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Is farmer-to-farmer extension effective? The impact of training on technology adoption and rice farming productivity in Tanzania

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ABSTRACT

Agricultural training is a potentially effective method to diffuse relevant new technologies to increase productivity and alleviate rural poverty in Sub-Saharan Africa (SSA). However, since it is prohibitively expensive to provide direct training to all the farmers in SSA, it is critically important to examine the extent to which technologies taught to a small number of farmers disseminate to non-trained farmers. This paper investigates the technology dissemination pathways among smallholder rice producers within a rural irrigation scheme in Tanzania. As an innovative feature, we compare the performance of three categories of farmers: key farmers, who receive intensive pre-season training at a local training center; intermediate farmers, who are trained by the key farmers; and other ordinary farmers. By collecting and analyzing a unique five-year household-level panel data set, we estimate difference-in-differences models to assess how the gap in performance evolve as the technologies spill over from the trained farmers to the ordinary farmers. To disentangle the technology spillover process, we also examine the extent to which social and geographical network with the key and intermediate farmers influences the adoption of technologies by the ordinary farmers, by incorporating social relationship variables into spatial econometric models. We found that the ordinary farmers who were a relative or residential neighbor of a key or intermediate farmer were more likely to adopt new technologies than those who were not. As a result, while the key farmers' technology adoption rates rose immediately after the training, those of the non-trained ordinary farmers caught up belatedly. As the technologies disseminated, the paddy yield of the key farmers increased from 3.1 to 5.3 tons per hectare, while the yield of the ordinary farmers increased from 2.6 to 3.7 tons per hectare. Our results suggest the effectiveness and practical potential of farmer-to-farmer extension programs for smallholders in SSA as a cost effective alternative to the conventional farmer training approach.

1. Introduction

Technological change is a necessary step in the development process. This is especially true for agricultural development in Sub-Saharan Africa (SSA), where agricultural productivity has been largely stagnant for many years. This is in sharp contrast to the experience of Asia, where the Green Revolution has significantly improved grain yields for the last several decades (Otsuka & Kalirajan, 2005; Otsuka & Yamano, 2005). Among major cereals, rice is considered to be one of the most promising crops to achieve the African Green Revolution (Otsuka & Kijima, 2010; Seck, Tollens, Wopereis, Diagne, & Bamba, 2010; Tsusaka & Otsuka, 2013). Fertilizer-responsive, high-yielding modern rice varieties developed in Asia have exhibited high yield potential and adaptability, especially in irrigated areas in SSA (Nakano, Bamba, Diagne, Otsuka, & Kajisa, 2013; Otsuka & Larson, 2013). Despite their significant high yield potential, however, modern varieties, chemical fertilizers, and improved agronomic practices have yet to be widely adopted in SSA (Nakano, Kajisa, & Otsuka, 2015). Since such high-potential technologies are already available, it is vitally important to investigate how these technologies diffuse among small-scale farmers for the improvement of rice productivity in SSA.

One potentially effective method to diffuse these new technologies is agricultural training (Anderson & Feder, 2007; Feder, Just, & Zilberman, 1985; Otsuka & Larson, 2015). However, since it would

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be prohibitively expensive to train all the farmers in SSA on new rice cultivating technologies, examining the extent to which technologies taught to a small number of farmers disseminate to non-trained farmers through social and neighborhood networks may lead to more practical alternatives. Recently there has been increasing empirical interest in social learning as a means of technology dissemination and some studies observe that social leaning or "learning from others" plays a significant role in agricultural technology adoption (Adegbola & Gardebroek, 2007; Bandiera & Rasul, 2006; Case, 1992; Conley & Udry, 2010; Foster & Rosenzweig, 1995; Maertens & Barrett, 2012; Moser & Barrett, 2006; Munshi, 2004). If social learning works effectively, new technologies taught to a small number of farmers should diffuse to other farmers through social networks. However, the existing empirical results on the diffusion of technologies from trained farmers to non-trained farmers are mixed. In some studies, technologies did not spread from trained farmers to non-trained farmers as effectively as expected (Feder, Murgai, & Quizon, 2004; Tripp, Wijeratne, & Piyadasa, 2005), while other studies document technology diffusion of the sort, though the extent of technology spillover is not fully assessed (see Davis et al., 2012 for the review).

This paper investigates the effectiveness of farmer-to-farmer training programs on rice cultivation technologies provided by the Japan International Cooperation Agency (JICA) and the Ministry of Agriculture Training Institute (MATI) of Tanzania in 2009. JICA and MATI sought to establish a farmer-to-farmer training scheme, called TANRICE training,[1] as a potentially cost-effective way of disseminating agricultural technologies. As a first step, 20 farmers (designated "key farmers") in a regional irrigation scheme were trained on new cultivation technologies at a nearby training institute for 12 days before the start of the main crop season of 2009. Once the season was underway, these key farmers, together with officers of MATI and the village extension officer, held training sessions at a demonstration plot. For these in-season training sessions, each key farmer was responsible for inviting five additional farmers. The invited farmers were referred to as "intermediate farmers" and were expected to later train other non-trained "ordinary farmers." This training structure provided a unique opportunity to examine whether technologies taught to a small number of selected farmers would effectively disseminate to non-trained farmers.

We formulated two hypotheses: (1) First, since the key farmers are the most intensively trained, they adopt the new technologies and achieve higher yield rapidly after training, which expands the yield gap between the key farmers and the others. Subsequently, the intermediate farmers follow the key farmers, which narrows the yield gap between the key and intermediate farmers and widens the yield gap between the intermediary and ordinary farmers. However, in the course of time, the ordinary farmers also catch up by learning technologies from the key and intermediate farmers, thereby closing the gaps in yield and technology adoption. (2) Our second hypothesis is that the ordinary farmers learn new technologies by communicating with the key and intermediate farmers through social and geographical networks.

In order to examine these hypotheses, a five-year panel data set was constructed to cover the period before and after TANRICE training by combining survey data collected in 2010, 2011, and 2012, and recall data for 2008 and 2009 collected in 2010. In examining our first hypothesis, we employ fixed effects difference-in-differences (FE-DID) and propensity score matching difference-in-differences (PSM-DID) models to estimate the changes in impact of TANRICE training on the adoption of technologies by the key, intermediary, and ordinary farmers, and assess its effect on their productivity. To address our second hypothesis, we utilize spatial econometric method to investigate the facilitating role of the key and intermediate farmers in the adoption of technologies by the ordinary farmers. In the spatial models, we also control for possible spillover effects among the ordinary farmers, since early adopters may also influence the behavior of other ordinary farmers.

We found that the technology adoption rates, productivity, and profitability of the key farmers rose immediately after training, which resulted in a wider gap between the key farmers and the other farmers in the initial stage of the program. In a remarkable finding, however, the gap decreased within a matter of a few years due to technology dissemination from the key and intermediate farmers to the ordinary farmers. Over the course of the study, the paddy yield of the key farmers increased from 3.1 tons per hectare in the year preceding the training to a high of 5.3 tons per hectare, while the yield of the ordinary farmers increased from 2.6 to 3.7 tons per hectare. These results suggest the effectiveness and potential of farmer-to-farmer agricultural training programs.

Our paper is organized as follows: Section 2 describes the study site and data collection method, followed by descriptive analyses in Section 3. Section 4 shows the FE-DID and PSM-DID analyses of the impact of TANRICE training on the adoption of technologies and the paddy yield for the three categories of farmers. Changes in income and profit over time, for each category of farmers, are also examined. In Section 5, spatial econometric analyses are performed to examine the influential role of the key and intermediate farmers in the technology adoption by the ordinary farmers through social and geographical networks. Section 6 concludes the paper.

2. Study site and data

2.1. Study site

The panel surveys were conducted among rice farming households in the Ilonga irrigation scheme in the Kilosa district, Morogoro region, of Tanzania. The irrigation scheme is located nearly 15 km from the nearest town of Kilosa. The main crop season in this area runs from November to May, during which farmers produce rice on irrigated plots, while other crops such as maize, beans, and vegetables are grown on rainfed upland plots. During the short crop season from July to September, some farmers produce vegetables on the irrigated plots.

For farmers in the irrigated area, JICA provided the TANRICE training on rice production technologies before and during the main crop season from November 2008 to May 2009. (Hereinafter this particular crop season will be referred to as the 2009 crop season; likewise, prior and subsequent crop seasons will be referenced by the year in which they end.) The program covered several technologies: the use of modern varieties of rice, the application of chemical fertilizer, improved bund construction, plot leveling, and transplanting in rows. Improved bund construction entails piling soil solidly around the plots, while plot leveling involves flattening the ground for better storage and equal distribution of water on paddy fields. Transplanting seedlings in rows allows rice growers to control plant density precisely and remove weeds easily.

As noted earlier, intensive training was offered to 20 farmers, called key farmers, at the nearby training institute (MATI Ilonga) over a period of 12 days in November 2008 prior to the 2009 crop season. Subsequently, during the 2009 main crop season, each key farmer invited five intermediate farmers to training sessions held at a demonstration plot within the irrigation scheme. The key farmers and MATI jointly provided three-day training sessions to the intermediate farmers at three different stages of farming—nursery preparation, transplanting, and harvesting. Following

[1] The formal name for the TANRICE training program is Technical Cooperation in Supporting Service Delivery Systems of Irrigated Agriculture (TC-SDIA).

these “in-field training” sessions, both key and intermediate farmers were expected to disseminate technologies to the remaining farmers (i.e., the ordinary farmers). One day of the in-field training was open to attendance by all the farmers in the scheme, including the ordinary farmers.

The key farmers were selected by MATI based on such criteria as age, literacy, gender balance, residence within the irrigation scheme, and the practice of rice farming, and were confirmed at an all-villagers meeting. The intermediate farmers were selected personally by the key farmers but not by MATI. Thus, the selection of the key and intermediate farmers was purposive. Neither the key nor the intermediate farmers were paid for attending the training.

Our data show that only six households out of a total of 202 had received any training in rice cultivation before TANRICE training was implemented. From 2008 to 2012, there were only two other interventions in the villages. The fertilizer subsidy program, in which farmers can purchase chemical fertilizer at discounted prices, was begun in 2009. The other intervention involved a randomized controlled trial of micro credit conducted by the authors in collaboration with a micro credit organization, BRAC in 2012. Since participation in these programs was endogenously determined by farmers, participation is not an appropriate variable for us to include unless properly treated for endogeneity bias. The detailed impacts of these interventions are out of the scope of this paper. Thus, in some analyses we present the results without explicitly controlling for participation in these programs. Note, however, that the main results of our analysis are robust to the inclusion of farmer participation in the other programs.

2.2. Data

Three rounds of the survey were implemented, in 2010, 2011, and 2012. In the first survey, we randomly selected 208 farmers from the farmer roster in the irrigation scheme and asked the respondents to identify the most important rice plot for their livelihood, which is hereafter referred to as the farmer’s “sample plot.”[2] Farmers were asked in detail about rice cultivation on their sample plot, which included detailed information on their use of labor, capital, and other inputs in 2010. Similar information on the sample plot was collected for the 2011 and 2012 crop seasons as well. This enables us to calculate not only paddy yield and technology adoption but also the income and profit of rice cultivation for these three years.

During the first survey in 2010, we collected relevant recall data on rice cultivation on the sample plot for the 2008 and 2009 main crop seasons, which were before and during the TANRICE training, respectively. We observed that it was relatively easy for farmers to recall their technology adoption and harvest for the previous two years, but somewhat difficult for them to remember all the details of input use and past prices. Thus, we restrict ourselves to using recall data only for technology adoption and paddy yield, while we rely on the 2010–2012 data for revenue, costs, income, profit, and social network variables.

Recall data have been widely used to address various research questions on smallholder agriculture in rural household surveys (e.g., Erenstein, Farooq, Malik, & Sharif, 2008; Muller & Zeller, 2002). The potential for measurement error and other possible biases has been examined comprehensively by, for instance, Dex (1991) and Bound, Brown, and Mathiowetz (2001). The conclusions from these studies are consistent: recall data are rather reliable when the recall period is shorter, the activity being measured is salient, and the practice is habitual over a long period. In our context, the participation in smallholder farmers in agriculture tends to be habitual over years and involve salient events that directly determine their harvest and thus their livelihoods. Regarding the recall period, Lunn (2010) admits that recall data are prone to measurement errors when dating back for decades, and Powers, Goudy, and Keith (1978) show that ten years’ recall data are unsuitable for descriptive purposes. We assume that our use of recall for two years is not extreme and will not significantly jeopardize the implications of our results. Another aspect to consider is the type of variables. Dex (1991) suggests that face-to-face surveys and aided recall (lists of prompts) improve accuracy. The present survey was carried out face-to-face and respondents were adequately prompted.

We also asked farmers in detail about their relationship with the key and intermediate farmers, including whether they are a relative, residential neighbor, or a member of the same church or mosque. The GPS coordinates of the sample plots were recorded in order to calculate geographical distances among the sample plots.[3] Fig. 1 maps all the sample plots cultivated by the key, intermediary, and ordinary farmers. In addition, the information on basic household characteristics, including demography, land and asset holdings, was collected during the first survey.

Data cleaning was performed by dropping those households that took erroneous values in important variables for analyses and those that did not grow rice on the sample plot. Those households that were interviewed in the first round of the survey but not found in the second and third rounds were also omitted. This resulted in 171 usable observations for 2008, 182 for 2009, 202 for 2010, 168 for 2011, and 167 for 2012.[4] In order to examine the seriousness of attrition bias, we estimated an attrition probit model and confirmed that the attrition had occurred randomly with respect to the observed set of variables.[5] This implies that analysis using the available observations (i.e., both balanced and unbalanced panel data) will not suffer attrition bias. Thus, we basically use the unbalanced panel data, which have more information due to the larger sample size, while we employ balanced panel data for our spatial models as a computational requirement.[6]

3. Descriptive analyses

This section provides an overview of the transformation taking place in the studied community by way of lucid descriptive statistics. The arguments in this section will be more formally tested in

[2] In our sample, key farmers were slightly more over-represented than were the intermediary and ordinary, while the key farmers were also a minority. We have examined the extent to which sample weight adjustment would affect our results. This correction resulted in almost identical estimates, and thus we have safely decided to omit this adjustment.

[3] We can emphasize two relevant facts pertinent to possible concerns as to omission of plots other than the most important plot. First, a considerable portion of the sampled farmers own one plot only. These farmers do not cause the issue being raised. Second, according to Santos and Barrett (2008), random sampling data perform fairly well when ties between individuals are also constructed randomly. In our context, a pair of plots being in the geographical neighborhood is not completely random but much more exogenous than the case of social network formation. Hence, although our plot data are not as perfect as those based on census data, we still believe that they are fairly conducive to representing the population’s plot neighborhood structure in our study area.

[4] Note that the number of observations in 2008 and 2009 is smaller than in 2010 because the first round of the survey was conducted in 2010 and some of the respondents did not cultivate the sample plots in 2008 and 2009.

[5] The results of the attrition probit model are available upon request. In the estimated model, the dependent variable takes a value of 1 if the sample was observed in the first round of the survey in 2010 but not in other years. We include all the household characteristics used in our main analysis as independent variables. Joint significance tests of all the independent variables failed to obtain statistical significance at 10%. See Baulch and Quisumbing (2011) for more details on attrition probit model.

[6] We also confirmed that the main results of our analysis did not change when we used balanced panel data.

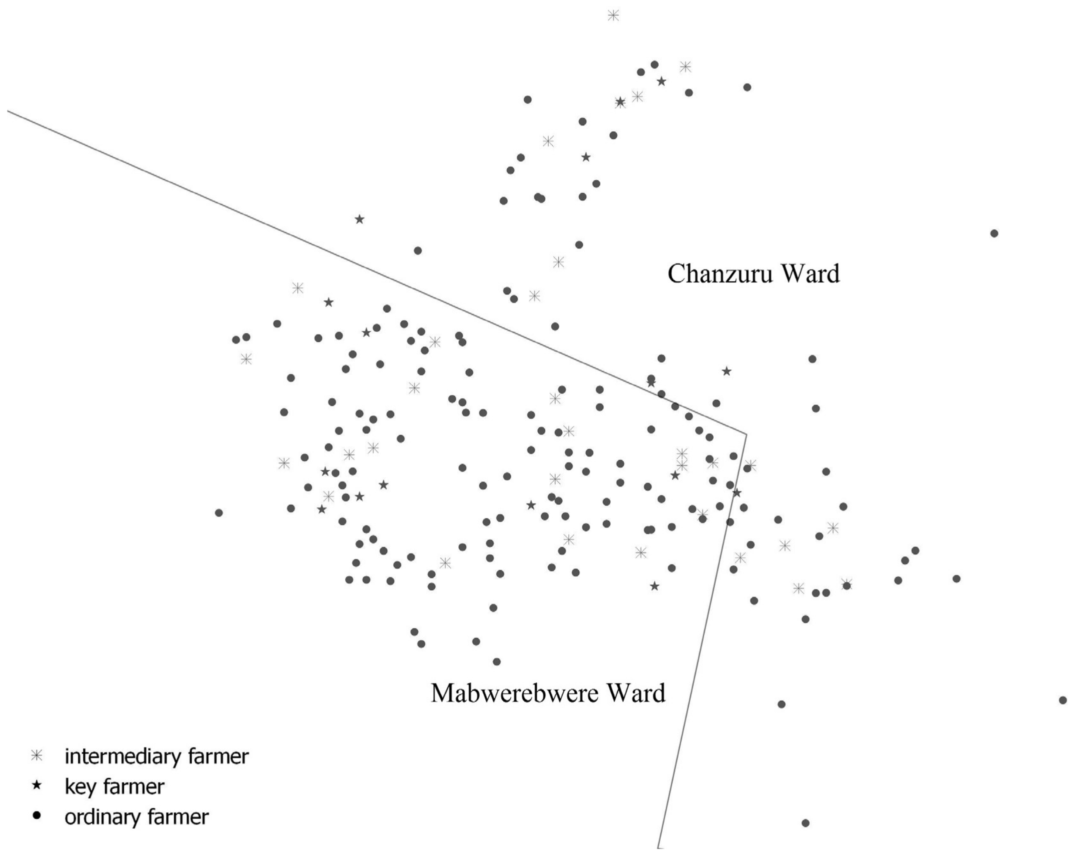

Fig. 1. The map of sample plots. *Sources:* Adapted from the Survey Data and Esri Boundary Data.

the latter sections by using econometric models. Table 1 compares the basic household characteristics of the key, intermediary, and ordinary farmers. The results of *t*-tests for continuous variables and χ^2-tests for dummy variables used in comparisons of the key and intermediate farmers to the ordinary farmers are shown in the table, with asterisks indicating the associated level of significance. As explained earlier, the selection of the key and intermediate farmers was purposive, and thus we observe some differences in their characteristics and those of the ordinary farmers. We find that the key farmers, on average, have larger numbers of household family members, had slightly more years of education, are more likely to be members of the same church or mosque as other key or intermediate farmers, and have more relatives in the village. The intermediate farmers are more likely to be older, have a female head of household, and have larger plots in lowland areas. They are also more likely to be residential neighbors of other key and intermediate farmers. We will take these differences between the trained farmers and the ordinary farmers into consideration in our analyses.

Table 2 presents the changes in the average paddy yields and the adoption of technologies by the key, intermediary, and ordinary farmers. Again, the results of *t*-tests and χ^2-tests comparing the key and intermediate farmers to the ordinary farmers are shown. Note that the TANRICE training was conducted immediately before and during the 2009 main crop season. The table shows that even prior to the training (i.e., in 2008), the key farmers obtained a slightly higher yield than did the ordinary farmers, presumably due to the higher adoption rates of technologies. The key farmers' yield clearly increased soon after the training, from 3.1 tons per hectare in the pre-training year 2008 to 4.4 tons per hectare in 2009, owing to their increased rates of technology adoption. They continued to achieve higher yields than the ordinary farmers, reaching 5.3 tons per hectare in 2011 and 4.7 tons per hectare in 2012. The key farmers' adoption rates for modern varieties, improved bund construction, transplanting in rows, and chemical fertilizer use also rapidly increased in 2009 and remained significantly higher than the ordinary farmers until 2012, contributing to a high yield in each year.

In contrast, the change in yield from the 2008 base year for the intermediate farmers is not as rapid as that of the key farmers. Even so, soon after receiving the training during the 2009 season, the technology adoption rates for the intermediate farmers including modern varieties, improved bund, and transplanting in rows began increasing, eventually boosting the yield to a significantly higher level than the ordinary farmers in 2011. These results indicate that the effect of the training, both in terms of magnitude and immediacy, is greater for the key farmers than for the intermediate farmers; however, the intermediate farmers caught up with the key farmers over the years.

The paddy yield for the ordinary farmers also rose, from 2.6 tons per hectare in 2008 to 3.7 tons per hectare in 2012, though the change was neither rapid nor drastic when compared with the key and intermediate farmers. This increment can be attributed to an increase in the use of chemical fertilizer and improved agronomic practices. The belated, yet significant, technological changes seen in the ordinary farmers indicate that technologies taught in the TANRICE training spilled over from the key and intermediate farmers to the ordinary farmers over the years. In fact, the yield gap between the key and ordinary farmers ranged from 1.7 to 2.3 tons per hectare between 2009 and 2011, while it diminished to one ton per hectare in 2012. These results are consistent with our first hypothesis that the key farmers' performance improves

Table 1
Household characteristics of key, intermediary, and ordinary farmers in 2010.

	Key	Intermediary	Ordinary
=1 if female headed household	0.13	0.35**	0.18
	[0.34]	[0.49]	[0.39]
Number of adult household members	3.25**	2.97	2.70
	[1.69]	[1.28]	[1.25]
Age of household head	46.44	50.45*	46.74
	[9.88]	[11.70]	[14.67]
Average years of schooling of adult household members	7.29**	6.72	6.31
	[1.38]	[1.31]	[2.25]
Size of sample plot (ha)	0.43	0.43	0.41
	[0.15]	[0.18]	[0.22]
Size of owned plots in upland area (ha)	0.15	0.12	0.09
	[0.51]	[0.28]	[0.23]
Size of owned plots in lowland area except sample plot (ha)	0.32	0.38*	0.24
	[0.35]	[0.44]	[0.45]
Value of household asset (million Tsh)	0.58	0.46	0.58
	[0.37]	[0.47]	[1.06]
=1 if he/she is member of same church/mosque as key or intermediate farmers	1.00**	0.87	0.80
	[0.00]	[0.34]	[0.40]
=1 if he/she is relative of key or intermediate farmers	0.69	0.61	0.55
	[0.48]	[0.50]	[0.50]
=1 if he/she is residential neighbor of key or intermediate farmers	0.81	0.94**	0.68
	[0.40]	[0.25]	[0.47]
Number of relatives in the village	13.25*	8.32	9.17
	[11.50]	[7.63]	[11.22]
Irrigation block B	0.31	0.45	0.43
	[0.48]	[0.51]	[0.50]
Irrigation block C	0.19	0.19	0.28
	[0.40]	[0.40]	[0.45]
Irrigation block D	0.00	0.03	0.05
	[0.00]	[0.18]	[0.21]
Observations	16	31	155

Standard deviations in brackets. ***Statistically significant at 1%, **5%, and *10% in a *t*-test for continuous variables, or in a *chi-square* test for dummy variables, comparing key and intermediate farmers to ordinary farmers.

rapidly after the training, while the ordinary and intermediate farmers eventually catch up with the key farmers, resulting in a smaller gap in yield and technology adoption in later years.

It is important to note that annual rainfall in the post-training years was not higher than that in the pre-training year (2008) except for year 2011, when farmers enjoyed abundant rainfall. In particular, rainfall in the 2012 season was the lowest in several years, which may have resulted in slightly lower adoption rates for several technologies, including plot leveling and chemical fertilizer, than in 2011. Although admittedly the superior performance in 2011 should be partly attributed to the abundant rainfall, the intermediate and ordinary farmers still achieved high yields even in 2012, the dry year. This fact suggests that the productivity improvement reported in our study is not an accidental result of rainfall conditions, but rather it is due to the adoption of the new technologies taught in the training. Subsidized fertilizer use significantly declined in 2011 because of the delay in the delivery of subsidy.

It would seem reasonable to question how the adoption of yield-enhancing technologies, which entails extra costs, affects household earnings from rice production. Table 3 summarizes the average per-hectare gross output value, costs, income, and profit from rice cultivation for the three categories of farmers, from 2010 to 2012. Gross output value includes self-consumed rice evaluated at the market price, as well as the value of rice sold. Income is defined as gross output value minus the paid-out costs of hired labor, rental machinery, draft animals, and other purchased inputs. Profit is defined as gross output value minus the paid-out costs and imputed costs of self-produced seeds, family labor, and owned machinery and animals, evaluated at village market prices. Profit thus can be interpreted as the return to land and management practices. Again, to underscore the difference among the various categories of farmers, the *t*-test is used in comparisons of the key and intermediate farmers to the ordinary farmers. As explained earlier, these financial data are available only for 2010–2012, the three-year period after the training.

The table shows that both gross output value and costs are generally increasing for all three categories of farmers during this three-year post-training period, resulting in increasing income and profit in 2011 and 2012. The key farmers achieved higher income and profit than did the ordinary farmers in 2010 and 2011 because the key farmers adopted new technologies quickly after the training. Both profit and income for the intermediary and ordinary farmers also increased steadily from 2010 to 2012. Especially, the ordinary farmers earned profit as high as USD 575 per hectare in 2012, which indicates no significant difference from that of the key and intermediate farmers. Note again that rainfall in 2012 was scanty, suggesting that the increase in income and profit for the ordinary farmers is not due to abundant rainfall. In any event, the results indicate that the intermediary and ordinary farmers succeeded in catching up to some degree with the key farmers in terms of not only yield and technology adoption but also income and profit, which is consistent with our first hypothesis.[7]

4. Effects of TANRICE training

4.1. Difference-in-differences

In order to evaluate the effects of TANRICE training on the adoption of rice cultivation technologies and paddy yield, we estimate difference-in-differences (DID) models with multiple time periods and multiple treatment groups (Imbens & Wooldridge, 2007; Meyer, 1995) using our five-year panel data. The dependent variables are paddy yield (tons per hectare) and the following set of technology adoption variables: a dummy variable for MV adoption, the amount of chemical fertilizer use (kg per hectare), and dummy variables for the adoption of improved bund construction, plot leveling, and transplanting in rows, respectively.

It is vitally important to address two potential problems associated with our DID estimation framework. First, as discussed earlier, the selection of the key and intermediate farmers was purposive, which could be a cause for selection bias in estimating the effects of the training on each category of farmers. Second, DID estimation requires the common trends assumption (Lechner, 2010), which essentially asserts that the group participating in the program would have experienced the same change in the outcome variable between the pre-program and the post-program periods as those not participating. If this assumption holds and we can credibly rule out any other over-time changes that may confound the treatment, then the estimators are highly reliable. In order to circumvent these problems, we employ two relevant measures, as illustrated in the subsequent subsections, using: (1) a difference-in-differences with household fixed effects model (FE-DID) and (2) a propensity score matching difference-in-differences model (PSM-DID).

4.2. Estimation model 1: FE-DID

In FE-DID, we utilize the panel structure of our data set to control for unobservable time-invariant household-specific characteristics which may influence participation in training as well as the

[7] Since the opportunity cost of family labor for African rural smallholders tends to be lower than the hired wage (Tsusaka, Msere, Homann-KeeTui, Orr, & Ndolo, 2015), profit tends to be underestimated, which partly explains the negative average profit observed in 2010.

Table 2
Changes in paddy yield and technology adoption by training status (key and intermediate farmers).

	2008	2009	2010	2011	2012
	Pre-training	During training	Post-training		
Key farmer					
Paddy yield (tons/ha)	3.07*	4.40***	4.81***	5.34***	4.67**
	[1.37]	[1.32]	[1.43]	[2.36]	[2.43]
Adoption rate of MVs (%)	46.15	69.23***	75.00***	54.44***	66.67***
	[51.89]	[48.04]	[44.72]	[46.92]	[47.14]
Chemical fertilizer use (kg/ha)	63.42	115.82***	137.73***	178.26***	131.28***
	[71.81]	[86.07]	[74.45]	[89.52]	[67.07]
Adoption rate of improved bund (%)	15.38**	23.08**	31.25***	40.00**	15.38
	[37.55]	[43.29]	[47.87]	[50.71]	[37.55]
Adoption rate of plot leveling (%)	46.15	76.92	81.25	86.67	76.92
	[51.89]	[43.85]	[40.31]	[35.19]	[43.85]
Adoption rate of transplanting in rows (%)	23.08	76.92***	93.75***	93.33***	92.31***
	[43.85]	[43.85]	[25.00]	[25.82]	[27.74]
Subsidized fertilizer user (%)	0.00	30.77	50.00	66.67***	68.00***
	[0.00]	[48.04]	[0.52]	[48.8]	[49.77]
Borrower from BRAC (%)	–	–	–	–	38.46*
					[50.63]
Observations	13	13	16	15	13
Intermediate farmers					
Paddy yield (tons/ha)	2.47	2.57	2.84	4.63***	3.93
	[1.13]	[1.39]	[1.39]	[2.40]	[2.15]
Adoption rate of MVs (%)	30.43	44.44*	54.84**	34.38	49.48**
	[47.05]	[50.64]	[50.59]	[46.52]	[48.97]
Chemical fertilizer use (kg/ha)	22.20**	49.00	79.05	103.85**	95.23
	[34.86]	[41.31]	[50.44]	[63.94]	[58.63]
Adoption rate of improved bund (%)	13.04**	18.52**	22.58**	33.33**	33.33***
	[34.44]	[39.58]	[42.50]	[48.15]	[48.15]
Adoption rate of plot leveling (%)	43.48	70.37	74.19	79.17	62.50
	[50.69]	[46.53]	[44.48]	[41.49]	[49.45]
Adoption rate of transplanting in rows (%)	13.04	44.44***	64.52***	45.83**	58.33**
	[34.44]	[50.64]	[48.64]	[50.90]	[50.36]
Subsidized fertilizer user (%)	4.35	22.22	38.71	20.83	21.25
	[20.85]	[42.37]	[0.50]	[41.49]	[42.31]
Borrower from BRAC (%)	–	–	–	–	29.17
					[46.43]
Observations	23	27	31	24	31
Ordinary farmers					
Paddy yield (tons/ha)	2.57	2.67	2.53	3.58	3.67
	[1.34]	[1.41]	[1.36]	[1.70]	[2.00]
Adoption rate of MVs (%)	26.67	26.76	32.26	23.62	32.85
	[44.39]	[44.43]	[46.90]	[39.33]	[44.04]
Chemical fertilizer use (kg/ha)	46.52	58.31	69.72	85.79	83.16
	[54.63]	[62.95]	[67.59]	[59.49]	[61.57]
Adoption rate of improved bund (%)	2.96	4.93	7.74	16.15	11.54
	[17.02]	[21.73]	[26.81]	[36.95]	[32.07]
Adoption rate of plot leveling (%)	54.81	64.08	69.03	76.15	66.92
	[49.95]	[48.15]	[46.39]	[42.78]	[47.23]
Adoption rate of transplanting in rows (%)	11.11	19.01	25.81	26.92	36.92
	[31.54]	[39.38]	[43.90]	[44.53]	[48.45]
Subsidized fertilizer user (%)	11.11	21.13	32.26	26.15	26.68
	[31.54]	[40.97]	[0.47]	[44.12]	[44.00]
Borrower from BRAC (%)	–	–	–	–	19.23
					[34.17]
Observations	135	142	155	130	130
Annual rainfall (mm)	1027.4	869.2	917.3	1546.9	651.1
Rainfall during the main season (mm)	980.9	925.7	966.6	1326.0	783.6

Standard deviations in brackets. ***Statistically significant at 1%, **5%, and *10% in *t*-test comparisons of key and intermediate farmers to ordinary farmers (i.e., paddy yield, and chemical fertilizer use) or in a *chi-square* test in the case of dummy variables (i.e., being a subsidized fertilizer user, borrowing money from BRAC, adoption rates of MVs, improved bund, plot leveling, and transplanting in rows, respectively). Credit intervention by BRAC was made only in 2012.

trends in the outcomes. The following econometric model is estimated:

$$Y_{it} = \alpha + C_i + \beta T_t + \rho T_t S_i + u_{it} \tag{1}$$

where C_i is the time-invariant household-specific effect for household i; T_t is a vector of four year dummies in year t, with a base year of 2008; S_i is a vector of two training status dummies (i.e., key farmer and intermediate farmer dummies, with their base group being ordinary farmers); T_tS_i is a vector of all pairwise interactions between T_t and S_i; and u_{it} is the stochastic error term. Note that in basic DID models, the terms of time-invariant training status dummies S_i are included. In our case, however, this term is absorbed by C_i, as we control for the household fixed effects.

Table 3
Gross output value, costs, income and profit from rice cultivation (USD/ha) by training status (2010–12).

	2010	2011	2012
Key farmer			
Gross output value (USD/ha)	1328.3***	1691.2***	1823.9**
	[429.36]	[726.86]	[923.77]
Paid-out costs (USD/ha)	333.6	467.2	516.0
	[170.8]	[238.3]	[271.3]
Imputed costs (USD/ha)	812.6	1168.0	1025.1
	[259.9]	[432.19]	[542.24]
Income (USD/ha)	994.8***	1223.9***	1307.9
	[405.53]	[697.61]	[917.16]
Profit (USD/ha)	515.7***	523.2***	798.8
	[424.47]	[742.64]	[972.68]
Observations	16	15	13
Intermediate farmer			
Gross output value (USD/ha)	786.2	1477.0***	1550.7
	[378.20]	[794.76]	[802.73]
Paid-out costs (USD/ha)	257.2	437.8	463.4
	[217.2]	[355.3]	[247.7]
Imputed costs (USD/ha)	916.6	1066.2	922.7
	[396.72]	[450.49]	[235.55]
Income (USD/ha)	528.9	1039.2**	1087.3
	[394.21]	[745.08]	[721.95]
Profit (USD/ha)	−130.5	410.9**	628.0
	[547.2]	[766.6]	[754.6]
Observations	31	24	24
Ordinary farmer			
Gross output value (USD/ha)	718.3	1161.0	1500.8
	[390.81]	[554.37]	[818.70]
Paid-out costs (USD/ha)	271.2	388.5	469.6
	[217.5]	[263.8]	[287.3]
Imputed costs (USD/ha)	923.4	1095.2	925.7
	[406.88]	[496.94]	[336.30]
Income (USD/ha)	447.1	772.5	1031.2
	[358.09]	[527.12]	[742.99]
Profit (USD/ha)	−205.1	65.8	575.1
	[450.9]	[704.4]	[782.7]
Observations	155	130	130

Standard deviations in brackets. ***Statistically significant at 1%, **5%, and *10% in *t*-test comparisons of key and intermediate farmers to ordinary farmers. Paid-out costs include costs of current inputs, rental machinery, and hired labor. Imputed costs include imputed costs of self-produced seeds, use of owned machinery, and family labor evaluated at village market price, rental, and wage rate, respectively.

Years 2009–2012 are all post-treatment years, while 2008 is pre-treatment. Thus, the interaction term coefficients ρ associated with the interaction between the year dummies and training status dummies are the DID estimates of interest to capture the gap in the effects of the training between the trained (key and intermediate) farmers and the ordinary farmers. The strength of this model is that the term C_i absorbs the unobservable time-invariant household characteristics which are likely to affect participation in the treatment. In other words, a potential selection bias is largely controlled for. The year-specific effects represented by β capture the changes in the outcome variables for the ordinary farmers. It is assumed that these year dummies capture the indirect effects of training on the ordinary farmers through knowledge spillover from the trained farmers, in addition to other year-specific characteristics such as weather.

It is important to note that in our case, ρ, the vector of DID estimators, should not be interpreted as the "pure" impact of training, i.e., the difference in growth between the factual and counterfactual situations for the key and intermediate farmers with and without the training intervention, respectively. Rather, ρ is designed to capture the differences between the effect on the key and intermediate farmers and the effect on the ordinary farmers, since β captures the changes in performance of the ordinary farmers, which incorporates the spillover from the key and intermediate farmers. Thus, as the ordinary farmers catch up with the key and intermediate farmers, ρ is expected to become smaller.[8]

4.3. Estimation model 2: PSM-DID

Matching techniques such as the propensity score matching (PSM) create a control subsample with the same observable characteristics as the treatment sample (Heckman, Ichimura, & Todd, 1997). If the dynamics of the outcome variable are based on these observable characteristics, this would eliminate the selection bias and also enhance the credibility of the common trends assumption of DID.

The matching methods are designed to estimate the average treatment effect on the treated (ATT), which is the average difference between the outcomes of training participants and their counter-factual outcomes that would have been obtained if they had not participated in the training. We estimate ATT separately for the key and intermediate farmers. ATT for the key farmers is estimated by matching the key farmers with the ordinary farmers, while ATT for the intermediate farmers is estimated by matching the intermediate farmers with the ordinary farmers.[9] In either case, ATT is formulated as follows:

$$ATT = E(Y_i(1) - Y_i(0)|D_i = 1) \tag{2}$$

where D_i is a dummy variable indicating farmer i's training status, and Y_i is the outcome variable of farmer i, as a function of D_i. To identify ATT, unconfoundedness and overlap are assumed (Rosenbaum & Rubin, 1983). The unconfoundedness assumption implies that, given a set of observable characteristics X_i, potential outcomes are independent of training status. The overlap assumption ensures a positive probability of participation and non-participation.

For matching, we employ PSM methods developed by Rosenbaum and Rubin (1983), as this is the most commonly used in the literature. Other matching methods include Mahalanobis metric matching (Rubin, 1980) and inverse probability weighting (IPW) (Hirano, Imbens, & Ridder, 2003). We estimate the propensity score for participating in training based on the covariates in 2010 in light of the discussion on data collection in Subsection 2.2, assuming that the basic household characteristics had not changed markedly in two years. The results of the propensity score estimation are shown in Appendix Table 1. Given the unconfoundedness and overlap assumptions, potential outcomes are independent of treatment, conditional on the probability that the farmer participates in training $P(X_i)$, and hence ATT becomes:

$$ATT = E(Y_i(1)|D_i = 1, P(X_i)) - E(Y_i(0)|D_i = 0, P(X_i)) \tag{3}$$

where an estimate of the first term on the right-hand side of Eq. (3) can be the average of actual outcomes of the participants, while an estimate of the second term is the average outcome of the non-participants who are matched with training participants according to their propensity scores.

Since panel data are available in our study, we follow the PSM-DID procedure proposed by Heckman et al. (1997) and applied by

[8] Dieye, Djebbari, and Barrera-Osorio (2014) point out that ignoring the spill-over effect on program evaluation causes errors in the estimation results and that the sign of the error depends on the direction of the program impact. In our case, we assume that training of the key and intermediate farmers would generate positive externality to the performance of the ordinary farmers through knowledge spillover. Therefore, ρ is a conservative estimate of the impact of training on key and intermediate farmers. Note, however, that we cannot totally deny the possibility that the adoption of technology by the key and intermediate farmers has a negative impact on the performance of the ordinary farmers through higher adoption costs caused by increased input prices.

[9] At present, PSM involving more than two treatment statuses simultaneously is an ongoing area of research.

Todo and Takahashi (2013), to examine the treatment effect on the over-time change in the outcome variables. Formally, the PSM-DID estimator used in this study is defined as:

$$ATT_{DID} = N^{-1}\sum_{i\in S_1}\left[\Delta Y_i(1) - \sum_{i\in S_0} W(P(X_i), P(X_j), \Delta Y_j(0))\right] \quad (4)$$

where $\Delta Y_i \equiv Y_{it} - Y_{i2008}$ and t is the post-training year: 2009, 2010, 2011, or 2012. S_1 and S_0 are, collectively, the trained farmers and the matched ordinary farmers, respectively. N is the number of observations for the trained farmers. W is a weight determined by the distance in propensity scores between the trained and the matched ordinary farmer observations.

After trying different PSM algorithms, we chose kernel matching (Caliendo & Kopeinig, 2008) with the Epanechnikov kernel function (DiNardo & Tobias, 2001) and the bandwidth (Pagan & Ullah, 1999) of 0.06. The bootstrapped standard errors (Guan, 2003) with 500 repetitions of resampling are presented. We also conduct balancing tests on the differences in means after matching, as shown in Appendix Table 2. We find that no covariates are significantly different between the key and ordinary farmers and between the intermediary and ordinary farmers after matching, suggesting that our matching procedure is successful in generating relevant comparison groups (Wooldridge, 2010).

If there are unobserved variables that affect assignment into treatment and the dependent variable simultaneously, a hidden bias might arise to which matching estimators are not robust. To gauge the extent of this issue, we follow the bounding approach proposed and applied by Rosenbaum (2002), DiPrete and Gangl (2004), and Becker and Caliendo (2007). In short, the approach allows us to determine how strongly an unmeasured variable may influence the selection process to undermine the implications of the matching analysis. Sig+ (p-value) is obtained from Wilcoxon signed rank tests for the ATT while setting the level of hidden bias to a certain value Γ, which reflects our assumption about unmeasured heterogeneity or endogeneity in treatment assignment expressed in terms of the odds ratio of differential treatment assignment due to an unobserved covariate. At each Γ, a hypothetical significance level is calculated, which represents the bound on the significance level of the treatment effect in the case of endogenous self-selection into treatment status. By comparing the Rosenbaum bounds at different levels of Γ, we can assess the strength that unmeasured influences would require in order for the estimated ATT to have arisen purely through selection effects. We present the critical value of Γ that satisfies $p < .10$.

Lastly, when there are many time periods in panel data, the standard errors for autocorrelation need to be adjusted (Bertrand, Duflo, & Mullainathan, 2004). The easiest remedy is to cluster on the household identifier which allows for arbitrary correlation of the residuals among household-specific time series. Although there are not many time periods in our study, we employed clustering to obtain robust standard errors.

4.4. Regression results

Table 4 presents the results of the FE-DID estimation on paddy yield and technology adoption. The year fixed effects are found to be positive and significant in 2009–2012 for the use of chemical fertilizer and the adoption of plot leveling and transplanting in rows; in 2010–12, for improved bund construction; and in 2011–2012, for paddy yield. The adoption of MVs also increased in 2012. This indicates a steady increase in the adoption of technologies as well as paddy yield for the ordinary farmers. We should note that these positive coefficients should not be interpreted as direct effects of TANRICE training on the performance of the ordinary farmers. Rather, it captures the spillover effect from the key and intermediate farmers to ordinary farmers, as well as year specific effects. It is also important to note that this steady increase in yield and technology adoption was not solely attributed to rainfall conditions, since the annual rainfall in 2008 was no lower than in the following years.

For paddy yield, the DID estimates are significant for the key farmers in 2009 and 2010, indicating that training for the key farmers took immediate effect, which is consistent with our first hypothesis. Our results suggest that the impact of training on key farmers' yield is larger by 1.2–1.7 tons per hectare as compared to the yield of the ordinary farmers in 2009 and 2010, respectively. This rapid increase in paddy yield can be attributed to the fast adoption of technologies by the key farmers. The increase in chemical fertilizer use by the key farmers vs. ordinary farmers is larger by 41.8 kg in 2009, 56.3 kg in 2010, and 78.0 kg in 2011. The increase in the adoption rate of transplanting in rows is also steadily higher for the key farmers from 2009 to 2012.

A more striking finding, however, is the absence of significant yield effects of the interaction term between the key farmer dummy and the 2011 and 2012 dummies. This suggests that the key farmers' "yield premium" disappeared by 2011 and 2012. Given that the performance of the ordinary farmers was steadily improving over the period from 2010 through 2012, these results support our first hypothesis that the ordinary farmers catch up with the key and intermediate farmers because of knowledge spillover from the two sources.

We do not observe significant coefficients for the interaction terms of the intermediary and year dummies for paddy yield. On the other hand, these coefficients are positive and significant for chemical fertilizer use in 2010 and 2011 and transplanting in rows in 2009 and 2010. The increase in chemical fertilizer use by the intermediate farmers is larger than that of the ordinary farmers by 22.4 kg in 2009 and 28.5 kg in 2010. The impact of training on the adoption rate of transplanting in rows is also larger for the intermediate farmers, by 21% in 2009 and 34% in 2010 (vs. the ordinary farmers). These results imply that the intermediate farmers adopted new technologies more rapidly than the ordinary farmers, although their productivity increase is no faster than those of the ordinary farmers. Although results are not shown, we obtained consistent results even when we control for the participation in other programs, including fertilizer subsidy and credit program provided by BRAC. This suggests the robustness of our results.

Table 5 summarizes the estimation results of the PSM-DID models on the impact of the key and intermediate farmers. Note that since we estimate ATT by matching key with ordinary farmers and intermediary with ordinary farmers, we do not obtain a year trend in our PSM-DID models. Yet the coefficients for the key and intermediate farmers in each year are comparable with those in the FE-DID models. We obtained largely consistent results in both the PSM-DID and FE-DID models. Namely, key farmers achieve higher yield in years 2009 and 2010 by adopting new technologies, while this 'yield premium' disappears in 2011 and 2012, suggesting that the ordinary farmers are catching up in later years. We do not observe a significant difference in paddy yield for the intermediate farmers. Yet the adoption rate of transplanting in rows increased more rapidly for the intermediate farmers than for ordinary farmers. These results suggest the robustness of our results even after we control for the selection of the key and intermediate farmers and apply a relaxed assumption of common trend in DID estimation.

Table 6 shows the results of the FE-DID estimation for gross output value, costs, income, and profit per hectare from 2010 to 2012, with the base year being 2010. As noted previously, these variables are available only for the post-training period. In this period from 2010 to 2012, the ordinary farmers enjoyed steady increases in gross output value, income, and profit, as indicated

Table 4
Estimation results of difference-in-differences with household fixed effects models for paddy yield (tons/ha) and technology adoption (2008–12).

	(1) Paddy yield (tons/ha)	(2) MVs	(3) Chemical fertilizer use (kg/ha)	(4) Improved bund	(5) Plot leveling	(6) Transplanting in rows
Key * 2009	1.214***	0.233*	41.706**	0.057	0.204	0.480***
	[0.355]	[0.121]	[18.514]	[0.076]	[0.133]	[0.179]
Key * 2010	1.662***	0.173	56.250***	0.057	0.158	0.594***
	[0.459]	[0.161]	[20.969]	[0.080]	[0.134]	[0.129]
Key * 2011	1.135	0.138	78.019**	0.047	0.099	0.596***
	[0.743]	[0.190]	[33.401]	[0.188]	[0.204]	[0.137]
Key * 2012	0.280	0.028	36.415	−0.143	0.147	0.460***
	[0.651]	[0.175]	[26.750]	[0.147]	[0.181]	[0.142]
Intermediary * 2009	−0.226	0.079	3.640	0.030	0.145	0.213**
	[0.243]	[0.088]	[9.963]	[0.050]	[0.097]	[0.094]
Intermediary * 2010	0.141	0.095	22.391*	0.014	0.111	0.340***
	[0.329]	[0.116]	[12.319]	[0.054]	[0.102]	[0.105]
Intermediary * 2011	0.843	−0.026	28.446*	−0.006	0.100	0.139
	[0.525]	[0.117]	[14.794]	[0.147]	[0.133]	[0.117]
Intermediary * 2012	−0.108	0.037	17.926	0.093	0.023	0.173
	[0.574]	[0.148]	[15.020]	[0.149]	[0.134]	[0.119]
Year 2009	0.119	−0.002	10.691***	0.020	0.104***	0.059**
	[0.084]	[0.027]	[3.801]	[0.016]	[0.032]	[0.024]
Year 2010	−0.085	0.049	19.169***	0.030**	0.150***	0.122***
	[0.107]	[0.036]	[4.874]	[0.015]	[0.034]	[0.033]
Year 2011	0.973***	0.022	36.652***	0.111***	0.232***	0.119***
	[0.153]	[0.039]	[5.617]	[0.032]	[0.052]	[0.039]
Year 2012	1.101***	0.130***	34.333***	0.056*	0.133**	0.233***
	[0.178]	[0.049]	[6.152]	[0.031]	[0.061]	[0.046]
Constant	2.653***	0.305***	47.778***	0.075***	0.524***	0.146***
	[0.073]	[0.023]	[2.943]	[0.013]	[0.025]	[0.021]
Observations	891	891	891	891	891	891
R-squared	0.194	0.034	0.164	0.031	0.059	0.144
Number of households	202	202	202	202	202	202

2008–2012 unbalanced panel. Standard error clustered at household level in brackets. ***$p < .01$, **$p < .05$, *$p < .1$. Base year is 2008.

by the year fixed effects, which is consistent with their adoption behaviors in the same years (Table 4). Again, since the rainfall in 2012 was considerably lower than in the other years, these increases in income and profit cannot be explained by weather conditions. Furthermore, the most important finding here is that for income and profit, none of the DID estimators for the key and intermediate farmers is positive and statistically significant, indicating that in these years, increase in income and profit were no longer higher for the key and intermediate farmers than for the ordinary farmers. This suggests that the ordinary farmers successfully caught up with the key and intermediate farmers not only in terms of technology adoption and paddy yield but also income and profit from rice cultivation. Although the results are not shown, we applied the PSM-DID models as in Table 5 for these dependent variables. We confirm that we still do not observe significant differences between the key and ordinary farmers and between the intermediary and ordinary farmers for gross output value, profit, and income, suggesting the robustness of our argument.

5. The influence of key and intermediate farmers on technology adoption by the ordinary farmers

5.1. Estimation model

We examine the effects of social network and spatial network on the technology spillover from the trained farmers to the ordinary farmers by constructing and incorporating social relationship variables into the spatial econometric model. As we will elaborate shortly, the social relationship variables are included to examine the effects of social network, while the spatial model is used to assess the effects of sample plot proximity to the key and intermediate farmers who were adopters. These variables of interest were drawn from the 2010 data, as they were most reliable. As these variables were assumed to be largely time-invariant, we pooled the data from 2009 to 2012 to examine the influence of the social network variables. In addition, the household fixed effects model is also estimated for a robustness check on the time-variant variables. Year 2008 is excluded, as we include a dynamic variable with a one-year lag and because it is a pre-training year.

The spatial model controls for a possible mutual spillover effect among the ordinary farmers themselves, in view of the possibility that the early adopters will influence the behavior of the other ordinary farmers. In the following analysis, our primary interest is in technology adoption by the ordinary farmers (i.e., the recipients of spillover), and thus the sample used in the estimations consists only of the ordinary farmers.

The dependent variables are the set of technology adoption variables: the dummy variable for MV adoption; the amount of chemical fertilizer use (kg/ha); the dummy variables for improved bund construction, leveling of plot, and transplanting in rows, where each dummy variable takes the value of 1 if the corresponding technology is adopted; and the paddy yield (tons/ha).

To estimate the effect of social network with the key and intermediate farmers, we construct three binary variables that take the value of 1 if the ordinary farmer has a key or intermediate farmer as (1) a member of the same church or mosque, (2) a relative, or (3) a residential neighbor. Since people cannot easily select or change their relatives, their church or mosque membership rolls, or their residential neighbors, these variables are assumed to be adequately exogenous for qualitative assessment purposes, though care must be taken in the quantitative interpretation of the coefficients. Furthermore, we attempt to control for certain other factors, including the farmer's own experience with successful adoption, which is represented by the adoption dummy for the previous year multiplied by the yield difference from the peer non-adopters' average in the previous season. We have also included a dummy for participation in the fertilizer subsidy program, a dummy for borrowing money from BRAC, and added variables representing

Table 5
Estimation results of propensity score matching difference-in-differences models for paddy yield (tons/ha) and technology adoption (2008–12).

		(1) Paddy yield (tons/ha)	(2) MVs	(3) Chemical fertilizer use (kg/ha)	(4) Improved bund	(5) Plot leveling	(6) Transplanting in rows
Key * 2009	ATT	1.380***	0.180	39.648**	0.022	0.200	0.553***
	Bootstrap s.e.	[0.415]	[0.126]	[19.227]	[0.093]	[0.175]	[0.206]
	Rosenboum odds ratio	4.85	–	1.40	–	–	1.90
Key * 2010	ATT	2.157***	0.212	52.904**	0.026	0.127	0.810***
	Bootstrap s.e.	[0.493]	[0.180]	[24.935]	[0.094]	[0.202]	[0.138]
	Rosenboum odds ratio	5.65	–	1.80	–	–	3.75
Key * 2011	ATT	0.817	0.251	106.638**	0.161	0.149	0.5187***
	Bootstrap s.e.	[1.058]	[0.213]	[43.714]	[0.248]	[0.316]	[0.170]
	Rosenboum odds ratio	–	–	1.75	–	–	2.90
Key * 2012	ATT	0.382	0.171	54.269	−0.158	0.192	0.493**
	Bootstrap s.e.	[0.863]	[0.206]	[37.013]	[0.227]	[0.293]	[0.229]
	Rosenboum odds ratio	–	–	–	–	–	1.70
Intermediary * 2009	ATT	−0.148	0.058	8.901	0.051	0.172	0.250**
	Bootstrap s.e.	[0.259]	[0.095]	[10.572]	[0.052]	[0.107]	[0.107]
	Rosenboum odds ratio	–	–	–	–	–	–
Intermediary * 2010	ATT	0.074	0.150	21.166	0.082	0.174	0.389***
	Bootstrap s.e.	[0.326]	[0.139]	[14.610]	[0.065]	[0.112]	[0.127]
	Rosenboum odds ratio	–	–	–	–	–	1.40
Intermediary * 2011	ATT	0.388	−0.052	21.160	0.046	0.079	0.242*
	Bootstrap s.e.	[0.674]	[0.131]	[20.50]	[0.154]	[0.171]	[0.131]
	Rosenboum odds ratio	–	–	–	–	–	–
Intermediary * 2012	ATT	0.117	0.049	18.141	0.054	−0.051	0.138
	Bootstrap s.e.	[0.560]	[0.202]	[20.314]	[0.143]	[0.198]	[0.147]
	Rosenboum odds ratio	–	–	–	–	–	–

2008–2012 unbalanced panel. *** $p < .01$, ** $p < .05$, * $p < .1$.We use an Epanechnikov kernel matching with bandwidth of 0.06 and obtain standard errors by bootstrapping with 500 replications.

Table 6
Estimation results of difference-in-differences with household fixed effect models for gross output value, costs, income, and profit from rice cultivation (USD/ha) (2010–12).

	(1) Gross output value (USD/ha)	(2) Paid-out costs (USD/ha)	(3) Total costs (USD/ha)	(4) Income (USD/ha)	(5) Profit (USD/ha)
Key * 2011	−83.754	4.682	153.857*	−88.436	−242.293
	[228.288]	[59.440]	[80.742]	[230.186]	[233.703]
Key * 2012	−307.942	−28.578	200.147	−279.363	−479.510
	[266.581]	[63.093]	[183.550]	[275.993]	[295.708]
Intermediary * 2011	293.602*	68.079	−40.678	225.523	266.200
	[167.525]	[77.634]	[87.160]	[183.052]	[179.957]
Intermediary * 2012	−86.989	12.507	27.169	−99.496	−126.665
	[193.590]	[49.620]	[86.470]	[177.877]	[175.342]
Year 2011	445.156***	118.464***	56.041	326.692***	270.651***
	[47.998]	[20.813]	[44.565]	[47.325]	[64.266]
Year 2012	793.653***	202.346***	−193.550***	591.306***	784.856***
	[66.436]	[23.383]	[42.145]	[60.194]	[71.932]
Constant	775.612***	272.877***	635.416***	502.734***	−132.681***
	[27.949]	[10.387]	[18.168]	[26.854]	[31.240]
Observations	538	538	538	538	538
R-squared	0.373	0.247	0.107	0.259	0.299
Number of households	202	202	202	202	202

2010–2012 unbalanced panel. Standard error clustered at household level in brackets. *** $p < .01$, ** $p < .05$, * $p < .1$. Base year is 2010. Paid-out costs include costs of current inputs, rental machinery, and hired labor. Total costs include paid out costs and imputed costs of self-produced seeds, use of owned machinery, and family labor evaluated at village market price, rental, and wage rate, respectively.

the farmer's total number of relatives in the village and other household characteristics, as shown in Table 7.

In order to estimate the influence of geographical proximity to the key and intermediate farmers, we included the spatial weighted average of the key and intermediate farmers' outcome variables, using the inverse squared distance from each ordinary farmer's plot as weights. The distance between plots is calculated from the GPS coordinates collected in the 2010 survey. In addition, we need to carefully consider spatial interdependence in both the dependent variables and error terms (e.g., Anselin, 1988; LeSage & Pace, 2009; Tsusaka, Kajisa, Pede, & Aoyagi, 2015). In our context, the former can be interpreted as the learning effect among vicinal ordinary farmers, while the latter is regarded as the resemblance in adoption behavior arising from common unobservable conditions such as soil quality and water availability due to the proximity of the sample plots. Specifically, we estimate a spatial autoregressive disturbance (SARAR) model (LeSage & Pace, 2009). In this model, the spatial dependence in both dependent variables and the disturbance term is controlled for.[10] Let K, I, and O represent the number of observations for the key, intermediary, and ordinary farmers, respectively. The main estimation model (i.e., the pooled specification) is expressed as follows:

$$Y_o = S_o\alpha + \gamma W_k Y_k + \delta W_i Y_i + \rho W_o Y_o + X_o\beta + u_o \quad (5)$$

[10] For details of the spatial model derivation, see Anselin (2010), for example.

Table 7
Spatial estimation of technology adoption and paddy yield (tons/ha).

Variables	(1) MV	(2) MV	(3) Chemical fertilizer use	(4) Chemical fertilizer use	(5) Improved bund	(6) Improved bund	(7) Plot leveling	(8) Plot leveling	(9) Transplant in rows	(10) Transplant in rows	(11) Paddy yield	(12) Paddy yield
Own successful experience of past adoption	0.003		7.716***		0.002		−0.011		0.125***			
	[0.022]		[1.937]		[0.038]		[0.020]		[0.029]			
Weighted average of the technology adoption by the key farmers	−0.010	−0.011	−0.017	−0.037	−0.084*	−0.109**	−0.106	−0.073	−0.008	0.043	−0.122*	−0.135**
	[0.046]	[0.044]	[0.040]	[0.027]	[0.051]	[0.056]	[0.103]	[0.095]	[0.097]	[0.098]	[0.063]	[0.064]
Weighted average of the technology adoption by the intermediate farmers	−0.037	−0.038	0.080	0.101	−0.035	−0.015	0.010	0.002	−0.034	−0.018	−0.133***	−0.131***
	[0.059]	[0.059]	[0.101]	[0.081]	[0.048]	[0.051]	[0.086]	[0.082]	[0.070]	[0.072]	[0.046]	[0.046]
=1 if he/she is a member of the same church/mosque as key or intermediate farmers+	−0.020	−0.025	8.226	10.573	0.006	0.008	0.134*	0.127*	0.080	0.077	0.160	0.147
	[0.062]	[0.061]	[7.601]	[8.195]	[0.043]	[0.044]	[0.070]	[0.070]	[0.063]	[0.065]	[0.217]	[0.218]
=1 if he/she is a relative of key or intermediate farmers+	−0.104**	−0.102**	0.036	−1.606	0.062**	0.062**	0.136***	0.130***	0.092*	0.095**	0.152	0.158
	[0.044]	[0.043]	[5.450]	[5.847]	[0.031]	[0.032]	[0.050]	[0.049]	[0.047]	[0.048]	[0.155]	[0.156]
=1 if he/she is a residential neighbor of key or intermediate farmers+	0.056	0.058	8.119	12.837*	−0.029	−0.020	−0.095	−0.087	0.034	0.051	0.117	0.162
	[0.051]	[0.051]	[6.448]	[7.000]	[0.036]	[0.037]	[0.059]	[0.058]	[0.053]	[0.054]	[0.183]	[0.183]
Number of relatives in the village	0.000	0.000	0.504**	0.424*	0.001	0.001	0.002	0.002	−0.001	−0.001	0.007	0.006
	[0.002]	[0.002]	[0.211]	[0.229]	[0.001]	[0.001]	[0.002]	[0.002]	[0.002]	[0.002]	[0.006]	[0.006]
Fertilizer subsidy program	0.027		54.015***		0.072**		0.068		0.049		0.302*	
	[0.045]		[6.199]		[0.036]		[0.058]		[0.054]		[0.165]	
BRAC borrower	−0.002		20.357*		−0.005		0.111		−0.119		0.266	
	[0.078]		[10.399]		[0.062]		[0.105]		[0.095]		[0.281]	
Female headed household	−0.047	−0.049	2.743	1.728	−0.052	−0.055	−0.164***	−0.147***	0.041	0.034	−0.050	−0.071
	[0.045]	[0.044]	[6.090]	[5.707]	[0.034]	[0.036]	[0.057]	[0.056]	[0.052]	[0.052]	[0.162]	[0.162]
Number of adult members squared	−0.028**	−0.028**	−1.348	−1.817	−0.006	−0.005	−0.002	−0.002	0.023*	0.019	−0.082*	−0.082*
	[0.013]	[0.013]	[1.588]	[1.656]	[0.009]	[0.009]	[0.015]	[0.015]	[0.013]	[0.014]	[0.046]	[0.046]
Number of adult household members	0.159*	0.162*	14.616	16.255	0.029	0.027	0.019	0.017	−0.166*	−0.143	0.484	0.474
	[0.089]	[0.088]	[10.895]	[11.629]	[0.062]	[0.064]	[0.101]	[0.100]	[0.092]	[0.094]	[0.312]	[0.313]
Age of household head squared /1000	−0.064	−0.058	−6.108	−10.573	0.061	0.050	−0.214*	−0.219*	−0.261**	−0.230**	0.462	0.361
	[0.099]	[0.094]	[13.222]	[12.652]	[0.072]	[0.072]	[0.124]	[0.121]	[0.111]	[0.113]	[0.355]	[0.351]
Age of household head	0.006	0.005	−0.239	0.003	−0.009	−0.008	0.023*	0.023*	0.024**	0.021*	−0.069*	−0.059
	[0.010]	[0.010]	[1.369]	[1.320]	[0.007]	[0.008]	[0.013]	[0.012]	[0.012]	[0.012]	[0.037]	[0.036]
Years of education squared/1000	0.333	0.349	−72.685	−181.620	−0.213	−0.493	1.199	1.009	−1.386	−0.855	7.000	6.180
	[1.980]	[1.880]	[256.388]	[224.953]	[1.401]	[1.479]	[2.409]	[2.323]	[2.173]	[2.193]	[7.077]	[7.111]
Average years of schooling of adult household members	0.004	0.004	−0.246	1.195	0.011	0.014	−0.019	−0.016	0.016	0.015	−0.056	−0.048
	[0.022]	[0.021]	[2.925]	[2.551]	[0.016]	[0.017]	[0.027]	[0.026]	[0.025]	[0.025]	[0.079]	[0.079]
Size of sample plot (ha)	0.175*	0.178*	11.498	2.464	0.031	0.036	0.128	0.139	0.067	0.098	−1.275***	−1.251***
	[0.105]	[0.104]	[12.871]	[13.311]	[0.072]	[0.075]	[0.122]	[0.119]	[0.112]	[0.114]	[0.363]	[0.365]
Size of owned plots in upland area (ha)	−0.007	−0.016	−4.920	−16.240	0.114*	0.098	0.153	0.113	−0.156*	−0.158*	−0.124	−0.235
	[0.088]	[0.087]	[10.946]	[11.956]	[0.062]	[0.062]	[0.102]	[0.100]	[0.091]	[0.092]	[0.304]	[0.300]
Size of owned plots in lowland area except sample plot (ha)	0.100**	0.097**	1.890	−2.424	0.037	0.035	−0.004	−0.010	0.038	0.005	−0.242	−0.272
	[0.048]	[0.048]	[6.203]	[6.567]	[0.035]	[0.036]	[0.057]	[0.056]	[0.053]	[0.053]	[0.172]	[0.172]
Value of household asset (million Tsh)	−0.049	−0.050	1.689	5.873	−0.037	−0.033	−0.104***	−0.098**	0.034	0.054	0.307**	0.326***
	[0.034]	[0.033]	[4.259]	[4.459]	[0.024]	[0.025]	[0.039]	[0.039]	[0.036]	[0.037]	[0.121]	[0.121]
year = 2010	−0.000	0.003	−7.168	−1.167	−0.007	−0.000	0.032	0.033	0.050	0.034	0.001	0.032
	[0.026]	[0.025]	[5.613]	[3.605]	[0.021]	[0.025]	[0.041]	[0.036]	[0.043]	[0.043]	[0.098]	[0.098]
year = 2011	−0.005	−0.003	1.850	−0.337	0.024	0.043	0.099**	0.062	0.039	0.033	0.342*	0.387**
	[0.026]	[0.026]	[7.717]	[5.145]	[0.024]	[0.029]	[0.050]	[0.048]	[0.041]	[0.042]	[0.175]	[0.175]
year = 2012	0.007	0.003	4.794	0.011	0.003	−0.004	0.024	0.031	0.104*	0.069	0.089	0.130
	[0.037]	[0.033]	[6.926]	[4.252]	[0.031]	[0.028]	[0.049]	[0.039]	[0.056]	[0.050]	[0.176]	[0.160]
Constant	−0.515**	−0.498**	−12.392	−21.434	0.211	0.229	−0.114	−0.310	−0.361	−0.391	2.440***	2.500***
	[0.210]	[0.207]	[29.722]	[26.025]	[0.164]	[0.174]	[0.292]	[0.276]	[0.276]	[0.282]	[0.937]	[0.943]
Irrigation block dummies	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included	Included
Observations	392	392	392	392	392	392	392	392	392	392	392	392
Spatial lag	1.267***	1.267***	0.688***	1.041***	0.749***	0.560***	0.299	0.590**	0.489***	0.566***	0.976***	0.938***
	[0.090]	[0.087]	[0.136]	[0.141]	[0.161]	[0.201]	[0.219]	[0.230]	[0.167]	[0.180]	[0.139]	[0.138]
Spatial error	−1.187***	−1.188***	−0.734***	−2.008***	−0.752***	−0.542**	−0.516**	−0.660***	−0.500***	−0.512***	−0.951***	−0.930***
	[0.196]	[0.195]	[0.192]	[0.207]	[0.186]	[0.217]	[0.204]	[0.173]	[0.176]	[0.167]	[0.196]	[0.198]
Joint test for social relationship variables (+) (*chi-square*)	5.93	5.82	5.36	9.25**	4.13	3.89	10.29**	9.53**	9.34**	10.52**	3.36	4.16

Standard errors in brackets. ***$p < .01$, **$p < .05$, *$p < .1$.

$u_o = \lambda W_o u_o + \varepsilon_o$

where

Y_o: The O-by-1 vector of outcome variables for O ordinary farmers;
S_o: The O-by-3 matrix of the three social relationship dummy variables for O ordinary farmers;
X_o: The O-by-m matrix of m household characteristics and other control variables for O ordinary farmers;
Y_k: The K-by-1 vector of adoption of technologies by K key farmers;
Y_i: The I-by-1 vector of adoption of technologies by I intermediate farmers;
W_o: The O-by-O weight matrix representing the quadratic distance decay among O ordinary farmers (row standardized);
W_k: The O-by-K weight matrix representing the quadratic distance decay between O ordinary farmers and K key farmers (row standardized);
W_i: The O-by-I weight matrix representing the quadratic distance decay between O ordinary farmers and I intermediate farmers (row standardized);
u_o: The O-by-1 vector of error term that may have a spatial process;
ε_o: The O-by-1 vector of random error term assumed to be i.i.d. with constant variance.

The main variables of interest in this model are S_o, to represent the social network, and W_kY_k, W_iY_i, and W_oY_o, to represent the geographical network. Accordingly, coefficient α indicates the social network effects, while γ and δ indicate the spatial network effects from the key and intermediate farmers, respectively. The coefficient ρ captures the spillover from nearby the ordinary farmers. Spatially correlated effects of unobservable factors in the neighborhood are captured by the coefficient λ.[11] Note that Eq. (5) is a structural form equation because Y_o and u_o enter on both sides. In the estimation process, we follow the Generalized 2SLS strategy proposed by Kelejian and Prucha (1998), refined by Lee (2003), and applied by Kelejian and Prucha (2008), Bramoullé et al. (2009) and Ward and Pede (2014).[12] This procedure yields an asymptotically optimal IV estimator when the errors are i.i.d. and reduces to a two-step estimation method in our case, where W_oS_o, W_oX_o, $W_o^2S_o$ and $W_o^2X_o$ are used as instruments.[13] Note that Eq. (5) represents a spatial LPM (linear probability model) in the cases of binary outcomes. According to Table 8.9 in Beron and Vijverberg (2004), spatial LPM yields conservative estimates of ρ and λ as compared to spatial Probit estimators.[14]

5.2. Estimation results

Table 7 shows the results of the spatial panel estimations for the adoption of technologies by the ordinary farmers. The models (1), (3), (5), (7), (9), and (11) include the 'own experience', fertilizer subsidy, and borrowing money from BRAC variables. Since these variables can be endogenous, we also show the results without these variables. Note, however, that we obtained largely consistent results in models both with and without these variables.

The dummy variable for being a relative of key or intermediate farmers has positive coefficients for the adoption of improved bund, plot leveling, and transplanting in rows. The same coefficient was negative for the adoption of MVs, for which we do not have a convincing interpretation. Note, however, that the joint significance tests of the social network variables for MVs are insignificant, while those for plot leveling and transplanting are statistically significant, as shown in the last line of the table. Being members of the same church or mosque has a positive coefficient for the adoption of plot leveling. Overall, these results suggest that interaction with the key and intermediate farmers through social networks plays a significant role in technology adoption by the ordinary farmers.

On the other hand, we do not find any positive effect of plot proximity to adopting key or intermediate farmers' on the adoption by the ordinary farmers. Intriguingly, however, the spatial lag term is generally significant, which implies that mutual learning among the ordinary farmers has a positive influence on technology adoption. This mixed result can be attributable to the different geographical 'densities' of the key, intermediary, and ordinary farmers. Since there are only a few key and intermediate farmers in the entire irrigation scheme, while there are many ordinary farmers, farmers may have more opportunities to learn from nearby the ordinary farmers than the key or intermediate farmers, whose presence is relatively sparse within the irrigation scheme. We have no convincing explanation for the negative and significant coefficient of the weighted average of the key and intermediate farmers' adoption on improved bund and paddy yield. Note, however, that we do not observe this negative impact when we control for household fixed effects as shown in Table 8.

Own successful experience of past adoption has a positive and significant coefficient for chemical fertilizer use and the adoption of transplanting in rows, suggesting that farmers also make their adoption decision by learning from their own past experience. The coefficient for receiving the fertilizer subsidy has a positive and significant coefficient for fertilizer use and paddy yield, suggesting that the availability of cheaper fertilizer may contribute to increased fertilizer use and enhanced paddy yield. Borrowing money from BRAC has positive impact on the use of chemical fertilizer but has no impact on the adoption of other technologies. This implies that there is no serious credit constraint for the adoption of agronomic practices except for chemical fertilizer use. Being a female household head negatively affects the adoption of plot leveling. Size of sample plot has a negative coefficient for paddy yield, which is consistent with the well-known inverse relationship between agricultural productivity and plot size due to the family labor constraint (Otsuka, 2007). However, number of family member has no clear positive impact while neither plot size nor land holdings has negative relationship with the adoption of technologies, except for the coefficient of the size of owned plot in upland area being negative for the adoption of transplanting in rows. These results make it less clear if there is any severe labor constraint for the adoption of new technologies. Size of plot and size of owned plots in the lowland area have positive and significant coefficients for the adoption of MVs. This may be because farmers with large land holdings are able to take the risk of adopting new varieties.

In Table 8, we summarize the results of our spatial panel estimation with household fixed effects. The basic estimation strategy is the same as the models shown in Table 7, except that household fixed effects are included, and thus, all the time-invariant household characteristics are omitted from the estimation. We obtained largely consistent results regarding the impact of plot-neighboring farmers in both models. The weighted average of

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[11] For detailed discussions of correlated spatial effects and the associated estimation problems known as the *reflection problem*, see the pioneer work by Manski (1993). To ensure the identification of spatial effects in the presence of correlated social effects, we also conducted the test for necessary and sufficient conditions for identification proposed by Bramoullé, Djebbari, and Fortin (2009) and passed it with rank 4, which means that the matrices I. W_o W_o^2. and W_o^3 are linearly independent.

[12] Spatial models need to be estimated by MLE, GMM, or Generalized 2SLS, as use of OLS regressions would suffer severe endogeneity bias.

[13] The model estimation was handled by STATA codes as illustrated by Drukker, Prucha, and Raciborski (2013).

[14] For the spatial specifications including spatial errors, methods of standard error clustering are not clearly available to date.

Table 8
Spatial estimation of technology adoption and paddy yield (tons/ha) with household fixed effects.

Variables	(1) MV	(2) MV	(3) Chemical fertilizer use	(4) Chemical fertilizer use	(5) Improved bund	(6) Improved bund	(7) Plot leveling	(8) Plot leveling	(9) Transplant in rows	(10) Transplant in rows	(11) Paddy yield	(12) Paddy yield
Own successful experience of past adoption	−0.071**		2.990		−0.047		−0.027		0.030			
	[0.033]		[2.568]		[0.044]		[0.027]		[0.037]			
Weighted average of the adoption of technology by neighbor key farmers	−0.073	0.086	0.008	−0.010	−0.045	−0.069	−0.178	−0.004	0.023	0.042	−0.051	−0.032
	[0.079]	[0.088]	[0.047]	[0.031]	[0.064]	[0.117]	[0.207]	[0.102]	[0.088]	[0.043]	[0.103]	[0.102]
Weighted average of the adoption of technology by neighbor intermediate farmers	−0.079	−0.068	0.108	−0.046	−0.051	−0.017	0.005	−0.012	0.067	−0.006	−0.097	−0.068
	[0.092]	[0.103]	[0.148]	[0.150]	[0.057]	[0.060]	[0.182]	[0.096]	[0.098]	[0.059]	[0.068]	[0.069]
Fertilizer subsidy program	0.135**		48.160***		0.048		0.015		−0.028		0.103	
	[0.055]		[7.131]		[0.044]		[0.071]		[0.057]		[0.204]	
Borrowing from BRAC	0.216**		35.050***				0.113		−0.037		0.152	
	[0.092]		[11.100]				0.116		[0.091]		[0.335]	
year = 2010	0.044	0.054	−7.227	−2.404	−0.004	0.000	0.042	0.013	−0.001	−0.018	−0.045	−0.028
	[0.045]	[0.056]	[6.395]	[4.238]	[0.023]	[0.027]	[0.054]	[0.017]	[0.040]	[0.019]	[0.133]	[0.114]
year = 2011	−0.017	−0.016	0.346	−8.301	0.022	0.014	0.151**	−0.032	−0.012	−0.033	0.528*	0.327
	[0.046]	[0.052]	[8.879]	[5.765]	[0.030]	[0.081]	[0.063]	[0.044]	[0.042]	[0.023]	[0.293]	[0.408]
year = 2012	0.130**	0.152*	1.942	−5.598	0.032	−0.015	0.023	0.006	−0.005	−0.053	0.435	0.246
	[0.059]	[0.087]	[8.071]	[4.756]	[0.037]	[0.043]	[0.065]	[0.024]	[0.071]	[0.038]	[0.289]	[0.405]
Spatial lag	−0.127	−0.226	0.662**	1.549***	0.805***	0.923	−0.055	1.291***	0.979***	1.257***	0.576**	0.783*
	[0.172]	[0.581]	[0.272]	[0.358]	[0.242]	[0.963]	[0.244]	[0.304]	[0.283]	[0.193]	[0.254]	[0.407]
Spatial error	−0.077	0.038	−0.378	−1.295	−0.573**	−0.387	−0.083	−1.901***	−0.469	−2.086***	−0.365	−0.557
	[0.309]	[0.316]	[40.040]	[39.160]	[0.252]	[0.259]	[0.399]	[0.346]	[0.316]	[0.289]	[1.173]	[1.156]
Observations	392	392	392	392	392	392	392	392	392	392	392	392

Standard error in brackets. $^{***}p < .01$, $^{**}p < .05$, $^{*}p < .1$.

technology adoption by the key and intermediate farmers has no significant impact on the adoption of technologies by the ordinary farmers. On the other hand, the spatial lag terms which capture the spill-over effects from neighboring ordinary farmers are significant for the adoption of chemical fertilizer use, improved bund, plot leveling and transplanting in rows, as well as paddy yield. These results consistently suggest that plot proximity to ordinary adopters is more important than proximity to adopting key or intermediate farmers.

6. Conclusion

While the adoption and dissemination of agricultural technologies among small-scale farmers are of paramount importance in achieving an African Green Revolution, little work has been done to determine whether or to what extent technologies can disseminate from a small number of selected and trained farmers to non-trained farmers within rural farming communities. This paper investigated the outcome of a farmer-to-farmer training program with a particular focus on how the gap in adoption of rice cultivation technologies and paddy yield evolved due to technology spillover within an irrigated rice farming community in Tanzania. Our results showed that new technologies were first adopted by the trained key and intermediate farmers and that, as a result, the yield gap initially widened between the trained farmers and the non-trained ordinary famers. However, in the course of time, the technologies diffused gradually from the key and intermediate farmers to the ordinary farmers. Consequently, the paddy yield of the key farmers substantially increased from 3.1 tons per hectare to 5.3 tons per hectare, while that of the ordinary farmers was noticeably boosted from 2.6 tons per hectare to 3.7 tons per hectare, with a time lag. This suggests that society's aggregate gain from an enhancement of the performance of the ordinary farmers would be substantial, given the dominance of the ordinary farmers in the population.

A notable implication of our results pertains to the channels of technology spillover from trained farmers to non-trained farmers. It was found that a social relationship with the key and intermediate farmers contributed to the process of technology adoption by the ordinary farmers, which is consistent with Lambrecht, Vanlauwe, Merckx, and Maertens (2014), who point out the importance of social interaction in the awareness and adoption of new technologies. By contrast, we observed only a limited impact of plot proximity to trained farmers, while plot proximity to other ordinary farmers exhibited a positive and significant effect. These results suggest that technologies first disseminate from the trained farmers to those ordinary farmers who have social ties with the trained farmers, and then further disseminate among the non-trained farmers through plot proximity.

Overall, our paper provides support for farmer-to-farmer extension strategies, provided that the lead farmers selected by the community receive an intensive training program on production technologies. Given that extension officers or aid agencies can train only a limited number of farmers at a time, farmer-to-farmer extension offers a reasonable option for technology dissemination programs. This is in line with Krishnan and Patnam (2013), who found in Ethiopia that, while the initial impact of training by extension agents was high, the importance of learning from neighbors increased over time in the adoption of fertilizer and improved seeds. Maertens and Barrett (2012) also point out that ordinary farmers receive information from progressive farmers. These results are consistent with our finding that intensive training to selected farmers can enhance the performance of other farmers.

Within our study site, it took a few years for non-trained farmers to adopt newly introduced technologies[15] and increase their productivity through social learning from trained farmers and neighborhood peer learning. This implies that the impact evaluation of a farmer-to-farmer extension program should be conducted not in the short-run but by allowing at least a few years' time to pass in order to fully capture the impact of spillover from trained farmers to non-trained farmers.

[15] This observation is consistent with Tsusaka, Velasco, and Yamano (2015), who described the time it takes for a majority of the rural population to adopt agricultural technologies in five south Asian countries.

One notable limitation of this paper is that it does not provide a formal impact assessment of the training program. Rather, its focus is on estimating how the performance gap between trained and non-trained farmers shifted over time due to the expected technology spillover to the ordinary farmers. It should also be noted that profit data were unavailable for the years 2008 and 2009, which preceded or included the training period. Hence, a formal benefit-cost analysis incorporating profitability with and without the training program was not possible. This should be the subject of future research that could potentially strengthen the evidence of the present paper.

The applicability of this study's findings to other farming communities will clearly be affected by the type of constraints facing the community's farmers. These would include knowledge constraints, capital constraints, labor constraints, etc. Based on our hands-on experience with, and insights into our study site, it is apparent that inadequate extension services are a significant cause of low adoption of production technologies. Although capital and labor admittedly play a role in the adoption of new technologies, proper training in their use is crucial. While improved seeds and fertilizers are available in the markets of our study site, their adoption must be accompanied by appropriate agronomic practices and thus require training for successful use. It is also important to note that whether this type of farmer-to-farmer extension can work effectively may depend on geographical conditions. Since our study site is a relatively small irrigation scheme, whether a similar type of farmer-to-farmer extension can work in different geographical settings such as spatially scattered communities or mountainous areas should be the subject of future investigation.

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Appendix

Appendix Table 1
Probit estimation results of being key or intermediate farmers.

	(1) Key farmer	(2) Intermediate farmer
=1 if female headed household	−0.382	0.636*
	[0.698]	[0.329]
Number of adult household members	−0.858	−0.435
	[0.695]	[0.476]
Number of adult members squared	0.123	0.051
	[0.088]	[0.065]
Age of household head	0.309*	0.215**
	[0.171]	[0.099]
Age of household head squared/1000	−2.954*	−2.002**
	[1.712]	[0.975]
Average years of schooling of adult household members	0.809	0.705
	[0.838]	[0.491]
Years of education squared/1000	−49.063	−57.941
	[58.423]	[38.159]
Size of sample plot (ha)	0.083	−0.401
	[0.871]	[0.727]
Size of owned plots in upland area (ha)	−2.065	−0.261
	[1.804]	[0.623]
Size of owned plots in lowland area except sample plot (ha)	0.115	0.000
	[0.505]	[0.306]
Value of household asset (million Tsh)	−0.067	0.340
	[0.707]	[0.268]
=1 if he/she is member of same church/mosque as key or intermediate farmers	–	0.225
		[0.504]
=1 if he/she is relative of key or intermediate farmers	0.158	0.155
	[0.405]	[0.314]
=1 if he/she is residential neighbor of key or intermediate farmers	0.422	0.758*
	[0.508]	[0.450]
Number of relatives in the village	0.026	−0.001
	[0.016]	[0.016]
Irrigation block B	−0.457	0.052
	[0.454]	[0.389]
Irrigation block C	−0.336	−0.568
	[0.511]	[0.497]
Irrigation block D	–	−0.383
		[0.749]
Constant	−11.017**	−8.606***
	[4.767]	[2.788]
Observations	118	158

Standard errors in brackets. *** $p < .01$, ** $p < .05$, * $p < .1$.

Appendix Table 2
Balancing test on covariates between key and ordinary farmers (Kernel Matching). Balancing test on covariates between intermediary and ordinary farmers (Kernel Matching).

	2009			2010			2011			2012		
	Treated	Control	*t*-test	Treated	Control	*t*-test	Treated	Control	*t*-test	Treated	Control	*t*-test
=1 if female headed household	0.08	0.14	−0.46	0.08	0.14	−0.40	0.09	0.08	0.06	0.11	0.14	−0.19
Number of adult household members	3.17	3.17	0.00	3.17	3.15	0.02	3.18	3.01	0.27	2.67	2.83	−0.27
Number of adult members squared	12.17	12.81	−0.13	12.17	12.50	−0.07	12.46	10.79	0.36	8.44	9.42	−0.26
Age of household head	48.33	47.74	0.14	48.33	47.76	0.14	49.36	47.50	0.43	47.11	48.83	−0.33
Age of household head squared /1000	2.43	2.38	0.12	2.43	2.38	0.12	2.53	2.35	0.4	2.33	2.49	−0.30
Average years of schooling of adult household members	7.02	6.98	0.08	7.02	7.03	−0.02	6.78	7.06	−0.51	6.69	6.91	−0.32
Years of education squared /1000	0.05	0.05	0.10	0.05	0.05	−0.01	0.05	0.05	−0.6	0.05	0.05	−0.37
Size of sample plot (ha)	0.44	0.42	0.37	0.44	0.47	−0.33	0.44	0.51	−0.57	0.47	0.49	−0.17
Size of owned plots in upland area (ha)	0.03	0.04	−0.32	0.03	0.04	−0.25	0.03	0.02	0.34	0.01	0.02	−0.21
Size of owned plots in lowland area except sample plot (ha)	0.24	0.23	0.09	0.24	0.22	0.14	0.27	0.25	0.13	0.17	0.26	−0.53
Value of household asset (million Tsh)	0.50	0.44	0.44	0.50	0.45	0.34	0.51	0.53	−0.16	0.49	0.46	0.19
=1 if he/she is a member of the same church/mosque as key or intermediate farmers	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00	1.00	1.00	0.00
=1 if he/she has a relative among key or intermediate farmers	0.67	0.72	−0.26	0.67	0.72	−0.28	0.64	0.76	−0.62	0.78	0.69	0.40
=1 if he/she is a relative of key or intermediate farmers	0.83	0.79	0.26	0.83	0.81	0.16	0.82	0.88	−0.39	0.78	0.81	−0.17
Number of relatives in the village	12.50	11.90	0.12	12.50	11.48	0.19	11.82	12.22	−0.06	14.44	12.03	0.34
Irrigation block B	0.42	0.42	−0.04	0.42	0.42	−0.01	0.36	0.42	−0.27	0.33	0.42	−0.37
Irrigation block C	0.25	0.25	0.02	0.25	0.24	0.06	0.27	0.18	0.48	0.33	0.24	0.43
Irrigation block D	0.00	0.00	–	0.00	0.00	–	0.00	0.00	–	0.00	0.00	–
Pseudo R-squared	0.035			0.027			0.163			0.082		
Sample Size	116			118			101			97		
Off support	2			1			1			2		
=1 if female headed household	0.32	0.27	0.33	0.32	0.26	0.34	0.29	0.25	0.22	0.31	0.31	0.00
Number of adult household members	3.00	2.90	0.24	3.00	2.90	0.24	3.21	2.83	0.73	3.31	2.76	1.07
Number of adult members squared	10.79	9.97	0.25	10.79	9.96	0.25	12.36	9.58	0.68	13.15	8.56	1.16
Age of household head	49.90	49.03	0.22	49.90	49.02	0.23	50.79	48.95	0.39	48.85	50.22	−0.29
Age of household head squared/1000	2.63	2.54	0.23	2.63	2.53	0.24	2.72	2.54	0.38	2.51	2.65	−0.30
Average years of schooling of adult household members	6.62	6.47	0.29	6.62	6.49	0.25	6.47	6.45	0.03	6.47	6.42	0.08
Years of education squared/1000	0.05	0.04	0.27	0.05	0.04	0.23	0.04	0.04	−0.02	0.04	0.04	−0.05
Size of sample plot (ha)	0.40	0.40	0.16	0.40	0.41	−0.03	0.42	0.42	0.00	0.40	0.43	−0.36
Size of owned plots in upland area (ha)	0.09	0.09	−0.01	0.09	0.08	0.01	0.03	0.10	−0.88	0.06	0.10	−0.42
Size of owned plots in lowland area except sample plot (ha)	0.32	0.32	0.05	0.32	0.31	0.07	0.24	0.34	−0.58	0.24	0.32	−0.49
Value of household asset (million Tsh)	0.52	0.46	0.29	0.52	0.47	0.28	0.52	0.51	0.05	0.56	0.48	0.35
=1 if he/she is a member of the same church/mosque as key or intermediate farmers	0.89	0.86	0.35	0.89	0.86	0.34	0.93	0.85	0.67	0.92	0.80	0.86
=1 if he/she has a relative among key or intermediate farmers	0.63	0.57	0.40	0.63	0.57	0.38	0.64	0.63	0.08	0.54	0.60	−0.32
=1 if he/she is a relative of key or intermediate farmers	0.89	0.86	0.36	0.89	0.86	0.34	0.86	0.83	0.18	0.85	0.85	−0.03
Number of relatives in the village	9.21	9.32	−0.04	9.21	9.24	−0.01	7.21	10.13	−0.89	8.62	9.35	−0.20
Irrigation block B	0.58	0.64	−0.38	0.58	0.64	−0.35	0.57	0.58	−0.05	0.62	0.61	0.01
Irrigation block C	0.21	0.13	0.64	0.21	0.13	0.66	0.29	0.16	0.76	0.23	0.14	0.56
Irrigation block D	0.05	0.04	0.15	0.05	0.04	0.15	0.00	0.03	−0.60	0.00	0.03	−0.61
Pseudo R-squared	0.02			0.018				0.103		0.139		
Sample Size	156			158				132		131		
Off support	4			4				3		4		

T-statistics are shown in the *t*-test columns.

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