The longer-term adoption patterns of organic farming practices

Results strictly following PAP

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Abstract:

This study investigates the causal impact of a repeated training intervention on the longer-term adoption of organic farming practices among Indonesian smallholder farmers. The intervention provides information and two rounds of training on organic farming practices. The intervention is implemented as a randomized controlled trial (RCT). This study relies on a four-wave panel data set (baseline, two midline and endline survey) and substantial qualitative field research. Whereas a first study has focused on the short-term effects with respect to knowledge, perceptions, awareness and experimentation (Grimm and Luck, 2023), this study will take a longer horizon and focus on the adoption of organic farming practices and the conversion from conventional to organic farming. The research design enables us to estimate the causal effect of repeated organic farming training on the adoption of organic farming practices. Given the local context of frequent over-application of chemical fertilizers, we are particularly interested to investigate whether the training exposure leads to a substitution of chemical fertilizers with organic fertilizers. The research design also permits the exploration of farmers' adoption behavior across multiple years and in response to repeated training exposure.

Summary Results (PAP)

We find that providing Indonesian smallholder farmers with repeated training significantly increases the adoption of organic farming methods. The ITT estimates indicate statistically significant and meaningful impacts, such as a 14.7 percentage point increase in the use of organic fertilizer other than manure. We also observe some substitution of chemical fertilizers with organic alternatives. We find no effect of training on full adoption of organic farming, which aligns with qualitative findings where farmers expressed concerns about lower yields and market access challenges associated with fully transitioning to organic practices.

More details, including an explorative analysis of adoption dynamics will be published in a separate paper. This document refers purely to the outcomes outlined in the PAP.

Key outcomes and empirical estimation

Research Question: What is the causal effect of repeated organic farming training on farmers' adoption of organic farming practices, use of chemical inputs, and full adoption of organic farming?

We are interested in studying the effect of treatment on several outcomes of interest. All outcomes were measured in the fourth wave of the survey which took place between February and March 2023.

We differentiate between three families of outcomes: (i) adoption, (ii) knowledge, and (iii) perception. We further differentiate between primary and secondary outcomes. Since the key concern of the training was to enable interested farmers to experiment and adopt organic farming, the primary focus of our analysis is on adoption outcomes. Knowledge and perception outcomes allow us to additionally explore other, related dimensions of the training impact and to better understand the mechanisms linking the training and adoption. Jones (2002), for example, argues that awareness is a pre-condition for behavioral change towards more sustainable farming.

Organic farming as a system farming approach can encompass a range of practices, including for example fermented manure or organic pesticide. At the same time, it implies the disadoption of other practices such as applying chemical inputs. To facilitate the interpretation of our results, we categorize adoption outcomes into primary and secondary outcomes. Secondary outcomes allow exploring the mechanisms of the training impact further, in particular, whether any observed effect is driven by self-produced or purchased organic inputs. In the following, “P-O” denotes “primary outcome” and “S-O” denotes “secondary outcome”.

The <u>first family</u> of outcomes focuses on **adoption**.

The first domain of adoption outcomes includes measures of organic input use.

1. <u>Fermented manure</u>
   In the context of this study, fermented manure refers to manure that either underwent a longer drying process or was composted by farmers. Fermentation was promoted during the training.
   a. <u>P-O:</u> Applied fermented manure (binary variable) =1 if the respondent applied fermented manure. Fermented manure may be produced by farmers themselves or bought.
   b. <u>S-O:</u> Applied self-produced fermented manure (binary variable) =1 if the respondent applied fermented manure which was produced by the farmer herself/himself.
   c. <u>S-O:</u> Applied purchased manure (binary variable) =1 if the respondent applied purchased fermented manure.

2. <u>Other organic fertilizers</u>
   In the context of this study, “other organic fertilizer” comprises different types of organic growth promoting inputs other than manure. During the training sessions, farmers were taught about different liquid organic fertilizers (e.g. from animal urine or plants). They were also taught about PGPR (Plant Growth promoting rhizome) and local microorganisms.
   a. <u>P-O:</u> Applied organic fertilizer (binary variable) =1 if the respondent applied organic fertilizer other than manure during the last planting season. The organic fertilizer may be produced by farmers themselves or bought.

b. S-O: Applied self-produced organic fertilizer (binary variable) =1 if the respondent applied self-produced organic fertilizer other than manure during the last planting season.
c. S-O: Applied purchased organic fertilizer (binary variable) =1 if the respondent applied purchased organic fertilizer other than manure during the last planting season.

3. Organic pesticide
   a) P-O: Applied organic pesticide (binary variable) =1 if the respondent applied self-produced or purchased organic pesticide during the last season.
   b) S-O: Applied self-produced organic pesticide (binary variable) =1 if the respondent applied self-produced organic pesticide during the last season.
   c) S-O: Applied purchased organic pesticide (binary variable) =1 if the respondent applied purchased organic pesticide during the last season.

4. Plant residues
   During the training, the trainers encouraged farmers to leave the pant residues on the plot. Rice residues are, for example, very high in the nutrient Phosphate (K). Returning the rice straw to the soil can thus reduce the need for additional K-fertilizer. The trainers in particular discouraged the burning of plant residues. In some cases, farmers or other people also take the plant residues as feed for livestock.
   a) P-O: Returned pant residues to the soil (binary variable) =1 if the respondent returned at least part of the plant residues to the soil and did not burn the remaining part. If the respondent returned, for example, 60% and took the remaining 40% away as livestock feed the variable would be coded as 1.
   b) S-O: Burnt plant residues (binary variable) =1 if the respondent burned all or some part of the plant residues.

5. P-O: Sum of organic practices used
   This outcome is a count variable from 0 to 4 for the number of practices applied. It is coded as 4 for farmers who applied fermented manure, organic fertilizer, organic pesticide and who returned plant residues to the soil. Both purchased and self-produced inputs are considered for this variable.

The second domain of adoption outcomes includes practices that we label “good agricultural practices”. These practices were promoted to the farmers during the training to increase the effectiveness of applying organic farming practices.

1. S-O: Lime application (binary variable) =1 if the respondent applied lime during the last planting season. According to the Indonesian Organic Certification standard, SNI 6729:2016, limited lime application is allowed. During the second training session, a

significant share of farmers who tested their soils observed that their soil is acidic. The trainers recommended lime to these farmers. Thus, lime application is not necessarily recommended for all farmers but given the high share of plots which are acid and the awareness rising with regard to pH levels in the training session, we may expect that farmers in the treatment group are more likely to apply lime.

2. S-O: Leaf Color Chart (binary variable) =1 if the respondent reported to have monitored rice plants Nitrogen levels during the last planting season.

The third domain of adoption outcomes considers the application of agrochemical inputs.

1. Chemical fertilizer use
   We collect detailed data on chemical fertilizer use. Farmers may use different fertilizers that contain N, common types in our research locations are Urea or NPK. For the vast majority of fertilizer types, we can derive the nutrient content, i.e. the share of N, P and K in these fertilizers. This allows us to closely estimate the quantity of nutrients that was applied through agrochemical fertilizers.

   - S-O: Chemical fertilizer application (binary variable) =1 if the respondent applied chemical fertilizer during the last planting season.
   - S-O: Chemical fertilizer application quantity of N, P and K in tons/ha (continuous variable): We will estimate this variable based on the reported quantity of different fertilizer types applied during the last planting season *for rice*.
   - P-O: Expenditure on chemical fertilizers in IDR/ha (continuous variable): reported expenditure on chemical fertilizers which were applied during the last planting season. This variable is top-coded at the 95th percentile of the overall distribution.

2. Chemical pesticide use
   'Pesticide' is used as an umbrella term that encompasses for example pesticides, fungicides, nematicides. Farmers in our research region use a wide variety of different pesticides from different brands and in different formats (granules, liquids). We therefore cannot estimate a weight quantity.

   - S-O: Chemical pesticide application (binary variable) =1 if the respondent applied chemical pesticide during the last planting season.
   - P-O: Expenditure on chemical pesticide in IDR/ha (continuous variable): reported expenditure for chemical pesticides which were applied during the last planting season. This variable is top-coded at the 95th percentile of the overall distribution.

Finally, we also measure the impact of the training on full adoption, the fourth domain of outcomes.

- P-O: Full adoption on all plots (binary variable):
  Farmers are considered full adopters if they applied no chemicals in the last season while at the same time applying at least one of the practices described in the family 1 outcomes. The variables is coded as 1 if the farmer fulfills these criteria. The variable will not be coded as 1 if the farmer used neither chemical inputs nor any organic inputs. This is to avoid that organic farming “by accident” or lack of resources is classified as a decision to fully adopt organic farming.
  Based on the previous survey waves, we do not expect a large share of full adopters. Yet, the additional 2 years and thus two more potential years of transition as well as the additional training may have motivated some farmers to completely substitute chemical inputs with organic inputs.

- S-O: Full adoption of at least one plot (binary variable):
  In addition to full adoption on all plots, we also consider the possibility that farmers decide to fully adopt organic farming only on some plots/for some crops. This variable is coded as 1 if a farmer reports to have used only organic inputs on at least one plot.

Knowledge and Perception

Given that the training sessions provided the farmers with both practical and some theoretical knowledge, we expect that farmers in the treatment group perform better on knowledge questions related to organic farming and sustainable soil management. Knowledge questions are further not prone to social desirability bias. We thus explore whether treatment effect patterns are similar across self-reported farming practices and knowledge. However, our previous study (Grimm & Luck, 2023) based on survey waves one and two provided no indication of such a bias.

The second family of outcomes focuses on **knowledge**.

Knowledge Score: This outcome will be a count variable from 0 to 6 for the number of correct answers to six knowledge questions. Some of the questions are open-ended, this reduces the probability that respondents get the answer right by chance. The following knowledge questions will be considered:

1. A farmer who sells his/her products as organic is allowed to a) use some chemical inputs but less than for conventional farming b) no chemical inputs c) same amount of chemical inputs as conventional farmers d) Don’t know (correct answer b)
2. What is the optimal pH level for rice (open ended question, answers between 5.5 and 7 will be coded as correct)
3. As organic farmer, is it permitted to burn plant residues? a) yes, b) no, c) Don’t know (correct answer is b)
4. If previous question was answered correctly, why is land burning not considered an acceptable practice in organic farming? (open ended questions, coded as correct if respondent mentions at least one of the following aspects: Air pollution, kills micro-organisms, reduced nutrient content)

5. Can you use animal manure directly on the plot in organic farming? a) yes, b) no, c) I don't know (correct answer is b)
6. If previous question was answered correctly: How can you check whether the manure is ready for use? Open ended question, coded as correct if the respondent provides one out of the following: test for color, temperature, smell, consistency)

The trainers further discussed the potential benefits of organic farming with the attending farmers. We therefore expect that farmers in the treatment group have a more positive perception of organic farming.

The third family of outcomes will focus on **perception**.

Perception

1. Higher market price organic products (binary variable)=1 if the respondent thinks that organic products in Indonesia are usually sold for a higher price than non-organic products.
2. Organic inputs sufficient (binary variable)=1 if the respondent thinks that it is possible to manage a plot without chemicals and provide the plants with all it needs.
3. Chemicals environment (binary variable)=1 if the respondent thinks that that high and frequent use of chemical fertilizer and pesticide has a negative impact on the environment.
4. Organic farming equally or more profitable (binary variable)=1 if the respondent thinks that organic farming is more or equally profitable.

Empirical Strategy for Intent-to-Treat Effects

To measure the impact of the repeated training on our key outcomes of interest, we run regressions of the following form:

(1) $$Y_{iv} = \beta_{0\,iv} + \beta_1 T_v + \beta_2 X_{ij}^0 + \beta_3 Y_{iv}^0 + \beta_4 S_v + \varepsilon_{ij}$$

where Y_{iv} is the outcome of interest for a given respondent *i* in village *v* measured at the time of the fourth survey wave. T_v is a binary variable indicating whether the respondent lives in a village that was assigned to the training intervention. β_1 captures the treatment effect. While the treatment was randomized, we use additional covariates to increase the precision of the estimates. X_{ij}^0 denotes a vector of control variables, measured at baseline. Y_{iv}^0 denotes the outcome variable at baseline. We will include this variable as a control whenever available. Because this variable is not available for all outcomes and because for some outcomes, the baseline and endline measurements are not completely identical, we choose this ANCOVA treatment effect model. S_v captures the randomization strata and ε_{ij} denotes the individual level error term, that is clustered at the village level.

Multiple hypothesis testing

For the main outcomes of interest (Table 2), we will present two types of p-values. First, we will present the standard p-values based on robust standard errors clustered at the village level. Second, we will carry out multiple hypothesis testing adjustment and present the False Discovery Rate (FDR) adjusted p-values (Benjamini & Hochberg, 1995). To compute the FDR-adjusted p-values, called sharpened q-values we will follow (Anderson, 2008). This adjustment acknowledges that an increase in the number of outcomes tested also increases the probability of a type I error, i.e. a false rejection of the null.

Descriptives and Balance

Table 1
Baseline summary statistics (2018)

	Sample mean	sd	Control group mean	Treatment group mean	C-T
Individual and household characteristics					
Male (=1)	0.83	0.38	0.79	0.87	-0.08***
Age (in yrs.)	53.75	11.78	54.40	53.09	1.31
Muslim (=1)	0.96	0.18	0.95	0.97	-0.02
Completed junior high school (=1)	0.47	0.50	0.46	0.48	-0.02
Refrigerator (=1)	0.37	0.48	0.34	0.40	-0.05
Washing machine (=1)	0.14	0.35	0.13	0.15	-0.03
Financial difficulty last 12 months (=1)	0.55	0.50	0.55	0.56	-0.01
Farming is main activity (=1)	0.78	0.41	0.79	0.78	0.00
Farmers' decisions matter (perception) (=1)	0.57	0.49	0.58	0.56	0.02
Agr. environmental pollution is a problem (perception) (=1)	0.46	0.50	0.46	0.45	0.01
Agricultural characteristics					
Cultivated land (in ha)	0.35	0.44	0.30	0.41	-0.11***
Land ownership share	0.61	0.43	0.62	0.61	0.01
Rice (=1 if respondent planted rice)	0.93	0.26	0.94	0.91	0.03*
p-value for joint orthogonality test			0.03		
p-value for joint orthogonality test (13 land outliers (>2ha) dropped)			0.17		

Note: Total N= 1,200 respondents at baseline, from a total of 60 villages with 20 respondents per village. The treatment group comprises 600 farmers and the control group comprises 600 farmers. C-T denotes the difference in means, significant differences are denoted as follows: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 1 reports baseline summary statistics by treatment status. We employ a joint orthogonality F-test to assess baseline balance between the control and treatment groups. Despite randomization, we obtain a *p*-value below 10% ($p = 0.03$). This appears to be driven by differences in gender composition and cultivated land sizes. Re-estimating the joint orthogonality F-test but excluding outliers with cultivated land sizes greater than 2 hectares increases the *p*-value substantially to 0.17. Apart from these two variables, baseline characteristics are well-balanced between the groups. Additionally, there are no substantial differences between the treatment and control group with respect to any other structural variables not shown in Table 1.

At baseline, data were collected from the full sample of 1,200 respondents. The sample size decreased to 1,148 in the first follow-up, 1,017 in the second, and 942 in the third follow-up survey, reflecting an attrition rate of 22% from baseline to 2023. Attrition was primarily due to respondents passing away, health issues preventing interviews, discontinuation of farming activities (mainly due to age), or migration.

Results

ITT effects on adoption

Table 2
Treatment effects (ITT): Organic inputs

	(1) Fermented manure (=1)	(2) Organic fertilizer (not manure) (=1)	(3) Organic pesticide (=1)	(4) Residues (=1)	(5) Adoption index (0-4)	(6) Full adoption (=1)
Treatment	0.114**	0.147***	0.118***	0.070	0.431***	-0.007
	(0.021)	(0.002)	(0.002)	(0.183)	(0.000)	(0.526)
	[0.036]	[0.006]	[0.006]	[0.218]		[0.526]
Outcome 2018	0.247***	0.086**	0.153***	0.161***	0.292***	0.295*
	(0.000)	(0.031)	(0.001)	(0.000)	(0.000)	(0.058)
Control mean (2023)	0.443	0.277	0.103	0.579	1.367	0.032
N	942	942	942	873	873	942
R-squared	0.110	0.121	0.100	0.153	0.199	0.094

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust p-values (clustered at the village level) in parentheses. Number of villages=60. Multiple hypothesis adjusted q-values in square brackets. The adoption index (Col. (5)) is not included in the multiple hypothesis ranking as the index is, by itself, an adjustment for multiple hypothesis testing. All regressions include strata fixed effects and the following controls: gender 2018, age 2018, junior high school 2018, asset ownership 2018, farming main job 2018, land share owned 2018, land size cultivated 2018. Cols. (4) – (5) only refer to respondents who cultivated rice as returning of rice residues is only applicable to them - the sample size is thus smaller.

Table 2 reports ITT estimates of repeated organic farming training on the use of fermented manure, other organic fertilizers, organic pesticides, and the practice of leaving plant residues on rice fields at the third follow-up in 2023. The training substantially increased adoption of these practices except for leaving plant residues.

Five years after the first training and one year after the second, treatment group farmers are 11.4 percentage points more likely to use manure, 14.7 percentage points more likely to use organic fertilizer other than manure, and 11.8 percentage points more likely to use organic pesticides compared to the control group. These results remain robust after FDR adjustment.

To explore the mechanisms underlying the training's impact, we investigate whether the observed effects are driven by self-produced or purchased organic inputs. Tables 3-5 present the ITT estimates disaggregated by self-produced and purchased inputs for manure, organic fertilizer (excluding manure), and organic pesticide, respectively. The results reveal different patterns across practices.

For fermented manure, the training impact appears to be primarily driven by purchased manure. This may be due to the fact that manure use is strongly correlated with livestock ownership, and among farmers with significant livestock holdings (e.g., a cow or several goats), manure use is already high in both the treatment and control groups at baseline. The training may have motivated farmers without livestock to purchase manure by emphasizing its positive effects on soil structure and health.

For organic fertilizers (other than manure) and organic pesticides, the training impact is predominantly driven by self-produced inputs. Producing these inputs was a key component of the training sessions, which included practical exercises on how to make them using locally available or inexpensive materials. This suggests that the training played a critical role in enabling farmers to adopt these practices.

The ITT estimates also show statistically significant and economically meaningful impacts on the use of lime and the LCC at third follow-up in 2023 (Table 7).

Table 3
Treatment effects (ITT): Fermented manure

	(1) Fermented manure (=1)	(2) Fermented manure *self-produced* *(=1)*	(3) Fermented manure *bought* (=1)
ANCOVA	0.114**		
	(0.021)		
Outcome 2018	0.247***		
	(0.000)		
POST	0.098*	0.040	0.058***
	(0.072)	(0.409)	(0.007)
Control mean (2023)	0.443	0.368	0.076
N	942	942	942
R-squared (A)	0.110		
R-squared (P)	0.060	0.059	0.061

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust p-values (clustered at the village level) in parentheses. Number of villages=60. All regressions include strata fixed effects and the following controls: gender 2018, age 2018, junior high school 2018, asset ownership 2018, farming main job 2018, land share owned 2018, land size cultivated 2018. At baseline, we have no data differentiated by source (self-produced vs. bought), therefore, we report POST treatment effects.

Table 4
Treatment effects (ITT): Organic fertilizer

	(1) Organic fertilizer (=1)	(2) Organic fertilizer *self-produced* (=1)	(3) Organic fertilizer *bought* (=1)
ANCOVA	0.147***		
	(0.002)		
Outcome 2018	0.086**		
	(0.031)		
POST	0.154***	0.158***	0.043
	(0.001)	(0.000)	(0.341)
Control mean (2023)	0.277	0.074	0.229
N	942	942	942
R-squared (A)	0.121		
R-squared (P)	0.115	0.156	0.061

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust p-values (clustered at the village level) in parentheses. Number of villages=60. All regressions include strata fixed effects and the following controls: gender 2018, age 2018, junior high school 2018, asset ownership 2018, farming main job 2018, land share owned 2018, land size cultivated 2018. At baseline, we have no data differentiated by source (self-produced vs. bought), therefore, we report POST treatment effects.

Table 5
Treatment effects (ITT): Organic pesticide

	(1) Organic pesticide (=1)	(2) Organic pesticide *self-produced* (=1)	(3) Organic pesticide *bought* (=1)
ANCOVA	0.118***		
	(0.002)		
Outcome 2018	0.153***		
	(0.001)		
POST	0.113***	0.085***	0.033
	(0.004)	(0.009)	(0.115)
Control mean (2023)	0.103	0.074	0.040
N	942	942	942
R-squared (A)	0.100		
R-squared (P)	0.088	0.093	0.029

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust p-values (clustered at the village level) in parentheses. Number of villages=60. All regressions include strata fixed effects and the following controls: gender 2018, age 2018, junior high school 2018, asset ownership 2018, farming main job 2018, land share owned 2018, land size cultivated 2018. At baseline, we have no data differentiated by source (self-produced vs. bought), therefore, we report POST treatment effects.

Table 6
Treatment effects (ITT): Residues (rice plants)

	(1) Applied residues (=1)	(2) Burned residues (=1)
ANCOVA	0.070	
	(0.183)	
Outcome 2018	0.161***	
	(0.000)	
POST	0.075	-0.049
	(0.165)	(0.212)
Control mean (2023)	0.579	0.167
N	873	873
R-squared (A)	0.153	
R-squared (P)	0.139	0.094

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust p-values (clustered at the village level) in parentheses. Number of villages=60. All regressions include strata fixed effects and the following controls: gender 2018, age 2018, junior high school 2018, asset ownership 2018, farming main job 2018, land share owned 2018, land size cultivated 2018. Col. (2) reports the treatment effect on respondents' probability to have burned residues on at least 1 plot (as the training discouraged this, we expect the effect to be negative).

Table 7
Treatment effects (ITT): Good agricultural practices

	(1) Agr. Lime (=1)	(2) Leaf Color Chart (=1)
Treatment	0.053*	0.123***
	(0.061)	(0.000)
Control mean (2023)	0.052	0.013
N	942	873
R-squared (P)	0.100	0.094

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust p-values (clustered at the village level) in parentheses. Number of villages=60. All regressions include strata fixed effects and the following controls: gender 2018, age 2018, junior high school 2018, asset ownership 2018, farming main job 2018, land share owned 2018, land size cultivated 2018. The treatment estimates are POST estimates, as we have no baseline data on these outcomes. The sample size for the LCC is smaller because it is restricted to farmers who grew rice.

Table 8
Treatment effects (ITT): Chemical fertilizer

	(1) Chemical fertilizer Rp(000)/ha	(2) Chemical fertilizer used (=1)	(3) Nitrogen kg/ha	(4) Phosphate kg/ha	(5) Kalium kg/ha
Treatment	-199.085	0.004	-19.107*	-1.262	0.646
	(0.146)	(0.799)	(0.077)	(0.347)	(0.842)
Outcome 2018	0.220***	0.317***	0.187***	0.056***	0.085***
	(0.000)	(0.004)	(0.000)	(0.008)	(0.000)
Control mean (2023)	2016.841	0.956	161.430	9.636	8.212
N (P)	810	942	810	810	810
R-squared (A)	0.110	0.125	0.094	0.162	0.103

Note: Robust p-values (clustered at the village level) in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Number of villages=60. Controls include: Gender 2018, age 2018, junior high school 2018, asset refrigerator 2018, asset washing machine 2018, farming main job 2018, land share owned 2018, land size cultivated 2018. In Col. (1), (2) and (3), the number of observations is 810 as the sample is restricted to farmers who grew rice in 2018 and 2023.

Table 8 presents the ITT effects of the training on chemical fertilizer expenditure and nutrient application. There is no statistically significant effect on chemical fertilizer expenditure (column 1) or on the probability of abstaining from chemical fertilizer use. However, the ITT estimate for nitrogen application is statistically significant and economically meaningful, indicating a reduction in nitrogen use in response to the training. There are no effects on phosphate or potassium application. For chemical pesticides, Table 9 shows statistically significant reductions in both pesticide expenditure and the probability of any use. However, the significance of the expenditure effect (column 1) depends on the handling of outliers: with the pre-specified 95% top-coding, the effect is significant; with 99% top-coding, the p-value rises to around 0.11 and is no longer conventionally significant at conventional levels but very close. Expenditure data are generally noisy due to factors such as recall error, input subsidies, and the practice of purchasing inputs for use across seasons, which complicate detection of precise effects. In sum, the training reduced chemical pesticide use and lowered nitrogen application.

Table 9
Treatment effects (ITT): Chemical pesticide

	(1) Chemical pesticide Rp(000)/ha	(2) Chemical pesticide used (=1)
Treatment ANCOVA	-80.683*	-0.091**
	(0.084)	(0.029)
Outcome 2018	0.342***	0.203***
	(0.000)	(0.000)
Treatment POST	-90.850*	-0.094**
	(0.087)	(0.036)
Control mean (2023)	371.031	0.742
N (A)	810	942
N (P)	873	942
R-squared (A)	0.141	0.101
R-squared (P)	0.246	0.189

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust p-values (clustered at the village level) in parentheses. Number of villages=60. All regressions include strata fixed effects and the following controls: gender 2018, age 2018, junior high school 2018, asset ownership 2018, farming main job 2018, land share owned 2018, land size cultivated 2018. In Col. (1) N for ANCOVA is 810 (R who grew rice in 2018 and 2023) and for POST 873 (all rice growers in 2023).

Table 10
Treatment effects (ITT): Full adoption

	(1) Full adoption (all plots) (=1)	(2) Full adoption (min. 1 plot) (=1)
Treatment ANCOVA	-0.007	
	(0.526)	
Outcome 2018	0.295*	
	(0.058)	
Treatment POST	-0.006	-0.049
	(0.659)	(0.282)
Control mean (2023)	0.032	0.305
N	942	942
R-squared (A)	0.094	
R-squared (P)	0.044	0.126

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust p-values (clustered at the village level) in parentheses. Number of villages=60. All regressions include strata fixed effects and the following controls: gender 2018, age 2018, junior high school 2018, asset ownership 2018, farming main job 2018, land share owned 2018, land size cultivated 2018.

ITT effects on perception and knowledge

A knowledge score summarizes the number of correct responses to six different knowledge questions. The ITT estimate in Table 11 indicates that training increased the number of correctly answered questions by around 0.7. In other words, respondents in the treatment group answered, on average, nearly one more question correctly compared to respondents from the control group.

On perception, results show that training increased farmers' likelihood to state the belief that organic farming can be as profitable as conventional farming. Notably, this belief was already high among control group farmers, with 67.9% agreeing with the statement. We further observe a 15.9 percentage point increase in the stated perception that organic products receive higher prices on the market. By contrast, the ITT estimates for awareness of the negative impacts of chemical inputs are not statistically significant.

Table 11
Treatment effects (ITT): Knowledge & Perception

	(1) Knowledge score (max.6)	(2) Organic equally profit.	(3) Chemical neg. env. Impact	(4) Organic inputs sufficient	(5) High price organic product
Treatment POST	0.677***	0.123***	0.049	0.071*	0.100***
	(0.000)	(0.000)	(0.228)	(0.084)	(0.003)
	[0.001]	[0.001]	[0.229]	[0.105]	[0.005]
Control mean (2023)	2.964	0.679	0.441	0.359	0.647
N	942	942	942	942	942
R-squared	0.167	0.067	0.082	0.052	0.053

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust p-values (clustered at the village level) in parentheses. Number of villages=60. Multiple hypothesis adjusted q-values in square brackets. All regressions include strata fixed effects and the following controls: gender 2018, age 2018, junior high school 2018, asset ownership 2018, farming main job 2018, land share owned 2018, land size cultivated 2018.

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