers to a randomly selected group of non-trained farmers. We minimized the effect of program placement bias through the control group selection procedure and the use of propensity score estimators.

The first was achieved by applying exactly the same criteria to select control farmers as had been used to select training participants. The enumerators did a random walk in each of the ten villages to select 4–5 farmers from each quarter of the village. These farmers were asked for their help in making a list of other farmers who met the selection criteria of being vegetable growers, having no previous experience in off-season tomato, and having less than 1 ha of land. Farmers were randomly selected from this list and then visited. Farmers were only included in the control group if they had land suitable for off-season tomato production and expressed an interest in adopting the technology.

3.2. Propensity score estimators

The study used propensity score matching and inverse probability weighting as alternative methods to lend robustness to the analysis. Both methods have been widely used in the impact evaluation literature (e.g. Gitonga et al., 2013; Fischer and Qaim, 2012; Abebaw et al., 2010; Becerril and Abdulai, 2010). Both are non- parametric methods, which, unlike parametric methods, make no assumption about the functional relationship between outcomes and predictors of outcomes.

Propensity score matching and inverse probability weighting both start by regressing program placement (trained vs. non- trained) on a set of independent farm and household characteristics that simultaneously influence program placement and out- comes. Credible covariates included in the model were: (a) the number of working age adults in the household as vegetable production is labour-intensive; (b) the number of non-working age household members, which together with the number of working age adults represents household size and is a driver of land use intensity; (c) the amount of land owned, which is also a driver of land use intensity as smaller farms are more likely to opt for more intensive forms of land use such as vegetables; (d) age and education of the farm manager, as proxy for know-how and willingness to innovate; (e) years of experience in vegetable production, as previous experience in vegetable growing was a selection criteria used by the project; and finally (f) membership of a farmers' organization (yes/no) as proxy for innovativeness.

Parameters were estimated using a log it model and the predicted values of program placement were calculated from all covariates independent of significance levels. These predicted values are the propensity score variable and reflect the probability of a household being included in the training, conditional on confounding covariates. In effect it reduces a multi-dimensional set of observable farm and household characteristics into a single variable.

The propensity score matching method (Heckman et al., 1998 and implemented in Stata by Leuven and Sianesi, 2003) ranks households according to their propensity score. Using nearest neighbour matching, it finds the nearest ranked non-trained house- hold while for each non-trained household it finds the nearest ranked trained household. The difference in outcome variables is calculated for each matched pair, after which these differences are averaged over the entire sample to obtain the average treatment effect. It is also possible to match each trained household to more than one non-trained household and vice versa. We tested if the results were sensitive to this.

Inverse probability weighting (Wooldridge, 2007; Imbens, 2004) uses the inverse of the propensity score variable as weights in calculating the average value of the outcome variable. Different from propensity score matching, inverse probability weighting does not match trained with non-trained households. Households with a low predicted probability of participating in the training receive a lower weight, while those with a high predicted probability receive a higher weight. The basic idea is that a household with a low predicted probability of getting the training, but that was actually trained, will represent a larger group of households that did not receive the training, and thus get a higher weight in calculating the average. The average treatment effect is then calculated as the difference between the weighted averages of trained and non-trained households.

Nearly all households that received the training adopted the technology afterwards, but not all continued its use in the second year. It is therefore relevant to know if the training had a differential impact on farmers who continued and discontinued using the technology. We therefore estimated the treatment effect for each household and tested if the difference between the two groups was statistically significant using a t-test.

3.3. Testing of assumptions

The use of propensity scores, in matching as well as in weighting, requires that the distribution of covariates in the trained and non-trained groups be similar (balanced). This was checked using three methods as Lee (2013) showed that different methods can show contradictory results. First, we tested the balancing requirement using an unpaired t-test: after matching there should be no significant differences in mean values of the covariates between the intervention and control groups. Second, we compared the pseudo-R2 before and after matching, which should be fairly low after matching. Finally, we interpreted the standardized percentage bias, which after matching should be less than 20% for each covariate and less than 10% on average over all covariates (Rosenbaum and Rubin, 1983).

Another requirement in the use of propensity scores is that there is common support or overlap in the propensity scores of the intervention and control groups. It ensures that for every trained household there exists a non-trained household with similar enough characteristics. This requirement was visually checked by plotting the propensity score distributions of the two groups.

The use of propensity score estimators assumes that the assignment to the training only depends on observed covariates such as age, farm size, and education level. Hidden bias arises if unobserved covariates simultaneously affect program placement and the outcome variable (Rosenbaum, 2002). Possible unobserved covariates include entrepreneurial ability, work ethic, and risk aversion. Some authors have argued that if it is plausible to assume that unobserved and observed covariates are correlated, then the effect of the unobserved covariates will be swept away, but this assumption cannot be verified from data. We therefore checked the sensitivity of our results to hidden bias using the Rosenbaum bounds test (Rosenbaum, 2002 and implemented in Stata by DiPrete and Gangl, 2004).

3.4. Outcome indicators

The impact of the training program was assessed on the following outcome indicators, which all refer to the 6-month period of the kharif season:

a. Crop output (USD): the sum of usable crop production valued at farm gate selling prices. It includes cash revenues, home consumption and the sharing of crops with people outside the household.

b. Land productivity (USD/ha): the sum of crop output, livestock output and aquaculture output divided by the area of the farm. The farm area was calculated as the land owned, plus land rented in, minus land rented out.

c. Farm profit (USD): the sum of crop output, livestock output, aquaculture output and agricultural land rented out minus the value of variable inputs (fertilizers, pesticides, seeds, hired labour, and other inputs), land rental cost, annualized fixed costs (using a straight-line depreciation and assuming zero salvage value), and interest payments on outstanding loans. This is the net income households receive from their farm operations. d. Total per capita income (USD/capita): the sum of net farm, non-farm and off-farm income divided by the number of people in the household. Farm income included income from crops, livestock and aquaculture and is in our case the same as farm profits. A household was defined as persons regularly sharing food during the previous six months.

e. Pesticide use: kilograms of formulated (undiluted) pesticide products used per hectare of cultivated farmland.

3.5. Data collection

All farmers trained in 2012 were selected for this study. After visiting each of them it appeared that four households had sent two members to the training, one trainee had migrated, one trainee could not be identified, and four trainees had not tried to grow off-season tomato after the training. The sample of 104 project beneficiaries was therefore reduced to 94 farm households. Of these, 52 came from Sambalpur district and 42 from Angul district in Central-Odisha, India. They were distributed over 24 villages.

The control group was selected from nearby villages that were not included in the project to avoid possible spill over effects likely to occur between farmers within the same village. We started by creating a list of sub-districts where the project had worked and then divided the list in intervention and non-intervention villages. From the list we randomly selected five villages in each district (ten in total). If it appeared that a randomly selected village was not growing vegetables or if agro-ecological or socioeconomic conditions were obviously different from the intervention villages, then it was replaced with another randomly selected village. Six- teen villages had to be replaced this way.

Data were collected using a structured questionnaire. Enumerator training and field practice took one week. Interviews were conducted by 16 enumerators and completed within 10 days in mid-November 2013. A large number of enumerators ensured the data collection was completed quickly because of the tense political situation in Bangladesh at the time of the survey, which made travel difficult and unsafe.

The questionnaire consisted of a household-level and a crop- level module and used a 6-month recall period covering the kharif season. We used a 6-month rather than the more usual 12-month period because it would have been difficult to recall inputs and outputs from the preceding rabi season, particularly because farmers grow many crops on relatively small areas. The crop module was completed for each crop separately and recorded all inputs and outputs. This was time-consuming and it took 3–4 h to complete an interview.

We included all seasonal crops planted between April and August and all annual and perennial crops that were harvested between April and October. Cropping calendars do not perfectly follow the kharif season from May to October. For example, most rice is planted during the peak of the monsoon in August and September and the harvest was largely incomplete at the time of the survey. We asked for the share of harvest completed and used this together with the average price per district to estimate the total output. The total output was then multiplied by a factor capturing the proportion of the cropping cycle completed. For example, if the revenue from selling eggplant was USD 100 and 50% of the harvest was complete and the growing period was 75% complete, then the estimated output value for the kharif season was 100 100/50 75/100 = 150. Missing values, which for instance occurred if harvesting had not yet started, were replaced by sample averages per district.

The household module of the questionnaire recorded socio- demographic characteristics of the household, pesticide use practices, fixed costs, interest payments, non-farm income, and revenues and costs of livestock and aquaculture. Data were entered into a customized data entry form using MS Access to check for completeness and consistency. Monetary values were converted to 2013 USD values using the average official exchange rate at time of the survey (1 USD = 77.63 Bangladesh Taka).

4. RESULTS

4.1. Farm characteristics

The average trained and non-trained household is very similar in terms of the area of land owned, household size, and household composition (Table 1). Yet, the two groups show marked differences in the characteristics of the person managing farm operations. For the trained households, this person is younger, more literate, better educated and more often a member of a farmers' organization. This suggests that, in spite of the careful selection of control households aimed at minimizing program placement bias, the two groups are not directly comparable. This justifies the use of the propensity score estimators.

4.2. Technology adoption and discontinuation

Of the 94 households that initially adopted off-season tomato production after the training in 2012, 29 households (31%) had continued its use in 2013 when data for this study were collected. Nearly all the trained farmers said that their main constraint was the high incidence of pests and diseases (Table 2). They felt that they had to spend a lot of money on pesticides and some were concerned about the impact on their health. Farmers also mentioned the high investment costs on rain shelters and lack of access to quality tomato seed. Many farmers felt that off-season tomato production required a lot of their time when they were already occupied with other crops. Many farmers also felt that profits were lower than what they had expected because yields were disappointing and costs were higher than anticipated. We note that none of the household characteristics listed in Table 1 were significantly different between continuing and discontinuing farmers.

For those farmers continuing off-season tomato production in the second year (2013), nearly all applied all six components of the technology package, including the heat tolerant variety, seed- ling nursery, raised planting beds, chemical fertilizers, rain shelters, and plant growth regulators. One farmer did not use a seedling nursery and raised planting beds, while another farmer did not apply plant growth regulator. On average, trained households planted 66 m2 of off-season.

Tomato in 2019 (Table 3), but this includes 65 households that did not plant tomato. Households that continued the technology planted 214 m2 on average. This is a relatively small area (about 15 15 m), yet much larger than the 81 m2 most had planted in the previous year. The main cultivated crops included paddy rice, jute, gourds and papaya.

The results suggest that trained households planted a significantly ($p < 0.01$) larger area of off-season cabbage and (in-season) gourds, but planted a smaller area of paddy rice and jute. It is likely that the training in off-season tomato production stimulated farmers' interests in growing more vegetables, including other off- season vegetables. It is also possible that farmers applied what they had learned in the training to other crops.

Table 4 compares the average gross margin for the ten most widely cultivated kharif crops. Jute and paddy rice have a low average profitability. This is in line with the observation of Hassan et al. (2005) for Pakistan that net returns from vegetables are several times higher than from rice. Our data suggest that profits from tomato and papaya are high, yet we note that these are relatively long-duration crops compared to beans, eggplant, cabbages and

Table 1: Average characteristics of the sampled households and farm managers.

5.06Charecteristics	**Trained househilds(n=94)**	**Standrd deviation**	**Non-trained house holds(n=160)**	**Standard deviation**
	Sample mean		**Sample mean**	
House hold charecteristics	5.06	1.58	4.83	1.42ns
Household size(persons)	3.30	1.20	3.07	1.19ns
Persons of working age	1.79	1.28	1.76	1.21ns
Develoment persons	0.48	0.40	0.48	0.32ns
Land owned (ha)				
Farm mananger Charecteristics				
Age (Years)	41.45	12.05	45.64	12.86***
Can read and write (Proportion)	0.85	0.36	0.74	0.44**
Education (Years)	7.60	4.13	5070	3.85***

Vegetable growing experience(Years)	11.61	6.71	10.69	6.83ns
Member of farmers organization (propotion)	0.61	0.49	0..29	0.46**

Notes-*,** and*** denote significance of mean differnceat the 10%, 5% and1% level respectively. n=not significancantat 10%.

a.Person s of working age defined as16-60 years old. Depedants are are persons outside this age range.

b.Difference in mean tested using Chi ^{2,}, unpaired t=total used otherwise.

Table 2: Main constraints to off-season tomato production according to farmers who had participated in the training .in % of farmer per group.

Constraint	Continued using the technology (n= 30)	Discontinued using the technology (n=65)
Insect pests and diseases	97	87
High investment costs for rain shelter	35	32
Lack of quality seed	29	37
High input costs	16	38
Low selling price	3	16
Flooding	6	
Difficulty finding a buyer	3	3

Table 3: Average area planted during the 2019 kharif season, in m^2 per household.

Crop	Trained households(n=94) Sample mean	Standard deviation	Non-trained households(n=160) Sample mean	Standard deviation
Beans and pulses (variation sps)	155	321	122	375ns
Cabbage (Variation sps)	146	495	24	178***
Chili	31	245	54	208ns
Eggplant	141	375	135	372ns
Gourds(variation sps)	248	415	13	320***
Jute	246	722	501	872***
Papaya	227	855	235	845ns
Paddy rice	1,508	1,521	1,958	1,346**
Tomato	67	142	0	0***
Other crops	267	595	195	426ns

Notes-*,** and*** denote significance of mean differnciat the 10%, 5% and1% level respectively. n=not significancantat 10%.

Tomato growers often remove the shelters and continue the crop in early rabi when prices remain high through October. Our data show the average gross margin of off-season tomato is 8,788 USD/ha. Zaman et al. (2006) estimated its gross margin to be 8,959 USD/ha (in 2013

USD equivalents). The results suggest that farmers have many crops from which to choose, and there is a substantial opportunity cost to cultivating off-season tomato.

4.3. Average treatment effects

The balancing requirement was satisfied in the three tests we used (see Table A.1 in Appendix A): the unpaired t-test showed no significant differences in mean values of the covariates of the intervention and control groups; the pseudo-R2 was 0.16 before matching but only 0.01 after matching; and the standard percent- season, in m2 per household.

Table 4: Per crop, Average value of output and inputs in Indian rupee per hectare.

Crop	nCrop	Output	Crop input	Gross marin
Beans and pulses	41	4,268	978	3,290
Cabbage	16	4,912	1,17	3,534
Chili	25	5,272	1,217	4,054
Eggplant	43	5,086	1,012	4,065
Gourds(Various)	33	2,634	833	1,801
Jute	34	1,414	568	821
Papaya	27	9,037	791	8,245
Paddy rice	207	1,260	875	403
Tomato	29	11859	3,017	8,788
Other crops	65	7,35	1,391	5,959

Note: n= Number of observations

Average value of output and inputs per crop, in US dollar per hectare. age bias was less than 20% for each covariate and the mean absolute standardized bias was less than 10%. This shows that the use of propensity score estimators effectively reduced the bias in observable characteristics between the trained and non-trained groups. The propensity score distributions of the trained and non-trained farmers shows that there might be a lack of overlap at the left- and right-hand side of the distributions (Fig. B.1 in Appendix B). We will therefore test if average treatment effects are sensitive to dropping observations outside the area of common support.

The results in Table 5 show that training in off-season tomato production significantly ($p < 0.01$) increased the value of crop out- put per farm by 39%, based on propensity score matching and

Table 5: Average treatment effects of off-season Tomato production for the kharif season.

Outcome variable	Average treatment effected(ATE)	Standard error	z-score (sign)	Potential out-come(PO) meanATE as% of PO mean	ATE as% of PO mean
Crop output (USD)					
-PSM	285.9	101.0	2.83***	736.1	3838
-IPW	286.4	108.1	2.65***	722.9	39.6
Landproductivity(USD/hct)					
-PSM	766.9	301.6	2.54**	1584.2	43.4
-IPW	661.0	340.8	1.94**	1474.8	44.8
Farm profitability(USD/farm)					
-PSM	290.2	125.3	2.32**	581.2	49.9
-IPW	274.6	117.9	2.33**	551.0	49.8
Total income(USD/Capital)					
-PSM	85.975.3	33.4	2.57**	170.0	50.5
-IPW		32.1	2.35**	166.7	45.2
Pesticide use(kg/hct)					
-PSM	2.0	0.9	1.13**	3.4	53.4
-IPW	1.7	0.8	2.12**	3.3	53.0

Notes:- PSM = propensity score matching; IPW = inverse probability weighting *',**, and ***denote significance of mean difference at the 10%, 5%, and 1% level, respectively; ns = not significant at 10%.

Inverse probability weighting. The two methods gave nearly identical results. The average treatment effect for land productivity was also significant ($p < 0.05$). The effect was 48% for propensity score matching and 45% for inverse probability weighting. The effect on net farm profit was 50% for both methods. Average treatment effects on per capita income were 51% for propensity score matching and 45% for inverse probability weighting.

Farmers trained in off-season tomato production used a significantly ($p < 0.05$) greater quantity of pesticides per hectare of farm- land than the control farmers. Average usage was higher by about 53–58% from an initial average level of 3.3 kg/ha. This appears consistent with the earlier observation that farmers identified pests and diseases as the main constraint to off-season tomato production.

The results were moderately sensitive to hidden bias (Table A.2 in Appendix A). All lower bounds had significance levels of $p < 0.01$, but the upper bounds became insignificant (p >

0.10) if the gamma was increased by a factor 2 for crop output, 2.2 for land productivity, and 1.6 for farm profitability, per capita income and pesticide use. This does not prove that any of the assumptions are violated but some caution is needed in interpreting the results.

Inverse probability weighting and propensity score matching gave very similar results in terms of size and significance of the average treatment effects. However, the weighting method gave about 5% lower estimates of average treatment effects than the matching method for land productivity, total income and pesticide use. We further tested the sensitivity of the results to seven alternative options in the matching method, such as varying the number of matching neighbours and excluding 13 households (10 control and 3 intervention) that lay outside the area of common support (Table A.3 in Appendix A). We used the coefficient of variation as a measure of sensitivity. The results show that crop output, farm profitability and per capita income were not very sensitive to alternative matching methods as their average treatment effect varied by less than 5% around the mean. Land productivity was somewhat more sensitive at 8% while pesticide use was the most sensitive, showing 19% variation around the mean. For both variables the average treatment effect was higher when using a smaller number of neighbours for the matching. The results with regard to pesticide use must therefore be interpreted with more caution than the other variables. Heterogeneous effects were analyzed by estimating the treatment effect for each household that had received the training. The two-sample t-test showed that the average treatment effect on per capita income for the group that continued using technology was USD 189 while it was USD 62 for those that discontinued using it ($p < 0.05$). Still, the average treatment effect for those that discontinued using technology is significantly greater than zero ($p < 0.05$), which confirms that both groups benefitted from the training. There were no significant differences between the two groups for any of the other outcome variables. The limited number of samples ($n = 94$) constrained us from doing a more detailed analysis of the variation in treatment effects.

4.4. Pesticide risk

Higher average pesticide use does not necessarily imply higher pesticide risk because pesticide risk is a function of toxicity and exposure as well as dose. Pesticide exposure depends on how farmers handle pesticides such as wearing protective gear during spraying and following proper sanitation methods after spraying. If the training program can be shown to have improved handling practices, then the pesticide risk might be lower even if application rates are higher.

Table 6 compares handling practices between trained and non- trained households. The results show that trained farmers better covered different parts of their body such as the mouth, head, hands, legs, and feet, whereas such practices were less common among non-trained farmers. This suggests that they might have a better understanding of the routes of entry of pesticides into the body. A higher percentage of trained farmers indicated that they changed clothes and washed themselves immediately after spraying, which also suggests a lower risk behaviour. However, the results also show that a higher percentage of the trained farmers mixed different pesticides together for a single spray. The use of such mixtures is a common practice in Bangladesh (e.g. Kabir et al., 1996) but not recommended because it may increase the toxicity to humans and reduce their effectiveness in controlling pests.

Finally, the results show that the average trained farmer observed more symptoms of pesticide poisoning after spraying, such as eye irritations, skin rashes, and vomiting than the average non-trained farmer. Yet, the average treatment effects are largely insignificant for both propensity score estimators. We can there- fore not conclude that trained farmers experienced more pesticide poisoning symptoms.

5. DISCUSSION

Diversification of agricultural production in Bangladesh from rice and jute to high value fruits and vegetables is important to sustain and improve rural livelihoods that are under pressure from

Table 6: Pesticide Handling Practices of Trained Versus Non-Trained Farmers, In Proportion of The Total Number of Farmers Per Category.

	Mean		**Average treatments effects**	
	Non-trained households (n=160)	**Trained households (n=94)**	**Proponsity score matching**	**Inverse probability weighting**
Body parts normaly covered while spraying				
- Mouth	0.31	0.79***	0.40***	0.46***
-Head	0.23	0.65***	0.47***	0.41***
-Arms	0.92	0.93	0.00	0.07
-Hands	0.40	0.65***	0.20**	0.25***
-Legs	0.59	0.78***	0.16*	0.21***
-Feet	0.01	0.10	0.14	0.09
Usual practice after spraying				
-Wash hands	0.88	0.90	0.02	0.00
-Change clothes	0.79	0.93***	0.09*	010*

-Wash body	0.77	0.99***	0.20***	0.17***
Mixing different pesticide products	0.81	0.90**	0.13**	0.12***
Symptoms experienced after spraying				
-eyes irritation	0.19	0.03**	0.06	0.09
-skin rashes	0.05	0.15**	0.01	0.04
Upset stomach	0.01	0.12	0.00	0.04
-Headache	0.17	0.21	0.05	0.03
-Dissiness	0.17	0.27**	0.10*	0.09
-Vomiting	0.09	0.17	0.07	0.05

Notes: *, **, and ***denote significance of mean difference at the 10%, 5%, and 1% level, respectively.

a Difference in means tested using a Mann–Whitney two-sample statistic.

Land fragmentation and population growth. Our study showed that diversification into vegetables can lead to dramatic increases in land productivity, farm profits and per capita incomes. Our results are consistent with Weinberger and Genova II (2005) who estimated that training in improved vegetable production methods increased annual incomes by 30%, though their study did not correct for selection bias. However, it must be noted that the results of this study only apply to a rather specialized group of smallholder vegetable farmers with an existing interest in off-season tomato production and not to the average farm household.

Another key finding of our study is that households that did not continue using the off-season tomato technology also benefitted from the training, though their benefit in terms of total income was lower. Casual observation confirmed that before the training many of the farmers did not use improved vegetable varieties, but the training convinced them about the importance of using good varieties and high quality seed. We also observed that farmers benefitted from better crop management practices such as planting bed preparation and drainage, fertilization, and adopted other off-season vegetables. The follow-up visits in the first year were intensive and the farmers gained much agricultural know- how from the regular visits of experts, although we are unable to pinpoint precisely what new knowledge and consequent behavioural changes contributed to the higher income.

The results also showed that training farmers in off-season tomato production significantly increased the intensity of pesticide use. This confirms some of the concerns noted in other studies (e.g. Mahmoud and Shively, 2004). Our own field observations confirm to put more emphasis on integrated pest management and to teach farmers to use pesticides as little as possible and with precaution if they do. Yellow sticky traps and sex pheromone traps for fruit borer also have been included in the intervention package and farmers have begun to use them, albeit at limited scale. New heat-tolerant tomato yellow leaf curl-resistant tomato lines and hybrids are also in the pipeline for release to farmers. Accompanied by sufficient training and awareness raising, such technologies can help reduce pesticide risk. However, the finding that land use intensification increases pesticide use is certainly not unique to off-season tomato production and can be generalized to diversification into high value crops (e.g. Riwthong et al., 2015 for Thailand). In a study on land use intensification and pesticide use for 119 high-, middle- and low- income countries, Schreinemachers and Tipraqsa (2012) found that a 1% increase in agricultural output per hectare was on average associated with a 1.8% increase in pesticide use per hectare. In comparison, our study (Table 5) showed that a 1% increase in agricultural output per hectare was associated with a 1.2% increase in pesticide use per hectare Nevertheless, our results show that there is trade-off between higher financial returns and higher health risk from pesticides (as well as environmental risk to ecosystems and financial risk from increase expenditure on inputs). Policies promoting agricultural diversification must therefore include a strategy how to minimise these risks. The promotion of vegetable production, particularly in the off-season, requires particular and careful attention to pest and disease management Mahmoud and Shively, 2004). Our own field observations confirm that farmers relied heavily on the use of synthetic pesticides although the trainers had not suggested that they use more pesticides. Yet, when farmers saw that their investment was at risk of damage by insects or diseases, they did not want to take any risk of losing output. The project, in the scope of which this study was conducted, has taken steps to improve the intervention design the off-season, requires particular and careful attention to pest and disease management.

6. CONCLUSIONS

Agriculture in Odisha is in the process of diversifying from subsistence rice production into higher value crops such as vegetables. The hot and humid kharif season is traditionally the main period for growing paddy rice. Our study shows that the training of smallholder vegetable farmers in off-season tomato production can dramatically improve their crop output (+39%), land productivity (+47%), profitability (+50%) and net household income (+48%) in the kharif season. Farmers who discontinued the technology in the second year also benefitted from the training through an increased net household income, but at a lower level than those who continued using the technology. The main constraint to off-season tomato production as identified in this study is the high incidence of pests and diseases. The study estimated a 56% increase in pesticide use during the kharif season from an initial rate of 3.3 kg/ha. Yet, trained farmers protected themselves better during spraying, although compliance with good agricultural practices remained incomplete and farmers tended to mix pesticides together. Effective and low-risk methods of pest and disease control are needed to protect farmers' health and the environment and avoid a trade-off between income and health.

Appendix

Table A.1: Logit regression results and results of balancing test after matching.

Co-variation	Logit regression (n=245)			Balancing tests after matching		
	Coefficient	Standard error	Sign	t-value	sign	%bias
Persons of working age	0.087	0.133	ns	0.24	ns	3.6
Dependant persons	0.037	0.126	ns	0.34	ns	501
Land owned (ha)	0.321	0.462	ns	0.17	ns	2.4
Age (years)	0.042	0.014	***	098	ns	13.7
Education (years)	0.139	0.042	***	0.78	ns	10.9
Vegetable growing experience (years)	0.058	0.025	**	0.80	ns	13.0
Membersof farmers organisation	1.540	0.318	***	0.60	ns	9.0
Constant	1.079	0.573	ns			
Pseudo R^2 Mean absolute bias	1.079			0.007		
Mean absolute bias						8.3

Table A.2: Sensitivity of the average treatment effects to hidden bias as based on the bounds test, p-values.

Gamma	Crop output	Land productivity	Farm profitability	Total Income	Pesticide use
1.0	0.000	0.000	0.001	0.002	0.01
1.2	0.001	0.000	0.008	0.015	0.012
1.4	0.007	0.001	0.036	0.062	0.050
1.6	0.025	0.007	0.103	0.158	0.132
1.8	0.066	0.022	0.211	0.297	0.257
2.0	0.135	0.052	0.493	0.453	0.405
2.2	0.228	0.102	0.626	0.602	0.553
2.4	0.338	0.170	0.737	0.727	0.682
2.6	0.435	0.254	0.822	0.821	0.785
2.8	0.563	0.347	0.884	0.888	0.860
3.0	0.662	0.442	0.834	0.932	0.612

Notes: gamma is the log odds of differential assignment due to unobserved covariates. The p-values refer to the upper bound significance levels for overestimation of the treatment effects (all lower bound significance levels had $p < 0.001$).

Appendix B

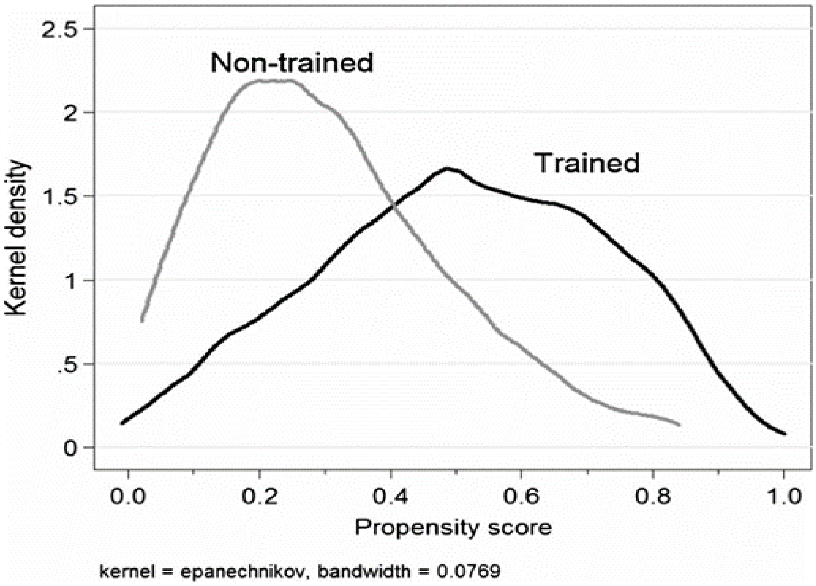

Fig. B.1: Kernel density distribution showing overlap between trained and non- trained farmers.

Appendix.AB. Graph

Table A.3: Sensitivity tests for average treatment effects to alternative matching methods.

Outcome variable	Crop output (USD)	Land productivity (USD/ha)	Farm profitability (USD/farm)	Total income (USD/Cap)	Pesticide use (kg/ha)
IPW	286.4	661.0	274.6	75.3	1.7
PSM(NN,n=1)	285.9	766.5	290.2	85.9	2.0
PSM(NN,n=3)	287.4	756.5	276.7	85.4	1.4
PSM(NN,n=5)	296.6	6660.5	297.8	83.7	1.3
PSM(NN,n=1) overllo	301.0	749.4	304.5	86.7	1.7
PSM(NN,n=3)overlap	301.5	748.9	288.3	87.8	1.8
PSM(NN,n=5)overlap	300.7	633.4	300.0	82.7	1.2
Coefficient of variation %	2.5	7.9	3.9	4.9	19.4

Notes: IPW = inverse probability weighting; PSM = propensity score matching; NN = nearest neighbour method; n = minimum number of non-trained matching neighbours per trained farmer. Overlap means that trained households are dropped whose propensity score is higher than the maximum or lower than the minimum propensity score of the non-trained farmers, and vice versa. All options for PSM are with replacement and tied propensity scores.

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