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Long-term and Spillover Effects of Rice Production Training in Uganda

By

Yoko Kijima

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National Graduate Institute for Policy Studies
7-22-1 Roppongi, Minato-ku,
Tokyo, Japan 106-8677

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Yoko Kijima*

Abstract

Using panel data from 2009, 2011, and 2015, this study estimates the impact of rice production training conducted in Uganda on the adoption of improved cultivation practices and productivities. Since the training program encouraged participants to share information with fellow farmers, we estimate the effects of the training on non-participants living in training villages (spillover effects). Due to the non-random assignment of project villages and training participation, a difference-in-differences model with household fixed effects was combined with inverse probability weighting approach to mitigate biases. Spillover effects to non-participants in training villages are indicated by increased total rice production by 0.4 tons and expanded cultivation area by 0.26 hectare. Although training increases adoption rates for better cultivation practice, namely, transplanting in rows among training participants, both in the short and long term, there were no measurable improvements in non-participants' rice cultivation knowledge or in rice productivity.

Keywords: Agricultural training project, Spillover effects, Impact evaluation, Sub-Saharan Africa

*National Graduate Institute for Policy Studies (GRIPS)

1. Introduction

Agricultural productivity in Sub-Saharan African (SSA) countries has been stagnant for a prolonged period (FAOSTAT 2017). Since improved agricultural technologies form the basis for productivity enhancement, increasing their adoption rate is an important research question to resolve low agricultural productivity. One reason for the low agricultural technology adoption rate in many SSA countries is poorly functioning public extension systems (Anderson and Feder 2007), through which extension workers normally deliver agricultural technologies developed by scientists. To mitigate these constraints, international aid agencies and development organizations provided programs that supplement public extension systems.

"Agricultural training" is one such program that takes a top-down approach and promotes a specific package of technologies. It has been successful and efficient in targeted areas with similar farming systems suitable for packaged technologies (Davis et al. 2012). Recent evidence shows that direct farmer training enhances the adoption rate of improved cultivation practices in the short run (Kondylis et al. 2017; Takahashi et al. 2018; Nakano et al. 2018). However, although agricultural training effectively enhances trainees' technology adoption, the provision thereof to all farmers is too costly. Projects that induce a greater extent of farmer-to-farmer diffusion are more cost-effective. and central to practice. Although previous studies found social learning to be important for the diffusion of agricultural technologies (Foster and Rosenzweig 1995; Munshi 2004; Bandiera and Rasul 2006; Conley and Udry 2010), the findings on its effectiveness, compared with direct training, are mixed. Moreover, Kondylis et al. (2017) showed that while direct training of farmers increases technology adoption, there is no farmer-to-farmer knowledge spillover. Furthermore, BenYishay and Mobarak (2018) found that trained farmers do not have incentive to share knowledge unless they are paid. Additionally, Takahashi et al. (2018) and Nakano et al. (2018)

found that directly trained farmers adopt technologies one year after training, but that non-trained farmers could catch up with trained farmers later through social learning. Information spillover was strong when control group knew who received training and that the information learned could be beneficial (Takahashi et al. 2018). Thus, to determine the effectiveness of agricultural training, more empirical studies are needed to evaluate whether agricultural training induces knowledge spillover from trained to non-trained farmers and the context in which social learning occurs. We therefore examined whether agricultural training induces knowledge spillover from trained to non-trained farmers.

Furthermore, this study examined whether agricultural training provided directly to farmers is an effective way to enhance technology adoption in the long term. We thus assessed the long-term impact of rice farming training on technology adoption and agricultural productivities. There are at least two reasons why long-term effects can differ from short-term effects. First, participants may adopt the technologies immediately after training but may stop using them when project support is terminated. Therefore, although the project impacts technology adoption positively in the short term, the long-term impact can dissipate. Second, when the diffusion process is lengthier, the spillover effects of the project (which are not identified in the short term) can be found in the long term. Therefore, whether the long-term effect of the project is greater than the short-term effect remains unclear.

We considered a case of rice cultivation training in Uganda as the productivity of rice (which is one of the important cash crops since the mid-2000s) is far below its potential. Several agronomic practices—such as straight-row transplanting, which have proved to boost rice yield in tropical Asia, as well as in other SSA countries—have not been adopted widely (David and Otsuka 1994; Otsuka and Larson 2013, 2016). There is room for agricultural training to improve the performance of rice production. In October 2009, the Japan

International Cooperation Agency (JICA) provided lowland rice farming training in Eastern Uganda. We conducted household surveys three times: as a baseline just before the training (September/October 2009); two years after the training (November 2011); and six years after the training (November 2015). We randomly sampled households from half of the villages with training sites (project villages) and from villages without training sites (non-project villages).

We adopted a difference-in-differences (DID) model that included household fixed effects combined with inverse probability weighting approach due to the non-random assignment of project villages and training participation. We compared training participants and households in non-training villages to determine the direct impact of the training and compared non-participants in the training villages and households in non-training villages to assess spillover effects (Benin et al. 2011; Benin et al. 2012; Calderon et al. 2020). We found that the training increased the adoption rates of improved cultivation practices among participants, in the short and long term (two and six years after the training, respectively). Furthermore, the short-term impact of training on rice production is 0.59 tons (a 50% increase from the baseline). Although non-participants in the training villages increased the total rice production due to area expansion in the short term, there was no evidence that non-participants' knowledge of rice cultivation and productivity improved. Even in the long term, there was no evidence that non-participants increased the adoption rates of improved cultivation practices.

The rest of the article is structured as follows. Sections 2 and 3 describe the JICA project, the data, and the rice cultivation practices adopted by training participants and non-participants. The empirical framework is explained in section 4, and results are shown in section 5. The last section concludes the article.

2. Background

In Uganda, banana, maize, sweet potato, and cassava are widely cultivated and consumed in rural areas. Rice production was once negligible and rice was rarely consumed by rural households until the early 2000s, when the vice president initiated a campaign to promote the cultivation of upland rice, called New Rice for Africa (NERICA) developed by the Africa Rice Center (then the West African Rice Development Association). NERICA was disseminated to Ugandan farmers who had never cultivated rice before; many farmers could earn higher incomes from rice production (Kijima et al. 2008). Given the success of the campaign, the Ugandan Government recognized rice production as key to food security and poverty reduction (MAAIF 2008). In 2008, Uganda joined the Coalition for African Rice Development, whose objective was to double rice production within 10 years. However, at the time, there was no agronomist or other researcher specializing in rice cultivation at the National Crops Resources Research Institute (NaCRRI), and no extension workers were trained in rice cultivation in Uganda (Kikuchi et al. 2013).

The Japan International Cooperation Agency Project

JICA initiated the Sustainable Irrigated Agricultural Development (SIAD) project in 2008 and gradually expanded it in later years to strengthen extension services for rice production. This was achieved by training extension workers to acquire sufficient knowledge on rice cultivation to train farmers. This was expected to increase rice production through increasing the adoption rate of better cultivation practices. JICA experts identified the low adoption of sustainable rice cultivation practices as a major problem in Ugandan rice production prior to the inception of the project. These practices were widely adopted in Asia and was important in increasing rice production. Although chemical fertilizers and high-yield rice varieties (HYV) are critical for enhancing productivity, the effectiveness is perceived as limited without application of these cultivation practices. Additionally, since it was uncommon for farmers to apply chemical fertilizers to any crops in Eastern Uganda, and HYV rice was not officially released in Uganda when the project began,[1] promoting the adoption of chemical fertilizers and HYV rice was unrealistic. Therefore, the JICA project focused only on training and provided neither credit nor grants (including chemical fertilizers, other chemicals, and construction materials).

The project covered almost all districts of Eastern Uganda; field training was provided in 59 project sites (lowland area) selected by JICA experts. Training was provided by both JICA experts and extension workers. The selection of these sites was purposive since lowland rice cannot be grown in upland areas. Indeed, all project sites were wetlands with seasonal or year-round springs or streams. The sites selected by JICA were more or less similar in terms of the environment for rice cultivation.[2]

Once JICA experts found a suitable location for lowland rice cultivation with a reliable water source, they communicated with rice growers in the location to determine their interest in the training program. If they were interested, the farmers were requested to form a group to make it easier for project coordinators to pass information and implement training. There was one demonstration plot per village. Training participants were not selected by JICA experts.

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[1] Lowland rice seeds tend to be recycled (reused) and traded locally among farmers. There are two popular lowland varieties: one is the modern rice variety crossed with local varieties, a popular variety called “K5,” “K85,” or “Kaiso,” developed initially for the Kibimba irrigation 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 the origin of K5 is one of the early Asian modern varieties, the origin of Supar is less clear. It takes more time for Supar to be harvested than the K-series (six months and four months). Supar has an aroma valued more in Uganda and its price is higher than that of the K-series. Since many farmers do not know the variety, this study does not examine the adoption of HYV.

[2] The size of the wetland is around 20–30 hectares, and the number of rice growers using wetland is 90 to 150, residing in 7–11 villages. The percentage of households growing lowland rice is relatively low (30–40%). Most rice growers started cultivating rice in the late 1990s or early 2000s.

Group chairpersons were requested to advise group members and interested community members of the training dates. Therefore, training participants could be more motivated toward rice farming than non-participants.

A three-day intensive training on rice cultivation and small irrigation management practices was conducted with the district agricultural officers (DAO) and extension workers at the NaCRRI before the field training of farmers. Thereafter, the JICA experts and trained extension workers provided field training to farmers at demonstration plots in each project site, with the plots ranging from 0.2 to 0.4 hectares. The field training consisted of four parts: (1) establishing a demonstration plot and constructing irrigation canals in the surrounding area for three days; (2) preparing nursery beds and seedlings, constructing bunds,[3] and leveling the main field for half a day (preparation for transplanting method); (3) transplanting in rows[4] and weeding for half a day; and (4) harvesting and threshing for half a day. On each day, extension workers first explained the cultivation practices using flip charts and thereafter requested all participants to implement these practices on the demonstration plot to ensure that they could implement it on their own fields. Once all participants understood the purpose and methods of cultivation practices, the training participants were asked to implement what they learnt on the demonstration plot, together with the extension workers. Thereafter, a brief wrap-up session was conducted for extension workers to provide feedback and answer questions from

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[3] Constructing bunds allows the field to hold water and is an important practice in areas where the water supply is not reliable.

[4] In sample areas, all rice cultivation practices are done manually. No machinery for planting and harvesting is available. There are three methods of planting rice in sample areas: broadcasting, transplanting in rows, and not transplanting in rows. Transplanting requires growing seedlings in nursery beds for 2–3 weeks, and thereafter planting them onto the main rice field. Transplanting can be done by planting in line or not in line. In sample areas, transplanting is commonly implemented, but not in line. In the broadcasting method, seeds are spread into the field directly. In terms of the labor requirement of planting, broadcasting is the most labor-saving method, while transplanting in rows takes more time. However, transplanting in rows is best for plant growth (and higher production) due to easiness of weeding and proper spacing between plants.

the participants. The contents of field training were simple and concise in order for training participants to easily remember what they learned.

The project implementers were responsible for setting up the demonstration plots and building the water canals that connected the demonstration plots with a source of water identified by JICA experts. The farmers were required to construct their water canals with guidance and help from JICA experts; they dug ditches using hand hoes to ensure that rice plots were irrigated before transplanting seedlings. This small irrigation scheme did not require establishing systematic water distribution facilities. Normally, water canals were not maintained communally. The farmers only cleaned the canals adjacent to their own plots, and there were no devices for metering the intake of water on individual fields.

JICA experts and extension workers verbally encouraged training participants to share their training knowledge with neighbors and friends interested in rice cultivation, although they were not trained on information sharing and effectively training others. As the contents of each training session were simple and covered three to four aspects simultaneously, training participants could comprehend and remember the contents, enabling them to share the contents with non-participants. Based on the first follow-up survey, 27% of non-participants in training villages discussed the training with participants, and 36% of them visited demonstration plots between the baseline and first follow-up survey. This farmer-to-farmer knowledge diffusion was considered a cost-effective model as public extension systems tend to lack financial sustainability (BenYishay and Mobarak 2018).

Although this training project covered the entire agricultural season, it was less intensive and less complicated than the Farmer Field School (FFS) model. FFS was developed as an alternative to the top-down extension method, to enable farmers to solve complex problems. It is time consuming (weekly meetings conducted during the entire cropping season) and expensive (Anderson and Feder 2007). The JICA training included rice cultivation practices, with three to four training sessions in each agricultural season; a few rice cultivation practices were taught during each session, and farmers implemented knowledge acquired from extension workers on demonstration plots. The similarity with FFS is that trained farmers are expected to develop into farmer-trainers who disseminate the acquired knowledge to other farmers.

3. Data

The baseline survey was conducted in October 2009 in villages with and without JICA projects to collect information from October 2008 to September 2009. JICA experts were requested to select training sites for the second season of 2009, but the field training was not implemented at the time of data collection. Out of eight sites selected by the expert, we randomly selected four sites in two districts for evaluation. In each training site, 35–40 households were selected based on the distance from the demonstration plot to the rice plot of each household in the baseline survey to capture the diffusion process beginning from the demonstration plot (150 households in total).[5] We sampled 35–40 households in each project village. The total number of sample households in treatment villages was 150. Participants were not randomly selected due to JICA's request. Training sessions were open to anyone who was interested. Therefore, from the sample of 150 households, those that participated in

[5] The sample lowland areas are oval-shaped. Across the short diameter, there are 6–10 plots. One plot was selected randomly at approximately every 25-meter interval from the demonstration plot in two directions along the long diameter. We selected sample rice growers based on their rice plots by walking on the ditch in the northern direction from demonstration plot. We selected one plot from our right-hand side, then walked 25 m and picked one plot from our left-hand side. We continued this until 20 plots were chosen. We repeated this process from the demonstration plot, but in the southern direction, to select 20 more plots. There are six households listed as rice growers, but we found that they did not grow rice in the survey.

the training was not known ahead of time. According to the first follow-up survey, 64 households participated in training and 86 households did not. The proportion of participants was different across villages, ranging from 30% to 53%. All sampled households grew rice at the time of data collection. The sample size in JICA villages for the baseline survey was 139 as there were 11 households with incomplete information. Additionally, 24 households located in one village from each of the project districts were excluded from the sample, as none of them harvested rice due to serious drought in 2009. The effective sample size for project villages in 2009 was thus 115.

We selected five lowland rice cultivating districts to cover different rice cultivation experiences and agro-ecological conditions for non-project villages. However, we excluded districts with project sites at the time of the data collection, where field training had been offered before the baseline survey. In each district, two sub-counties with active rice production and access to wetlands were deliberately selected as JICA experts did not select project sites for the 2010 cropping seasons. Sixty villages were randomly drawn as sample communities from these sub-counties. In each village, 10 households were randomly sampled; there were 600 sampled households in non-project villages. In non-JICA project villages, all sample households did not grow lowland rice. In the baseline survey, 396 households cultivated rice.[6] Most households in 12 of the 60 non-project villages had access to modern irrigation facilities. We excluded these villages from our analysis as they were not comparable to project villages. The effective sample size for non-project villages in 2009 was 280. Thus,

[6] Households in sample areas grow many types of crops, such as maize, beans, cassava, and ground nuts. In the baseline survey, the rice planted area was around 35–40% of the cultivated area. The rice price received by farmers is 1.5–2 times higher than that of maize. Therefore, it is locally considered a cash crop rather than a food crop. Although there is no evidence, the consumption of rice has been increasing even in rural areas owing to increased rice production.

the total number of sample households was 395.[7]

Based on the population shares of districts in 2009 which were estimated by using the population census of 2002 and 2014, the overall baseline sample used in this study was more or less representative at the district level, except in two districts. Although we used sampling weights to adjust the over- and under-sampling of these two districts, the main results remained the same qualitatively.

The first follow-up survey was conducted in 2011, including rice production in 2010–2011. The second follow-up survey was conducted in 2015, including rice production in 2014–2015 (Figure 1). Attrition in JICA project villages was minor in both the first and second follow-up surveys: three households (3%) were not interviewed, as they migrated to different districts. The attrition rate, for non-project villages, in the follow up survey was 12% (16 households were not interviewed in the follow-up survey). Three and 32 households grew rice in 2011 or 2015 from the JICA and non-JICA village sample, respectively. Our analyses on rice-growing panel households therefore included 109 and 232 households in project and non-project villages, respectively.[8]

Insert Table 1 here

Table 1 shows pre-treatment household characteristics separately for training participants, non-participants in the project villages, and households in non-project villages. The means of all the variables are not statistically different between participants and non-participants in project villages, except for one variable (see column c). The only difference is that participants' rice plots are closer to the demonstration plot than non-participants. There

[7] Based on rice yield of pilot data, we calculated the minimum number of samples to detect the effect was 363 (121 for program villages and 242 for control villages).

[8] As shown in Appendix Table 1, the baseline characteristics are not statistically different between panel rice-growing households and households that did not grow rice in the follow-up surveys, considered separately by treatment status.

are few baseline characteristics that are different between households in project and non-project villages (see columns a and b). Households in non-project villages are less likely to be members of local groups than those in the project villages[9]. Although the training project was not randomly assigned, this table suggests households in project villages are neither more educated or experienced in rice cultivation nor more endowed with land and family labor than those in non-project villages.[10]

Insert Table 2 here

Table 2 shows adopted rice cultivation practices and rice production information (yield, total production, revenue per adult equivalent, and income per hectare) separately for the treatment status and survey years.[11] Since not all panel households did not grow rice every year, the number of observations for each survey round is different (see last column). We did not exclude households who grew rice in every survey round to minimize the sample selection bias. Moreover, the sample includes households who grew rice in baseline and one of the

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[9] To identify the membership of local group, we excluded the group that was formed only to receive the training in the project villages.

[10] We checked whether our sample households are comparable to those in nationally representative survey in Uganda by using the Uganda National Panel Survey (UNPS) 2009 and 2013. Since our target population is lowland rice growers, we compared the characteristics of rice growers in the UNPS. Although there is no information on rice experience and local group membership in the UNPS, we found no statistically significant difference in all other characteristics than the share of lowland owned in our sample and UNPS (see Appendix, Table 2).

[11] Cultivation practices and rice production measures were calculated at the household level, as the main objective of this study is to measure the long-term impact of training. Constructing plot-level panel data over the long term is not possible and led to selection bias, due to the rental of approximately 40% of rice plots, and land rental arrangements are seasonal or on an annual basis. More than 80% of sample households planted rice on one plot per season and two-thirds of households grew rice once a year. Regarding the adoption of cultivation practices, we calculated the share of plot size where a cultivation practice is applied over the total rice area in that year. Moreover, when we conducted the same analyses at plot level, rather than household level, the results did not change. The household-level total rice yield is calculated by dividing total rice production in a year by the total area size under rice production in that year. Income and revenue are at 2009 price levels, adjusted by food price index (Uganda Bureau of Statistics). There are separate indexes for several cities in Uganda, and those in Jinja and Mbale are used in this study due to the proximity to the sample households.

follow-up surveys.[12] We considered transplanting, transplanting in rows, and constructing bunds as they are the main practices taught in the training and easily observed when implemented. Although the use of chemical fertilizers was not taught during training, we examined their adoption since training might induce participants to change their decision on modern input use when adopting other cultivation practices that can increase marginal productivity. Productivity measures for rice production—rice yield (rice harvest per hectare) and income per hectare—were examined. Since the project aimed to increase total rice production and income of rice-growing households in Uganda, total harvests, rice revenue, and income per adult equivalent[13] were also examined.

There were no differences between training participants and non-participants in the adoption rates of cultivation practices before training. After training, the proportion of training participants who planted rice by transplanting and transplanting in rows increased. Notably, the planting method changed from broadcasting to transplanting among participants and non-participants in project villages. However, the proportion of households in non-project villages and the second follow-up survey that used transplanting did not change significantly.

Among those who transplanted, most households did not transplant in rows in the baseline survey, but 21% of the training participants and 10% of non-participants in the JICA training villages adopted transplanting in rows in the first follow-up survey. Subsequently, the adoption rate did not increase among both participants and non-participants. Transplanting in rows takes significantly more time for farmers in sample villages, than transplanting randomly, which may explain the slow diffusion of the former method.

The proportion of households constructing or maintaining bunds increased among

[12] Detailed explanation on the number of observations is provided in Appendix, Table 3.
[13] Adult equivalent is calculated with the weight of 1 for an adult aged 15–64 and 0.5 for the other age group.

the training participants in the first follow-up survey (from 51 to 90%), but did not increase further. This rapid enhancement of the bunds construction rate by training participants seemingly arose due to the training, since it did not increase significantly among non-participants in project villages and in non-project villages.

The rice yield before training was lower in training villages (1.2 tons for participants and 1.4 for non-participants) than that in non-project villages (1.6 tons). Two years after training, the yield increased significantly to 1.9 tons for participants. The difference between participants and households in non-project villages dissipated, while the yield did not increase significantly among non-participants. However, from 2011 to 2015, non-participants caught up with participants in terms of rice yield, resulting in yields of 2 tons in 2015. This change in yield differed with that in non-project villages, where the change in average yield was moderate over time. Overall, there were similar trends in total rice production, revenue per adult equivalent, and rice income per hectare.

The comparison of means suggests that the training project increased the adoption rate of improved cultivation practices and rice yield among participants and non-participants in the project villages. The difference was in the timing of such changes: the adoption rates among participants improved soon after the training, while those among non-participants did not increase in the short term. During the same period, there were no significant changes in productivity and cultivation practices in non-training villages. This suggests a spillover effect from training participants to non-participants within training villages. Therefore, we estimate both the direct impact of training on participants and spillover effect to non-participants, as explained in the next section.

4. Empirical Framework

Impact on Training Participants

This article estimates the impact of the rice cultivation training project on the adoption of improved cultivation practices and productivity (average treatment effect on the treated, ATT) in the short and long term by a DID inverse probability weighting approach using panel data (Imbens and Wooldridge 2009). The method is preferred over the cross-sectional matching estimators when there is a geographic mismatch between the treatment group sample and the comparison group sample (Heckman et al. 1998). Since we selected the comparison group from households in non-project villages, the inverse probability weighting approach was preferred.

Since training participation was not randomly assigned, training participants would be different from non-participants in the project's absence. If treatment status correlates with the error term, the estimated impact of the training is thus biased. To mitigate this problem, inverse probability weighting approach was applied to ensure higher weights are assigned to the households in non-project villages with similar observable characteristics as the treatment households in the pre-treatment period. As explained in the previous section, it is possible that knowledge spillover from training participants to non-participants exists in training villages. Hence, using non-participants residing in project villages as counterfactuals of the treatment group violates the stable unit treatment assumption, which can underestimate ATT (Benin et al. 2012). Therefore, we selected comparable households only from non-project villages as a potential comparison group, which is the control group when estimating the direct effect of the training.[14] Under a set of assumptions (conditional mean independence and common support), applying propensity score weights resulted in unbiased impact estimates for the ATT

[14] We cannot rule out that extension agents were more likely to visit households in the project areas. However, according to the follow-up surveys, none of the sample households in the project villages had received agricultural training related to rice after the JICA training.

(Hirano et al. 2003).

Propensity scores (P) are estimated by a probit model using pre-training observable characteristics as explanatory variables. The chairmen of local groups provided training information; membership in local groups or social capital is expected to increase the probability of participating (Davis et al. 2012). Human capital, measured by the household head's education and rice cultivation experience, can be positively or negatively associated with participation in training since educated and experienced farmers may think that they already know the information provided during training (Godtland et al. 2004). Endowment of family labor and physical capital (land and livestock) are other observable relevant household characteristics that can be associated with participation in training (Nakano et al. 2018). The estimated propensity scores are used as weights and an unbiased estimate of ATT is obtained through a weighted regression framework.[15] The results of the probit model with robust standard errors are shown in column 1 of Appendix, Table 4. Compared with households in control villages, households whose head is older, more educated, and is a member of local groups are more likely to participate in the JICA rice training. In terms of non-participants, shown in column 2, households with bulls, older head, and higher share of female adults tend not to participate in training programs. To estimate propensity scores, we used the commonly used kernel matching (the Epanechnikov kernel; Caliendo and Kopeinig 2008).[16] Average baseline characteristics between treatment and comparison groups were well balanced after applying propensity score weights (see Appendix, Table 5; Appendix, Figure 1).

Moreover, after constructing a comparable control group based on observed

[15] For treatment group, one over propensity score (1/P) is the weight while for the control group, 1/(1-P) is the weight.
[16] In kernel matching, Epanechnikov is the most commonly used second-order kernel. There were 6 observations without common support, which were not used in the analyses.

characteristics, it is possible that unobserved household characteristics affect training participation and outcome variables simultaneously. Since we possess household-level panel data before and after training, household fixed effects were controlled to mitigate bias because of time-invariant unobservables, such as risk and time preference, managerial ability, and soil quality of rice field (Smith and Todd 2005).

Thus, we estimated ATT by the following model:

$$y_{it} = \sum_t \gamma^t Participant_i \times Post_t + \beta Participant_i + \sum_t \delta^t Post_t + \rho X_{it} + \alpha_i + e_{it}, \qquad (1)$$

where y is the outcome variable, such as the adoption of cultivation practices and rice production; *Participant* takes the value of 1 if household *i* participated in the training, and 0 otherwise; *Post* takes the value of 1 when *t* is either 2011 or 2015 (after the training), and 0 for baseline data; $\boldsymbol{X}$ is a set of household time-variant observables; α represents unobserved household fixed effects; and e is an error term. The coefficients of the interaction terms (γ) for the first and second follow-up surveys are the ATTs for the short and long terms, respectively.

Although using panel data has advantages, it can cause bias through sample attrition, since our outcome variables were observed only when households grew rice. As indicated above, not all households that cultivated rice in the pre-project period grew rice in post-project periods. If the decision to grow rice is not randomly made (i.e., better performing farmers are more likely to cultivate rice in the post-project period than the rest), then ATT can be biased. Consequently, we adopted the correction procedure suggested by Fitzgerald, Gottschalk, and Moffitt (1998), and used attrition weights in all analyses. We first estimated a probit model to explain whether a household was found and grew rice in the follow-up surveys,[17] and obtained

[17] For estimating attrition weights, we ran the probit model, with an indicator variable taking the value of 1 if the household was not interviewed and/or did not grow rice in the follow-up survey and 0 otherwise as a dependent variable. We included rice growing experience as explanatory variables. This is because, in this

a predicted probability of a household remaining in the panel data. The attrition weights were calculated as the inverse of the predicted probabilities, to provide higher weights to households with lower probabilities of growing rice in the post-project periods, as they grew rice. Since propensity score weights were also used, the attrition weights were multiplied with the propensity score weights (Fitzgerald et al. 1998).

Since the DID model is valid only when the common trend assumption holds, it is important to verify whether it holds or not. We have retrospective data on rice yield from 2007–2008, collected in the baseline survey. Using this variable, we can test whether the pre-training trend of rice productivity (yield) from 2007–2008 to 2008–2009 for training participants is same as that for the control group. Appendix, Table 7 shows no difference in the pre-training trend between training participants and control households, assuring that the estimated impacts are not due to the other over-time changes confounded by the treatment status. Since we have only two time periods before the intervention, this only provides a limited picture of the pre-intervention trends.

Spillover Effects (indirect effect on non-participants in the project villages)

Although JICA designed the project to enhance knowledge spillover from training participants to non-participants, whether the spillover effect exists, and its size are not examined in detail. Similar to Benin et al. (2012) and others, non-participants in the project villages are those households that were indirectly treated and the control group is households in non-project

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study, households that did not grow rice in the follow-up survey did not remain in the sample in our main analyses. We expect households that are more experienced in rice cultivation to grow rice in follow-up surveys as well. The estimation results are shown in Appendix Table 6, where a dependent variable takes the value of 1 if the household was not interviewed in both follow-up surveys in column 1. In the follow-up years, households with an older household head and those who are in project villages and less experienced in rice cultivation are less likely to be interviewed. The pseudo R-squared in column 1 shows relatively high explanatory power for the attrition probit model (Baulch and Quisumbing 2010).

villages.[18] The spillover effects from training participants to non-participants are estimated by the following model:

$$y_{it} = \sum_t \gamma^t NonParticipant_i \times Post_t + \beta NonParticipant_i + \sum_t \delta^t Post_t + \rho X_{it} + \alpha_i + e_{it}, \quad (2)$$

where y is the outcome variable, such as the adoption of cultivation practices and rice production; *NonParticipant* is assigned a value of 1 if household *i* lives in project villages but did not participate in the training, and 0 otherwise. The other variables are the same as before. We examined a possible spillover effect from training participants to non-participants within project villages by testing whether or not γ is positive and statistically significant from 0. Propensity score weights were estimated, and comparable control households were selected from non-project villages, given baseline characteristics.[19]

5. Results

Impact of the Training Project on Adoption of Cultivation Practices

The estimated effects of the training on cultivation practices are shown in Table 3 and Table 4. Table 3 shows the average effect of the training on participants, while Table 4 indicates the spillover effect of the training (indirect effect on non-participants in project villages). The first three columns show the results for the adoption of cultivation practices. In the short term, the adoption rate of transplanting in rows increased among the training participants and the impact is sustainable even in the six years after training. We do not find evidence for a spillover

[18] Feder, Murugai, and Quizon (2004) separately estimated the direct and indirect effects of FFS in Indonesia as there is diffusion from FFS graduates to others who live in villages with FFS graduates. Benin et al. (2012) defined three control groups (non-participants who claimed to have benefited indirectly in program sub-counties, non-participants who did not claim to have benefited in program sub-counties, and non-participants in non-program sub-counties) and separately estimated the impact of the NAADS program on agricultural revenue.
[19] The result of the probit model estimating the propensity score is presented in column 2 of Appendix, Table 4.

effect on technology adoption in the short run. However, for non-trainees in training villages, the adoption rate of transplanting method increased in the long term. This result may suggest that it takes time for spillover effects to be realized. It is important to note that a type of technology adopted by non-participants is different from that by participants. In a section of analyzing heterogenous treatment effects, we examine why there is a difference. Finally, as shown in column four, we do not find evidence that there are impacts on the adoption rate of chemical fertilizers for participants and non-participants in the short and long terms. This is not surprising since the training neither taught about chemical fertilizer use nor provided chemical fertilizer to the participants.

Insert Table 3 and 4 around here

Impact of the Training Project on Rice Production

The rest of the columns in Table 3 and Table 4 present the estimation results on rice productivity (yield per hectare), rice income per hectare, total rice production per household, and rice revenue per adult equivalent. In the short term, the program had no detectable effects on rice productivity for training participants. However, in the long term, we found the positive impact on rice yield only among training participants. In the short term, as will be explained next, participants increased the rice area cultivated, which may cancel out the effect of intensification on rice yield enhancement. In terms of the spillover effect, there are no evidence that the training increased the rice productivity among non-participants in the training villages. This result is not surprising and implies that adopting transplanting method only does not result in higher yield.

In contrast, total rice production increased by 0.59 ton for both training participants and by 0.43 ton for non-participants in the project villages in the short term. This short-term effect on total rice production is economically significant since it accounts for a 50% gain from the baseline there was no significant improvement in rice yield in the short term, the short-term impact on total rice production is mainly due to the expansion of rice cultivation area. According to the data, the costs of hiring labor also increased especially among training participants such that the overall rice income did not rise. In the long term, no evidence was found to show that both participants and non-participants increased rice cultivation areas and total rice production.

Since rice is locally considered a more labor-intensive crop than crops such as maize, a higher rice production for training participants could be due to the increased household size. If so, the welfare of each household member may not have improved significantly, although total rice production increased. To take this into consideration, we also test whether revenue per adult equivalent decreased by increasing the number of household members by, for example, the introduction of a second spouse to the household or accepting an adult relative joining the household. The estimation results show no evidence that the training decreased rice revenue per adult equivalent.

Mechanisms

In this subsection, we examine the possible mechanisms under which training increases the adoption of transplanting among non-participants in the training villages but there is no evidence of spillover effects on increased rice productivity. One possibility is that non-participants adopted transplanting by mimicking training participants' rice plots. If so, timing of the transplanting, which depends on the age of seedlings, and space between seedlings may not be right, which can have no impacts on rice yields. We test this possibility by examining whether there is a knowledge spillover from training participants to non-participants. We use the test scores from four questions regarding seed preparation before planting, best timing of transplanting (seedling age), planting space, and density of seedlings. The scores range from values from 0 to 4, with equal weights for each question. Since all questions are about the transplanting method, a low score indicates that transplanting may have been done poorly. Since we did not collect test scores in 2015, we can estimate only the short-term impact. We adopt the same model as in equations 1 and 2 with test scores as a dependent variable. The results are shown in Table 5. We found that the test scores of training participants increased. In contrast, we do not find evidence that there is knowledge spillover to non-participants in the training villages. This may suggest that the knowledge about transplanting acquired by the training participants was not shared with non-participants in the project villages, at least not in a proper way to increase the test score among non-participants.

Insert Table 5 around here

Next, we examine who are more likely to adopt transplanting methods among non-participants by testing if there are heterogenous spillover effects based on geographical proximity to and contact with training participants. Specifically, we test three possibilities: (1) experience of visiting the demo plot, which provides some idea of what kind of practices were adopted but the accurate information may not be obtained; (2) proximity to the demo plot from one's rice plot, which increases the probability that non-participants in the program villages are exposed to methods adopted in the demo plot but does not guarantee that one visits the demo plot; (3) communication with training participants, which provides the opportunity to learn about the cultivation practices.[20] Since these variables are obtained only from the first follow-up survey, it is not time-variant.

[20] It is relevant to examine if spillover effects are greater between similar types of people such as women to women, men to men, and same education level. However, there are more than one who were trained in each village in this study's setting. It is not possible to examine if information obtained from the training is spilled over more when the social distance (sex, age, education) between trained and non-trained is closer or not.

The heterogeneous spillover effect is estimated similarly to the main analyses, but these heterogeneous characteristics (*Z*) are made to interact with *NonParticipant* x *Post* whose coefficients are expected to capture the difference in contacts with training participants and proximity to the demo plot. Estimation model is as follows:

$y_{it} = \sum_t \gamma^t NonParticipant_i \times Post_t + \beta NonParticipant_i + \sum_t \delta^t Post_t + \sum_t \tau^t NonParticipant_i \times Post_t \times Z_i + \rho X_{it} + \alpha_i + e_{it}$, (3)

where Z is either an indicator variable with the value of 1 if non-participant i visited a demonstration plot and zero otherwise, an indicator variable with the value of 1 if the rice plot of the household i is closer to the demonstration plot and zero otherwise,[21] or an indicator variable with the value of 1 if a non-participant i talked about rice cultivation with training participants and zero otherwise. The estimated coefficient τ measures the heterogeneous spillover effect. Since these three variables can be correlated with each other, one variable is used as Z at a time. Although these variables Z are likely to be endogenous, we do not have proper instrumental variables for them. Thus, we need to keep in mind that the estimated coefficient can be upward biased. The reason we added endogenous variables, "visit demo plot" and "talk with participants" is to understand if just observing the demo plot and obtaining information from participants makes a difference in adopting transplanting method. As an outcome variable, we estimated only the effect on adoption of the transplanting method as we found spillover effects only in transplanting method as shown in Table 4.[22]

The estimation results are provided in Table 6. Similar to the main results shown in Table 4, there is no spillover effect in the short term on average, while the non-participants

[21] The distances between rice plots are measured using their GPS coordinates in the baseline survey. We divide non-participants into two categories using the median distance as a cutoff point.

[22] Although we did this exercise for other outcome variables, we do not find evidence that there are heterogenous spillover effects (please see Appendix, Table 8).

who visited demonstration plots are more likely to adopt the transplanting method. In the long term, as shown in columns 2 and 3, non-participants increased their adoption rate as per the main results, while we do not identify any heterogeneous impacts by proximity to the demo plot and communication with training participants. Since the demonstration plot is prepared mainly for field training, it may not be used after training. Therefore, the information spillover from the demonstration plot can decay over time, as Table 6 shows.

Insert Table 6 around here

Robustness Checks

In this section, we present the results of two robustness checks: different approaches to propensity score weights and attrition weights; and sampling weight for making the overall baseline sample representative at the district level.

Regarding the propensity score inverse probability weighting approach, we provide the results estimated by using the propensity score pre-screening DID (Crump et al. 2009), where observations with estimated propensity scores outside [0.1, 0.9] are dropped. This method is recommended since the inverse probability weighting approach does not work when there are a few observations with exceptionally large propensity scores. This systematic approach ensures that the regression is estimated only for the sample in which the covariate distribution overlaps for the treated and non-treated samples, as shown by Angrist and Pischke (2009). We ran the same model as equations 1 and 2 but used a smaller number of observations by excluding ones with propensity scores less than 0.1 and greater than 0.9. We found that the results in Appendix, Table 9 are similar to the main results showing that the training participants enhanced rice cultivation area without improving rice yield. The differences from the main results are that the short-term direct effect on total rice production and the long-term direct effect on rice yield turn is insignificant.

Thereafter, we adopt a different adjustment method for panel attrition as the attrition across rounds significantly differ across project and non-project villages (Appendix, Table 6). We also obtained the lower bounds to show the robustness of our main results.[23] Following Karlan and Valdivia (2011), we examined the cases where attritors in treatment villages were slightly less successful than non-attritors, while attritors in control villages were slightly more successful than non-attritors for estimating lower bounds of the treatment effects. Specifically, we imputed outcome variables by deducting 0.1 and 0.25 standard deviations (SD) of the observed treatment distribution from the mean to the attrited households in the treatment group and by adding 0.1 and 0.25 SD of the observed control distribution to the mean to the attrited households in the control group. For this analysis, additional household controls (X) cannot be included in explanatory variables as these are also missing for follow-up surveys. The results are presented in Appendix Table 10 for ATT and Appendix Table 11 for spillover effects. In both tables, Panel A shows lower bound with 0.1 SD, while Panel B shows lower bound with 0.25 SD. We found that the short-term direct effect and spillover effect on rice cultivation area and the long-term direct effect on adoption of transplanting in rows are robust results while the long-term direct effect on rice yield is found marginally significant (p-value=0.06).

Lastly, we estimate the average treatment effect of having the program at village level. In this analysis, we do not separate the effects of the program on training participants and non-participants. As program placement is non-random in this setting, we need an instrumental variable for addressing program placement bias. There is, however, no suitable instrumental

[23] Although we also estimated upper bounds, we do not present the results show similar, but larger and significant, impacts of training on both participants and non-participants.

variable for program placement. Thus, we estimated the effect of the program by using a double robust method using cross-sectional data separately for 2011 and 2015 (Appendix Table 12) as well as the same model DID with household fixed effects (Appendix Table 13). We found consistent results on the short-term effect increasing the adoption of transplanting in rows and the long-term effects increasing the adoption of transplanting and rice yield (Appendix Table 12). The results shown in Appendix Table 13 are qualitatively similar to the main results.

Discussion

In this short sub-section, we provide a back-of-the-envelope measure of cost effectiveness of the training project examined in this study and compare it with that of the other extension method, FFS, and the similar training project examined in Kondylis et al. (2017).

Since the JICA project did not provide any input or materials to farmers in the field, the cost of field training comprised the expert labor and car hire costs. In total, there were approximately seven training days (including preparation) and approximately 15–20 participants per site. The estimated cost per farmer is USD 125–163 at 2009 prices. Based on the estimates in Table 3, the training participants increased rice production was approximately 590 kg from 2009 to 2011. The increased 2011 rice production is equivalent to approximately USD 240, in 2009 prices. In sum, in at least two years after the project, the net benefit per farmer was more than USD 77. This is approximately the same as that of the project in Mozambique studied by Kondylis et al. (2017), where farmers were centrally trained on soil conservation practices and no spillover effects were found. [24] Since there were also spillover

[24] To estimate the benefits, we used revenue (value of products), instead of income here to compare with the existing studies. One of the reviewers suggested using income as net benefits. Similar to rice income per hectare shown in Table 3, we did not find evidence that the training enhanced total rice

effects on total rice production of this study site, which is equivalent to approximately USD 175, the net benefit per farmer was therefore USD 133.

Although we prefer to compare the cost-effectiveness with other extension methods, such as FFS, both costs and benefits of the projects are not available in the published documents.[25] One of the studies that shows benefits is Davis et al. (2012) which estimates the impacts of participation in FFS on the value of crops per acre to be USD 58 and USD 26 in Kenya and Tanzania (in 2007). Since we do not have information on the project costs spent, we cannot make an accurate comparison on cost-effectiveness. However, the impact on the value of the crop produced estimated in this study is higher than what was obtained in Davis et al. (2012). A study showing the cost per participant of a method of FFS is Quizon et al. (2001) which estimated the costs including start-up and recurrent costs per participant of FFS in Indonesia and the Philippines at USD 62 and USD 48, respectively, in 1999, which are approximately USD 168 and USD 76 at 2009 price level. This is probably due to the JICA training examined in this study did not require inputs other than labor. When local extension workers are used as trainers, the cost is expected to decline significantly. Thus, in terms of the costs, there is no significant difference between the direct training method studied here and the FFS method at least in the project studied by Quizon et al. (2001).

6. Conclusion

Existing studies showed that agricultural training is an effective method to enhance the

income. When income instead of revenue is used as a measure of farmers' benefits, the returns to the project turn negative. Since there is no increase in rice production by participants in 2015, we cannot interpret the cost-effectiveness in the long run based on the estimation results.

[25] As FFS was introduced for integrated pest control in many countries, the program evaluation was made to test if pesticide use is decreased without sacrificing productivity. Most of the studies conducted in Asian countries show that FFS participants decreased pesticide use and even slightly increased the crop yield. Van den Berg and Jiggins (2007) summarize such comparisons.

adoption rate of improved cultivation practices and productivity in rice producers in SSA in the short term. Although the long-term effects can affect the cost-effectiveness of the project, they have not been examined thoroughly. Furthermore, previous studies found mixed results on social learning from training participants to non-participants. This study examined the short- and long-term impacts of a rice training project on the adoption of improved cultivation practices and rice productivity. We also examined the spillover effects from training participants to non-participants in project villages. To mitigate the bias caused by the non-randomness of project assignment, we estimated ATT using the DID model with household fixed effects, combined with propensity score weighting. Due to the project design, wherein participants were encouraged to share information with fellow farmers, we selected the comparison group from non-project villages. We estimated the effects of the training on non-participants in project villages to assess whether the training project created knowledge and technology spillovers within the community.

Our results showed that training participants adopted the improved cultivation practice, namely straight-row transplanting method, taught by the project, in the short term and long term. We found a positive spillover effect of the project on adoption of transplanting method among non-participants in the long term but not in the short term. In terms of the effects on rice production, we found that the training had a positive impact on total rice production both on participants and non-participants in the project villages in the short term. This accounted for 50% of the total production in the pre-project period. In the long run, however, the effect dissipated. Although the main analyses showed the positive effect of the training on rice yield among training participants overall, this impact was not so robust. In contrast, we did not find evidence to indicate that non-participants increased rice yield in the short and long terms.

To understand the differential direct and indirect effects of the training on rice cultivation, we examined the effect on test scores which measured the knowledge of training participants and non-participants regarding the transplanting method. We found that knowledge improved only among training participants. This finding combined with analyses of heterogenous spillover effects suggests that increased adoption of transplanting method by non-participants was realized through observing demonstration plots, and was not due to knowledge and information transfer from the participants to non-participants in the project village.

Although the impact of the program on the area expansion has been not examined in the related studies, we found that the program had an impact on expansion of rice cultivation area in the short run without increasing rice yield. This could be due to the training which increased the expectation on rice production as a profitable income source. In contrast, overall, we did not find such evidence. A possible reason why training participants did not continue expanding their rice cultivation area is that rice income both per hectare and per adult equivalent did not increase.

One of the objectives of the SIAD project was to increase total rice production for households. The results showed that the project achieved its objective, as training participants and non-participants, had higher total rice production. Increased total rice production among non-participants was realized by expanding rice cultivated areas, and not by improving productivity (yield). This finding may suggest that spillover effects on total rice production will diminish over time as the lowland areas suitable for rice production becomes scarcer. Yield enhancement is indispensable to sustainably increase rice production.

Although this article did not examine the impact of information sharing via social networks on technology adoption, the results of the heterogeneous effects on technology adoption showed that short-term spillover effects were found only for non-participants who visited the demonstration plots. In contrast, communicating with training participants did not make any significant difference in the adoption rate of transplanting. Combined with the results on test scores, this result suggests training projects using demonstration plots can be effective in promoting easily observable agricultural technology to non-participants as well. However, the unobservable part of the technology was difficult to disseminate from training participants to non-participants.

This study suggests adding direct training to farmers as an effective way to increase adoption of technologies in the short and long term. There was, however, no evidence to indicate that direct training induces word-of-mouth dissemination from participants to non-participants. This could be because non-participants failed to notice the benefit and returns of the technologies (Hanna et al. 2014). We did not have data regarding the kind of information non-participants obtained from participants, and therefore could not examine this matter further. How to enhance the social learning among training participants and non-participants is an important research area to improve agricultural productivity in general and rice production in particular in SSA.

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Table 1. Household Characteristics in 2009 by Training Participant Status

	Training participants	Non-participants in project villages	Non-project villages	(1)-(3) t-statistics	(2)-(3) t-statistics
	(1)	(2)	(3)	(4)	(5)
Rice experience in years	12.09	11.64	9.841	1.574	1.410
	(8.09)	(9.557)	(8.89)		
HH head's age	40.93	40.31	43.18	1.129	1.610
	(12.99)	(14.46)	(12.04)		
Head's years of education	5.622	5.742	5.970	0.633	0.495
	(3.904)	(3.234)	(3.261)		
No. of HH members	8.933	8.000	8.797	0.208	1.420
	(3.627)	(3.595)	(4.075)		
Share of male aged 15-64	0.231	0.249	0.243	0.556	0.328
	(0.105)	(0.176)	(0.133)		
Share of female aged 15-64	0.229	0.264	0.231	0.133	2.109
	(0.108)	(0.158)	(0.095)		
Size of land owned (ha)	2.013	2.087	1.881	0.447	0.751
	(1.810)	(1.753)	(2.486)		
Share of lowland size owned	0.197	0.235	0.215	0.344	0.453
	(0.318)	(0.283)	(0.322)		
Local group member (dummy)	0.711	0.641	0.513	2.461	1.819
	(0.458)	(0.484)	(0.501)		
Ownership of bulls (dummy)	0.511	0.500	0.353	2.002	2.142
	(0.506)	(0.504)	(0.479)		
Distance to demo plot (km)	0.681	1.291			
	(0.590)	(0.495)			
Number of sites/villages	3	3	48		
No. of panel HHs 2009 &2011/15	45	65	232		
(No. of attrition)	3	2	48		
No. of HHs who grew rice in 2009	48	67	280		
No. of rice growers who were not interviewed in 2011	1	2	16		
Number of rice growers in 2009 who were interviewed in 2011 but did not grow rice in 2011	8	6	86		
Panel rice growers 2009&2011	39	59	178		
No. of rice growers who were not interviewed in 2015	1	2	16		
Number of rice growers in 2009 who were interviewed in 2015 but did not grow rice in 2015	11	8	90		
Panel rice growers 2009&2015	36	53	174		

Notes: The figures are means and those between parentheses are standard deviations.
Columns (4) indicates t-statistics testing if means of pre-training characteristics between training participants (column 1) and households in non-project villages (column 3) are statistically different. Columns (5) indicates t-statistics testing if means of pre-training characteristics between non-participants in the project villages (column 2) and households in non-project villages (column 3) are statistically different.

Table 2. Rice Yield and Cultivation Practices by Year and Training Participation Status

2009	Training participants (1)	Non-participants in project villages (2)	Non-project villages (3)	(1)-(3) t-statistics (4)	(2)-(3) t-statistics (5)
Transplanting	0.667	0.637	0.517	1.646	1.532
Transplanting in rows	0.000	0.016	0.030	1.179	0.634
Bunds construction	0.511	0.609	0.483	0.347	1.798
Chemical fertilizer application	0.000	0.031	0.009	0.623	1.388
Yield (ton/ ha)	1.239	1.354	1.596	2.808	2.240
Rice income per ha	1.143	1.298	1.294	1.041	0.028
Total rice production (ton)	0.522	0.49	1.073	2.519	3.186
Rice revenue per adult equivalent	0.117	0.121	0.169	1.587	1.848
Rice income per a.e.	0.092	0.099	0.146	1.847	1.937
Rice cultivation area (ha)	0.451	0.383	0.684	2.066	3.204
No. of obs.	45	64	232		
2011					
Transplanting	0.795	0.661	0.472	3.761	2.543
Transplanting in rows	0.205	0.102	0.051	3.320	0.009
Bunds construction	0.897	0.678	0.680	2.774	0.953
Chemical fertilizer application	0.154	0.085	0.017	4.010	2.526
Yield (ton/ ha)	1.946	1.575	1.840	0.147	1.676
Rice income per ha	2.116	1.875	2.348	0.714	1.690
Total rice production (ton)	1.322	0.961	1.148	0.797	1.091
Rice revenue per adult equivalent	0.249	0.240	0.240	1.861	0.001
Rice income per a.e.	0.298	0.218	0.232	1.461	0.299
Rice cultivation area (ha)	0.698	0.637	0.619	0.735	0.200
No. of obs.	39	59	180		
2015					
Transplanting	0.917	0.774	0.546	4.311	3.006
Transplanting in rows	0.222	0.075	0.075	2.720	0.018
Bunds construction	0.889	0.623	0.546	3.953	3.006
Chemical fertilizer application	0.222	0.283	0.167	0.794	1.882
Yield (ton/ ha)	2.068	2.029	1.859	2.077	2.280
Rice income per ha	2.466	2.455	2.013	1.317	1.571
Total rice production (ton)	1.140	1.117	1.378	0.545	0.718
Rice revenue per adult equivalent	0.301	0.281	0.354	0.574	1.522
Rice income per a.e.	0.241	0.225	0.254	0.280	0.597
Rice cultivation area (ha)	0.545	0.592	0.700	1.404	1.134
No. of obs.	36	53	172		

Notes: The figures are means and those between parentheses are standard deviations.
Columns (4) indicates t-statistics testing if means of pre-training characteristics between training participants (column 1) and households in non-project villages (column 3) are statistically different. Columns (5) indicates t-statistics testing if means of pre-training characteristics between non-participants in the project villages (column 2) and households in non-project villages (column 3) are statistically different.

Table 3. Average Impact of Training on Participants (DID, Household Fixed Effects Model, with Inverse Probability Weight)

	Trans-planting	Trans-planting in row	Bunds construction	Chemical fertilizer application	Yield (ton/ha)	Rice income per ha	Total rice production (ton)	Rice revenue per a.e	Rice income per a.e	Rice cultivation area (ha)
Participants x 2011	0.136	0.122*	0.377	0.196	0.348	-0.270	0.593*	0.108	0.067	0.301*
	(0.069)	(0.070)	(0.111)	(0.108)	(0.255)	(0.310)	(0.207)	(0.051)	(0.056)	(0.102)
	[0.1371]	[0.0511]	[0.1341]	[0.1221]	[0.1381]	[0.4454]	[0.0561]	[0.1962]	[0.2412]	[0.0501]
Participants x 2015	0.196**	0.206**	0.369	-0.065	0.539*	0.438	0.113	-0.054	-0.008	0.065
	(0.107)	(0.088)	(0.120)	(0.086)	(0.267)	(0.405)	(0.291)	(0.077)	(0.063)	(0.131)
	[0.0110]	[0.0100]	[0.2803]	[0.6366]	[0.0521]	[0.5676]	[0.7748]	[0.6597]	[0.8909]	[0.6316]
Year 2011	-0.007	0.005	0.149**	0.000	0.203	0.857**	-0.164	0.044	0.063**	-0.214**
	(0.026)	(0.033)	(0.047)	(0.022)	(0.119)	(0.203)	(0.147)	(0.032)	(0.031)	(0.076)
Year 2015	-0.036	-0.013	0.048	0.182**	-0.149	0.711*	-0.053	0.111	0.083**	-0.234
	(0.048)	(0.064)	(0.068)	(0.061)	(0.165)	(0.311)	(0.233)	(0.059)	(0.042)	(0.147)
Constant	0.884**	-0.199	0.638**	-0.289	0.532	1.449	-1.844	-0.136	-0.207	-1.039
	(0.147)	(0.246)	(0.216)	(0.247)	(0.739)	(1.440)	(0.965)	(0.249)	(0.226)	(0.610)
Number of observations	704	704	704	704	677	642	694	694	642	704
R-squared	0.057	0.127	0.193	0.164	0.125	0.212	0.082	0.130	0.126	0.197
Number of HHID	277	277	277	277	277	275	277	277	275	277

Notes: Figures between parentheses are standard errors clustered at household level. Figures in brackets are p-value based on the wild cluster bootstrap method with 999 replications at community level. ** and * represent statistical significance at the 1 and 5% levels, respectively. Propensity score weighting and attrition weights are used. Additional controls are age, education, and gender of household head, number of household members, shares of male and female members aged 15-64, size of land owned, and share of lowland owned.

Table 4. Spillover effects (DID, Household Fixed Effects Model, with Inverse Probability Weight)

Panel B: Spillover effects	Transplanting	Transplanting in rows	Bunds construction	Chemical fertilizer application	Yield (ton/ ha)	Rice income per ha	Total rice production (ton)	Rice revenue per a.e.	Rice income per a.e.	Rice cultivation area (ha)
Non-participants x 2011	0.029	-0.008	-0.026	0.070	-0.128	-0.390	0.428*	0.040	0.055	0.257**
	(0.060)	(0.028)	(0.075)	(0.047)	(0.239)	(0.305)	(0.153)	(0.049)	(0.050)	(0.076)
	[0.7177]	[0.7598]	[0.7347]	[0.1451]	[0.7528]	[0.2953]	[0.0360]	[0.4164]	[0.2142]	[0.0000]
Non-participants x 2015	0.148*	0.019	0.066	0.063	0.078	0.437	0.287	0.003	0.075*	0.145
	(0.059)	(0.042)	(0.078)	(0.080)	(0.239)	(0.300)	(0.208)	(0.047)	(0.043)	(0.107)
	[0.0511]	[0.7497]	[0.5536]	[0.3273]	[0.7598]	[0.2903]	[0.1481]	[0.9399]	[0.0480]	[0.3373]
Year 2011	-0.012	0.023	0.187**	0.013	0.443**	0.864**	-0.080	0.076**	0.066***	-0.137**
	(0.028)	(0.023)	(0.048)	(0.020)	(0.143)	(0.172)	(0.117)	(0.026)	(0.023)	(0.048)
Year 2015	-0.040	0.021	0.056	0.193**	0.692**	0.890**	0.056	0.116*	0.069**	-0.143
	(0.040)	(0.039)	(0.061)	(0.052)	(0.260)	(0.318)	(0.189)	(0.045)	(0.033)	(0.091)
Constant	0.681**	-0.042	0.862**	0.008	2.657*	2.971	-0.336	0.202	-0.008	-0.001
	(0.100)	(0.105)	(0.217)	(0.180)	(1.148)	(1.579)	(0.656)	(0.168)	(0.123)	(0.260)
Number of observations	760	760	760	760	726	691	750	742	691	755
R-squared	0.035	0.030	0.091	0.165	0.117	0.195	0.062	0.131	0.133	0.230
Number of HHID	296	296	296	296	296	294	296	296	294	296

Notes: Figures between parentheses are standard errors clustered at household level. Figures in brackets are p-value based on the wild cluster bootstrap method with 999 replications at community level. ** and * represent statistical significance at the 1 and 5% levels, respectively. Propensity score weighting and attrition weights are used. Income and revenue are in million Ugandan shilling at 2009 price level. Additional controls are age, education, and gender of household head, number of household members, shares of male and female members aged 15-64, size of land owned, and share of lowland owned.

Table 5. Test Score in 2009 and 2011 (DID Household Fixed Effects Model)

	Test score (Participants vs. control)	Test score (Non-participants vs. control)
Participants x 2011	0.564**	
	(0.170)	
	[0.0100]	
Non-participants x 2011		-0.285
		(0.176)
		[0.0941]
Year 2011	-0.043	0.058
	(0.102)	(0.098)
Constant	1.361**	1.329**
	(0.042)	(0.041)
Number of obs.	434	592
R-squared	0.068	0.015
Number of HHID	217	296
Mean test scores	Pre-training	Post-training
Participants	1.322	1.820
	(0.782)	(0.839)
Non-participants	1.347	1.244
	(0.822)	(0.775)
Control	1.365	1.322
	(0.839)	(0.846)

Notes: Figures between parentheses are standard errors clustered at household level. Figures in brackets are p-value based on the wild cluster bootstrap method with 999 replications at community level. ** and * represent statistical significance at the 1 and 5% levels, respectively.

Table 6. Heterogeneous Average Impact of Training on Adoption of Transplanting by Non-Participants (Household Fixed Effects Model, Inverse Probability Weights for Attrition)

Dependent variable	1 if adopted transplanting method		
Z	Visit demo plot	Plot near demo plot	Talk with participants
	(1)	(2)	(3)
Non-participants x 2011	-0.072	0.011	0.032
	(0.0710	(0.075)	(0.077)
Non-participants x 2011x Z	0.246**	0.059	-0.007
	(0.111)	(0.101)	(0.071)
	[0.0000]	[0.5986]	[0.9239]
Non-participants x 2015	0.085	0.141*	0.147*
	(0.044)	(0.058)	(0.059)
Non-participants x 2015x Z	0.122	-0.016	-0.039
	(0.094)	(0.085)	(0.076)
	[0.1051]	[0.8759]	[0.7427]
Year 2011	-0.022	-0.022	-0.022
	(0.029)	(0.029)	(0.029)
Year 2015	-0.052	-0.052	-0.052
	(0.031)	(0.031)	(0.031)
Constant	0.552**	0.552**	0.552**
	(0.037)	(0.027)	(0.037)
No. of Observations	760	760	760
R-squared	0.042	0.021	0.020
Number of HHID	296	296	296

Notes: Figures between parentheses are standard errors clustered at household level. Figures in brackets are p-value based on the wild cluster bootstrap method with 999 replications at community level. ** and * represent statistical significance at the 1 and 5% levels, respectively. Among non-participants (64), 25 households visited demonstration plots between 2009 and 2011. Propensity score weighting and attrition weights are used.

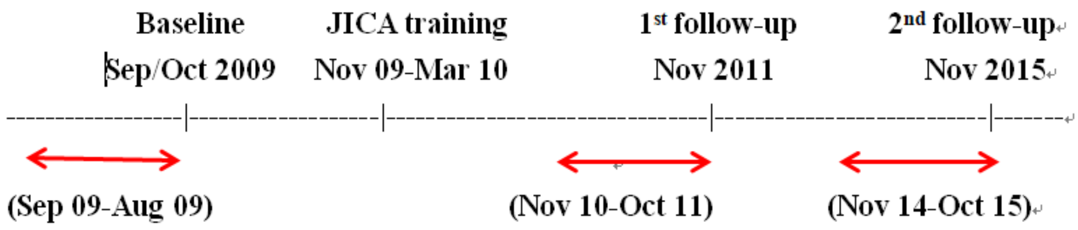
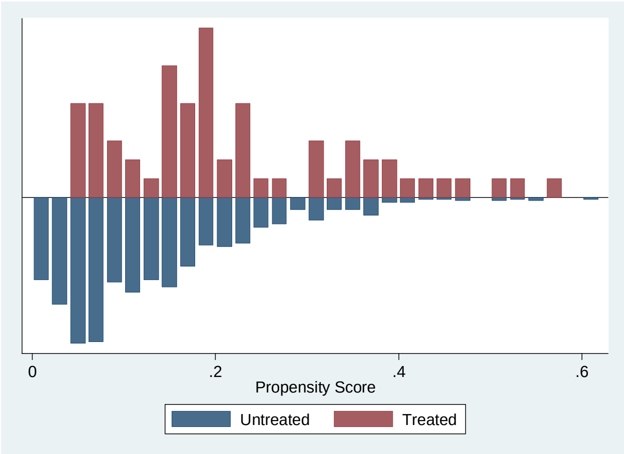


Figure 1. Timeline

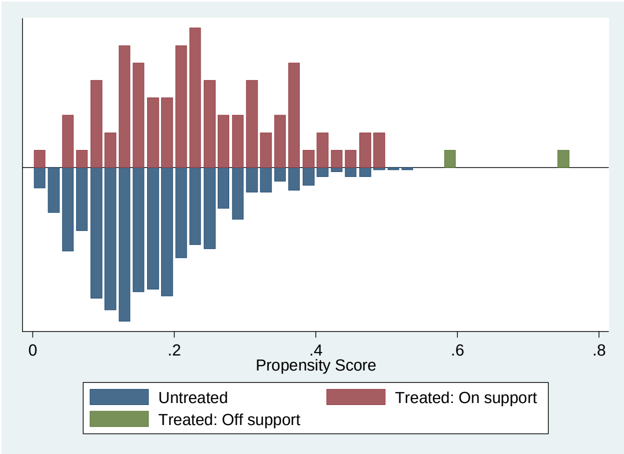
Note: The arrows indicate the production period inquired during the survey.

Appendix Figure. Distribution of propensity scores

A. Participants vs. non-JICA villages



B. Non-participants in JICA village vs. non-JICA villages



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Appendix Table 1. Attrition and Balance of Baseline Characteristics by Treatment Status

	Participants in JICA training in 2009		Non-participants in training	
	Coefficient of Attrition dummy	F-statistics	Coefficient of Attrition dummy	F-statistics
Rice experience in years	-2.195	0.996	-2.195	0.807
	(1.416)		(1.446)	
HH head's age	2.282	0.741	2.282	0.990
	(2.009)		(2.048)	
Head's years of education	-0.366	0.732	-0.366	0.666
	(0.530)		(0.511)	
No. of HH members	-1.381	0.753	-1.381	0.684
	(0.817)		(0.815)	
Share of male aged 15–64	-0.045	0.318	-0.045	0.486
	(0.030)		(0.022)	
Share of female aged 15–64	0.016	0.962	0.016	0.679
	(0.016)		(0.018)	
Size of land owned (ha)	0.013	0.975	0.013	0.611
	(0.361)		(0.356)	
Share of lowland size owned	-0.011	0.993	-0.011	0.393
	(0.051)		(0.050)	
Local group member	-0.055	0.234	-0.055	0.936
	(0.078)		(0.079)	
Ownership of bulls	-0.041	0.466	-0.041	0.829
	(0.076)		(0.077)	

Notes: To demonstrate the composition of the sample has not changed over time, we estimate the following regression: $Y = a_0 + b_1 T + b_2 \text{ Attrit} + b_3 (T \times \text{Attrit}) + e$, where Y is the baseline variable, T is an indicator for treatment group (training participants or non-participants in training village), and Attrit is an indicator for attrition. If $b_3 - b_2$ is not statistically significant for each baseline variable, the attrition using an F test. The coefficient of Attrit, b_2, describes how the baseline variables differ by attrition status. Numbers in the parentheses are standard error.

Appendix Table 2. Comparison of Baseline Sample Households with Rice Growers in Uganda National Population Survey (UNPS 2009)

	Whole sample households	Rice growing households	UNPS Eastern region (rural)	UNPS rice growing households (rural)
HH head's age	44.02	42.60	46.41	45.72
	(14.08)	(12.81)	(15.48)	(14.00)
Head's years of education	5.91	5.93	4.23	5.09
	(3.48)	(3.34)	(3.70)	(3.36)
No. of HH members	7.92	8.33	6.25	7.22
	(3.66)	(3.79)	(3.53)	(4.44)
Share of male aged 15–64	0.240	0.240	0.227	0.251
	(0.143)	(0.138)	(0.210)	(0.139)
Share of female aged 15–64	0.240	0.239	0.218	0.224
	(0.127)	(0.120)	(0.148)	(0.097)
Size of land owned (ha)	1.86	1.79	1.38	1.99
	(2.12)	(2.04)	(2.79)	(2.19)
Share of lowland size owned	0.378	0.434	0.050	0.032
	(1.336)	(1.211)	(0.278)	(0.114)
Ownership of bulls	0.352	0.369	0.246	0.384
	(0.478)	(0.483)	(0.431)	(0.492)
No. of observations	750	540	569	45

Notes: Column 1 and 2 are calculated from the data collected in 2009 by the authors while columns 3 and 4 are from UNPS data. The figures are means and those between parentheses are standard deviations.

Appendix Table 3. Sample

	Training participants in project villages (A)	Non-project villages (B)	Non-participants in project villages (C)	Observations for training impact (D) = (A + B)	Observations for spillover effect (E) = (B+C)
Number of households in 2-year panel	15 (9 for 2011, 6 for 2015)	112 (60 for 2011, 52 for 2015)	16 (11 for 2011, 5 for 2015)	(15+112) x 2 = 254	(112+16) x 2 =256
Number of households in 3-year panel	30	120	48	(30+120) x 3 =450	(120+48) x 3 = 504
	45	232	64	704	760

Appendix Table 4. Results of a Propensity Score for Participation in Training Program (Probit Model)

	Propensity score	
	Training participants vs. Control (1)	Non-participants vs. Control (2)
Rice experience	0.025	0.021
	(0.015)	(0.016)
Head age	-0.025***	-0.019*
	(0.008)	(0.011)
Head years of education	-0.173*	-0.011
	(0.099)	(0.067)
Head education squared	0.011*	-0.001
	(0.006)	(0.005)
Number of HH members	0.004	-0.037
	(0.028)	(0.032)
Share of male aged 15–64	0.015	-0.106
	(0.580)	(0.622)
Share of female 15–64	-0.428	1.149**
	(1.191)	(0.492)
Size of land owned (ha)	0.029	0.038
	(0.034)	(0.032)
Share of lowland owned	-0.087	0.022
	(0.333)	(0.291)
Local group membership	0.509***	0.232
	(0.144)	(0.225)
Ownership of bulls	0.448	0.394*
	(0.369)	(0.212)
Constant	-0.154	-0.423
	(0.636)	(0.767)
No. of Observations	277	296

Notes: ***, **, and * represent statistical significance at the 1, 5, and 10% levels, respectively. The figures are coefficients and those between parentheses are standard errors.

Appendix Table 5. Balancing Test Results

Panel 2009 and 2011	Partici-pants	Control	t-stats	Non-partici-pants	Control	t-stats
Rice experience years	11.38	10.53	0.87	10.24	10.43	0.83
HH head's age	40.42	41.10	0.38	40.72	42.58	0.13
Head's years of education	6.032	5.932	0.25	5.957	5.888	0.83
No. of HH members	8.191	8.51	0.85	8.222	7.617	0.06
Share of male aged 15–64	0.225	0.234	0.71	0.236	0.239	0.85
Share of female aged 15–64	0.241	0.234	0.58	0.254	0.268	0.22
Land owned (ha)	2.161	2.154	0.03	1.976	2.089	0.57
Share of lowland size	0.203	0.178	0.77	0.252	0.181	0.01
Local group member	0.730	0.700	0.65	0.617	0.608	0.83
Ownership of bulls	0.429	0.487	1.13	0.358	0.398	0.36

Note: t-stats for the mean are different between two groups.

Appendix Table 6. Results of Attrition Regression (Probit Model)

	1 if not in sample in neither 2011 nor 2015 (1)
Rice experience	-0.028**
	(0.012)
Head age	0.016***
	(0.006)
Head years of education	0.004
	(0.065)
Head education squared	-0.002
	(0.005)
Number of HH members	-0.082***
	(0.025)
Share of male aged 15–64	-2.571***
	(0.623)
Share of female 15–64	1.010
	(0.653)
Size of land owned (ha)	0.031
	(0.032)
Share of lowland owned	-0.088
	(0.212)
Local group membership	-0.060
	(0.166)
Ownership of bulls	0.043
	(0.172)
Project villages	-0.799***
	(0.223)
Constant	-0.396
	(0.487)
Pseudo R2	0.139
No. of Observations	394

Notes: ***, **, and * represent statistical significance at the 1, 5, and 10% levels, respectively. The figures are coefficients and those between parentheses are standard errors.

Appendix Table 7. Pre-Project Yield Trend
(Dependent Variable, Δyield = yield 2008/9 - yield 2007/8)

	Participants vs. control	Non-participants vs. control
Participants	0.297	
	(0.297)	
Non-participants		-0.000
		(0.000)
Number of obs.	151	148
R-squared	0.130	0.099
Mean Yield (ton/ha) 2008		
Participants/ Non-participants	1.078	1.075
	(0.743)	(0.893)
Control	1.424	1.437
	(0.806)	(0.794)

Notes: Robust standard errors between parentheses. Propensity score weighting and attrition weights are used. Village fixed effects are controlled for. Since we conducted survey once before the training, no other household-level characteristics in 2007 were controlled for as explanatory variables.

Appendix Table 8. Heterogeneous Spillover Effects on Adoption of Straight-row Transplanting and Bunds by Non-Participants (Household Fixed Effects Model, Inverse Probability Weights for Attrition)

Dependent variable	1 if adopted straight-row transplanting method			1 if adopted bunds		
Z	Visit demo plot	Plot near demo plot	Talk with participants	Visit demo plot	Plot near demo plot	Talk with participants
	(1)	(2)	(3)	(4)	(5)	(6)
Non-participants x 2011	-0.023	-0.005	-0.024	0.018	0.037	0.004
	(0.021)	(0.030)	(0.021)	(0.098)	(0.098)	(0.086)
Non-participants x 2011x Z	0.031	-0.014	0.054	-0.071	-0.146	-0.052
	(0.037)	(0.026)	(0.057)	(0.112)	(0.095)	(0.131)
Non-participants x 2015	0.011	-0.002	0.003	0.069	0.101	0.052
	(0.049)	(0.041)	(0.044)	(0.074)	(0.077)	(0.062)
Non-participants x 2015x Z	-0.014	0.024	0.015	0.076	-0.009	0.157
	(0.059)	(0.073)	(0.071)	(0.099)	(0.094)	(0.131)
Year 2011	0.027	0.027	0.027	0.164***	0.164***	0.164***
	(0.020)	(0.020)	(0.020)	(0.046)	(0.046)	(0.046)
Year 2015	0.045*	0.045*	0.045*	-0.023	-0.023	-0.023
	(0.026)	(0.026)	(0.026)	(0.047)	(0.047)	(0.047)
Constant	0.022***	0.022***	0.021***	0.525***	0.525***	0.525***
	(0.008)	(0.008)	(0.008)	(0.018)	(0.018)	(0.018)
No. of Observations	760	760	760	760	760	760
R-squared	0.018	0.018	0.019	0.065	0.066	0.068
Number of HHID	296	296	296	296	296	296

Notes: Figures between parentheses are standard errors clustered at household level. ** and * represent statistical significance at the 1 and 5% levels, respectively. Among non-participants (64), 25 households visited demonstration plots between 2009 and 2011. Propensity score weighting and attrition weights are used.

Appendix Table 9. Average Impact of Training (Pre-Screening DID, Household Fixed Effects Model)

Panel A: Impact on Participants	Transplanting	Transplanting in row	Bunds construction	Chemical fertilizer application	Yield (ton/ha)	Rice income per ha	Total rice production (ton)	Rice revenue per adult equivalent	Rice income per ae	Rice cultivation area (ha)
Participants x 2011	0.143	0.120*	0.435	0.188	0.415	-0.243	0.567	0.100	0.065	0.268*
	(0.107)	(0.047)	(0.071)	(0.123)	(0.117)	(0.481)	(0.070)	(0.174)	(0.059)	(0.042)
Participants x 2015	0.218**	0.207**	0.406	-0.087	0.478	0.337	-0.004	-0.097	-0.038	0.040
	(0.010)	(0.013)	(0.204)	(0.583)	(0.114)	(0.650)	(0.993)	(0.509)	(0.072)	(0.803)
Number of obs.	464	464	464	464	464	401	464	464	401	464
Number of HHID	179	179	179	179	179	169	179	179	169	179
Panel B: Spillover effects										
Non-participants x 2011	0.031	-0.012	-0.003	0.084	-0.038	-0.372	0.461**	0.056	0.053	0.239**
	(0.746)	(0.774)	(0.828)	(0.123)	(0.785)	(0.350)	(0.037)	(0.287)	(0.053)	(0.007)
Non-participants x 2015	0.159*	0.020	0.087	0.054	0.125	0.447	0.294	-0.006	0.071	0.128
	(0.040)	(0.788)	(0.380)	(0.410)	(0.662)	(0.261)	(0.126)	(0.966)	(0.045)	(0.358)
Number of obs.	672	672	672	672	672	574	672	672	574	672
Number of HHID	261	261	261	261	261	244	261	261	244	261

Notes: Figures between parentheses are p-value from wild bootstrap-t, clustered at village level (999 replications). ** and * represent statistical significance at the 1 and 5% levels, respectively.

Propensity score weighting and attrition weights are used. Additional controls are age, education, and gender of household head, number of household members, shares of male and female members aged 15–64, size of land owned and share of lowland owned.

Appendix Table 10. Average Impact of Training on Participants (DID Model with Household Fixed Effects) Lower Bounds (-/+0.1 SD, -/+ 0.25SD)

Panel A: 0.1 SD	Trans-planting	Trans-planting in row	Bunds construction	Chemical fertilizer application	Yield (ton/ha)	Rice income per ha	Total rice production (ton)	Rice revenue per a.e	Rice income per ae	Rice cultivation area (ha)
Participants x 2011	0.111	0.118	0.167	0.145*	0.214	-0.249	0.467	0.079	0.060	0.321*
	(0.173)	(0.107)	(0.247)	(0.017)	(0.257)	(0.292)	(0.061)	(0.201)	(0.039)	(0.017)
Participants x 2015	0.077	0.206*	0.389	-0.045	0.408	0.225	0.099	-0.086	-0.007	0.123
	(0.354)	(0.024)	(0.365)	(0.716)	(0.062)	(0.657)	(0.727)	(0.419)	(0.035)	(0.241)
Number of observations	984	984	984	984	984	984	984	984	984	984
Number of HHID	328	328	328	328	328	328	328	328	328	328
Panel B: 0.25 SD										
Participants x 2011	0.087	0.108	0.145	0.100*	0.480	-0.397	0.350	0.044	0.027	0.275*
	(0.280)	(0.112)	(0.290)	(0.024)	(0.569)	(0.162)	(0.108)	(0.358)	(0.038)	(0.032)
Participants x 2015	0.049	0.187*	0.360	0.291	0.680	0.071	-0.049	-0.122	-0.037	0.084
	(0.505)	(0.049)	(0.424)	(0.655)	(0.160)	(0.888)	(0.874)	(0.225)	(0.035)	(0.444)
Number of observations	984	984	984	984	984	984	984	984	984	984
Number of HHID	328	328	328	328	328	328	328	328	328	328

Notes: Figures between parentheses are p-value from wild bootstrap-t, clustered at village level (999 replications). ** and * represent statistical significance at the 1 and 5% levels, respectively. Propensity score weights are used.

Appendix Table 11. Spillover Effect of Training (Household Fixed Effects Model), Lower Bounds (-/+ 0.25SD)

Panel A: 0.1 SD	Transplanting	Transplanting in row	Bunds construction	Chemical fertilizer application	Yield (ton/ha)	Rice income per ha	Total rice production (ton)	Rice revenue per adult equivalent	Rice income per ae	Rice cultivation area (ha)
Non-participants x 2011	0.039	0.004	-0.040	0.012	-0.435	-0.570**	0.165	-0.038	-0.027	0.314**
	(0.631)	(0.900)	(0.507)	(0.727)	(0.425)	(0.002)	(0.259)	(0.436)	(0.055)	(0.000)
Non-participants x 2015	0.068	-0.001	0.071	0.016	-0.093	0.309	0.078	-0.136**	-0.016	0.103
	(0.205)	(0.990)	(0.378)	(0.779)	(0.519)	(0.185)	(0.416)	(0.014)	(0.052)	(0.255)
Number of obs.	1,038	1,038	1,038	1,038	1,038	1,038	1,038	1,038	1,038	1,038
Number of HHID	346	346	346	346	346	346	346	346	346	346
Panel B: 0.25 SD										
Non-participants x 2011	0.012	-0.008	-0.064	0.004	-0.520	0.732**	0.075	-0.065	-0.058	0.275**
	(0.856)	(0.795)	(0.275)	(0.939)	(0.336)	(0.001)	(0.590)	(0.217)	(0.058)	(0.003)
Non-participants x 2015	0.041	-0.016	0.045	-0.004	0.233	0.152	-0.087	-0.173	-0.048	0.058
	(0.426)	(0.732)	(0.558)	(0.947)	(0.203)	(0.555)	(0.334)	(0.001)	(0.055)	(0.437)
Number of obs.	1,038	1,038	1,038	1,038	1,038	1,038	1,038	1,038	1,038	1,038
Number of HHID	346	346	346	346	346	346	346	346	346	346

Notes: Figures between parentheses are p-value from wild bootstrap-t, clustered at village level (999 replications). ** and * represent statistical significance at the 1 and 5% levels, respectively. Propensity score weights are used.

Appendix Table 12. Average Treatment Effect of Training (Doubly Robust Estimator)

	Program impact 2011		Program impact 2015	
Transplanting	0.251	(0.156)	0.288**	(0.056)
Transplanting in row	0.085**	(0.033)	0.056	(0.039)
Bunds construction	0.107	(0.095)	0.197**	(0.060)
Chemical fertilizer application	0.105*	(0.047)	0.101	(0.054)
Yield (ton/ha)	-0.116	(0.151)	0.404**	(0.149)
Rice income per ha	-0.100	(0.229)	0.596**	(0.211)
Total rice production (ton)	0.004	(0.172)	-0.238	(0.216)
Rice revenue per adult equivalent	0.022	(0.039)	-0.096*	(0.051)
Rice income per adult equivalent	0.066	(0.052)	0.007	(0.043)
Rice cultivation area (ha)	0.030	(0.052)	-0.122**	(0.062)

Notes: Average treatment effects of the training program are estimated by teffects ipwra command in stata.
Program impact: Treatment is village-level.
Figures between parentheses are standard errors clustered at village level. ** and * represent statistical significance at the 1 and 5% levels, respectively.
Propensity score weighting and attrition weights are used. Additional controls are age, education, and gender of household head, number of household members, shares of male and female members aged 15–64, size of land owned and share of lowland owned.

Appendix Table 13. Impact of Village-Level Training Placement (DID Model with Household Fixed Effects)

	Trans-planting	Trans-planting in row	Bunds construction	Chemical fertilizer application	Yield (ton/ha)	Rice income per ha	Total rice production (ton)	Rice revenue per a.e	Rice income per ae	Rice cultivation area (ha)
Program villages x 2011	0.065	0.069	0.067	0.081*	0.187	-0.115	0.673**	0.114	0.100	0.337**
	(0.045)	(0.040)	(0.066)	(0.045)	(0.160)	(0.231)	(0.238)	(0.049)	(0.040)	(0.080)
	[0.323]	[0.098]	[0.714]	[0.069]	[0.413]	[0.724]	[0.004]	[0.114]	[0.250]	[0.000]
Program villages x 2015	0.142*	0.109**	0.120	0.068	0.804*	0.772	0.499	0.039	0.106**	0.195*
	(0.049)	(0.044)	(0.073)	(0.050)	(0.175)	(0.249)	(0.262)	(0.054)	(0.043)	(0.088)
	[0.050]	[0.026]	[0.363]	[0.479]	[0.042]	[0.164]	[0.088]	[0.555]	[0.110]	[0.041]
Year 2011	0.010	0.014	0.190**	0.010	0.271**	0.865**	-0.165	0.048	0.065***	-0.161**
	(0.027)	(0.024)	(0.040)	(0.028)	(0.097)	(0.140)	(0.145)	(0.030)	(0.024)	(0.049)
Year 2015	0.003	0.001	0.077	0.179**	-0.158	0.509**	-0.061	0.090**	0.035	-0.111
	(0.037)	(0.033)	(0.055)	(0.037)	(0.136)	(0.189)	(0.198)	(0.041)	(0.033)	(0.066)
Constant	0.854**	-0.120	0.615**	0.100	0.688	1.241	-0.859	0.042	-0.078	-0.128
	(0.146)	(0.128)	(0.214)	(0.147)	(0.539)	(0.732)	(0.769)	(0.157)	(0.126)	(0.260)
Number of observations	880	880	880	880	847	805	870	865	805	880
R-squared	0.041	0.062	0.095	0.152	0.105	0.189	0.069	0.114	0.122	0.122
Number of HHID	341	341	341	341	341	339	341	341	339	341

Notes: Figures between brackets are p-value from wild bootstrap-t, clustered at village level (999 replications). Numbers between parentheses are robust standard errors clustered at household level. ** and * represent statistical significance at the 1 and 5% levels, respectively. Additional controls are age, education, gender of household head, number of household members, shares of male and female members aged 15–64, size of land owned and share of lowland owned.