Chapter 5
The Case of Uganda: Long-Term and Spillover Effects of Rice Production Training

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Abstract Using the case of rice production training in the rainfed lowlands of Eastern Uganda, this chapter examines the extent to which training continues to enhance participants' technology adoption and productivity five years after the provision of training and the extent to which the training effect spills over to non-training participants. Rice production data was collected from training participants and non-participants in program villages and rice farmers in non-program villages one year before and one year and five years after the training. According to descriptive statistics, the gap in the average rice yield between the training participants and non-participants within a program village opens up right after the training, but it disappears in the long term. To identify program and spillover effects, propensity score matching and difference-in-differences method were used (PSM–DID). This study finds that training enhanced adoption rates for improved cultivation practices not only in the short term but also long term, while rice yield increased only in the long term. Although the adoption rate of improved cultivation practices did not increase among non-participants in training villages relative to their counterparts in non-program villages, rice yield increased after five years, which suggests signs of spillover within training villages in the long term.

5.1 Introduction

This chapter examines the long-term and spillover effects of rice cultivation training on technology adoption and rice productivity in rainfed-lowland production areas of Eastern Uganda. In Uganda, rainfed-lowland areas underpin the main rice production system, accounting for 52% of the production area and 58% of total rice production in 2018 (estimated) (MAAIF 2009). As shown in Chaps. 3 and 4, the information spillover from training participants to non-participants is likely to happen within

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irrigation schemes where rice farmers regularly interact for canal cleaning and maintenance organized by a water user association. However, it is common for farmers from different villages to rent plots in the same rainfed-lowland production area and plant rice without any coordination.[1] Given such differences in farmers' interactions between rainfed-lowland and irrigated areas, it is not obvious to what extent the information imparted by the training is shared among training participants and non-participants in rainfed-lowland areas. As discussed in Chap. 2, no study has identified the spillover effects of rice cultivation training in the rainfed-lowland rice production system in sub-Saharan Africa (SSA).

In a rainfed-lowland production system, farmers cannot control water availability (quantity and timing) well. Insufficient water during the critical growth period of rice plants is likely to depreciate the returns to recommended cultivation practices, potentially leading to the disadoption of such practices. Thus, there is no guarantee that the training effect on participants' technology adoption and productivity persists in the long term, particularly in rainfed areas. While project sustainability is crucial, long-term impacts are rarely assessed, primarily because of data limitations. In addition, the short-term impact may not capture the spillover effects in rainfed areas where the learning speed is expected to be slow if it occurs at all. In the context of upland non-rice crops, Kondylis et al. (2017) analyzed the effect of training for sustainable land management in the Zambezi Valley of Mozambique and found that only training participants adopted the practices, and there was no evidence suggesting that the training changed practices among non-participants. Since their endline survey was conducted two years after the training, the process of spillover might not have occurred sufficiently before the endline survey was conducted.

As discussed in Chap. 2, program evaluation without random assignment presents a methodological challenge, as program participants and non-participants are not usually comparable. I adopt the propensity score matching and difference-in-differences method (PSM–DID) to address potential selection bias. Furthermore, the difference between training participants and non-participants within program villages includes both the direct training effect and spillover effect, and each effect cannot be identified separately. In other words, when non-participants seem to catch up with training participants, this can be explained by decreasing direct training effects on participants and positive spillover effects on non-participants. To address this identification problem, I measure the direct training effect and spillover effect separately by using a comparison group outside program villages, arguably not affected by the training program or spillovers. Training participants are compared to similar rice farmers residing in non-program villages to assess the direct impact of the training. Training non-participants in program villages are compared with similar rice farmers in non-program villages to measure the spillover effects.

Section 5.2 describes the data collected, the study areas, and the rice training program implemented in Uganda. Section 5.3 explains the empirical framework, and the results are discussed in Sect. 5.4. Section 5.5 summarizes this chapter.

[1] In some cases, the plot size in rainfed-lowland areas is larger than the average plot size in the irrigation scheme areas.

5.2 Data, Study Area, and Rice Training

This chapter takes the case of a lowland rice farming training project implemented by the Japan International Cooperation Agency (JICA) and Uganda's Ministry of Agriculture under a sustainable irrigated agricultural development (SIAD) project in Eastern Uganda.[2] This project provides training in lowland rice cultivation practices based on experiences in Asia designed to enhance rice production and productivity by introducing sustainable rice cultivation practices. Such practices have been widely adopted in Asia but are not commonly employed in Uganda. The study area covered the Eastern region of Uganda in the second cropping season of 2009: two districts where the training was provided and five districts where the training was not offered.[3] JICA experts selected one lowland area as a project site in each district.

As the training aims at improving rice cultivation practices in rainfed lowlands, site selection was not random but targeted lowland areas with seasonal or year-round streams. Once such ecological conditions were met, JICA experts approached the rice growers and asked about their interest in participating in a training project. Once their interest was confirmed, JICA experts asked the farmers to form a group to ease communication. Lowland areas are approximately 20–30 ha and are cultivated by 90–150 rice growers in 7–11 different villages. In these villages, not all households grow rice. In the uplands, maize, cassava, and beans are mainly cultivated. Rice cultivation started around the early 2000s.

Field training was offered in a demonstration plot of each site following a cropping calendar on a learning-by-doing basis with simple explanations using flip charts to ensure that participants understood the contents. Primary trainers in the field training are local extension workers who took three-day training sessions on rice cultivation provided by JICA at the National Crops Resources Research Institute, a national agricultural research organization in Uganda. Firstly, in the 1–2 months before the planting season, training participants learned how to establish a demonstration plot followed by the trainer's instruction and prepared the demo plot for field training. Secondly, 2–3 weeks before the planting time, training participants prepared nursery beds and grew seedlings, constructed bunds around the demo plot, and leveled the demo plot. Thirdly, the improved transplanting method (straight-line planting) and weeding (timings and method) were taught and practiced in the field. Finally, trainees harvested rice in the demo plot and learned improved threshing techniques with a simple threshing device. The first training took 2–3 days while the other training took half to one day. Since the application of chemical fertilizer was not a part of JICA training, chemical fertilizer was not provided during the training. At the time of the project, there was no lowland rice variety in Uganda that was officially

[2] Please see Kijima (2022) for more details of the project.

[3] In these five districts, there are comparable rainfed-lowland areas. In selecting these districts, we considered different rice cultivation experiences.

recommended by the government. Thus, improved variety seeds were not given to participants during the training.[4]

The baseline survey was conducted in August 2009, before the training started in September 2009, and it collected information about farming activities from August 2008 to July 2009. The first follow-up survey was conducted in September 2011, gathering information about rice production from September 2010 to August 2011. Because the training period lasted until March 2010, this first follow-up survey captures the program's immediate impact. The second follow-up survey was conducted in September 2015, likely capturing the long-term training effect.

The sampling scheme differed between program villages and non-program villages. In each program site, sample households were randomly selected every 25 m based on the distance from the demonstration plot to their own rice plots. The total number of sample households in the program villages is 150. The share of training participants in each project site is different. For sampling households in non-program villages, the first five districts where the training had not yet been provided by 2009 were selected. In each district, two sub-counties with rice production and access to rainfed-lowland areas were selected. In each subcounty, six villages were randomly selected. In each village, ten households were randomly selected.

As shown in Table 5.1, the pre-program characteristics of training participants and non-participants within the program villages are similar. The means of all these variables are not statistically different between participants and non-participants in the program villages and between participants and control households in the non-program villages. The only difference found is that participants' rice plots are closer to the demonstration plot than non-participants. Although the training program was not assigned randomly, this table suggests that training participants are neither more educated/experienced nor more connected with other community members. Other than these observed characteristics, time and risk preferences are not statistically different, at least on average.[5] This finding demonstrates that the project did not select training participants based on their characteristics. Furthermore, households in non-project villages are comparable in terms of these pre-program characteristics.

Figure 5.1 presents the adoption rate of selected rice cultivation practices and rice yield per hectare separately for training participants (participant), non-participants in the program villages (non-participant), and households in the non-program villages

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[4] Lowland rice seeds tend to be self-produced by farmers and locally traded among farmers. There are two popular lowland varieties: the first is comprised of modern rice varieties crossed with local varieties and a popular variety called "K5," "K85," or "Kaiso," which was developed initially for the Kibimba Rice Scheme. The other is a local variety called "Supar" (meaning rice), which has been widely adopted in the lowland areas of Eastern Uganda, as well as in Tanzania. While K5 had its origins as one of the early Asian modern varieties, the origin of Supar is less clear.

[5] Time and risk preference measures are obtained from hypothetical questions. The household takes 1 for patience if it prefers to wait for 30 days to receive 10,000 shillings rather than a lower amount today. The hypothetical lottery (coin toss) offers five choices with different expected values: (a) Sh. 50,000 (heads) and Sh. 50,000 (tails), (b) Sh. 40,000 (heads) and Sh. 100,000 (tails), (c) Sh. 30,000 (heads) and Sh. 130,000 (tails), (d) Sh. 20,000 (heads) and Sh. 160,000 (tails), (e) Sh. 10,000 (heads) and Sh. 190,000 (tails). Risk averse is defined as a household selecting choice (a), while a household is considered to be risk loving if taking choice (e).

Table 5.1 Selected household characteristics in 2009 by training participation status

	Participants in JICA training	Non-participants in training	Non-JICA training villages
Rice experience in years	11.24 (8.10)	11.00 (9.78)	10.58 (9.56)
HH head's age	39.60 (12.38)	40.27 (13.82)	42.82 (11.87)
Head's years of education	6.069 (3.999)	5.854 (3.513)	6.083 (3.164)
Num. of HH members	8.517 (3.516)	8.089 (3.735)	8.569 (3.944)
Share of males aged 15–64	0.223 (0.109)	0.244 (0.167)	0.252 (0.136)
Share of females aged 15–64	0.235 (0.108)	0.266 (0.169)	0.231 (0.103)
Size of land owned (ha)	2.139 (1.725)	1.987 (1.703)	2.059 (5.227)
Share of lowland size owned	0.204 (0.319)	0.231 (0.282)	0.200 (0.315)
Local group member (dummy)	0.724 (0.451)	0.646 (0.481)	0.511 (0.501)
Own a bull (dummy)	0.466 (0.503)	0.519 (0.503)	0.330 (0.471)
Has patience (dummy)	0.741 (0.442)	0.737 (0.443)	0.666 (0.473)
Risk averse (dummy)	0.466 (0.503)	0.329 (0.473)	0.359 (0.481)
Distance to demo plot (km)	0.651 (0.552)	1.313* (0.482)	–
Population density per squared km (village level)	0.604 (0.350)	0.577 (0.332)	0.539 (0.367)
Number of observations	58	79	327

Source Authors' calculations. Figures are means, and numbers in parentheses are standard deviations
* Indicates mean differences between training participants and non-participants at a 5% significance level

(control) over the survey years. As Panel A shows, the transplanting method, rather than direct seeding, was relatively common in the training villages (about 65% of the rice growers) even before the training project. However, straight-row transplanting was not adopted before the program (Panel B). After the training program in 2011, the participants' adoption rates of transplanting and transplanting in rows jumped to 80 and 20%, respectively. In contrast, adoption rates did not change in the short term among the non-participants in the training villages and farmers in the control villages. The non-participants' adoption of transplanting increased in 2015 to reach

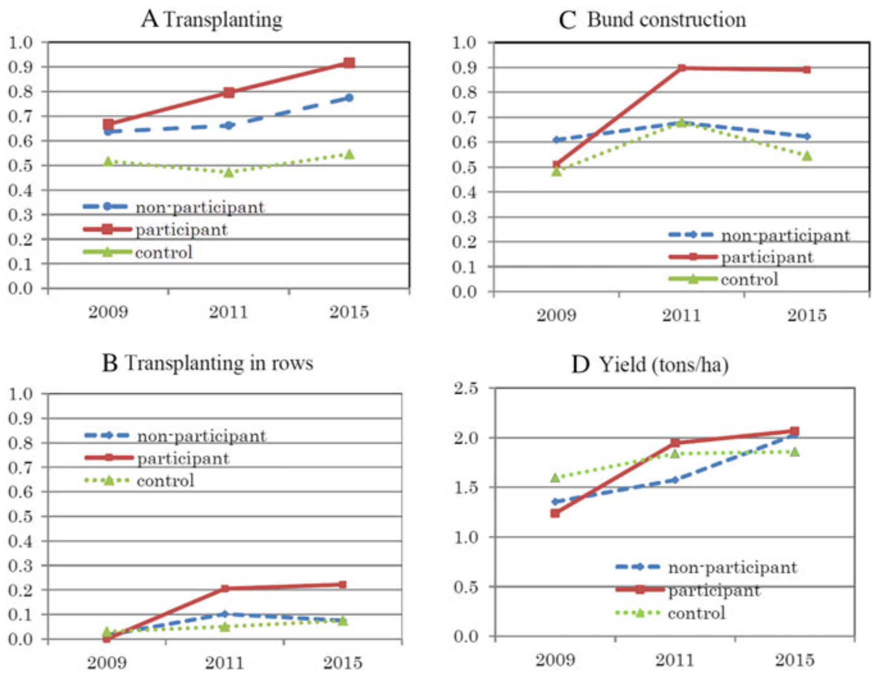

Fig. 5.1 Adoption of rice cultivation practices and productivity over time and training category

nearly 80%, while that of control households remained low. Training participants increased the adoption of transplanting to 90% by 2015, whereas the adoption of transplanting in rows stagnated after 2011. Similarly, training participants increased bund construction from 50 to 90% in the short term and maintained the same level until 2015. Although about 60% of non-participants constructed bunds in 2009, no further increase was observed.

Regarding rice yield, Panel D shows an interesting pattern. For both participants and non-participants, rice yield was about 1.3 tons per ha in 2009. After the training, it increased significantly to 2 tons per ha for participants, while non-participants experienced a moderate increase to 1.5 tons per ha in 2011. However, the yield gap disappeared in 2015. Notice that the speed of yield enhancement among participants slowed down after 2011, consistent with the stable adoption of the transplanting in rows method and bunds after 2011. In the case of non-participants, yield enhancement in 2015 may be due to the shift from broadcast planting methods to transplanting, among other factors. The emergence of a substantial yield gap between participants and non-participants in 2011 and its disappearance in 2015 suggests that non-participants learned new production methods from participants with a time lag. In other words, information spillover is likely to take place relatively slowly in rainfed areas.

5.3 Empirical Framework

This chapter first estimates the average training impact on the adoption of cultivation practices and rice yield (the average treatment effect on the treated, ATT). To estimate ATT, we need to obtain the counterfactual outcome of the training participants had they not participated in the training.

There are two empirical issues for estimating the training impact on adopting cultivation practices and rice yield in the current setting. The first empirical issue is the non-random assignment of training. Although the descriptive statistics show that participants and non-participants had similar observed characteristics before the training, unobserved characteristics may be different, and hence, they may have affected the training participation and outcomes. The second empirical issue is the knowledge spillover from participants to non-participants within the program village, potentially violating the stable unit treatment values assumption (SUTVA) necessary for appropriate program evaluation (Imbens and Rubin 2015).

To address the non-random program assignment, I use the propensity score matching (PSM) method to assure that the training participants are compared to similar rice farmers in non-program villages regarding the observed characteristics in the pre-training period. When the strong ignorability assumption holds, outcomes are independent of treatment once conditioning on the probability of participating in the training is included (Rosenbaum and Rubin 1983). ATT is identified, assuming that outcome variables are independent of treatment assignment once a set of observable characteristics before the training are controlled for:

$$\text{ATT}_t = E(Y_{it}(1)|T_i = 1, P(X_{i0})) - E(Y_{it}(0)|T_i = 0, P(X_{i0})) \tag{5.1}$$

where E() is an expectation operator, Y(1) is an outcome of household i with participating in the training, Y(0) is an outcome of the household i without participating in the training, T is an indicator variable taking unity if household i participated in the training, and P(X) is the propensity score or probability of training participation given observed pre-training characteristics X. The propensity scores are estimated by a probit model using pre-training observable characteristics as explanatory variables. Since farmers in non-program villages cannot participate in training due to the program design, I will use only samples in the program village to estimate the probit model and apply the estimated coefficients to non-program villages to predict their propensity scores.[6] This paper uses a kernel matching method and a common support condition for constructing a comparison group.

PSM estimator of ATT is denoted as

[6] In eight non-program villages, there have been training and/or programs related to rice cultivation such as NAADS. Although actual participants in such trainings and programs comprised just eight households in our sample, there might be spillover effects from the program to non-participants in such communities. To avoid this possibility, we dropped these eight communities to construct control groups as a way of estimating the direct and indirect effects of the training. The results are qualitatively similar to the main results. We believe there is no problem with the contamination from other rice programs.

$$\text{ATT}_t^{\text{PSM}} = \frac{1}{N_1} \sum_{i \in N_1} \left(Y_{it}(1) - \sum_{j \in N_0} W_{ij} Y_{jt}(0) \right) \quad (5.2)$$

where N_1 and N_0 are the numbers of matched treatment and control households, and W is the weights calculated from PSM. The validity of PSM is based on conditional independence and overlap in propensity scores across the participants and non-participants. To assure conditional independence, we use preference measures (hypothetically asked about risk aversion and time discount) to calculate the propensity scores that are usually unobserved to researchers but likely to affect participation.

Because unobserved characteristics may have affected the training participation and we have panel data before and after the training, I employ a PSM–difference-in-differences (DID) estimator of the ATT to mitigate the selection problem due to time-invariant unobservables (Smith and Todd 2005). We examine the training effect on the change in the outcomes from baseline (before the training), $\Delta Y_{it} \equiv Y_{it} - Y_{i0}$. The PSM–DID estimator is denoted as

$$\text{ATT}_t^{\text{PSMDID}} = \frac{1}{N} \sum_{i \in N_1} \left(\Delta Y_{it}(1) - \sum_{j \in N_0} W_{ij} \Delta Y_{jt}(0) \right) \quad (5.3)$$

To measure the direct impact of training, we exclude non-participants in the training villages from estimation and compare the training participants with non-program village farmers who have similar propensity scores. In contrast, to estimate the spillover effects, we compare the non-participants in the program villages with their counterparts in non-program villages who have similar propensity scores.

5.4 Results

5.4.1 Determinants of Program Participation

By using the data of training participants and non-participants in the program villages, the probability of participating in the training is estimated by the probit model. The estimation results are given in Table 5.2. Significant factors affecting the training participation are rice cultivation experience, risk aversion, and population density. Households with longer years of rice cultivation experience are more likely to participate in the training. This may be because they are more interested in rice cultivation or have previous experience with the challenges. Those with higher risk aversion are more likely to participate in the training, probably because the training is expected to reduce the risk of low production. The negative sign of a coefficient of population density may be because villages with higher population density in lowland rice areas have less room to expand or because higher population density is associated with the closeness of the town and the opportunity cost of attending the training is high. The coefficients estimated by the probit model are used to estimate the propensity scores of the households in control villages. The distribution of the propensity scores for training participants and households in control villages and for non-participants and households in control villages are shown in Panel A and Panel B of Fig. 5.2, respectively. After the matching based on propensity scores, 8% of the treatment households were not matched and dropped from the analyses. Table 5.3 shows balancing test results, indicating that matching was successful, although one of the variables shows unbalance between the participant and control groups.

Table 5.2 Determinants of participation in the training program in 2009 (probit model)

	Training participants versus non-participants
ln (rice experience)	0.103+ (1.83)
ln (head age)	0.055 (0.31)
Head years of education	−0.037 (1.10)
Head education squared	0.004 (1.49)
ln(number of HH members)	0.058 (0.49)
Share of males aged 15–64	−0.241 (0.68)
Share of females aged 15–64	−0.192 (0.46)
Size of land owned (ha)	−0.033 (1.00)
Share of lowland owned	−0.083 (0.50)
Local group membership	0.096 (0.97)
Owns a bull	−0.006 (0.06)
Risk averse	0.164+ (1.77)
Has patience	−0.092 (0.92)
Population density per squared km (village level)	−0.363** (2.90)
N	372

**, *, and + represent statistical significance at the 1, 5, and 10% levels, respectively. Marginal effects are shown. The numbers in brackets are z-statistics

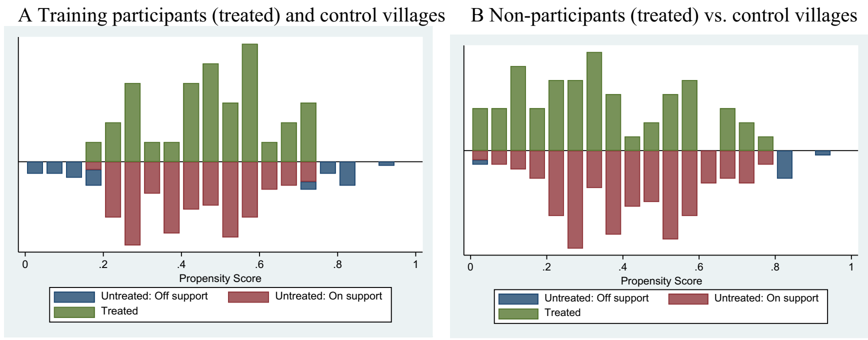

Fig. 5.2 Distributions of propensity scores

5.4.2 Training Impact on the Adoption of Cultivation Practices and Rice Yield

The estimated ATT by PSM–DID on cultivation practices and rice yield are presented in Table 5.4. Column 3 of Panel A shows the average direct effect of the training, while Column 3 of Panel B indicates the average spillover effect of the training. Regarding the adoption of transplanting in rows, the direct short-term and long-term average effects are 13 and 20 percentage points, respectively. The corresponding spillover effects are 5 and 2 percentage points, but they are not significantly different from zero. There was a long-term direct effect on bund construction and maintenance, whereas the short-term direct effect and the spillover effect in both short and long terms were not found.

Regarding rice productivity, both in the direct and spillover effects, the short-term impact is not statistically significant, while the long-term direct and spillover effects of training on rice yield are 0.84 and 0.47 tons per ha, respectively. Although the short-term direct impact on rice yield was not significant, the direct impacts on rice yield have gradually turned to positive. The improved productivity would likely attract non-participants to adopt the transplanting method, leading to a positive indirect effect on rice yield in the long term. As the training participants increased the adoption of transplanting in rows over time, it is probable that the direct effect on rice yield in the long term was brought about by the adoption of better transplanting methods.[7]

Although the training program resulted in enhancing productivity among the non-participants in the program villages in the long term, we did not find evidence that the adoption rate of the better cultivation practices increased among them. This seems puzzling but it can be explained by the fact that non-participants shifted from

[7] According to Kijima (2022), training participants increased the application of chemical fertilizer. Therefore, the increased yield might not be induced solely by the adoption of the transplanting in rows method.

Table 5.3 Balancing test results

	Participants (T)	Control C0	t-stats	Non-participants C1	Control C0	t-stats
Log (rice experience years)	2.203	1.915	1.42+	1.907	1.778	1.54
Log (HH hea"s age)	3.612	3.709	1.36	3.667	3.680	0.82
Head's years of education	6.061	6.185	0.14	5.527	5.792	0.63
Education squared	51.52	48.12	0.28	39.08	40.95	0.27
Log (num. of HH members)	2.042	2.157	0.98	1.976	2.082	1.12
Share of males aged 15–64	0.242	0.236	0.20	0.251	0.230	0.70+
Share of females aged 15–64	0.231	0.227	0.16	0.264	0.228	1.42+
Land ownership (ha)	1.708	1.857	0.37	2.251	1.931	0.90
Share of lowland size	0.182	0.189	0.10	0.270	0.236	0.58
Local group member	0.697	0.505	1.60	0.630	0.479	1.58
Owns a bull	0.485	0.347	1.13	0.519	0.321	2.11
Risk averse	0.485	0.379	0.86	0.370	0.238	1.50
Has patience	0.667	0.634	0.27	0.741	0.695	0.52
Population density	0.660	0.470	2.29*	0.556	0.631	1.48
# obs. on support	43	137		54	155	

t-stats for the mean difference between the 2 groups (* indicates the means between treatment and control groups are significantly different at the 5% level). + indicates that the variance ratios between the 2 groups (V(T)/V(C)) are outside of [0.47; 2.13]

broadcast planting to transplanting in the long term. It is also possible that non-participants learned a multiplicity of improved cultivation practices from participants through conversations and observations of participants' fields, which are not captured by selected cultivation practices in this study.

Table 5.4 Average impact of training (PSM–DID)

Panel A. Direct training effect		Participants	Control	ATT Direct	t-stat
		(1)	(2)	(3)	(4)
Transplanting	2011–2009	0.061	−0.026	0.086	0.65
	2015–2009	0.114	−0.068	0.182*	2.43
Transplanting in rows	2011–2009	0.152	0.022	0.129*	1.92
	2015–2009	0.229	0.028	0.200*	2.63
Bunds	2011–2009	0.333	0.202	0.131	1.32
	2015–2009	0.286	0.098	0.187+	1.83
Yield (ton/ha)	2011–2009	0.417	0.135	0.283	1.32
	2015–2009	0.861	0.024	0.837*	3.01
Panel B. Spillover effect		**Non-Participants**	**Control**	**ATT Indirect**	**t-stat**
		(1)	(2)	(3)	(4)
Transplanting	2011–2009	0.056	0.027	0.028	0.42
	2015–2009	0.061	−0.041	0.103+	1.81
Transplanting in rows	2011–2009	0.093	0.039	0.054	1.16
	2015–2009	0.082	0.060	0.021	0.45
Bunds	2011–2009	−0.074	0.162	−0.088	1.02
	2015–2009	−0.082	0.032	−0.114	1.27
Yield (ton/ha)	2011–2009	0.171	0.269	−0.098	0.57
	2015–2009	0.589	0.120	0.470*	2.17

* and + represents statistical significance at the 5% and 10% levels, respectively

5.5 Conclusion

This study examined the short-term and long-term impact of agricultural training. Furthermore, we assessed the program's direct and indirect impacts on cultivation practices and rice yield using the PSM–DID method. The results show that training enhanced the adoption of cultivation practices taught in the training session among training participants but not among non-participants in the program villages. We did not observe the disadoption of such cultivation practices even after five years among the training participants. The average direct impact of training on rice yield was 0.84 tons per ha in the long term. Since the pre-program average rice yield was about 1.5 tons per ha, the direct impact accounts for more than 50% of the increase. Given that the program did not provide chemical fertilizer or high-yielding varieties, this impact is surprisingly high. Thus, the training that imparts improved rice cultivation practices with training participants is considered to be effective and sustainable, even in the long term.

In terms of spillover effects, the average rice yield increased in the long term by 0.47 tons per ha among non-participants in the program villages. This finding suggests that there are spillover effects in the long term. Although non-participants adopted transplanting (not in line) in the long term, the adoption rate of the recommended cultivation practices (transplanting in rows and construction of bunds) was not enhanced even in the long term.

Can we conclude that there is a spillover effect? Kijima (2022) estimated the ATT of the same project by applying the difference-in-differences inverse probability weighting approach (Imbens and Wooldridge 2009) and found similar results to this chapter. The likely reason explained in the paper was that non-participants did not learn key concepts but mimicked the transplanting method and other numerous cultivation methods by observation, such as the appropriate timing of an appropriately shallow transplanting. This explanation was based on further analyses showing that knowledge of the transplanting method increased among training participants but was not enhanced among non-participants. Combined with these findings, what seemed to happen was that the yield enhancement among non-participants occurred as a result of the shift from the broadcast planting method to transplanting, among other factors. Such a shift can be induced by a higher adoption rate of transplanting in rows in the program villages, since non-participants can observe such changes in fields. Since non-participants did not adopt the entire set of better cultivation practices taught in the program, it may not be reasonable to expect that they will wholly catch up with the participants unless they can acquire the entire set of improved practices from participants. For such learning to be effective, non-participants need to know who took part in the training and be able to raise appropriate questions with former participants regarding their knowledge of improved cultivation practices. Developing ways to further enhance learning between training participants and non-participants, especially in the rainfed lowlands, is an important area for future research.

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