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The importance of farm management training for the African rice Green Revolution: Experimental evidence from rainfed lowland areas in Mozambique

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ABSTRACT

The effectiveness of basic farm management training (e.g., seed selection, nursery bed setup, field leveling, bund construction, and transplanting) for the African rice Green Revolution has not been fully examined. This study evaluated a randomized controlled trial (RCT) of such training in the remote rainfed lowland areas of Mozambique. The training taught these practices without introducing modern varieties or inorganic fertilizers. The intention-to-treat (ITT) effect on paddy yield was 447–546 kg/ha (29 %–36 % of the control group average yield), with statistical significance at 7 %–8%. The results indicate that the adoption of these basic practices alone can improve paddy yield without relying on modern purchased inputs, which are usually not readily available in remote local markets or affordable to cash-constrained farmers. Complementarity among these basic practices is also suggested in that the yield increase had the highest statistical significance when all five practices were adopted.

1. Introduction

Rice consumption in Sub-Saharan Africa (SSA) has been growing at a faster pace than local production (4.2 % and 3.5 % annually from 1960 to 2020, respectively) (USDA, 2021). Meanwhile, SSA has lagged far behind the areas blessed with Green Revolution (GR) technologies, awaiting their African versions (Evenson and Gollin, 2003; Gollin et al., 2021). Land productivity improvement or Asian-style GR should be one of the key components of their strategies to overcome these problems partly because the land-labor ratio in SSA has already reached a lower level than in tropical Asia in the 1960s and also because the Asian-type rice GR technologies are highly transferable to SSA (Otsuka and Larson, 2016, 2013). In addition, African GR must be realized in the rainfed area, at least in the short- or middle-term, because the proportion of area equipped with irrigation facilities remains marginal at approximately 3 % in the region (FAO, 2021).

However, a simple replication of Asia's experiences may not be enough for this purpose because it has been argued that the introduction of seed-fertilizer technologies alone is not enough for SSA. Instead, SSA's strategy can include training in basic management practices such as seed selection and nursery bed setup (for quality seedlings), field leveling and bund construction (for even water distribution), straight-row transplanting (for easier crop management and weeding), timely weeding, and water management, some of which were already common in Asia at the time of its GR (Balasubramanian et al., 2007; Barker and Hardt, 1985; Kijima et al., 2012). The effective adoption of such basic practices may not be the same as that of seed-fertilizer technologies. The former may need farmers to adopt the package of practices as an integrated system and, thus, are more complicated and knowledge-intensive. Moreover, farmers must properly adopt the right way of practicing and maintaining them. This is in contrast with the adoption of modern inputs, such as seed-fertilizer technologies, where the essence of technologies is embedded within the seed and fertilizer, and the benefits are realized by applying modern inputs to the field, although farmers still need to learn how to use them. This implies that the extension program for SSA can include training in basic practices, and extension systems should be effectively designed for the proper and sustained use of the learned practices.

This study aims to assess the effectiveness of training in basic rice farm management practices using a randomized controlled trial (RCT) of the training program provided by the Japan International Cooperation Agency (JICA) in remote rainfed lowland areas in Mozambique. Mozambique is an appropriate case because its rice productivity is still

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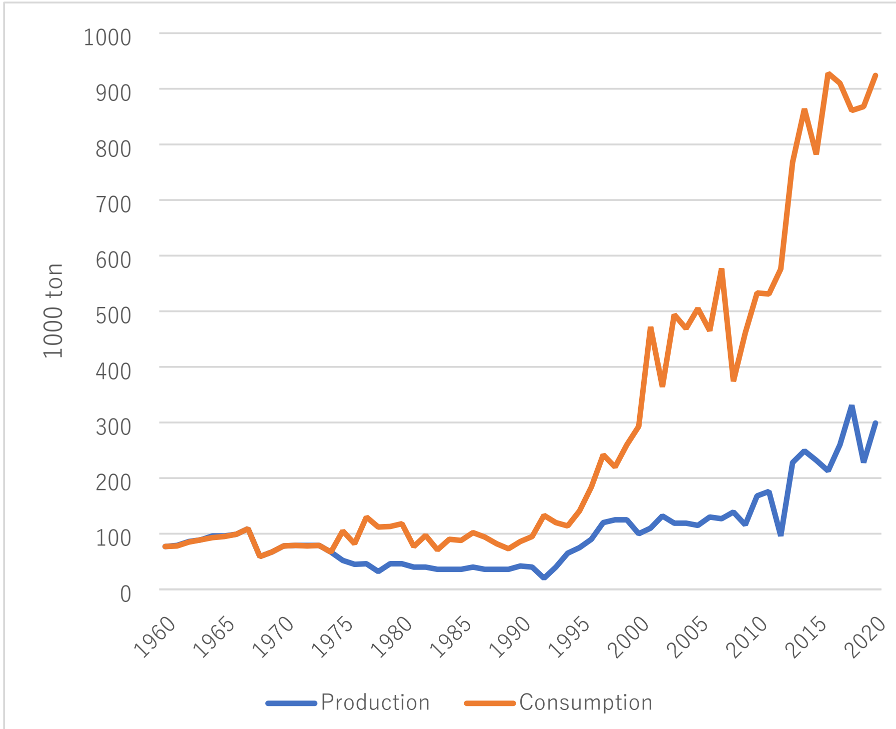

Fig. 1. Production and consumption of rice (milled bases) in Mozambique, 1960 – 2020. Data Sources: USDA: PSD Online April 2021; USBC: International Data Base, August 2006.

very low, approximately 1.5 t/ha of paddy on average in 2020, and the rice is mostly cultivated in rainfed lowlands (Kajisa, 2015; Kajisa and Payongayong, 2011).

Among many different types of training, ours joins the group of training with the following three features. First, the training was a combination of a conventional approach (farmer field school (FFS) at demonstration plots) and a contemporary approach (farmer-to-farmer extension (F2FE) through social learning). The conventional approach has been criticized as costly and not consistently successful in Asia (Antholt, 1998). Recent studies have stressed the importance of F2FE as a more inexpensive and effective method to compensate for this drawback (Behaghel et al., 2020; BenYishay and Mobarak, 2019; Conley and Udry, 2010; Fafchamps et al., 2021; Nakano et al., 2018b; Takahashi et al., 2020; Takahashi et al., 2019). Our case provides an example of a combination of conventional and recent approaches and examines its effectiveness. Second, the training did not provide any performance-based monetary incentives as a means of accelerating technology diffusion. Emerging issues in the F2FE include whether monetary incentives for dissemination activities matter. BenYishay and Mobarak (2019) found that monetary incentive enhanced the dissemination, whereas the case studies by Behaghel et al. (2020), Nakano et al. (2018b), and Takahashi et al. (2019) found substantial dissemination even without a monetary incentive to teaching farmers. Our case joins an example of the latter group. Third, the training did not rely on modern inputs, such as the newly developed improved varieties and inorganic fertilizers. Hence, our case provides useful lessons for remote rainfed farmers who are usually cash- and market-access-constrained.

Our study contributes to the policy design for the African Green Revolution, where case studies on rainfed lowlands are relatively scarce (Evenson and Gollin, 2003; Gollin et al., 2021; Otsuka and Larson, 2016, 2013).[1] Our analysis revealed three key points. First, the adoption of basic practices can be an effective component in improving rice yield for African GRs, and the training program can enhance the adoption of such practices. Second, yield improvement is possible even without modern purchased inputs, although the potential impact is not as high as with modern inputs under irrigated conditions. This means that even remote rainfed farmers can still benefit from such training. Third, the increase in yield is assured when the practices are adopted as a package, rather than individually. Although greater variations in adoption patterns would have generated more rigorous implications, our result still suggests the validity of an integrated farm management approach (Takahashi et al., 2020).

The remainder of the paper is organized as follows. Section 2 explains the study site, management training, and experimental design, and this is followed by our examination of summary statistics and the balancing test in Section 3. Section 4 presents our estimation strategies and regression results on the impact assessment of the training and identification of appropriate yield-improving practices. Finally, Section 5 concludes the paper.

2. Study Site, management training, and experimental design

2.1. Study site

The importance of rice in Mozambique has been increasing rapidly. Due to increased urbanization and the convenience of preparing rice meals, Mozambique, like other African countries, has witnessed a shift in consumer preference for rice (Hossain, 2006). Therefore, rice consumption (milled base) in Mozambique rapidly increased by 8.9 % annually from 1990 to 2020, faster than the increases in maize, 4.5 %, or wheat, 6.1 % (USDA, 2021). In response to this increase, production grew initially at 12.1 % annually from 1993 to 1998, but growth has largely stagnated since then (Fig. 1). As shown in Fig. 2, the modest growth in production is attributed to the expansion of the harvested area rather than paddy yield (un-milled base) improvements. Paddy yield has stagnated at a level of around 1 to 1.5 tons per hectare. This stagnation results in a rapid increase in rice imports, as indicated by the widening gap between consumption and production (Fig. 1).

[1] Exceptions include studies on rainfed rice by deGraft-Johnson et al. (2014) in Ghana, Kijima et al. (2012) in Uganda, and Nakano et al. (2018a) in Tanzania.

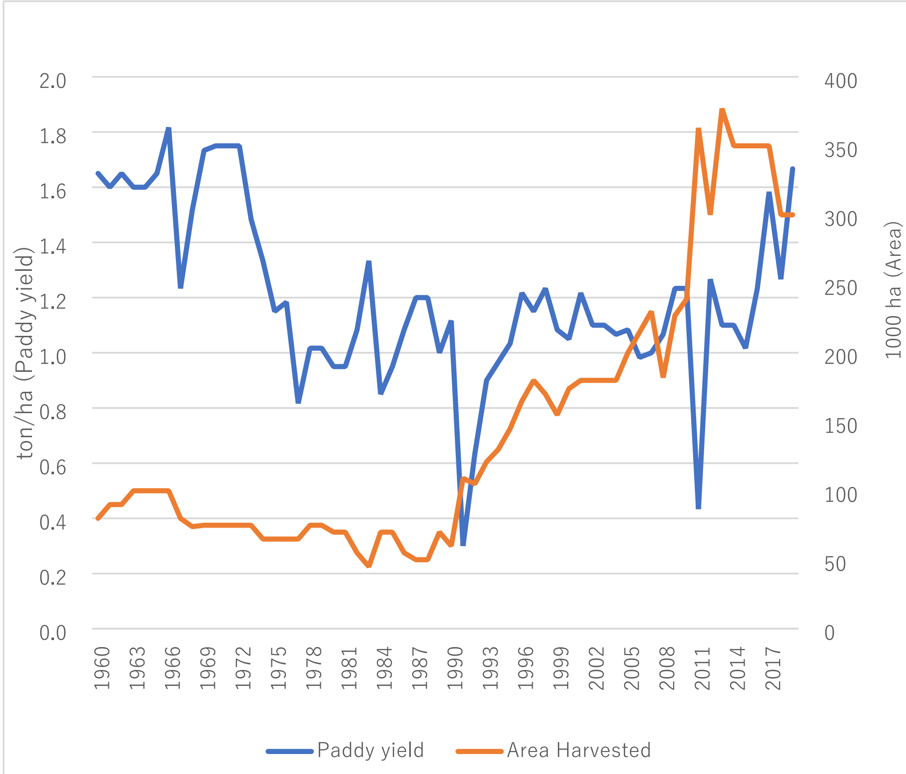

Fig. 2. Area harvested and paddy yield in Mozambique, 1960–2020. Note: Milled rice yields in the original data set were converted to paddy yields at 60% milling recovery rate. Data Sources: USDA: PS&D Online April 2021; USBC: International Data Base, August 2006.

Rice in Mozambique is produced mostly in the rainfed lowland ecological regions by smallholders, where farmers follow traditional cultivation practices. According to the report by Agrifood Consulting International (2005), the average landholding size of smallholders was 1.28 ha, and the rice farmers cultivated 0.3 ha of rice on average. The area equipped with irrigation facilities accounts for only 2 % of the arable land in the country.[2] Among the rainfed lowland areas, Zambézia Province, including the Zambézi River basin, is the dominant rice producing province (48 % of the total rice area), followed by Nampula (14 %), Sofala (12 %), and Cebo Delgado (10 %) (Anuário de Estatisticas Agrárias, 2015). In 2011, the average landholding size of smallholders computed from a representative sample of Zambézia and the adjacent Sofala provinces was 1.4 ha, of which cultivated rice area accounted for approximately 0.8 ha (Kajisa, 2015).

JICA selected five districts in the lowland areas of Zambézia Province for the project: Namacurra, Nicoadala, Inhassunge, Quelimane, and Mopeia, where rice has been traditionally grown for own consumption and sales (Fig. 3). The staple food in the areas is rice, followed by cassava, maize, and sweet potato. Rice is also the main cultivation crop for farmers.

2.2. Nature of management training

Rice farmers in Mozambique, including those in our study site, have cultivated rice with traditional cultivation practices, with little or at best partial use of improved management practices or modern improved varieties (Agrifood Consulting International, 2005). Therefore, gaps in knowledge about improved practices must be filled in order to transition to intensive rice cultivation. A common approach to this end is to provide training and extension on management practices.

[2] The largest irrigation scheme of the county is Chokwe irrigation scheme in Gaza district. The average farm size was 2.1 ha (Agrifood Consulting International, 2005). See Kajisa and Payongayong (2011) for more details.

Although the adoption of improved management practices increases labor cost, the existing impact assessments of rice training in Africa indicate that it increases not only yield but also profit: Nakano et al. (2028) in rainfed lowlands in Tanzania and Kijima et al. (2012) in minorly irrigated lowland in Uganda. An increase in yield and profit of rice production in lowland would be a motivation for change, under the condition of difficulty in cultivating other major crops such as maize and cassava in lowland areas.

Management training usually teaches a sequence of several improved practices throughout the rice cultivation season. The existence of complementarity among them is an important empirical question because it determines the specific recommendations given to farmers in training. To explore the existence of complementarity, literature on the system of rice intensification (SRI) is insightful because SRI recommends a package of practices. Varma (2019) found the adoption of plant management can make a positive impact if it is practiced together with water and/or soil management, implying the existence of complementarity. Meanwhile, Alem et al. (2015) and Takahashi and Barrett (2014) indirectly show that the change in the combination of practices does not alter the existence of the positive impact against no adoption, suggesting that full adoption is not necessarily needed in the case of SRI. In this regard, the empirical results on complementarity are mixed. All in all, we may claim that existing literature shows that there is a positive impact of management training on yield and profit, but that the complementarity among the practices is unclear.

2.3. JICA rice training

The project to improve rice productivity in Zambézia Province started in 2016 with financial support from JICA. The unit of intervention of the training was a farmer's association. Each association consisted of rice farmers who were regarded as local farmers living in a nearby village, excluding temporary migrant farmers who stayed at study sites only during the rice cultivation season. In this regard, the

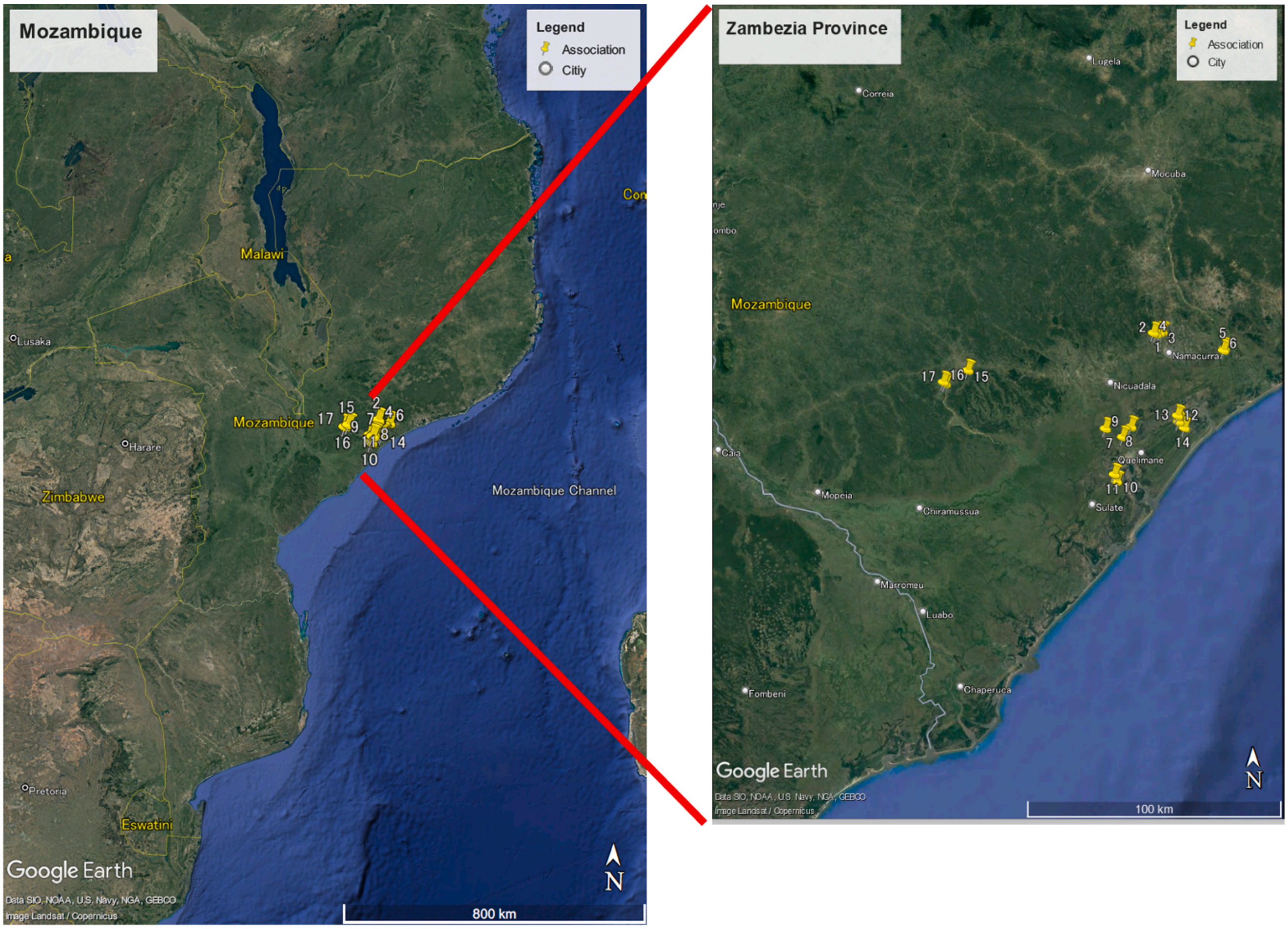

Fig. 3. Map of study site. Source: Google Earth. Assessed July 21st, 2022.

association may be characterized as a local community with regular face-to-face communications within. The JICA rice training project, in consultation with the Provincial Directorate of Agriculture and Fisheries (Direcção Provincial de Agricultura e Pescas, DPAP), selected functioning and rice-cultivating associations from a list at local offices: 17 associations in six localities (*localidade*) in the rainfed area and 5 associations in five localities in the irrigated area. In this impact assessment study, we focused on the 17 rainfed associations, given the purpose of the study and the delay in the rehabilitation projects with irrigation facilities in the selected area. The member size of these 17 associations varied from 20 to 50, with the mean and standard deviation of 26 and 8.

The project established demonstration plots in each association, using the association's common plots, usually located at an accessible and observable location in the association's rice area.[3] In collaboration with the staff of the National Directorate of Assistance to Family Farming (Direcção Nacional de Assistência a Agricultura Familiar, DNAAF), the JICA project staff, together with local official extension workers, provided four training sessions to the invited farmers (to be explained in the next paragraph) in the demonstration plots. The training sessions provided training in (1) the use of recommended varieties, (2) the seed selection method, (3) the nursery bed setup for seedlings, (4) land leveling, (5) bund construction, (6) straight-row transplanting or straight-row direct sowing, (7) weeding at the proper time, and (8) harvesting at the bottom of the plant, rather than the panicles.[4] The training program recommended that farmers adopt all practices. Among these practices, bund construction was emphasized as the core practice because the retention of water is the most important condition under rainfed conditions. A combination of bund construction, seed selection, and nursery bed construction is recommended as the basic package. All the recommended rice varieties were *local* varieties, rather than the modern varieties which have been developed recently and are usually sold at markets in towns. This was because the modern varieties were not easily accessible to the cash- and market-access-constrained farmers in remote areas. For the same reason, the use of inorganic fertilizers was not included in the training in the rainfed areas.

To disseminate the practices taught in the demonstration plots, the project selected five farmers (at maximum) from the association members and invited them to the plots for training. They were called lead farmers by the project. Later, due to strong requests from some of the other member farmers, any other members who wanted to participate in the training were invited to join the project. They were called replica farmers. A few farmers in each association became replica farmers. The lead and replica farmers can be regarded as the farmers directly treated in the treatment groups, while it was still up to them to adopt the learned practices on their own plots.

These directly treated farmers were expected to teach new practices to non-participant ordinary farmers to accelerate the dissemination of

[3] If the associations did not have common plots, the project leased-in private plots suitable for demonstration.

[4] The recommended seed selection method was to remove empty seeds floating in the water.

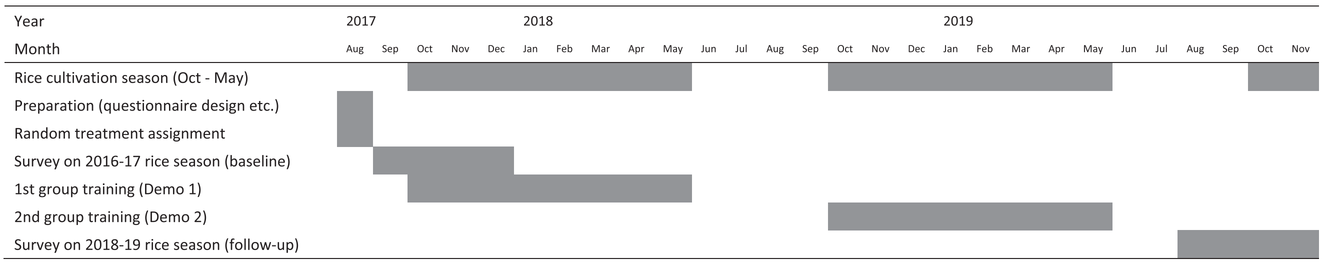

Fig. 4. Timeline of implementation.

Table 1
Baseline balance of sample households by treatment and attrition status.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Demo 1 Mean/SE	Demo 2 Mean/SE	Control Mean/SE	Difference (1)-(3)	Difference (2)-(3)	Non attrition Mean/SE	Attrition Mean/SE	Difference
Treated (=1)						0.696	0.796	−0.100
						[0.029]	[0.055]	
Household size	3.718	4.050	4.282	−0.564	−0.233	3.634	4.352	−0.718
	[0.226]	[0.211]	[0.299]			[0.220]	[0.542]	
Head's education (years)	3.846	3.574	3.500	0.346	0.074	3.634	4.352	−0.718
	[0.427]	[0.334]	[0.398]			[0.220]	[0.542]	
Log of asset value	7.563	7.677	7.477	0.085	0.199	7.581	7.208	0.374
	[0.184]	[0.139]	[0.247]			[0.108]	[0.259]	
Total plot area (ha)	0.813	0.621	0.703	0.110	−0.082	0.704	0.413	0.291**
	[0.122]	[0.078]	[0.107]			[0.058]	[0.044]	
Proportion of known members (%)	32.869	55.789	41.660	−8.79*	14.13**	44.545	72.627	−28.082***
	[2.933]	[3.713]	[4.028]			[2.179]	[4.679]	
Weather shock in the last rice season (=1)	0.115	0.149	0.154	−0.038	−0.005	0.140	0.315	−0.175***
	[0.036]	[0.036]	[0.041]			[0.022]	[0.064]	
Weather shock in the last non-rice season (=1)	0.795	0.772	0.833	−0.038	−0.061	0.798	0.907	−0.110*
	[0.046]	[0.042]	[0.042]			[0.025]	[0.040]	
N	78	101	78			257	54	
F-test of joint significance (F-stat)				1.641	2.577**			4.216***
F-test, number of observations				156	179			311

The values displayed for *t*-tests are the differences in the means across the groups. The values displayed for *F*-tests are the *F*-statistics. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

these practices through a social learning mechanism. Our RCT intends to evaluate the impact of the adoption by the lead, replica, and ordinary farmers as a whole.

2.4. Experimental design and sample

Fig. 4 indicates the timeline of the experiment implementation and the months of the rice cultivation season. There are three to four target associations in each locality, and we randomized the order of association-level training within each locality (cluster RCT). This means that one association was randomly selected from each of the six localities in the first project year, generating six treated associations. They are labeled Demo 1. The invited farmers were supposed to receive training throughout the season at the demo plot. The other six associations from each locality were selected in the second year, and they are labeled Demo 2. This leaves five associations as the control group. Note that Demo 1, Demo 2, and the control group associations are not concentrated in a particular locality because we randomized the order of training within each locality. We conducted a pre-training baseline survey in 2017 on the 2016–17 rice season, and after completing the training in the Demo 1 and Demo 2 groups, a follow-up survey in 2019 on the 2018–19 rice season. A face-to-face interview was conducted with a computer-assisted personal interview tool. The data on household characteristics and farming are self-report, while the size of the rice parcel was measured by GPS coordinates.

The locations of the 17 associations are indicated in Fig. 3. Given the low quality of road infrastructure and limited access to local transportation under our experimental design, we judge that the associations are only slightly connected to each other and, thus, that little spillover effect to the control group exists.[5] We also confirmed that no migration across our target associations occurred. In this regard, we believe that the stable unit treatment value assumption (SUTVA) is not violated. The weather in the baseline rice season was normal, but the follow-up season had irregular rainfall. Hence, on average, paddy yield decreased at the time of the follow-up survey.

Given the number of associations (clusters) in each experimental arm, we conducted a power calculation to obtain an appropriate sample size in

[5] The distance from the closest association ranges from 0.8 km to 10.3 km with the mean and standard deviation of 2.9 and 2.7 km. Among our sample associations, there are two pairs that are located less than or equal 1 km each other: 0.8 km in the first pair and 1.0 km in the second pair. However, these pairs were found to be in Demo 1 or Demo 2 and not in the control group. Therefore, we judged that the spillover to the control group can be avoided. As a robustness check in regression analysis, in addition to the impact assessment of Demo 1 and Demo 2 each (shown later as the main results in Table 6 and Appendix Table A2), we combine Demo 1 and 2 as a one treatment group and estimated its impact (Appendix Table A3), and confirmed that the qualitative results are the same.

Table 2
Changes in outcome variables by treatment status: baseline and follow-up.

	Baseline					Follow-up				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Variable	Demo 1 Mean/SE	Demo 2 Mean/SE	Control Mean/SE	Difference (1)-(3)	Difference (2)-(3)	Demo 1 Mean/SE	Demo 2 Mean/SE	Control Mean/SE	Difference (6)-(8)	Difference (7)-(8)
Seedlings preparation practices										
Seed test, water (=1)	0.256	0.337	0.231	0.026	0.106	0.769	0.644	0.141	0.628***	0.503***
	[0.050]	[0.047]	[0.048]			[0.048]	[0.048]	[0.040]		
Nursery bed setup (=1)	0.269	0.386	0.333	−0.064	0.053	0.872	0.812	0.333	0.538***	0.479***
	[0.051]	[0.049]	[0.054]			[0.038]	[0.039]	[0.054]		
Land preparation practices										
Plot bunding (=1)	0.192	0.267	0.218	−0.026	0.049	0.474	0.495	0.192	0.282***	0.303***
	[0.045]	[0.044]	[0.047]			[0.057]	[0.050]	[0.045]		
Plot leveling (=1)	0.141	0.188	0.244	−0.103	−0.055	0.667	0.455	0.038	0.628***	0.417***
	[0.040]	[0.039]	[0.049]			[0.054]	[0.050]	[0.022]		
Crop care practices										
Straight-row transplanting (=1)	0.013	0.000	0.000	0.013	N/A	0.462	0.356	0.000	0.462***	0.356***
	[0.013]	[0.000]	[0.000]			[0.057]	[0.048]	[0.000]		
Weeding at least once (=1)	N/A	N/A	N/A	N/A	N/A	0.628	0.455	0.359	0.269***	0.096
						[0.055]	[0.050]	[0.055]		
Harvesting practices										
Harvesting at the bottom of plant (=1)	0.038	0.010	0.051	−0.013	−0.041*	0.526	0.465	0.192	0.333***	0.273***
	[0.022]	[0.010]	[0.025]			[0.057]	[0.050]	[0.045]		
Using sickle to harvest (=1)	0.295	0.277	0.410	−0.115	−0.133*	0.615	0.426	0.321	0.295***	0.105
	[0.052]	[0.045]	[0.056]			[0.055]	[0.049]	[0.053]		
Rice varieties										
Using Chupa variety (=1)	0.128	0.050	0.026	0.103**	0.024	0.231	0.337	0.064	0.167***	0.273***
	[0.038]	[0.022]	[0.018]			[0.048]	[0.047]	[0.028]		
Using Mocuba variety (=1)	0.179	0.168	0.295	−0.115*	−0.127**	0.359	0.168	0.231	0.128*	−0.062
	[0.044]	[0.037]	[0.052]			[0.055]	[0.037]	[0.048]		
Using Mamima variety (=1)	0.179	0.139	0.269	−0.090	−0.131**	0.179	0.119	0.167	0.013	−0.048
	[0.044]	[0.035]	[0.051]			[0.044]	[0.032]	[0.042]		
Output										
Paddy yield (kg/ha)	1939.7	1527.1	1974.9	−35.191	−447.794*	1782.5	1751.5	1535.8	246.659	215.661
	[172.671]	[139.327]	[197.380]			[126.150]	[109.771]	[131.771]		
N	78	101	78			78	101	78		
F-test of joint significance (F-stat)				2.096**	2.294***				18.186***	11.436***
F-test, number of observations				156	179				156	179

N/A: No data available or no statistical comparison possible. The values displayed for *t*-tests are the differences in the means across the groups; The values displayed for *F*-tests are the *F*-statistics; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

each cluster.[6] We collected a random sample of 13 to 25 farmers proportionate to the size of each association, generating 311 observations in the baseline survey. In the follow-up survey, we collected data from 257 farmers in the baseline survey, with an attrition of 54 farmers. Our statistical analysis relies on a balanced panel of these 257 farmers in two periods (514 observations) while statistically controlling for attrition bias.

3. Descriptive statistics

3.1. Balance test and outcomes

Table 1, Columns (1)-(5) show the baseline balance of sample households by treatment. Of the 257 farmers, 78 samples (24 lead, 7 replica, and 47 ordinary farmers) were in Demo 1, and 101 samples (11 lead, 13 replica, and 77 ordinary farmers) were in Demo 2, while 78 farmers (no status was yet assigned) in the control group were not receiving any treatment.[7] The household characteristics consist of household size (heads), household head's schooling years (years), the log of household total asset value (000 MT), total plot area (ha) including non-survey plots, the proportion of known members (%), weather shock in the rice season of the survey year (dummy), and weather shock in the non-rice season immediately before the rice season of the survey year (dummy). The variable "proportion of known members" measures what percentage of sample farmers in the association are known by an interviewed sample farmer, indicating individual network size within the association. The dummy variable "weather shock" takes the value of 1 if farmers self-reported that their rice crop suffered from a flood, drought, or irregular rainfall.

The table shows that all the household characteristics, either in Demo 1 or Demo 2, except the proportion of known members, are not statistically different from those of the control group. A joint significance test between Demo 2 and the control (shown at the bottom of the table) was statistically significant, but it became insignificant if we removed the variable of the proportion of known members (the result is not shown in the table). From the table, we can compute the overall average total plot size as 0.7 ha. Admittedly, our sample farmers are relatively smaller than the provincial or national averages indicated in sub-section 2.1. However, note also that the rice cultivation area of our sample is 0.6 ha (not shown in the table),

[6] A project consultant conducted a pilot study in the study site before our baseline survey, providing useful summary statistics for a power calculation. Using these, we set the mean paddy yield at 1 t/ha, the standard deviation at 1 t/ha, the number of clusters in one experimental arm at 6, intra-cluster correlation (ICC) at 0.15, and, being conventional, the proportion of the yield explained by baseline covariates at 0. We set the significance level at 0.05 and the power of test at 0.8. Under these settings, the sample size of 15 in each cluster generates the minimum detectable effect (MDE) of yield by 0.81 t/ha. Moreover, because we took the baseline data in this project, if the proportion explained by the baseline covariates improves from 0 to 0.4, we can detect the effect by 0.74 t/ha. As the target of the project was to increase yield by 1 t/ha, we decided to set our target sample size in each cluster (association) at 15.

[7] The random sampling of sample farmers was made at the baseline survey before the training when farmers status (lead, replica, and ordinary) was not assigned. This means that stratified sampling based on farmer status was not possible.

Table 3
Changes in outcome variables by treatment status – unconditional DID: baseline and follow-up.

	Unconditional DID Follow-up - baseline	
	Demo 1	Demo 2
Variable		
Seed test, water (=1)	0.603***	0.397**
	[0.000]	[0.000]
Setting up a nursery bed in the plot (=1)	0.603***	0.426**
	[0.000]	[0.000]
Plot bunding (=1)	0.308***	0.253***
	[0.00255]	[0.00824]
Plot leveling (=1)	0.731***	0.472***
	[0.00]	[0.00]
Straight-row transplanting (=1)	0.449***	0.356***
	[0.000]	[0.000]
Harvesting at the bottom of plant (=1)	0.346***	0.314***
	[0.000]	[0.000]
Using sickle to harvest (=1)	0.410***	0.238**
	[0.00]	[0.019]
Using Chupa variety (=1)	0.064	0.249***
	[0.396]	[0.000]
Using Mocupa variety (=1)	0.244***	0.064
	[0.009]	[0.470]
Using Mamima variety (=1)	0.103	0.083
	[0.229]	[0.302]
Paddy yield (kg/ha)	281.85	663.45**
	[0.358]	[0.0219]
N	514	514

p-values in brackets; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

which is close to the average in this area.

Columns (6)–(8) of Table 1 compare the household characteristics by attrition status, in which we additionally compare the dummy of treatment. The table shows that although attrition had little to do with treatment, it occurred non-randomly because non-attrition households operated larger areas of farmland, knew fewer farmers in the same association, and were less likely to have experienced weather shocks in both the rice and non-rice seasons. These differences might constitute a source of bias in the impact assessment and thus need to be managed with an appropriate econometric technique.

Table 2 shows differences in outcome variables by treatment status at the baseline season (columns (1)-(5)) and the follow-up season (columns (6)–(10)). We also present unconditional difference-in-differences (DID) estimates of the treatment effect in Table 3, which compares the *changes* in outcome variables from the baseline to the follow-up. The outcome variables we examine are the adoption of the practices demonstrated by the training, namely, the adoption of seed selection by water (=1), setup of the nursery bed (=1), bund construction (=1), leveling (=1), straight-row transplanting (=1), conducting weeding at least once (=1), harvesting at the bottom of the plant (=1), use of sickle for harvesting (=1), and use of a recommended rice variety of either Chupa (=1), Mocuba (=1), or Mamina (=1). These varieties are local varieties that possess the characteristics of late maturity and high yield, unlike the other popular local variety Nene, which has the features of early maturity and low yield. The adoption of these three varieties is used as our outcome variable because these are the varieties preferred by farmers and recommended by the project. We also compare paddy yield (kg/ha) as the outcome of the project.[8] Note that the weeding variable is empty in the baseline because we failed to collect this information correctly.

The table shows that, at the time of the baseline survey, the adoption of practices was quite low (at largest, approximately 30 %), and the differences by treatment status were statistically insignificant, except for two variables related to harvesting (harvesting at the bottom of the plant and the use of sickle) in the Demo 2 group. Nevertheless, the adoption of these two practices was lower in the Demo 2 group than in the control group during the pre-training time; thus, a possible higher adoption rate at post-treatment does not mean that it was higher from the beginning. Meanwhile, we observe significant differences in rice variety choices.

The paddy yields were low at 1,940 kg/ha in Demo 1, 1,527 kg/ha in Demo 2, and 1,975 kg/ha in the control group, which was understandable under rainfed conditions even for a normal weather season. The low yield of Demo 2 was statistically different from that of the control group at the 10 % significance level. This could be the reason for the low adoption of improved *harvesting* methods by Demo 2. Farmers usually start using such practices when their productivity improves; that is, a causality manifests from yield to harvesting methods.[9] Note, however, that such a reverse causality can exist only for the harvesting practices but unlikely for the other practices. Even though the yield difference between Demo 2 and the control was statistically significant, we can still use this result to claim that even if the yield became higher after the training in the Demo 2 group, it was not higher from the beginning.

In the follow-up survey, the adoption rate of recommended practices increased sharply among the treated groups, resulting in statistically significant differences compared to the control group in most cases (approximately 30 to 50 percentage points higher than the control group's adoption levels). When comparing yield, we must note that the follow-up season suffered from irregular rainfall, and thus the *overall* average at the study site decreased slightly from approximately 1,800 kg/ha at the baseline to approximately 1,700 kg/ha at follow-up. However, we can still observe differential outcomes by treatment status; the reduction for Demo 1 was marginal, and Demo 1 achieved 1,783 kg/ha. Furthermore, Demo 2 improved its yield to 1,752 kg/ha, while the yield of the control group decreased to 1,536 kg/ha. Hence, the yields of Demo 1 and Demo 2 were approximately 200 kg/ha higher than those of the control group, although the differences were not statistically significant at any conventional level. Meanwhile, if we compare the changes by the unconditional DID analyses in Table 3, we observe a significantly positive impact of 663 kg/ha of change in the yield of the Demo 2 group. The results of the other unconditional DID estimators show significant increases in adoption, being consistent with the results of the mean comparison.

3.2. Practice adoption and its impact

One of the key research issues of this study is to identify the importance of management practices and their possible complementarity. To shed light on this issue, we focus on five practices: seed test by water (S), nursery bed setup (N), bund construction (B), field leveling (L), and straight-row transplanting (TP). We cannot include weeding due to the lack of baseline data.[10] In addition, we do not include the two recommended harvesting practices because they are not yield-improving practices, but rather a reverse causality from yield improvement to their adoption may exist in these practices.

Table 4 Panel A shows the percentage of adopters of individual practices, the subset of the practices, or their full package and corresponding yields among the entire sample ($n = 257$) at the baseline and follow-up seasons. The asterisks on the yield values indicate the significant mean difference from the yield under no adoption based on the *t*-test. In order to distinguish the impact of full adoption and those of partial adoptions, we do not include the farmers who adopted all five practices when we

[8] This study focuses on the yield as a primal indicator of Asian style intensification. Although the comparison of profit is important, we cannot use profit because the details of family labor input is not available in the dataset.

[9] These harvesting practices were recommended for the ease of threshing and recycling of rice straws.

[10] It is possible to show the status of weeding adoption and its impact at the follow-up. The trend of this practice is similar to those of the other practices. The yield of weeding adopters is lower than the non-adopters in the follow-up. This is partly due to self-selection; farmers who suffered weed problems did weeding more frequently.

Table 4
Practice and variety adoption and yield in the follow-up survey (balanced rainfed sample).

Panel A: Key practices

	Baseline		Follow-up	
Adoption status	Percentage of farmers (%)	Yield (kg/ha)	Percentage of farmers (%)	Yield (kg/ha)
No adoption	37	2098	20	1805
Individual or Partial adoption[a]				
(S) Seed test by water	28	1295***	41	1536
(N) Nursery bed setup	33	1611**	56	1596
(B) Bund construction	23	1262***	28	1613
(L) Leveling	19	1740	27	1506
(TP) Straight-row planting	0.4	2442	16	1326**
(B)+(S)+(N)	5	661***	12	1610
Any single or partial adoption	63	1609**	67	1571
Full adoption				
All 5 practices (S)+(N)+(B)+(L)+(TP)	0	na	12	2206

a) Individual or partial adoption does not include the case of all 5 adoption; *** $p < 0.01$, ** $p < 0.05$, the mean difference from the case of "No adoption"; Sample size = 257.

Panel B: Key varieties

	Baseline		Follow-up	
Adoption status	Percentage of farmers (%)	Yield (kg/ha)	Percentage of farmers (%)	Yield (kg/ha)
Neither Chupa, Mamima, nor Mocuba	53	1678	38	1698
Variety Chupa	7	1792	22	1493
Variety Manima	19	1486	15	1572
Variety Mocuba	21	2316**	25	1949

** $p < 0.05$, the mean difference from the case of "Neither Chupa, Mamima, nor Mocuba"; Sample size = 257.

calculate the yield under the solo or partial adoption of the five practices. For example, for the case of the adoption of the Seed test by water ((S) in the table), the results do not include the farmers who adopted all five practices—only the farmers who adopted the seed test alone or seed test plus some other practices but not all the other practices. If the adoption of (S) alone still has an impact, yield under (S) is expected to be higher than in the case of no adoption. The table shows the case of (B)+(S)+(N) as the adoption of the basic package. It also shows the case of combining any single or partial adoptions of five practices in the row above the case of full adoption. Hence, the sum of "No adoption," "Any single or partial adoption," and "All 5 practices" is 100 %.

Table 4 shows these three features. First, unexpectedly, at baseline, the case of no adoption showed the highest yield. This may be because farmers in very favorable agroecological conditions were able to achieve high productivity with conventional practices. Second, the proportion of no adoption decreased from 37 % to 20 %, and that of full adoption increased from 0 % to 12 %. Third, at the follow-up, the adoption of all five practices gave the highest yield at 2,206 kg/ha, although this was not statistically significant. Among the single or partial practice adopters, those of bund construction (B) and the (B)+(S)+(N) achieved relatively high yield at 1,613 or 1,610 kg/ha, respectively. For the same reason as with non-adopters, the adoption of practice could also have a self-selection problem. Farmers that can utilize the new practices fully and thus achieve a higher yield selectively adopt new practices. Also, farmers suffering from low yields may have a stronger incentive to adopt new practices. To control for the self-selection issue in adoption analyses as well as other controls, more statistically rigorous analyses will be provided in the next section.

Panel B in Table 4 shows the impact of variety adoption. Except for the use of the Mocuba variety at baseline, we did not find significant differences in yield. This may be because each farmer already used a variety suitable for their local conditions.

As background information for interpretation, we show how the above-mentioned adoptions occurred. Table 5 lists the most important information sources for new practices among adopters in the follow-up season. The sources are classified into six categories: through demonstration plot participation, from extension workers, from other farmers, through the observation of the plots of unrecognized farmers, and the cases where the practice was already known prior to the training. The results indicate that the demonstration plots or the extension workers were the two key sources where the farmers were exposed to the new practices for the first time, indicating that these two conventional means can serve as a starting point of dissemination to make farmers aware of the new practices. Meanwhile, at least in the short run (in one or two seasons), social learning seemed not to emerge clearly.

In summary, Tables 1 to 3 indicate that our RCT guaranteed a balanced sample for impact evaluation of a possible positive impact of farm management practice training. Table 4 suggests that a positive impact is more likely to be achieved when the recommended practices are adopted as a package of all five practices, rather than the partial or individual adoption of any of them. We examine these effects using regression analyses in the next section.

4. Impact assessment

4.1. Impact of training

To assess the causal influence of the provision of training on the outcomes of our interest, we estimate intention-to-treat (ITT) effects by

Table 5
Practice adoption and the most important information source in the follow-up survey.

Practices	Source of information among adopters (%)				
	Demonstration plot participation	Extension workers	From other farmers	Observation	Ever Known
(S) Seed test by water	39.39	55.56	4.05	0	0
(N) Nursery bed setup	39.40	55.60	5.05	0	0
(B) Bund construction	44.12	25.49	7.84	4.90	17.65
(L) Leveling	37.62	56.44	0	3.96	1.98
(TP) Straight-row transplanting	33.33	63.89	2.78	0	0
Rice variety (Mamima)	12.82	12.82	0	10.26	64.1
Rice variety (Mocuba)	9.52	68.25	7.94	7.94	6.35
Rice variety (Chupa)	29.82	38.60	3.51	15.79	12.28

Sample size = 257.

Table 6
Estimated results of ANCOVA model on the impact of training: rice productivity, practice adoption, and variety adoption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Paddy yield	Seed test by water	Nursery bed setup	Bund	Leveling	Straight-row TP	Use all 5	Use Mamima	Use Mocuba	Use Chupa
Demo 1 (treatment)	545.5*	0.570***	0.592***	0.376**	0.609**	0.508*	0.367*	0.0903*	0.0895	0.0899
p-value	[0.0795]	[0.0085]	[0.0005]	[0.0440]	[0.0390]	[0.0750]	[0.0635]	[0.0985]	[0.3710]	[0.6010]
Demo 2 (treatment)	447.5*	0.479*	0.461***	0.326**	0.416**	0.449**	0.200	−0.00583	−0.0568	0.289
p-value	[0.0650]	[0.0710]	[0.0000]	[0.0265]	[0.0400]	[0.0100]	[0.2015]	[0.8485]	[0.7730]	[0.1380]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Locality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
t-test (Demo 1 = Demo 2)	0.8372	0.7911	1.3768	0.5446	1.3559	0.4146	1.7405	2.0472*	1.8529	−1.7335
	[0.5005]	[0.5795]	[0.3330]	[0.7695]	[0.4005]	[0.7605]	[0.1900]	[0.0570]	[0.1910]	[0.2235]
Control mean value	1535	0.141	0.333	0.192	0.038	0.00	NA	0.167	0.231	0.064
Observations	257	257	257	257	257	257	257	257	257	257
R-squared	0.363	0.300	0.413	0.510	0.395	0.380	0.418	0.403	0.525	0.302

Wild bootstrap cluster robust *p*-values in [ ]; Inverse probability weights are used to control for attrition bias.
*** p < 0.01, ** p < 0.05, * p < 0.1.
See Appendix Table A2 for full regression results.

Table 7
Estimated results of ANCOVA model on the impact of practice adoption.

	(1)	(2)	(3)	(4)
	Paddy yield	Paddy yield	Paddy yield	Paddy yield
VARIABLES	IV	IV	IV	IV
Use all 5 practices	1077**	1456***	1540**	981**
p-value	[0.048]	[0.002]	[0.0104]	[0.0300]
Use at least one practice but not all 5	824.3			
p-value	[0.108]			
Use at least (B) but not all 5		1250*		
p-value		[0.097]		
Use at least (B) (S) (N) but not all 5			1973	
p-value			[0.453]	
Use only (B) (S) (N)				309
p-value				[0.7127]
Control variables	Yes	Yes	Yes	Yes
Locality FE	Yes	Yes	Yes	Yes
t-test (full adoption = partial adoption)	0.262	0.258	0.198	0.599
	[0.797]	[0.728]	[0.800]	[0.543]
Observations	257	257	257	98
R-squared	0.251	0.284	0.051	0.365

Wild bootstrap cluster robust *p*-values in [ ]; Inverse probability weights are used to control for attrition bias for the models (1)-(3) and sub-sample selection for the model (4).
Identifying instrumental variables for the IV model are Demo 1 and Demo 2 dummies.
*** p < 0.01, ** p < 0.05, * p < 0.1.
See Appendix Table A5 for full regression results of OLS and IV.

employing an analysis of covariance (ANCOVA) model specified below (McKenzie, 2012).

$$Y_{ijk1} = \beta_0 + \gamma Y_{ijk0} + \beta_1 D^1_{jk} + \beta_2 D^2_{jk} + \boldsymbol{X}_{ijk0}\boldsymbol{\delta} + \eta_k + \varepsilon_{ijk1} \quad (1)$$

where Y_{ijk1} and Y_{ijk0} are the follow-up and baseline outcome variables of the most important rice plot of household i in association j in locality (*localidade*) k; D^1_{jk} and D^2_{jk} are the treatment dummy variables, equal to 1 if association j in locality k sets up the demonstration plot in the first round (Demo 1) or the second round (Demo 2), respectively; $\boldsymbol{X}_{ijk0}$ is a set of baseline control variables; η_k is the locality fixed effect; ε_{ijk1} is the unobserved error term. Our primary outcome variable Y_{ijkt} is the paddy yield (kg/ha). Our Y_{ijkt} also includes individual practices, the package of five practices, and the variety adoption. When the outcome is binary, the model becomes a linear probability model. Our baseline control variables ($\boldsymbol{X}_{ijk0}$) are the variables used in the balance test in Table 1 and the squared terms for household size and total plot area.

A possible attrition bias was adjusted using the inverse-probability weighting method suggested by Wooldridge (2010). We run a probit regression model that estimates the probability of non-attrition and use the inverse of the probability as weights in equation (1).[11] The probit regression results are presented in Appendix Table A1.[12]

Table 6 shows the estimation results of the treatment effects (β_1 and β_2) in Equation (1). Hereafter, all the results present wild bootstrap cluster robust *p*-values because the number of clusters in our data is less than 42, the threshold for the use of cluster robust standard errors suggested by Angrist and Pischke (2009).[13] The *t*-test of an equal impact

[11] The explanatory variables consist of the same variables in $\boldsymbol{X}$ and the squared term of the head's education.

[12] The result of probit model shows the non-attrition farmers have shorter schooling years, larger asset values, and smaller networks (as statistically significant variables). These variables explain the propensity of non-attrition, and the estimated propensity is used to control for attrition bias.

[13] For wild bootstrap, see Roodman et al. (2019) and Wooldridge (2010).

between Demo 1 and Demo 2 (i.e., $\beta_1 = \beta_2$,) is shown in the lower part of the table. The full regression results with the other control variables are listed in Table A2 in the Appendix.

The results on the yield in Table 6 column (1) indicate that the project increased the yield of the Demo 1 group by 545.5 kg/ha at a p-value of 7.95 % and that of the Demo 2 group by 447.5 kg/ha at a p-value of 6.50 %, which corresponds to a 35.5 % or 29.1 % increase from the control group yield, respectively (see the control group mean of 1,535 kg/ha at the lower part of the table).[14] The t-test of equal impact does not reject the null hypothesis, indicating that a one-year lag in training implementation did not create a significant disadvantage. However, the magnitude is higher in Demo 1 by 98 kg/ha.

As the high adoption rates of the practices in Demos 1 and 2 in Table 2 suggest, the impact of the training on those outcomes is positive and statistically highly significant (columns (2)-(6)), with no statistical difference between β_1 and β_2. The impact of training for the full adoption of five practices (Column (7)) shows a significant result in the Demo 1 group at a p-value of 6.3 %, while Demo 2 gives a positive coefficient at 20 % of the p-value; a possible mechanism can be the requirement of a certain amount of time in a sequential adoption of five practices. The results for variety adoption (columns (8)–(10)) are ambiguous.

Two types of robustness checks were conducted. First, because the yield and the adoption of the five practices are the set of outcomes that the project aimed to achieve, we conducted multiple hypotheses testing to control for the false discovery rate (FDR). Using the procedure proposed by Anderson (2008), adjusted p-values in the form of sharpened q-values are reported in Appendix Table A4. The results show that our hypotheses continued to be rejected at sharpened q-values in the range of 0.2 %–5.6 %. Second, to check whether our sample was appropriate for impact evaluation as originally planned in the power calculation, we computed ex-post minimum detectable effects (MDE) (Appendix Table A4). It demonstrated that in most cases, our impacts were larger than the MDE at 80 % power; otherwise, they were larger at 70 % power, with the exception of the case of the bund construction, where the estimated impacts were slightly smaller than the MDE at 70 % power.[15]

4.2. *Impact of practice adoption on paddy yield*

This sub-section investigates the impact of practice adoption on paddy yield. As variety adoption provides ambiguous results, we focus on practice adoption only. The basic structure of the estimation model is the same as the previous analysis except for the point that treatment dummy variables are replaced with practice adoption dummies.

$$Y_{ijk1} = \beta_0 + \gamma Y_{ijk0} + \beta_1 P^f_{ijk1} + \beta_2 P^p_{ijk1} + \boldsymbol{X}_{ijk0}\boldsymbol{\delta} + \eta_k + \varepsilon_{ijk1} \quad (2)$$

where Y_{ijk1} and Y_{ijk0} are the follow-up and baseline paddy yield, P^f_{ijk1} is the dummy of full practice adoption (all five key practices) by plot-household i in association j in locality k at the follow-up survey time, P^p_{ijk1} is the dummy of particle adoption, keeping the remaining adoption status as the base category (to be explained later). The remaining variables are the same as in equation (1).

Two econometric issues are addressed. First, to control for a possible attrition bias, we apply the same inverse probability weighting method. Second, the endogeneity of practice adoption might remain. We apply an instrumental variable (IV) method by taking advantage of the RCT setting of our survey. The availability of Demo 1 and Demo 2 dummies as identifying instrumental variables allows us to use two endogenous variables P^f_{ijk1} and P^p_{ijk1} in equation (2).

An impact assessment of multiple technologies/practices is statistically cumbersome because there are many combinations. Some of these combinations are minor, and each of them is endogenously determined. A possible solution is to use the number of adopted practices; however, this is not an appropriate explanatory variable in our case because different combinations are classified in the same category so long as the number of the adopted practices is the same (for example, the number of adopted practice is three either for (B)+(S)+(N) or (B)+(L)+(TP)).

Under such conditions, to test complementarity among the five practices, we ran four models to examine each of the four major types of partial adoption status and compare its impact (β_2) with the impact of full adoption (β_1). We start with the broadest status of partial adoption, which is defined as the case of at least one practice adoption, but not all five (Model (1)), keeping non-adoption as the base category. To capture the impact of the core practice, Model (2) uses the adoption of at least (B) but not all five, and to capture the impact of the basic package, Model (3) uses the adoption of at least (B)+(S)+(N), with the base category of the other adoption or non adoption cases. However, a possible problem in Models (1)-(3) is that yield increase under partial adoption (β_2) can become insignificant simply because different yields are achieved under multiple combinations of practices. For example, not only (B)+(S)+(N) alone, but also (B)+(S)+(N) plus one more practice is included in the dummy in Model (3). Hence, the fluctuation may stem from the differential impacts under different combination of practices. To compare a single package of partial adoption against full adoption (another single package), we select the case of adoption of *only* (B)+(S)+(N) for which we still have a reasonable number of sample farmers. Model (4) estimates equation (2) using this adoption dummy with a sub-sample of full adopters, adopters of (B)+(S)+(N) only, and non-adopters (base category) ($n = 98$).[16]

Table 7 shows the estimation results. The t-test results for equal impact ($\beta_1 = \beta_2$) are reported at the lower part of the table. The full regression results with the other control variables as well as the OLS results are shown in Appendix Table A5. The most important finding from all the models is that the yield increased most significantly when the farmers adopted the full package of five practices. The magnitude of impact (β_1 in Model (1)), 1,077 kg/ha, against non-adoption (base category) is reasonable because it is consistent with the magnitude of 1.2 t/ha, which was estimated by crop cuts rather than by farmers' self-report, shown in the project report as the average impact among advanced practice adopters. Meanwhile, any other combinations of the practices do not provide statistically significant results, although the equal impact hypotheses are not rejected. These results suggest that the impact of yield improvement becomes stable when all practices are adopted as a package. Nevertheless, to make a more rigorous argument, we have to wait for future research with more variations in adoption packages as well as larger sample sizes under each package. As indicated in Table 5, to enhance full adoption, conventional extension methods (demo plots and extension worker training) seem to be effective, at least in the short run.[17]

5. Conclusion

This study evaluated the RCT of rice farm management training in

[14] As a robustness check, we combine Demo 1 and Demo 2 dummies and estimate the impact of the training as a whole (Appendix Table A3). The impact on yield is 481.9 kg/ha at a p-value of 4.4%. The qualitative results for the other dependent variables are also consistent with those in Table 6 (or Appendix Table A2).

[15] The MDE was obtained by multiplying the standard errors of each coefficient by the t-values to satisfy either 80% or 70% power.

[16] We apply inverse probability weights to control for the sub-sample selection of 98 sample farmers from 311 baseline sample farmers, using the same probit selection equation as the one used to control for the attrition bias.

[17] This feature may be seen as a supporting fact of our SUTVA assumption. Table 5 shows that social learning is a minor source of information on new practices. Also, the main regression results (Appendix Tables from A2 to A4) show that the network size (percentage of known members) does not significantly explain the outcomes (except for the weak significance for bund construction in Table A3). If the effects of social learning are null within associations, then so might be the effects across associations.

the rainfed lowlands of Mozambique. Our analyses found a positive impact from the training on the adoption of recommended practices and land productivity (paddy yield), indicating the importance of basic management practices for SSA's rice GRs. Our analyses also suggested that the impact could be stable if practices are adopted as a full package. Our findings indicate that, because it was possible to realize a positive impact in rainfed lowlands without relying on purchased modern inputs, the provision of management training could be an effective development strategy to improve the livelihood of poor farmers in remote areas. Note, however, that, as the Asian experience clearly indicates, the potential impact under rainfed conditions without modern inputs is limited, being not as high as that of irrigated conditions with modern inputs. It is an important future research agenda to assess the potential of irrigation development as a long-term development strategy in SSA.

Among the many possible training approaches, our case can be regarded as a combination of the farmer field schgool (FFS) and farmer-to-farmer extension (F2FE) approaches without a monetary incentive for those farmers who teach new practices to others. Because the proportion of full adopters remained low during the survey period (12 %), the exploration of the diffusion mechanism of new practices remains an important research issue. Our results relied on data from smallholding rice farmers in lowland agroecology, which is a dominant mode of rice production in the country. To extend the training beyond such an area, further research on external validity would provide a better understanding of the appropriate training design.

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CRediT authorship contribution statement

Kei Kajisa: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft. **Trang Thu Vu:** Software, Data curation, Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

See Tables A1-A5.

Table A1
Estimation results for the non-attrition probit model.

	Non-attrition = 1
Household size	−0.00415
	[0.916]
Head's education (years)	−0.0335*
	[0.080]
Head's education squared	0.000253*
	[0.071]
Log of asset	0.0866*
	[0.060]
Total plot area (ha)	−0.594
	[0.650]
Total plot area squared	0.521
	[0.405]
Proportion of known members (%)	−0.0107*
	[0.063]
Weather shock in the last rice season (=1)	−0.341
	[0.120]
Weather shock in the last non-rice season (=1)	−0.248
	[0.397]
Constant	1.382**
	[0.024]
Observations	311

Wild bootstrap cluster robust *p*-values in brackets. ** $p < 0.05$, * $p < 0.1$.

Table A2
Full estimation results of ANCOVA model on the impact of training: rice productivity, practice adoption, and variety adoption.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Paddy yield	Seed test by water	Nursery bed setup	Bund	Leveling	Straight-row TP	Use all 5	Use Mamima	Use Mocuba	Use Chupa
Y_0	0.139**	−0.0585	0.214**	0.0530	0.0596	−0.207	N/A	−0.0325	0.141	0.0469
	[0.0250]	[0.1760]	[0.0230]	[0.6040]	[0.2805]	[0.8035]		[0.6185]	[0.1710]	[0.4885]
Demo 1 (treatment)	545.5*	0.570***	0.592***	0.376**	0.609**	0.508*	0.367*	0.0903*	0.0895	0.0899
	[0.0795]	[0.0085]	[0.0005]	[0.0440]	[0.0390]	[0.0750]	[0.0635]	[0.0985]	[0.3710]	[0.6010]
Demo 2 (treatment)	447.5*	0.479*	0.461***	0.326**	0.416**	0.449**	0.200	−0.00583	−0.0568	0.289
	[0.0650]	[0.0710]	[0.0000]	[0.0265]	[0.0400]	[0.0100]	[0.2015]	[0.8485]	[0.7730]	[0.1380]
Household size	−50.13	0.00336	0.0117	−0.0886**	−0.0470	−0.0124	−0.0101	−0.0516	0.0243	0.0241
	[0.7935]	[0.9415]	[0.7195]	[0.0440]	[0.4720]	[0.6835]	[0.6135]	[0.1060]	[0.6995]	[0.5025]
Household size squared	6.379	−1.21e-05	−0.00158	0.00943**	0.00386	0.000529	0.00189	0.00537	−0.00286	−0.00510
	[0.7400]	[0.9980]	[0.6385]	[0.0310]	[0.5495]	[0.8305]	[0.3550]	[0.1430]	[0.5665]	[0.1475]
Head's education (years)	−9.454	−0.00581	−0.0110	−0.00308	6.11e-05	−0.0131	0.00323	−0.00110	−0.00589	0.00546
	[0.5520]	[0.4375]	[0.2720]	[0.6505]	[0.9975]	[0.2320]	[0.6085]	[0.7480]	[0.1570]	[0.5470]
Log of asset	52.09	0.0221	0.000723	0.0210	0.000923	0.0118**	0.00708	−0.00833	0.0223	−0.0249*
	[0.1280]	[0.1715]	[0.9640]	[0.1750]	[0.9670]	[0.0115]	[0.1505]	[0.1940]	[0.1080]	[0.0655]
Total plot area (ha)	−1563***	−0.0910	−0.0191	0.0476	−0.201*	−0.0425	−0.141	0.156*	0.0575	0.0456
	[0.0005]	[0.4460]	[0.8800]	[0.5050]	[0.0755]	[0.6575]	[0.1020]	[0.0620]	[0.4120]	[0.3550]
Total plot area squared	240.6***	0.0367	0.0141	−0.00230	0.0574**	0.0246	0.0353*	−0.0295	−0.0123	−0.00121
	[0.0000]	[0.1000]	[0.6005]	[0.8695]	[0.0270]	[0.1820]	[0.0675]	[0.1410]	[0.3420]	[0.9190]
Proportion of known members (%)	3.53	−0.00178	−0.000388	0.00213	0.000296	0.000119	0.000352	−0.000444	0.000147	−0.00120
	[0.1385]	[0.4065]	[0.8235]	[0.1070]	[0.9145]	[0.9570]	[0.9355]	[0.7640]	[0.9340]	[0.3040]
Weather shock in the last rice season (=1)	130.8	0.0317	−0.0932	0.0340	−0.152	0.0719	0.0852	−0.0312	−0.0490	−0.104
	[0.6210]	[0.6850]	[0.2270]	[0.2275]	[0.3960]	[0.3735]	[0.3490]	[0.6725]	[0.2080]	[0.3905]
Weather shock in the last non-rice season (=1)	−140.4	−0.136	−0.0140	0.0651	0.125	−0.0616	−0.0155	0.0665*	−0.0308	0.0596
	[0.7535]	[0.1005]	[0.8585]	[0.1620]	[0.1460]	[0.3565]	[0.5815]	[0.0860]	[0.5400]	[0.3820]
Constant	1735***	0.222	0.266*	0.173	0.0178	0.0317	0.0190	0.0961	0.226	0.316***
	[0.0010]	[0.1255]	[0.0960]	[0.4895]	[0.9205]	[0.8035]	[0.8065]	[0.4015]	[0.4950]	[0.0080]
Locality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
t-test (Demo 1 = Demo 2)	0.8372	0.7911	1.3768	0.5446	1.3559	0.4146	1.7405	2.0472*	1.8529	−1.7335
	[0.5005]	[0.5795]	[0.3330]	[0.7695]	[0.4005]	[0.7605]	[0.1900]	[0.0570]	[0.1910]	[0.2235]
Control mean value	1535	0.141	0.333	0.192	0.038	0.00	NA	0.167	0.231	0.064
Observations	257	257	257	257	257	257	257	257	257	257
R-squared	0.363	0.300	0.413	0.510	0.395	0.380	0.418	0.403	0.525	0.302

Wild bootstrap cluster robust *p*-values in brackets; Inverse probability weights are used to control for attrition bias.
N/A: No variation in the baseline observations. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3
Full estimation results of ANCOVA model on the impact of training: rice productivity, practice adoption, and variety adoption (Demo 1 and Demo 2 combined).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
VARIABLES	Paddy yield	Seed test by water	Nursery bed setup	Bund	Leveling	Straight-row TP	Use all 5	Use Mamima	Use Mocuba	Use Chupa
Y_0	0.141**	−0.0644	0.222*	0.0521	0.0519	−0.170	N/A	−0.0192	0.130	−0.0183
	[0.0200]	[0.1171]	[0.0330]	[0.6086]	[0.4234]	[0.8118]		[0.7688]	[0.2402]	[0.8759]
Demo 1 or 2 (treatment)	481.9**	0.511**	0.506***	0.344*	0.483**	0.470**	0.258	0.0285	−0.00709	0.226
	[0.0440]	[0.0250]	[0.0000]	[0.0380]	[0.0240]	[0.0140]	[0.1652]	[0.4214]	[0.9610]	[0.2352]
Household size	−49.32	0.00488	0.0138	−0.0877*	−0.0433	−0.0116	−0.00714	−0.0496	0.0266	0.0216
	[0.7888]	[0.9049]	[0.6637]	[0.0460]	[0.4484]	[0.7107]	[0.7417]	[0.1431]	[0.6537]	[0.5896]
Household size squared	6.165	−0.000290	−0.00197	0.00928*	0.00322	0.000365	0.00137	0.00507	−0.00329	−0.00453
	[0.7207]	[0.9469]	[0.5826]	[0.0300]	[0.5936]	[0.8989]	[0.5055]	[0.1481]	[0.5025]	[0.2482]
Head's education (years)	−8.254	−0.00464	−0.00930	−0.00244	0.00264	−0.0123	0.00539	0.000206	−0.00395	0.00258
	[0.6206]	[0.5085]	[0.3654]	[0.7027]	[0.7688]	[0.2322]	[0.3854]	[0.9550]	[0.4174]	[0.7323]
Log of asset	50.62	0.0207	−0.00116	0.0203	−0.00185	0.0110***	0.00476	−0.00998*	0.0199	−0.0221*
	[0.1301]	[0.1529]	[0.9479]	[0.1782]	[0.9219]	[0.0070]	[0.4104]	[0.0911]	[0.1528]	[0.0821]
Total plot area (ha)	−1562***	−0.0919	−0.0202	0.0471	−0.202*	−0.0430	−0.143	0.155*	0.0575	0.0537
	[0.0010]	[0.4084]	[0.8679]	[0.5045]	[0.0901]	[0.6376]	[0.1151]	[0.0721]	[0.4905]	[0.4444]
Total plot area squared	241.9***	0.0381*	0.0162	−0.00149	0.0602**	0.0255	0.0380*	−0.0280	−0.0102	−0.00513
	[0.0000]	[0.0861]	[0.5606]	[0.9209]	[0.0480]	[0.2132]	[0.0531]	[0.1702]	[0.5616]	[0.6957]
Proportion of known members (%)	2.859	−0.00241	−0.00133	0.00178*	−0.00107	−0.000285	−0.000810	−0.00111	−0.000878	0.000309
	[0.2663]	[0.1291]	[0.3033]	[0.0781]	[0.6256]	[0.8889]	[0.8739]	[0.5265]	[0.3423]	[0.7638]
Weather shock in the last rice season (=1)	140.5	0.0400	−0.0816	0.0383	−0.137	0.0769	0.0994	−0.0213	−0.0361	−0.123
	[0.6166]	[0.6056]	[0.3363]	[0.1752]	[0.4044]	[0.3574]	[0.3233]	[0.7818]	[0.2472]	[0.3043]

(*continued on next page*)

Table A3 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Weather shock in the last non-rice season (=1)	−138.6	−0.134	−0.0121	0.0659	0.128	−0.0608	−0.0126	0.0665	−0.0293	0.0513
	[0.3634]	[0.1011]	[0.8949]	[0.1522]	[0.1202]	[0.3804]	[0.6617]	[0.1011]	[0.5706]	[0.4825]
Constant	1755***	0.244*	0.295*	0.185	0.0637	0.0458	0.0574	0.119	0.269	0.272**
	[0.0000]	[0.0881]	[0.0881]	[0.4454]	[0.7257]	[0.6727]	[0.6376]	[0.2813]	[0.3323]	[0.0350]
Locality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control mean value	1535	0.141	0.333	0.192	0.038	0.00	NA	0.167	0.231	0.064
Observations	257	257	257	257	257	257	257	257	257	257
R-squared	0.362	0.296	0.402	0.508	0.373	0.378	0.381	0.393	0.507	0.270

Wild bootstrap cluster robust *p*-values in brackets; Inverse probability weights are used to control for attrition bias.
N/A: No variation in the baseline observations. *** p < 0.01, ** p < 0.05, * p < 0.1.

Table A4
Multiple hypothesis testing and ex-post minimum detectable effect (MDE) analyses on the impact of training: rice productivity and practice adoption (corresponding to Tables 6 and A2).

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Paddy yield	Seed test by water	Nursery bed setup	Bund	Leveling	Straight-row TP
Demo 1 (treatment)	545.5*	0.570***	0.592***	0.376**	0.609**	0.508*
p-value	[0.0795]	[0.0085]	[0.0005]	[0.0440]	[0.0390]	[0.0750]
sharpened *q*-values	{0.056}	{0.026}	{0.003}	{0.047}	{0.047}	{0.056}
Ex-post MDE (80 % Power)	601.3	0.319	0.268	0.429	0.440	0.388
Ex-post MDE (70 % Power)	535.0	0.284	0.239	0.382	0.391	0.345
Demo 2 (treatment)	447.5*	0.479*	0.461***	0.326**	0.416**	0.449**
p-value	[0.0650]	[0.0710]	[0.0000]	[0.0265]	[0.0400]	[0.0100]
sharpened *q*-values	{0.056}	{0.056}	{0.002}	{0.045}	{0.047}	{0.026}
Ex-post MDE (80 % Power)	464.3	0.460	0.325	0.377	0.427	0.392
Ex-post MDE (70 % Power)	413.1	0.409	0.289	0.336	0.380	0.349

Wild bootstrap cluster robust *p*-values in [ ]; Sharpened *q*-values for false discovery rate (FDR) among models (1)-(6) in { }; Ex-post minimum detectable effects (MDE) are based on the standard errors of estimated coefficients; Inverse probability weights are used to control for attrition bias.
*** p < 0.01, ** p < 0.05, * p < 0.1.
See Appendix Table A2 for full regression results.

Table A5
Full estimation results of ANCOVA model on the impact practice adoption.

	(1)		(2)		(3)		(4)	
	Paddy yield	Paddy yield	Paddy yield	Paddy yield	Paddy yield	Paddy yield	Paddy yield	Paddy yield
VARIABLES	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Y_0	0.142**	0.137**	0.143***	0.150***	0.141**	0.140*	0.240***	0.255***
	[0.019]	[0.023]	[0.000]	[0.005]	[0.0100]	[0.0681]	[0.0070]	[0.0040]
Use all 5 practices	489.4*	1077**	641.5***	1456***	500.2*	1540***	678.8*	981.0**
	[0.077]	[0.048]	[0.009]	[0.002]	[0.0611]	[0.0020]	[0.0861]	[0.0290]
Use at least one practice but not all 5	−1.230	824.3						
	[0.996]	[0.108]						
Use at least (B) but not all 5			265.9	1250*				
			[0.102]	[0.0.97]				
Use at least (B) (S) (N) but not all					93.37	1973		
					[0.6416]	[0.1311]		
Use only (B) (S) (N)							447.5	309.5
							[0.2162]	[0.7207]
Household size	−14.23	−82.33	2.409	57.41	−10.13	51.51	−376.3	−403.8
	[0.921]	[0.605]	[0.985]	[0.721]	[0.9469]	[0.7177]	[0.1612]	[0.1001]
Household size squared	2.000	9.241	0.330	−5.313	1.629	−4.155	35.37	37.51
	[0.898]	[0.640]	[0.985]	[0.745]	[0.9299]	[0.7718]	[0.8769]	[0.1321]
Head's education (years)	−12.02	−1.839	−10.60	−6.782	−11.76	−11.43	6.526	6.462
	[0.519]	[0.928]	[0.553]	[0.685]	[0.4935]	[0.4875]	[0.9109]	[0.8819]
Log of asset	49.56	47.70	44.39	23.44	48.77	26.92	7.975	−6.699
	[0.128]	[0.140]	[0.176]	[0.486]	[0.1261]	[0.4224]	[0.938]	[0.9429]
Total plot area (ha)	−1507***	−1567***	−1532***	−1579***	−1510***	−1421***	−1096**	−895.1*
	[0.000]	[0.000]	[0.000]	[0.004]	[0.0000]	[0.0000]	[0.0100]	[0.0901]
Total plot area squared	227.1***	237.3***	230.8***	233.1***	226.8***	181.4***	149.3*	109.0
	[0.000]	[0.000]	[0.000]	[0.003]	[0.0000]	[0.0000]	[0.0801]	[0.2593]
Proportion of known (%)	2.570	3.489*	2.137	0.895	2.578	3.921	−1.239	−1.142
	[0.413]	[0.219]	[0.483]	[0.758]	[0.3804]	[0.1391]	[0.8498]	[0.8438]

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Table A5 (*continued*)

	(1)		(2)		(3)		(4)	
	Paddy yield	Paddy yield	Paddy yield	Paddy yield	Paddy yield	Paddy yield	Paddy yield	Paddy yield
Weather shock in the last rice season (=1)	111.7	167.2	109.1	75.04	112.4	45.27	−16.34	−103.2
	[0.572]	[0.448]	[0.562]	[0.664]	[0.5716]	[0.8048]	[0.9750]	[0.8238]
Weather shock in the last non-rice season (=1)	−163.4	−165.4	−174.8	−208.0	−162.1	−104.7	−184.5	−186.9
	[0.333]	[0.316]	[0.351]	[0.278]	[0.3784]	[0.5696]	[0.5485]	[0.5325]
Constant	1870***	1509***	1799***	1486***	1850***	1270	2268***	2298***
	[0.000]	[0.000]	[0.000]	[0.004]	[0.0000]	[0.1081]	[0.0010]	[0.0010]
Locality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	257	257	257	257	257	257	98	98
R-squared	0.346	0.284	0.353	0.251	0.347	0.051	0.375	0.366

Wild bootstrap cluster robust *p*-values in brackets.
Inverse probability weights are used to control for attrition bias for the models (1)-(3) and sub-sample selection for the model (4).
Identifying instrumental variables for the IV model are Demo 1 and Demo 2 dummies. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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