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Cultivating Change: Long-Term Effects of Repeated Training on Organic Farming Adoption in Indonesia

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Abstract

Most impact assessments of agricultural training evaluate one-time interventions over short time horizons. However, farmers may initially show enthusiasm for a new technology but subsequently dis-adopt it after a trial period, while others may adopt practices gradually over time. This study investigates the causal impact of repeated agricultural training on the adoption of organic farming practices among Indonesian smallholder farmers. Using a randomized controlled trial and four waves of panel data spanning five years, we analyze adoption dynamics over time. Farmers in the treatment group received training twice, once in 2018 and again in 2022. Our findings show that repeated training significantly increased the adoption of organic farming practices, but no evidence that training motivated farmers to fully transition to organic farming. Adoption patterns reveal substantial dis-adoption, re-adoption, and late adoption following repeated training. The results contribute to understanding longerterm adoption dynamics after extension programs and provide insights into the challenges faced by smallholder farmers transitioning to sustainable agricultural practices.

JEL classification

C93, J24, J43, O12, O13, Q12, Q15, Q16

Keywords

organic farming, training, skills, technology adoption, information constraints, extension services, Indonesia

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1. Introduction

The adoption of improved farming practices is central to reducing rural poverty, enhancing food security, and promoting sustainable agricultural growth. While low- and middle-income countries have traditionally been associated with the underuse of external inputs, many countries, especially those that experienced the “Green Revolution”, now face negative consequences from chemical input overuse. Environmental consequences include biodiversity loss, water pollution, and declining soil health (Hazell, 2009; IAASTD, 2009; IFAD, 2013). Moreover, the adoption of sustainable practices is increasingly important in the context of climate change, as practices such as organic fertilizer use and intercropping have been shown to improve farmers’ resilience to rising temperatures (Maggio et al., 2022). As a result, after decades of promoting chemical fertilizer uptake, agricultural policy is increasingly prioritizing sustainable farming practices. Several studies highlight the potential of extension and training programs to encourage the adoption of sustainable practices among smallholder farmers (Hörner et al., 2021; Islam & Beg, 2021; Kondylis et al., 2017; Maertens et al., 2021). However, much of the existing work evaluates one-time interventions over short time horizons. Yet, adoption is a dynamic process, and understanding adoption dynamics is important for designing effective extension strategies.

This study investigates the causal impact of repeated training on the adoption of organic farming practices among Indonesian smallholder farmers. We implemented a randomized controlled trial and collected four waves of survey data over a five-year period. In 2018, we randomized access to organic farming training among 1,200 farmers in 60 villages, with half of the villages assigned to the treatment group. The training was hands-on and resembled standard government-led extension programs. In 2022, the treatment group was offered a second training session designed to reinforce key concepts and introduce new content related to soil health and soil testing. This design allows us to estimate the causal effect of repeated training on the adoption of organic farming practices and assess whether it encourages the substitution of chemical fertilizers with organic alternatives. This study is set in a context of long-term soil degradation, where decades of intensive cultivation and high chemical fertilizer use have increased soil acidity and reduced organic matter in Indonesian rice fields (Nyi et al., 2017; Turmuktini et al., 2012). In this context, training interventions may play an important role not only in promoting organic practices but also in encouraging more balanced input use.

The multi-year panel enables observation of adoption behavior over time and in response to repeated interventions. One year after the first intervention, we found that training increased the fraction of farmers experimenting with organic practices (Grimm & Luck, 2023). However, these results captured only a short-term snapshot; farmers who adopted in response to the training may dis-adopt if perceived benefits decline, others may adopt later, and some may also dis-adopt and then re-adopt following new extension efforts. Tracking adoption over five years allows us to not only identify late adopters but also observe responses to repeated interventions and shifting patterns of adoption and dis-adoption. By tracking adoption behavior over five years, we capture these dynamics, including late adoption, dis-adoption, and re-adoption following multiple extension efforts. To complement the quantitative analysis, we conducted focus group discussions (FGDs) with sample respondents from the treatment group to triangulate survey findings and explore mechanisms underlying the adoption process.

This study makes two main contributions. First, we contribute to the understanding of longer-term adoption dynamics following extension interventions. Prior research shows that adoption is a complex process, with many farmers dis-adopting after an initial trial period (Duflo et al., 2011; Kijima et al., 2011; Lambrecht et al., 2014; Moser & Barrett, 2006; Tamim et al., 2025). Yet, empirical evidence on the impact of repeated information provision and adoption behavior over multiple years remains limited. One exception is Barrett et al. (2022), who find that higher training intensity (two training sessions versus one) increases the adoption of the “System of Rice Intensification” (SRI) and reduces dis-adoption among farmers in Bangladesh. We extend this literature by examining adoption responses to repeated information over multiple years. Unlike Barrett et al. (2022), who use three survey waves, our study employs four waves, including two waves conducted between training sessions. This design enables us to capture re-adoption behavior, which has been rarely documented. Although the second training intervention was not re-randomized, descriptive analysis yields valuable insights into the longer-term and dynamic nature of adoption. We observe that the adoption rates of organic fertilizer use in 2023, following the second training, exceeded those in 2019 after the first intervention, while the smallest treatment effects were observed in 2021, two years after the first but before the second training. Our findings highlight the nonlinear nature of adoption, with late adopters, dis-adopters, and re-adopters accounting for a substantial share of the observed adoption dynamics. Re-adoption was more frequent among treated farmers, indicating that repeated training can encourage renewed engagement with previously abandoned technologies. Consistent with Barrett et al. (2022), this pattern provides suggestive (though not causal) evidence that repeated training can help sustain adoption levels over time.

Second, we add to the literature on organic farming by providing causal evidence on the long-term effects of information interventions. To date, only a few studies have estimated the causal impact of information on the adoption of organic farming practices (e.g., Grimm & Luck, 2023; Vu et al., 2020), and, to our knowledge, none have assessed the causal effects several years after the initial extension. We also examine whether training encourages farmers to substitute chemical fertilizers with organic alternatives and assess its impact on yields. Since fertilizer substitution poses significant risks for farmers, behavioral changes may occur only gradually. Consequently, evaluating adoption and yield outcomes over an extended period is important, especially since evidence suggests that the benefits of sustainable practices on yields tend to increase with longer adoption durations (Maggio et al., 2022). Our results show that repeated training increased the adoption of organic farming practices four years after the initial intervention. We find a reduction in the use of nitrogen application and a more moderate but still meaningful reduction in the use of chemical pesticide. We also find substantial knowledge effects and no negative effects on yields. Qualitative evidence suggests that the expectation of declining yields and perceived limited market access for organic products are barriers to full adoption. In contrast, improvements in soil quality are a key motivating factor for the adoption of single practices.

The remainder of this paper is structured as follows. Section 2 introduces the country context and the study area. Section 3 describes the sample and data, the randomization procedure, and the training. Section 4 outlines the empirical strategy. Sections 5 and 6 present quantitative and qualitative results, respectively. Section 7 concludes.

2. Context

This study was conducted in two regions of Java, Indonesia, the country's primary rice-producing area (BPS, 2024). While food security remains a policy priority, concerns about the environmental impact of intensive chemical input use are growing. Since the mid-2000s, chemical fertilizer subsidies have expanded significantly (OECD, 2023). These subsidies have become a substantial financial burden, as reference, between 2020 and 2024, annual government spending on fertilizer subsides exceeded the Ministry of Agriculture's annual program budget (Firdausi et al., 2025).[1] Yet, farmers still frequently face delays and shortages in accessing subsidized fertilizers, partly due to inefficient targeting (Firdausi et al., 2025). Recent policy frameworks, including Indonesia's Long-Term Strategy for Low Carbon and Climate Resilience, acknowledge the need to reduce chemical fertilizer use to lower greenhouse gas emissions (OECD, 2023). Among rice farmers, widespread over-application of nitrogen-rich fertilizers has increased crop vulnerability to pests and diseases, polluted groundwater, and reduced biodiversity (Bijay-Singh & Craswell, 2021; Kijima et al., 2011). The overuse of chemical inputs has also been identified as a major driver of soil degradation in Indonesia (Mariyono, 2014; Simatupang & Timmer, 2008).

Organic farming has emerged as one potential alternative to reduce the reliance on chemical inputs and address environmental concerns. Initially promoted by civil society organizations, organic farming gained policy attention in the early 2000s. The 2001 "GoOrganic 2010" campaign aimed to position Indonesia as a leading organic food producer. Although this goal was not achieved, it marked the beginning of political interest in organic farming. In 2003, the government introduced organic standards, and since 2008, fertilizer subsidies have included provisions for organic fertilizers. Regional governments have also launched their own programs to promote organic farming, and private businesses are increasingly involved in these efforts. Although organic agriculture remains a niche within Indonesia's agri-food system, demand has grown steadily in urban centers. Middle-class consumers in Java and Bali increasingly purchase organic rice and vegetables through supermarkets and, more recently, online channels (David & Alkausar, 2023; Najib et al., 2020).

Given this context, training on organic practices offers the potential to improve soil health, reduce farmers' dependence on chemical fertilizers, and ease fiscal pressures from chemical fertilizer subsidies.

[1] The budget for fertilizer subsidies comes from the central state budget, not from the Ministry of Agriculture's own budget.

3. Experimental design

3.1. Sample selection and randomization

The fieldwork was implemented in two administrative regions, the district of Tasikmalaya and the province of Yogyakarta. These regions were selected based on the local capacity of the NGO Aliansi Organic Indonesia (AOI), which implemented the training sessions in 2018. We employed a three-stage random sampling design to select 1,200 farmers.[2] In the first stage, we randomly chose 60 villages, 30 in Tasikmalaya and 30 in Yogyakarta. In the second stage, we randomly chose one to three farmer groups in each village, depending on group size.[3] In Indonesia, farmer groups function as social networks and operational units for implementing government programs and distributing subsidies. Typically, these groups meet monthly. They act as key contact points for extension workers, collectively source inputs such as seeds and fertilizers, and, in some cases, coordinate planting schedules. In the third stage, respondents were randomly sampled among the attendees of a two-hour information session on organic farming, to which all members of selected farmer groups were invited. We sampled 20 respondents per selected village, resulting in a baseline sample of 1,200 respondents from 60 villages.

The treatment was randomized at the village level and consisted of training on organic farming. Of the 60 villages in our sample, we randomly assigned 30 villages to the treatment group and 30 to the control group. Figure 1 depicts the location of treatment and control villages. We stratified the sample according to rural status and agricultural land area. In Tasikmalaya, we additionally used “travel distance to the district capital” as a stratification criterion, as the region is characterized by a lower level of transportation infrastructure. After the baseline data collection in 2018, we invited the 20 sampled farmers in each treatment village to participate in the first round of training. In 2022, respondents from treatment villages were offered a second round of training. The control group stayed the same.

[2] For more details on the sampling procedure, see Grimm and Luck (2023).
[3] Given that villages are, on average, larger in Yogyakarta than in Tasikmalaya and encompass more farmers, we then further randomized at the village level in Yogyakarta, i.e., one sub-village was randomly selected in each village.

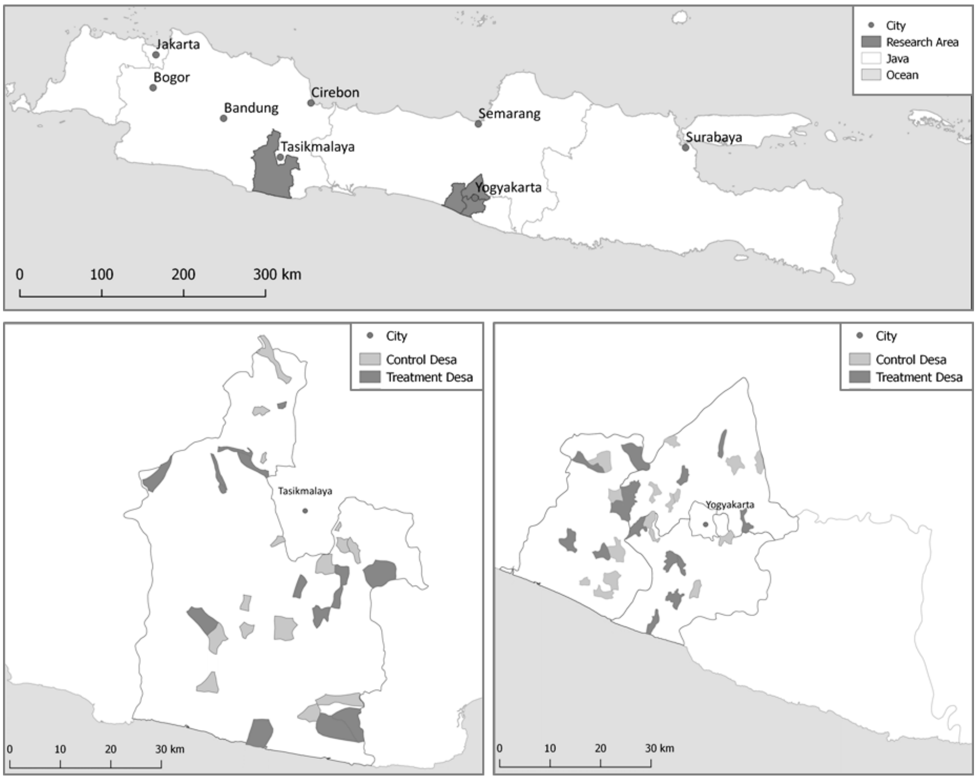

Figure 1: Study regions and random assignment

3.2. Data collection and sample characteristics

Our data comprises four rounds of farm-household surveys: a baseline survey conducted in 2018 prior to any training interventions and three follow-up surveys in 2019, 2021, and 2023. The follow-up surveys in 2019 and 2021 were conducted after the first but before the second training intervention, while the final survey in 2023 took place one season after the second training intervention. Figure 2 presents the timeline of surveys and training interventions.

The baseline and the first follow-up surveys collected data on socioeconomic characteristics, household information, agricultural input use and production, as well as knowledge and perceptions related to organic farming. Due to COVID-19 restrictions, the 2021 follow-up survey was conducted primarily by phone using a shorter questionnaire that excluded detailed numerical data such as the quantity of chemical fertilizer used. The third follow-up survey resumed complete data collection across all variables.

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. The main reasons for attrition included health issues preventing interviews, discontinuation of farming activities (mainly due to age), migration, or respondents passing away. In some cases, we could interview another household member who took over the farming business. We do not find statistically significant differential attrition between control and treatment groups (see Table A1, Online Appendix).

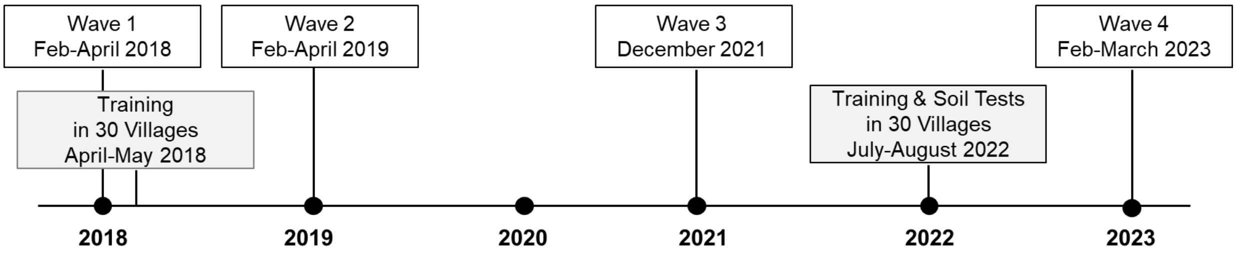

Figure 2: Timeline

Table 1 reports baseline summary statistics by treatment status. Most respondents are smallholders cultivating less than 0.5 hectares of land. The average farm size of 0.35 hectares is consistent with the broader Indonesian context, where 61% of agricultural households cultivate less than 0.5 hectares (BPS, 2023). Respondents are predominantly male, and on average 54 years old. Approximately 47% of respondents hold a high school degree. The majority (57%) agree that farmers' decisions impact the environment, and 46% agree that agricultural environmental pollution is a problem. While crop farming is the primary economic activity for most respondents, livelihood diversification is common. Farmers own about 60% of the land they cultivate and rent the remaining share under sharecropping or fixed-rent agreements. Rice is the dominant crop, with 93% of respondents planting rice on at least one plot during the last cropping season at baseline.

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.

We employ a joint orthogonality F-test to assess baseline balance between the control and the treatment group. Despite randomization, we obtain a *p*-value below 0.10 (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 13 outliers with cultivated land sizes greater than two hectares increases the *p*-value substantially to 0.17.[4] 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.

3.3. Intervention

The treatment comprised two rounds of organic farming training and one short follow-up visit, all conducted at the village level. Agricultural extension services in Indonesia face significant resource constraints. Most services are delivered face-to-face; however, only about half of the villages in Indonesia have access to an extension officer (Savelli et al., 2021). This gap is also reflected in our data, which show that in 2023, only 48 % of sample farmers reported contact with an extension worker in the previous year (besides our project). Given the government resource constraints, we opted for intensive but short training sessions lasting three and two days, respectively, rather than prolonged or continuous interventions, which require, if upscaled, more resources and are less feasible for local extension services to implement.

The first training was held in March and April 2018. It lasted three days and introduced farmers to organic farming concepts, which were unfamiliar to many prior to the training. Day one covered soil ecology and crop cultivation, including practical exercises on soil properties. Day two focused on integrated pest control and self-producing organic fertilizer. Day three addressed organic certification systems and marketing options for organic products. In November and December 2018, trainers returned for a two-hour follow-up visit in each treatment village to provide consultations and address farmers' questions.

The second training took place in July and August 2022. It lasted two days and focused on organic soil health management. Day one began with a discussion of farmers' experiences with organic farming over the past years, followed by sessions on soil nutrient concepts and the benefits of retaining rice residues rather than burning them. Farmers again practiced making different kinds of organic fertilizer and received a manual with simple instructions for fertilizer and compost production. Day two introduced farmers to a paddy soil test kit developed by the Indonesian Soil Research Institute.[5] With trainer guidance, farmers tested their own soil for nitrogen, phosphorus, potassium, and pH levels. Based on farmers' test results, trainers discussed strategies for meeting plant nutrient needs using organic methods. Farmers also learned to use the Leaf Color Chart (LCC), a simple tool for assessing nitrogen levels based on rice leaf color, and each attendee received an LCC after the session. The rationale for introducing soil testing tools is rooted in their potential to strengthen farmers' capacity to

[4] We are not dropping these outliers in the subsequent analysis, but control for cultivated land size at baseline.

[5] Now called Indonesian Soil and Fertilizer Standardization Institute (BPSI Tanah dan Pupuk).

manage nutrients effectively when transitioning to organic farming. While lower fertilization levels in organic farming can reduce yields (Knapp & van der Heijden, 2018), imbalanced application of organic inputs can cause environmental harm.

Attendance rates were high: 90% (18 out of 20 farmers per village) of the invited farmers participated in the first training in 2018, while 73% (12 out of 17 farmers per village) attended the second training in 2023 after adjusting for attrition. Attendees received a modest compensation for travel costs and lost working hours (approximately USD 3 per person per day).

4. Empirical strategy

4.1. Treatment effects

We estimate intention-to-treat (ITT) effects to evaluate the impact of the training intervention. The training aimed to enable and motivate farmers to adopt organic farming practices and to encourage (partial) substitution of chemical inputs with organic alternatives. Accordingly, our analysis focuses on adoption outcomes, which we examine across three domains: organic farming practices, other good agricultural practices, and chemical input use. Regarding organic farming practices, we focus on manure application, use of organic fertilizers other than manure, use of organic pesticides, and returning rice residues to the field. We construct an adoption index that counts how many of these four organic farming practices the farmer used, ranging from 0 to 4. We further construct a full adoption indicator that equals one if the farmers applied no chemical inputs and adopted at least one organic farming practice. Good agricultural practices comprise lime application and the use of the LCC, both of which were introduced during the training to improve the effectiveness of organic farming techniques. To investigate potential substitution effects resulting from the training, we examine changes in chemical input application. Beyond adoption, we assess impacts on knowledge and perception outcomes, harvest yields, as well as welfare indicators, including household labor allocation, and job satisfaction. [6]

To estimate the impact of repeated training on our outcomes of interest, we run ordinary least squares (OLS) regressions of the following form:

$$Y_{iv} = \beta_0 + \beta_1 T_v + \beta_2 X_{iv}^0 + \beta_3 Y_{iv}^0 + \beta_4 S_v + \varepsilon_{iv} \tag{1}$$

[6] We registered two pre-analysis plans, one for adoption outcomes (AEARCTR-0011018) and one for welfare indicators (AEARCTR-0011004). Both are publicly available from the American Economic Association's registry for randomized controlled trials. In this paper, we combine the results. The pre-analysis plans pre-specify the outcomes for the ITT estimations detailed in 4.1. There are some minor deviations for adoption outcomes, i.e., the use of manure instead of fermented manure as an outcome. Also, the pre-analysis plan for welfare includes more outcomes. We published the ITT results following the respective pre-analysis plans on the American Economic Association's registry.

where Y_{iv} is the outcome of interest of respondent *i* in village *v* measured in 2023. T_v is a binary variable indicating whether the respondent lives in a village that was assigned to the training intervention; β_1 therefore captures the ITT effect of organic farming training. X_{iv}^0 is a vector of baseline covariates in which we include the age, gender, education of the respondent, asset ownership (having a refrigerator, having a washing machine), whether farming is the respondent's main economic activity, the share of land owned, and the cultivated land size, all measured in 2018. Y_{iv}^0 denotes the outcome variable at baseline. We chose this ANCOVA specification whenever the outcome was also measured at baseline, which is the case for most outcomes. S_v captures the randomization strata and ε_{iv} is the individual level error term, clustered at the village level.

Ex-ante power calculations suggested that we can detect differences in organic fertilizer use as small as 13.9 percentage points, using a power of 0.8, a significance level of 0.05, an intra-village correlation of 0.21 (all three parameters taken from the baseline survey).[7] The minimum detectable effect sizes for manure and organic pesticide are 15.8 percentage points and 8.4 percentage points, respectively (not accounting for additional covariates). The minimum detectable effect sizes decrease with additional covariates, especially the baseline outcome.

For the main outcomes of interest, we report three types of *p*-values. First, standard *p*-values, based on robust standard errors clustered at the village level, are reported in parentheses. Second, False Discovery Rate (FDR) adjusted *p*-values or "*q*-values" (Anderson, 2008), which correct for multiple hypothesis testing, are reported in brackets. Third, randomization inference based p-values, which test the robustness of our results since they rely entirely on randomization without making any distributional assumptions about the test statistics (Heß, 2017), are reported in curly brackets.

Differential attrition across treatment arms was small and not statistically significant. To address potential concerns related to attrition, we estimate Lee bounds (Lee, 2009) and show robustness of key outcomes to using Lee bounds in Table B1 (Online Appendix). In Online Appendix C, we also provide evidence that spillover effects are unlikely.

4.2. Adoption dynamics

To investigate adoption dynamics in response to repeated extension efforts, we exploit the panel structure of our dataset. Since re-randomizing access to the second training was not feasible due to power constraints, the analysis is exploratory in nature, and we cannot establish the causal effect of adding a second training. First, we compare treatment effects over time and estimate Equation (1) for organic fertilizer use in 2019, 2021, and 2023.[8] Second, we classify farmers into adopter types to explore heterogenous adoption pathways. We then

[7] These assumptions equal those in our pre-analysis plan, except attrition. Here we take actual attrition, which was higher than we expected and is thus more conservative.

[8] The focus on organic fertilizer was chosen because previous research identified large short-term effects for this outcome (Grimm & Luck, 2023).

examine how these adopter types relate to training exposure and a set of socio-economic characteristics.

Following Barrett et al. (2022) we study adoption dynamics using a multinomial logit regression model:

$$(Y_{iv} = k) = \frac{\exp(\alpha_k+\theta_k T_v+X'_{iv}\beta_k)}{1+\sum_{j=2}^{K}\exp(\alpha_j+\theta_j T_v+X'_{iv}\beta_j)}, \text{ k=always, early, re, late, dis-adopter} \quad (2)$$

where Y_{iv} is a categorical variable indicating the adopter type of respondent *i* in village *v* in survey wave 4 (2023): always adopters (practice used in all waves), early adopters (continued use since the second survey wave), re-adopters, late adopters and dis-adopters. The omitted reference category is never adopters. The vector X'_{iv} includes gender, age, education, whether farming is the main activity, farmer group leadership, perceptions on whether farmers' decisions impact the environment, perceptions on whether agricultural environmental pollution is a problem, and livestock ownership (all covariates are measured at baseline). Multinomial logit models rely on the independence of irrelevant alternatives (IIA) assumption, which may not fully hold in our context. The results should therefore be interpreted as correlations rather than as causal effects.

4.3. Qualitative data

We further explore the mechanisms underlying these adoption dynamics in more detail using qualitative data. Qualitative fieldwork was conducted in August 2022 (after the second training intervention) and February 2023. This fieldwork comprised eight FGDs, all of which were conducted with six to eight participants from the treatment group. In 2022, two FGDs were held, each drawing respondents from two villages; in 2023, six FGDs were held with participants from one village each. The FGDs employed open-ended questions to explore several key themes, including factors motivating farmers to adopt organic inputs, barriers to adoption, interest in transitioning fully to organic farming, reasons for dis-adoption or continued adoption, and the perceived role of training in shaping adoption decisions. One of the co-authors attended each FGD, and all FGDs were recorded and transcribed with participants' consent.

5. Results

5.1. Treatment effects on adoption of organic farming practices

Table 2 reports ITT estimates of the impact of repeated organic farming training on the use of organic farming practices, measured at the third follow-up in 2023. The results indicate that training substantially increased the adoption of organic practices, with significant effects observed for all outcomes except for returning rice residues to the fields. Five years after the first training and one year after the second, treatment group farmers are 10.2 percentage points more likely to use manure (+19.0% relative to the control group),[9] 14.7 percentage points more likely to use other organic fertilizers (+53.1%), and 11.8 percentage points more likely to use organic pesticides (+114.6%). Treatment effects are robust to multiple hypothesis testing (false discovery rate (FDR) adjustment). On average, the number of applied organic practices is 0.4 higher in the treatment group, corresponding to a 30 % increase relative to the control group mean. However, as expected, the share of farmers who have fully transitioned to organic farming remains very low and is not statistically different from the control group. In contrast to other practices, the training did not significantly increase the share of farmers who returned rice residues to the field. Qualitative data suggest that social norms partly explain the absence of an effect. FGDs revealed that in some communities it is common to give rice residues to neighbors or agricultural laborers as animal feed, and farmers often feel obliged to comply with such requests despite knowing that returning rice residues is beneficial for their soil.

Table 2
Treatment effects (ITT): Organic inputs

	(1) 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	0.102**	0.147***	0.118***	0.070	0.431***	-0.007
	(0.016)	(0.002)	(0.002)	(0.183)	(0.000)	(0.526)
	[0.026]	[0.008]	[0.010]	[0.196]		[0.519]
	{0.029}	{0.005}	{0.004}	{0.220}	{0.000}	{0.578}
Outcome 2018	0.344***	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)	0.538	0.277	0.103	0.579	1.462	0.032
Standard deviation					0.965	
N	942	942	942	873	873	942
R-squared	0.163	0.121	0.100	0.153	0.206	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. P-values from randomization inference (5,000 permutations) in curly 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. 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.

[9] Unlike the specification in the pre-analysis plan, our analysis focuses on manure in general rather than exclusively on fermented manure. This decision was made because opinions about what classifies as fermented manure differed across respondents. Additionally, the diversity of manure types, combinations of animal sources, use of fermentation speed-increasing add-ins, and varying other management practices complicated binary classification for enumerators. The results based on respondents' own classification of fermented manure and strictly following the pre-analysis plan can be found on the American Economic Association's registry.

To explore the mechanisms underlying these impacts, we investigate whether the observed effects are driven by self-produced or purchased organic inputs. We find that patterns differ across practices. For manure, increased use is primarily driven by purchased manure, likely reflecting already high baseline adoption among farmers with significant livestock holdings (e.g., a cow or several goats) and increased uptake among non-livestock owners following training. For organic fertilizers and organic pesticides, the training impact is predominantly driven by self-produced inputs. Producing these inputs was a key component of the training, which included hands-on instructions in producing organic fertilizers and pesticides from locally available and inexpensive materials. This suggests that training played a critical role in enabling farmers to adopt these practices. Detailed results are shown in Tables D2-D4 (Online Appendix).

We further explore whether treatment effects differ across key farmer characteristics. To do so, we focus on the most relevant outcomes and test heterogeneity by age, gender, education, perceived severity of agricultural pollution, financial difficulty, and land ownership. For organic fertilizer and organic pesticide, we do not find evidence that treatment effects vary along any of these dimensions (for details see Online Appendix E).

5.2. Treatment effects on adoption of lime and the Leaf Color Chart (LCC)

The ITT estimates also show statistically significant and economically meaningful impacts of the training on the use of agricultural lime (+101.9%) and the LCC (+878.5%) at the third follow-up in 2023 (Table 3). Agricultural lime is a soil amendment that increases soil pH levels. While not all farmers should apply lime, the soil tests conducted during the second training intervention revealed that most tested soil samples were below the optimal pH level for rice cultivation. Low pH levels can result from overapplication of chemical nitrogen fertilizers and insufficient organic matter. Farmers in the treatment group were also more likely to use the LCC, a tool to assess plant's nitrogen needs based on leaf greenness and to help optimize fertilizer use. While LCC use was nearly absent in the control group, reported use rates reached about 14% in the treatment group. Both practices were discussed in detail during the second training.

Table 3
Treatment effects (ITT): Good agricultural practices

	(1) Agricultural lime (=1)	(2) Leaf Color Chart (=1)
Treatment	0.053*	0.123***
	(0.061)	(0.000)
	{0.092}	{0.000}
Control mean (2023)	0.052	0.014
N	942	873
R-squared	0.100	0.094

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust p-values (clustered at the village level) in parentheses. P-values from randomization inference (5,000 permutations) in curly 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. 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 last season.

5.3. Treatment effects on the use of chemical inputs

We next examine whether the training encouraged farmers to substitute chemical fertilizers with organic alternatives (Table 4). The ITT estimates indicate that farmers in the treatment group applied, on average, 20.7 kg less nitrogen per hectare, representing a 12.9% reduction relative to the control group. This effect is both economically meaningful and statistically significant at conventional levels but loses significance after adjustment for multiple hypothesis testing. We find no impact on the likelihood of entirely foregoing chemical fertilizers and no significant change in total chemical fertilizer expenditure. The latter is likely in part due to noise in the expenditure data. Fertilizer prices vary due to differences in subsidy access, regional price differences for non-subsidized fertilizer, the purchase quantity (e.g., per kg vs. per 50 kg sack), and the use of leftover stocks purchased at different prices in previous seasons. Furthermore, the reduction is specific to nitrogen, and we detect no effects on phosphate (P) or potassium (K) use (Online Appendix Table F1). This is consistent with the training's emphasis on avoiding nitrogen over-application and the introduction of the LCC. The observed reduction in nitrogen use appears to be driven by lower urea application (which contains only nitrogen), with no corresponding change in NPK fertilizer use (Online Appendix Table F1). Since urea, on average, accounts for less than half of chemical fertilizer expenditure, this also dilutes any aggregate spending effect. In sum, we find suggestive evidence of reduced nitrogen application from chemical fertilizers, but these effects are neither reflected in overall chemical fertilizer expenditure nor robust to multiple hypothesis testing.

Table 4
Treatment effects (ITT): Chemical inputs

	(1) Nitrogen kg/ha	(2) Chemical fertilizer used (=1)	(3) Chemical fertilizer IDR 1,000/ha	(4) Chemical pesticide used (=1)	(5) Chemical pesticide IDR 1,000/ha
Treatment	-20.745*	0.004	-199.085	-0.091**	-80.683*
	(0.071)	(0.799)	(0.146)	(0.029)	(0.084)
	[0.146]	[0.800]	[0.183]	[0.140]	[0.140]
	{0.132}	{0.819}	{0.255}	{0.052}	{0.164}
Outcome 2018		0.317***	0.220***	0.203***	0.342***
		(0.004)	(0.000)	(0.000)	(0.000)
Control mean (2023)	161.430	0.956	2016.841	0.742	371.031
Standard deviation	100.477		1236.595		449.319
N	873	942	810	942	810
R-squared	0.062	0.125	0.110	0.141	0.246

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. P-values from randomization inference (5,000 permutations) in curly 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. The variables nitrogen use kg/ha, chemical fertilizer (IDR 1,000/ha) and chemical pesticide (IDR 1,000/ha) are top-coded at the 95% level. In Cols. (3) and (5) the N is 810 as it includes only those who grew rice in 2018 and 2023.

To explore potential mechanisms, we look at the correlation of nitrogen use and total fertilizer expenditure with two measures of organic engagement (the number of organic practices adopted, and the duration of organic fertilizer use across survey waves). Farmers using more organic practices apply less nitrogen and spend less on chemical fertilizers. For nitrogen, the reduction becomes statistically significant from the use of two practices onwards, and larger when more organic practices are used. Expenditure on overall chemical fertilizer is only significantly reduced when farmers adopt all four practices. Sustained organic fertilizer use is associated with lower nitrogen application quantity, though not with lower total expenditure. Overall, the correlations suggest greater substitution behavior among farmers beyond the experimentation stage and those who apply organic farming practices more intensively (for details, see Online Appendix Table F2). Furthermore, the negative treatment effect on nitrogen use is stronger for farmers who already faced financial difficulties at baseline (see Table E1 in the Online Appendix for details). This pattern is consistent with the idea that information on how to reduce input use and associated costs is particularly relevant for financially constrained farmers. By contrast, there is no evidence of heterogeneous treatment effects by other characteristics such as education, age, or landownership.

For pesticide use, we find that the training reduced the application of any chemical pesticide by - 9.1 percentage points (12.3%) and expenditure on chemical pesticides (Table 4). Farmers in the treatment group spend, on average, IDR 80,683 less on chemical pesticides, corresponding to a decrease of 21.7% relative to the control group. However, while both effects are economically meaningful, they are not robust to multiple hypothesis testing. Taken together, these results provide evidence for a significant and sizeable reduction in Nitrogen use and a more moderate but still meaningful reduction in chemical pesticide use.

5.4. Treatment effects on knowledge and perceptions

The training aimed at equipping farmers with both practical and theoretical knowledge, enabling them to better understand and apply organic farming practices. To measure changes in knowledge, we construct a knowledge score which summarizes the number of correct responses to six different questions, for example, whether organic farmers are permitted to burn rice residues (for the full set of knowledge questions, see Online Appendix G). Knowledge questions also have the advantage of being less prone to social desirability bias. The ITT estimate in Table 5 indicates that training increased knowledge, with treated farmers answering, on average, 0.68 more questions correctly than the control group, corresponding to a 22.9% increase.

The training also increased the likelihood of stating that organic farming can be as profitable as conventional farming (+12.3 percentage points). Notably, this belief was also widespread among control group farmers. We further observe a 10.0 percentage point increase in the belief that organic products are sold for a higher price. Interestingly, the qualitative evidence from FGDs suggests that some farmers still expect lower yields from organic farming and perceive market access for organic products as a major challenge (see Section 6). Furthermore, training increased the likelihood of stating that organic inputs can be sufficient. The training did not significantly change farmers' awareness of the negative environmental impacts of chemical inputs (Col. (5)).

Table 5
Treatment effects (ITT): Knowledge & Perception

	(1) Knowledge score (0-6)	(2) Organic equally profit. (=1)	(3) High price organic product (=1)	(4) Organic inputs sufficient (=1)	(5) Chemical neg. env. Impact (=1)
Treatment	0.677***	0.123***	0.100***	0.071*	0.049
	(0.000)	(0.000)	(0.003)	(0.084)	(0.228)
	[0.001]	[0.001]	[0.005]	[0.105]	[0.229]
	{0.000}	{0.002}	{0.004}	{0.112}	{0.295}
Control mean (2023)	2.964	0.679	0.647	0.359	0.441
Standard deviation	1.672				
N	942	942	942	942	942
R-squared	0.167	0.067	0.053	0.052	0.082

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. P-values from randomization inference (5,000 permutations) in curly 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.

5.5. Adoption of organic fertilizer and pesticide over time

Table 6 compares treatment effects for organic fertilizer use in 2019, 2021, and 2023. In 2019, one year after the first training, treated farmers were 11.6 percentage points more likely to use organic fertilizer than farmers in the control group. The effect size declined to 8.3 percentage points in 2021, before increasing again to 14.7 percentage points in 2023. The decline in 2021, prior to the second training, indicates the potential of repeated extension to sustain adoption levels over time. While the absence of re-randomization for the second training prevents causal attribution, the observed pattern is consistent with Barrett et al. (2022), who find that the adoption of rice intensification increases with greater treatment intensity. Exploring adoption patterns for the use of organic pesticide and manure, we observe similar effect size patterns for organic pesticide, but not for manure (for details, see Online Appendix, Tables H1 and H2).

Table 6
Treatment effects over time (ITT): Organic fertilizer application (other than manure)

	(1) Organic fertilizer 2019 (=1)	(3) Organic fertilizer 2021 (=1)	(5) Organic fertilizer 2023 (=1)
Treatment	0.116***	0.083*	0.147***
	(0.001)	(0.059)	(0.002)
	{0.001}	{0.074}	{0.005}
Outcome 2018	0.522***	0.092**	0.086**
	(0.000)	(0.018)	(0.031)
Control mean	0.284	0.214	0.277
N	942	942	942
R-squared	0.316	0.091	0.121

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust p-values (clustered at the village level) in parentheses. P-values from randomization inference (5,000 permutations) in curly 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.

Several factors may account for the generally lower adoption rates of organic fertilizer in 2021 in both treatment and control villages. Qualitative interviews indicate that farmer group activities were largely suspended due to COVID-19 restrictions and slow to resume thereafter. This may have contributed to the observed pattern because some groups practice organic fertilizer production together. In addition, the 2021 survey was conducted primarily by phone, potentially introducing measurement challenges; however, the interview mode would have affected treatment and control groups equally.

5.6. Adoption dynamics

Next, we explore the adoption dynamics underlying the effect size variation observed in Table 6. For this purpose, we classify respondents into six categories based on their adoption status across survey waves: (i) early adopters: Farmers who began experimenting with the practice during the first follow-up survey and continued its application in all subsequent surveys, (ii) late adopters: Farmers who had not adopted the practice at the first follow-up but began doing so in a later survey wave, (iii) re-adopters: Farmers who used the practice at the first follow-up, discontinued at the second, and resumed its use by the time of the third follow-up, (iv) dis-adopters: Farmers who adopted the practice at an earlier wave but discontinued it in a later wave, (v) never adopters: Farmers who did not adopt the practice in any survey wave, and (vi) always adopters: Farmers who used the practice consistently in all survey waves.

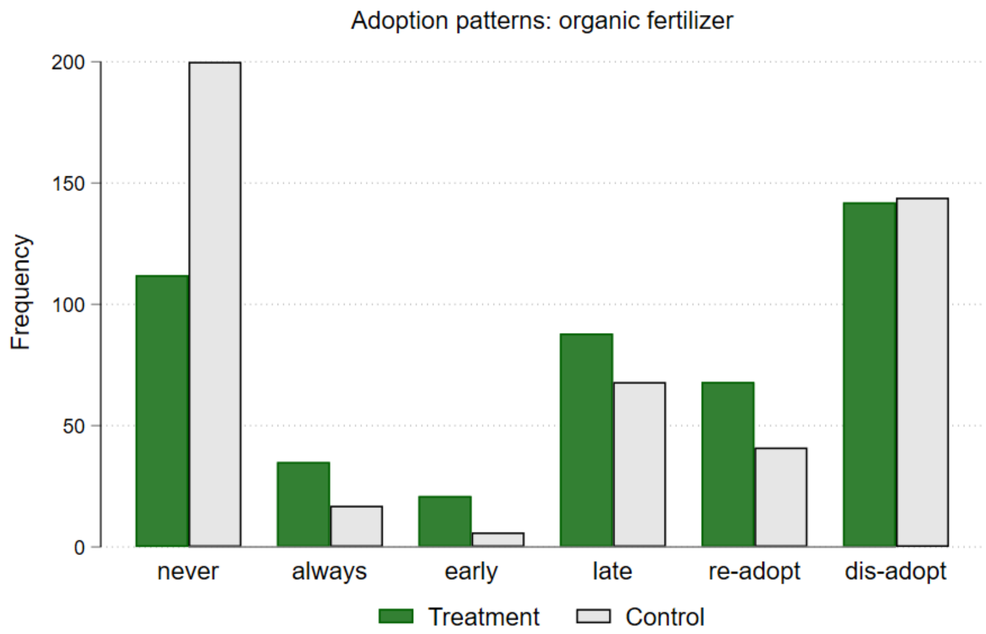

Figure 3: Adopter types across treatment status (2018-2023)

Figure 3 compares the distribution of respondents across adoption categories in the treatment and control groups for organic fertilizer use. Never adopters are more prevalent in the control group, whereas the treatment group has higher shares of always adopters, early adopters, late adopters, and re-adopters.

Notably, only a small proportion of farmers are early adopters, implying that few farmers adopted organic fertilizer immediately after the first training and continued its use without interruption. The treatment effect observed in 2019 is therefore partly driven by farmers who later dis-adopted, with some re-adopting by 2023 following the second training. A considerable share of farmers is classified as late adopters – farmers who began using organic fertilizer only after the first follow-up survey in 2019 – potentially reflecting increased motivation from repeated exposure to training, or social learning effects where farmers observed positive examples from peers who had adopted earlier. During the qualitative data collection, some farmer group heads, for example, reported that they try to lead by good example, because others first look at them to see whether it works.

Overall, the patterns suggest that farmers actively experiment with new technologies, with considerable levels of dis-adoption and re-adoption. The presence of re-adopters suggests that farmers can be motivated to re-engage with a technology they had previously abandoned. The two survey waves conducted between the training interventions uniquely position us to capture this re-adoption behavior, which has rarely been documented in previous studies.

Table 7
Use of organic fertilizer - Factors associated with adopter types (multinomial logit model)

	Versus never adopter				
	(1) Always adopter	(2) Early adopter	(3) Late adopter	(4) Re-adopter	(5) Dis-adopter
Treatment	1.398***	1.781***	0.855***	1.117***	0.597**
	(0.451)	(0.549)	(0.308)	(0.348)	(0.258)
Male (=1)	1.012*	0.542	0.192	0.706**	0.336
	(0.537)	(0.596)	(0.320)	(0.341)	(0.259)
Age (in yrs.)	0.009	-0.000	0.005	0.014	0.011
	(0.017)	(0.020)	(0.011)	(0.013)	(0.010)
Completed high school (=1)	1.447***	0.942**	0.595**	0.615**	0.269
	(0.347)	(0.409)	(0.238)	(0.250)	(0.223)
Farming main activity (=1)	0.114	-0.386	0.155	0.230	0.120
	(0.331)	(0.511)	(0.265)	(0.291)	(0.245)
Farmer group head (=1)	2.264***	0.846	1.182**	0.843*	0.418
	(0.465)	(0.840)	(0.469)	(0.510)	(0.418)
Financial difficulty (=1)	-0.523	0.431	0.066	-0.566**	-0.185
	(0.377)	(0.472)	(0.241)	(0.274)	(0.190)
Farmers' decisions matter (perception) (=1)	0.791	0.002	-0.276	0.849**	-0.037
	(0.592)	(0.515)	(0.252)	(0.367)	(0.266)
Agr. env. poll. Is problematic (perception) (=1)	-0.172	0.057	0.377	-0.295	0.470*
	(0.476)	(0.505)	(0.289)	(0.319)	(0.242)
Livestock ownership 2018 (=1)	-0.499	0.114	-0.261	0.063	-0.193
	(0.386)	(0.449)	(0.291)	(0.269)	(0.217)
N	942	942	942	942	942

Note: *** p<0.01, ** p<0.05, * p<0.1. *p*-values (clustered at the village level) in parentheses. Cols. (1) – (5) report the coefficients from a multinomial logit model where the base category is never adopter. Respondent and household characteristics capture values from the baseline survey in 2018.

Tables 7 and 8 report multinomial logit regression estimates (Equation (2)) of the association between adopter type – relative to the base category of never adopters – and both exposure to training and farmer characteristics measured at baseline. We focus on two practices, organic fertilizer (other than manure) and manure, because they differ in production requirements, input sources, and adoption constraints. Comparing them provides insight into whether the correlates of adoption pathways are technology-specific. Table 7 presents results for organic fertilizer, while Table 8 reports the estimates for manure (see also Figure H1 in the Online

Appendix for a more detailed descriptive comparison). Across both technologies, several variables emerge as important correlates of adoption status, but the patterns differ. For organic fertilizer, training exposure, education, farmer group participation, and farmer group leadership position dominate, whereas livestock ownership is central for manure.

For organic fertilizer, training exposure is positively and significantly associated with adoption across all adopter types, with the largest coefficients observed for always and early adopters. The positive and significant coefficient for always adopters may reflect motivation and confirmation effects when farmers' own farming practices align with recommendations by external experts. Education also matters: farmers with a completed high school education are more likely to be always, early, late, or re-adopters, compared to those who never adopt. This pattern is consistent with qualitative evidence that producing and applying organic inputs is perceived as more complex. Higher educational attainment may facilitate following written instructions for one's own organic fertilizer production. Serving as the farmer group head in 2018 is associated with a substantially higher likelihood of always adopting organic fertilizer. This likely reflects that group heads are typically elected for their knowledge and experience and are more often targeted by extension services.

Table 8
Use of manure - Factors associated with adopter types (multinomial logit model)

	Versus never adopter				
	(1) Always adopter	(2) Early adopter	(3) Late adopter	(4) Re-adopter	(5) Dis-adopter
Treatment	0.659	1.313***	0.671**	0.416	0.293
	(0.437)	(0.466)	(0.288)	(0.378)	(0.288)
Male	0.544	0.263	0.208	0.594	0.598*
	(0.416)	(0.478)	(0.350)	(0.393)	(0.319)
Age (in yrs.)	-0.015	0.017	0.009	-0.004	0.003
	(0.014)	(0.020)	(0.015)	(0.014)	(0.011)
Completed high school (=1)	-0.016	0.081	-0.442	-0.227	-0.179
	(0.314)	(0.396)	(0.272)	(0.292)	(0.245)
Farming main activity (=1)	0.795**	-0.150	0.021	0.576*	0.539
	(0.369)	(0.431)	(0.306)	(0.329)	(0.374)
Farmer group head (=1)	1.094**	1.872***	0.392	0.552	0.608
	(0.522)	(0.601)	(0.556)	(0.506)	(0.523)
Financial difficulty (=1)	-0.008	0.341	0.126	-0.176	0.137
	(0.266)	(0.402)	(0.296)	(0.262)	(0.250)
Farmers' decisions matter (perception) (=1)	0.418	0.472	0.400	-0.049	-0.072
	(0.370)	(0.383)	(0.452)	(0.320)	(0.263)
Agr. env. poll. Is problematic (perception) (=1)	0.027	-0.796*	-0.057	0.315	0.465*
	(0.382)	(0.461)	(0.392)	(0.314)	(0.275)
Livestock 2018	2.579***	0.768**	-0.159	1.577***	1.197***
	(0.307)	(0.381)	(0.342)	(0.278)	(0.258)
N	942	942	942	942	942

Note: *** *p*<0.01, ** *p*<0.05, * *p*<0.1. *p*-values (clustered at the village level) in parentheses. Cols. (1) – (5) report the coefficients from a multinomial logit model where the base category is never adopter. Respondent and household characteristics capture values from the baseline survey in 2018.

For manure, training exposure increases the likelihood of both early and late adoption but does not predict always adoption, re-adoption, or dis-adoption. This indicates that the treatment effects observed in Table 2 are primarily driven by early and late adopters. For continued manure use, livestock ownership in 2018 emerges as the key predictor.[10] The coefficient for always adopters is substantially larger than for any other adopter category, underscoring the central role of livestock resources in shaping manure use decisions. Livestock ownership is not significantly related to late adoption, indicating that in this group, training exposure is a more important determinant than baseline livestock holdings. Among early adopters, both training and livestock ownership are positively associated with uptake; however, the effect of training is comparatively stronger.

5.7. Treatment effects on performance and welfare outcomes

The overarching finding is that training exposure had no sizeable effect on welfare indicators. Specifically, there is no evidence that the training influenced respondents' satisfaction with their job, income, or free time. Likewise, we find no consistent and statistically significant effects on respondents' perception of farming (Online Appendix Table I1). Perception outcomes were elicited through respondents' agreement with the statements "farming is worthwhile for youth", "farming preserves nature", and "farming is an opportunity to become wealthy", measured on a six-point Likert scale from "strongly disagree" to "strongly agree". Responses coded as "agree" or "strongly agree" were assigned a value of one. While the perception that farming is worthwhile for youth shows a small positive effect, this result is not robust to an alternative coding specification (i.e., also classifying "slightly agree" as one).

Furthermore, there is no evidence that training exposure affected farm-level outcomes, including household labor allocated to farming, total farming expenditure, and disaggregated expenditures on chemical inputs, organic inputs, and hired labor (Online Appendix Table I2). The absence of an increase in labor input suggests that adopting organic practices, as promoted by the training, did not impose additional labor demands. This finding may be viewed positively, as increased labor requirements are typically seen as a challenge of organic farming (Jouzi et al., 2017). Restricting the analysis to rice-cultivating households, for which detailed harvest data are available, also reveals no effect on harvest quantities (Online Appendix Table I3). Although organic products could in principle command price premiums, this channel is not relevant in our study context, as very few farmers practice fully organic farming and only around 10% of rice production is sold, with the remainder self-consumed or, in the case of sharecropping, transferred to the landowner.

[10] We defined livestock ownership as equal to one if the household owns at least 10 chickens, or 2 goats, or 1 cow. This threshold was chosen to reflect livestock quantities that result in at least modest amounts of manure. The results remain robust when using alternative definitions, for example, if livestock ownership is set equal to one with 12 chickens, or 1 goat, or 1 cow.

6. Qualitative Results

6.1. Factors motivating farmers to use organic inputs

Quantitative results show that training motivated farmers to adopt organic fertilizers but had no statistically significant effects on welfare outcomes such as income or job satisfaction. This raises the question: what motivates farmers to adopt organic farming practices? Qualitative data suggests soil fertility and economic considerations as key motivations. Across FGDs, farmers emphasized improved soil fertility as a central reason for adopting organic practices. One farmer shared: *"We learned from the training that manure and organic fertilizer improve soil fertility over time."* Other participants reported improvements in soil quality after increasing their use of organic inputs. Farmers emphasized long-term soil fertility as a key benefit that offsets the perceived disadvantages of organic fertilizers, most notably their relatively slow effect.[11] As one farmer explained: "*Chemicals work quickly, while organic farming is slow, but in the future, the soil will be fertile.*"

Economic motivations were also frequently cited. Farmers pointed to rising prices of chemical fertilizers, attributed to declining subsidy levels, as a key incentive to adopt organic inputs.[12] Farmers emphasized the affordability of self-produced organic inputs, made from low-cost or freely available materials. While quantitative data show no significant decrease in spending on chemical fertilizers, the larger effect sizes associated with self-produced compared to bought organic fertilizers align with farmers' cost-saving rationale. As the heterogeneity analysis suggests, cost-saving considerations may have been particularly strong among farmers who faced financial difficulties and for whom we observe a stronger decline in chemical fertilizer. Additionally, health considerations emerged in two FGDs, with some farmers expressing a desire to grow rice with fewer chemicals since most is consumed by their own households.

6.2. Barriers to adopting organic farming practices

Farmers identified time constraints and slower results as key barriers. Preparing organic inputs was described as time-consuming across all FGDs, with alternative income-generating activities making it less appealing to invest time in labor-intensive organic farming practices. Some farmers expressed a preference for "*finished*" organic products similar to chemical fertilizers. This presents a tension between the low cost of self-production and the convenience of purchased organic products. Another recurring theme was the lack of follow-up support. Participants across FGDs expressed the need for ongoing, hands-on guidance, particularly

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[11] Organic fertilizers typically require more time to take effect compared to chemical alternatives, as their nutrients are released gradually through microbial activity and natural decomposition processes.

[12] Although reports suggest that the government's annual budget for fertilizer subsidies has increased, or at least remained stable (Heru Andriyanto & Prisma Ardianto, 2024), global market prices for several fertilizers have risen even more sharply in recent years. This divergence likely contributes to farmers' perception of declining subsidy levels despite the larger budget allocation.

practical demonstrations of successful organic farming. However, in practice, many extension offices lack the resources to offer intensive support, especially on a larger scale. Gender-specific challenges also emerged. Women managing family farms noted the difficulty of transporting heavy materials like manure to often distant fields.

6.3. Interest in fully converting to organic farming

Most farmers expressed a preference for semi-organic over fully organic farming. Many felt that some use of chemical fertilizers remained necessary for satisfactory results. One farmer explained that fruits require "*chemical stimulation*" to grow properly, a sentiment echoed by others in the group. Farmers raised concerns about lower yields and reduced profits when using solely organic inputs compared to semi-organic practices. Market access further complicated this issue; farmers reported receiving the same price for organic and non-organic products when selling through middlemen. In one FGD, farmers who had already experimented with organic farming expressed disappointment with unmet expectations concerning marketing opportunities and price premiums, including those promoted by the local government. Unlike most other farmer groups in our sample, this group focuses less on rice and more on cash crops, which may explain their stronger emphasis on market certainty as a key incentive for adoption. In two FGDs, farmers emphasized the need for additional government support and subsidies to make fully organic farming viable and attractive to farmers.

6.4. Adoption dynamics

Farmers in two FGDs reported that they had attempted fully organic farming but reverted to semi-organic practices as the harvest quantity fell short of expectations. One farmer noted that in addition to dissatisfaction with the harvest quantity, lab tests failed to certify his produce as fully organic, preventing him from selling it as such. Consequently, he returned to semi-organic farming. Similarly, dis-adoption of specific practices seems to stem mostly from dissatisfaction with harvest outcomes. Discussions indicate that some farmers decide already after one season whether to continue a new practice – a pattern consistent with our quantitative evidence of few early adopters but many late, re-, and dis-adopters. While such relatively fast decision-making is understandable given the importance of farming to livelihoods, this can be problematic for organic farming, which requires time for soil regeneration before results become evident. One farmer explained that it took several seasons for yields to return to previous levels after switching to mostly organic farming. Conversely, positive personal experiences reinforced adoption decisions, and farmers expressed a willingness to continue experimenting based on positive outcomes. For example, one farmer explained that he continued using organic inputs after seeing improved root development.

6.5. Role of training in adoption

Training influenced adoption through knowledge transfer and by motivating farmers. Participants reported that it encouraged them to try new practices. Across FGDs, farmers highlighted practical skills gained during the training, particularly in producing organic fertilizers. In two FGDs, farmers emphasized the training handbook as a useful reference for organic recipes and methods. Farmers also reported applying soil test recommendations, such as using agricultural lime, based on trainers' advice. Interestingly, some farmers still referred to their use of organic practices as a "*trial phase*", four to five years after the first training. This may be partly due to the second training, which introduced new fertilizer recipes and emphasized locally available, affordable ingredients, potentially re-motivating farmers to use organic inputs. Farmers' reflections help explain patterns of late and re-adoption observed after the second training. For example, one farmer perceived the second training as less prescriptive and more flexible, making partial adoption feel more manageable than a full transition. Soil test results were also cited as motivating, with higher organic matter levels observed for plots on which farmers already apply organic inputs. While one farmer group head felt the second training added little technical content, he emphasized that building belief in organic practices takes time and requires repetition to support lasting change.

7. Discussion and Conclusion

This paper presents experimental evidence from a multi-year randomized controlled trial on repeated organic farming training in a context of high chemical input use. It contributes to the growing literature on long-term agricultural adoption behavior, documenting non-linear adoption dynamics of adoption, dis-adoption, and re-adoption.

We find that providing Indonesian smallholder farmers with repeated training increased the uptake of organic farming practices, the use of lime, and the use of the Leaf Color Chart. The ITT estimates indicate statistically significant and meaningful impacts. We find a 14.7 percentage point increase in the use of organic fertilizer, this corresponds to an increase of 50% relative to the control group. Our index measure aggregating a bundle of taught practices increases by 30%. We also find the trained farmers adopt lime and the leaf color chart more often. This is consistent with evidence that training can help overcome information constraints to adoption (e.g., Aker & Jack, 2025; Barrett et al., 2022). We also find evidence for input substitution away from chemical inputs. For example, the training reduced the use of chemical fertilizers by almost 21 kg per hectare, this corresponds to a reduction of 13% relative to the control group. The share of farmers using chemical pesticides is lower by 12% relative to the control group and spending on chemical pesticides seems to decrease by almost 22%. Yet, there is no substantial reduction in the total spending on chemical inputs (yet). The findings are consistent, however, with qualitative evidence suggesting that the potential for cost savings through self-producing organic inputs is a key motivator for adopting organic farming practices. Next to economic considerations, farmers emphasized improved soil fertility as a central reason for adopting organic practices. In contrast, farmers explained that slower plant response, labor requirements, and yield concerns are obstacles to (more intensive) adoption. We do not find any evidence of negative effects on rice yields and (so far) we do not observe that the training motivated farmers to fully convert to organic farming.

Our results confirm that adoption is not a one-time, permanent decision but involves cycles of experimentation, dis-adoption, and re-adoption. A considerable share of farmers who adopted organic farming practices in response to training dis-adopted at a later stage, a finding consistent with other studies (Barrett et al., 2022; Tamim et al., 2025). The comparatively higher share of late adopters and re-adopters in the treatment group provides suggestive (though not causal) evidence that repeated training may help sustain adoption levels over time. Qualitative evidence emphasizes farmers' own trial experience as central to adoption dynamics. Prior work highlights two mechanisms behind dis-adoption: insufficient duration of use and missing complementarities. For instance, Maggio et al. (2022) show that yield benefits from adopting organic fertilizer and intercropping increase over time – a challenge for resource-constrained households whose production decisions are based on short-term optimization horizons. Benefits might thus not yet be visible when farmers decide whether to continue using a farming practice. Qualitative evidence suggests that some farmers indeed evaluate new practices after just one season, which is problematic for technologies such as organic farming, where benefits such as improved soil health may only become visible after several seasons. A second mechanism is that farmers may attribute disappointment with outcomes to the technology rather than to the lack of complementary investments or tasks (Miehe et al., 2025). In our context, these complementarities may depend on the availability of sufficient quantities of organic inputs, which may not be the case if their application remains experimental and small-scale, or on the need for close monitoring of plants' nitrogen levels.

In line with McCarthy et al. (2024), we further find that correlates of adoption pathways are technology-specific. Results from multinomial logit estimations suggest that for manure, persistent use is strongly linked to livestock ownership. At the same time, organic fertilizer adoption pathways are more associated with education, and farmer group leadership in addition to training.

Why should policymakers care about training in organic practices? Although, we observe, so far, no positive yield effects in the quantitative data, qualitative evidence suggests farmers perceive improvements in soil health, which plays a key role in sustaining long-term productivity. Additionally, reduced pesticide use likely benefits biodiversity, although these effects were not captured in our data. Furthermore, reductions in greenhouse gas emissions from decreased chemical nitrogen fertilizer use provide further social benefits.

In summary, we find that training increases the uptake of organic farming practices which are accompanied by reductions in chemical nitrogen and pesticide use. These changes are environmentally beneficial and align with the goal of "greening" the farming sector. Yet, promoting sustained adoption requires acknowledging the prevalence of non-linear adoption pathways. These adoption patterns raise important questions about how to re-engage dis-adopters and maintain long-term use. Our results provide suggestive evidence on the role of repeated training. While our five-year study provides a meaningful window into these dynamics, longer-term research is needed to fully understand adoption trajectories beyond this period. Given the challenges of securing funding for extended studies, our results underscore the importance of investing in long-term panel data to better capture the complexities of agricultural technology adoption over time.

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Online Appendix

Cultivating change: Long-term effects of repeated training on organic farming adoption in Indonesia

Nathalie Luck, Michael Grimm, and Kristian Tamtomo

Appendix A: Analysis of attrition

Table A1
Attrition

	(1)	(2)	(3)	(4)	(5)
	Attrited 2023	Attrited 2023	Attrited 2023	Attrited 2023	Attrited 2023
Treatment	0.017	0.020	-0.133	0.058	0.043
	(0.550)	(0.459)	(0.347)	(0.108)	(0.284)
Male		0.005	0.008	0.003	0.003
		(0.885)	(0.813)	(0.933)	(0.926)
Age (in yrs.)		0.005***	0.004**	0.005***	0.005***
		(0.001)	(0.047)	(0.001)	(0.001)
Treatment x Age			0.003		
			(0.275)		
Completed high school (=1)		0.054**	0.054**	0.094***	0.053*
		(0.047)	(0.049)	(0.008)	(0.054)
Treatment x completed high school				-0.080	
				(0.123)	
Refrigerator (=1)		0.019	0.022	0.019	0.018
		(0.505)	(0.451)	(0.500)	(0.545)
Washing machine (=1)		0.045	0.046	0.050	0.048
		(0.254)	(0.247)	(0.217)	(0.217)
Farming main activity (=1)		-0.039	-0.038	-0.036	-0.038
		(0.244)	(0.252)	(0.282)	(0.253)
Cultivated land (in ha)		0.000	0.002	-0.002	0.049
		(0.993)	(0.965)	(0.964)	(0.425)
Land ownership share		0.046	0.046	0.046	0.046
		(0.166)	(0.165)	(0.168)	(0.166)
Treatment x land ownership share					-0.068
					(0.350)
Observations	1200	1200	1,200	1,200	1,200
R-squared	0.031	0.056	0.058	0.058	0.057
Strata	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust p-values with standard errors clustered at the village level in parentheses. All control variables refer to the 2018 values. All regressions include strata fixed effects.

Appendix B: Lee bounds

Table B1
Lee bounds for treatment effects on main outcomes

	(1) Organic fertilizer (not manure) (=1)	(2) Organic pesticide (=1)	(3) Nitrogen kg/ha	(4) Chemical pesticide used (=1)	(5) Knowledge score (0-6)
Lower bound	0.173***	0.118***	-28.358**	-0.087*	0.737***
	(0.000)	(0.003)	(0.016)	(0.053)	(0.000)
Upper bound	0.193***	0.140***	-14.078	-0.066	0.860***
	(0.000)	(0.000)	(0.212)	(0.143)	(0.000)
Selected observations	932	932	858	932	932
Treatment missing rate	0.223	0.223	0.285	0.223	0.223
Control missing rate	0.207	0.207	0.260	0.207	0.207

Note: *** p<0.01, ** p<0.05, * p<0.1. Standard errors clustered at the village level in parentheses. This table presents the Lee bounds associated with the estimates for the treatment effects, following Lee (2009). Selected observations refer to the sample size after trimming. All Cols. are estimated using Equation (1) and by trimming the top/bottom of the control group by the difference in attrition between the treatment and control group. No control variables are included in these estimations, except for randomization strata fixed effects. The sample size for Col. (3) differs from the other Cols. as this variable is only recorded for respondents who grew rice the last season. As in the main outcomes, the variable “Nitrogen kg/ha” is top-coded at the 95% level. The missing rates are in relation to the original sample, i.e., 600 per treatment arm at baseline.

Appendix C: Spillover effects

Spillover effects could occur if farmers in the treatment group shared training information with control group farmers. This could occur since some of the sample villages share a common border, theoretically enabling communication about the training among farmers from different villages. Anecdotal evidence suggests that there are no substantial spillover effects. Enumerators did not report that control group respondents indicated any awareness of knowing other farmers who participated in the survey but received training. During FGDs with treatment group farmers, participants also did not indicate that they shared information with farmer groups from different villages; some reported sharing information with other farmer groups from the same sub-village. In Indonesia, villages commonly consist of several sub-villages and comprise a population of a few thousand people. Farmer groups are typically organized within sub-villages; many sub-villages also have several farmer groups. This structure further reduced the likelihood of spillovers across villages as farmer groups and neighboring plots are one of the main channels of communication.

We further test for spillover effects among villages that are within a 1km radius (this captures neighboring villages). Table C1 reports the results for key outcomes. Overall, these patterns provide no evidence for spillovers.

Table C1
Treatment spillovers

	(1) Organic fertilizer (not manure) (=1)	(2) Organic pesticide (=1)	(3) Nitrogen kg/ha	(4) Chemical pesticide used (=1)	(5) Knowledge score (0-6)
Main treatment effects (see Tables 2, 4, and 5)					
Treatment	0.147***	0.118***	-20.745*	-0.091**	0.677***
	(0.002)	(0.002)	(0.071)	(0.029)	(0.000)
Treatment effects accounting for spillovers within 1km					
(mean number of # treated villages within 1km: 0.45)					
Treatment	0.141**	0.164***	-22.598	-0.116*	0.754***
	(0.031)	(0.008)	(0.177)	(0.056)	(0.000)
Treatment x # treated villages	-0.037	-0.043	-16.238	0.034	-0.158
	(0.646)	(0.175)	(0.350)	(0.455)	(0.331)
# treated villages	0.028	-0.060	10.117	0.028	-0.059
	(0.764)	(0.364)	(0.643)	(0.713)	(0.773)
Baseline outcome	Yes	Yes	No	Yes	No
N	942	942	873	942	942

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Robust *p*-values (clustered at the village level) in parentheses. Number of villages=60. Regressions use the same controls and account for randomization strata. Controls include: gender 2018, age 2018, junior high school 2018, asset ownership 2018, farming main job 2018, land share owned 2018, and land size cultivated 2018. Cols. (1), (2) and (4) further include the baseline outcome as control; this variable is not available for the other columns. Col. (3) refers only to respondents who cultivated rice - the sample size is thus smaller.

Appendix D: Treatment effect by input source for organic practice adoption outcomes

Table D1
Treatment effects (ITT): Manure application

	(1) Manure (=1)	(2) Manure self-produced (=1)	(3) Manure bought (=1)
Treatment ANCOVA	0.102**		
	(0.016)		
Outcome 2018	0.344***		
	(0.000)		
Treatment POST	0.102*	0.048	0.070*
	(0.056)	(0.327)	(0.053)
Control mean (2023)	0.538	0.445	0.166
N	942	942	942
R-squared (ANCOVA)	0.163		
R-squared (POST)	0.055	0.056	0.069

Note: *** *p*<0.01, ** *p*<0.05, * *p*<0.1. Robust *p*-values (clustered at the village level) in parentheses. 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 D2
Treatment effects (ITT): Organic fertilizer application

	(1) Organic fertilizer (=1)	(2) Organic fertilizer self-produced (=1)	(3) Organic fertilizer bought (=1)
Treatment ANCOVA	0.147***		
	(0.002)		
Outcome 2018	0.086**		
	(0.031)		
Treatment 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 (ANCOVA)	0.121		
R-squared (POST)	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. 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 D3
Treatment effects (ITT): Organic pesticide application

	(1) Organic pesticide (=1)	(2) Organic pesticide self-produced (=1)	(3) Organic pesticide bought (=1)
Treatment ANCOVA	0.118***		
	(0.002)		
Outcome 2018	0.153***		
	(0.001)		
Treatment 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 (ANCOVA)	0.100		
R-squared (POST)	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. 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.

Appendix E: Heterogenous effects

Table E1
Heterogenous treatment effects

	(1) Organic fertilizer (not manure) (=1)	(2) Organic pesticide (=1)	(3) Nitrogen kg/ha	(4) Chemical pesticide used (=1)	(5) Knowledge score (0-6)
Main treatment effects					
Treatment	0.147***	0.118***	-20.745*	-0.091**	0.677***
	(0.002)	(0.002)	(0.071)	(0.029)	(0.000)
Age					
Treatment	0.271*	0.132	-24.819	-0.550***	0.485
	(0.096)	(0.292)	(0.461)	(0.001)	(0.372)
Treatment x Age	-0.002	-0.000	0.076	0.009***	0.004
	(0.472)	(0.902)	(0.895)	(0.002)	(0.716)
Gender					
Treatment	0.142	0.237***	-39.859*	-0.140	0.899***
	(0.109)	(0.008)	(0.095)	(0.117)	(0.000)
Treatment x Male (=1)	0.007	-0.142*	23.011	0.058	-0.264
	(0.944)	(0.085)	(0.320)	(0.545)	(0.276)
Education					
Treatment	0.070	0.108**	-30.227**	-0.102**	0.828***
	(0.236)	(0.043)	(0.027)	(0.047)	(0.000)
Treatment x High school (=1)	0.162**	0.022	20.688	0.023	-0.316
	(0.020)	(0.686)	(0.191)	(0.667)	(0.118)
Perception agr. pollution is problematic					
Treatment	0.144***	0.108**	-28.609**	-0.126**	0.587***
	(0.006)	(0.018)	(0.035)	(0.012)	(0.000)
Treatment x Perception agr. poll. problematic (=1)	0.006	0.025	16.731	0.076	0.240
	(0.928)	(0.572)	(0.261)	(0.264)	(0.224)
Financial difficulty					
Treatment	0.116*	0.077	-4.888	-0.134***	0.510***
	(0.051)	(0.106)	(0.724)	(0.004)	(0.001)
Treatment x Financial difficulty (=1)	0.057	0.076	-28.289*	0.079	0.303
	(0.403)	(0.140)	(0.082)	(0.151)	(0.117)
Land share owned					
Treatment	0.151**	0.082*	-11.455	-0.060	0.421**
	(0.017)	(0.057)	(0.307)	(0.296)	(0.021)
Treatment x Land share owned	-0.006	0.062	-15.861	-0.052	0.437*
	(0.944)	(0.411)	(0.350)	(0.505)	(0.092)
Baseline outcome	Yes	Yes	No	Yes	No
N	942	942	873	942	942

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 use the same controls and account for strata fixed effects. Controls include: gender 2018, age 2018, junior high school 2018, asset ownership 2018, farming main job 2018, land share owned 2018, land size cultivated 2018. All regressions include the column-specific interaction-related covariate measured at baseline as control. Cols. (1), (2), (4) also control for the outcome at baseline; for the other outcomes this information is not available. Col. (3) only refers to respondents who cultivated rice as returning rice residues is only applicable to them - the sample size is thus smaller.

Appendix F: Chemical fertilizer use, expenditure, and organic adoption

Table F1
Treatment effects (ITT): Chemical fertilizer

	(1) Nitrogen kg/ha	(2) Kalium kg/ha	(3) Phosphate kg/ha	(4) NPK fertilizer kg/ha	(5) Urea fertilizer kg/ha
Treatment	-20.745*	-0.551	1.129	-11.365	-39.184*
	(0.071)	(0.416)	(0.173)	(0.652)	(0.072)
Control mean (2023)	161.430	9.636	8.212	266.076	255.652
N	873	873	873	873	873
R-squared	0.062	0.218	0.198	0.097	0.087

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. All variables are top-coded at the 95% level. The sample in all cols. is restricted to respondents who grew rice in the last season in the 2023 survey.

Table F2
Nitrogen use and chemical fertilizer expenditures: Relationship with adoption index and years of use

	(1) Nitrogen kg/ha	(2) Nitrogen kg/ha	(3) Chemical fertilizer IDR 1,000/ha	(4) Chemical fertilizer IDR 1,000/ha
Organic adoption index				
1 practice	-8.509		-134.549	
	(0.439)		(0.343)	
2 practices	-18.278*		-216.792	
	(0.093)		(0.107)	
3 practices	-32.945***		-247.512	
	(0.008)		(0.105)	
4 practices	-57.970***		-515.088***	
	(0.000)		(0.002)	
Organic fertilizer - Continued use				
Used in 2023		-1.390		-32.419
		(0.863)		(0.756)
Used in 2023 & 2021		-8.356		-86.009
		(0.626)		(0.679)
Used in 2023 & 2021 & 2019		-51.357***		-354.476
		(0.007)		(0.194)
Used in all waves		-41.279***		-144.396
		(0.003)		(0.519)
Control mean (2023)	161.430	161.430	2016.841	2016.841
Baseline outcome	No	No	No	No
N	873	873	873	873
R-squared	0.071	0.066	0.093	0.088

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. All variables are top-coded at the 95% level. The sample in all cols. is restricted to respondents who grew rice in the last season in the 2023 survey.

Appendix G: Knowledge score questions

Knowledge score: This outcome is 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 are 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)

Appendix H: Adoption over time and adoption dynamics

Table H1
Treatment effects over time (ITT): Organic pesticide application

	(1) Organic pesticide 2019 (=1)	(3) Organic pesticide 2021 (=1)	(5) Organic pesticide 2023 (=1)
Treatment	0.094**	0.034	0.118***
	(0.015)	(0.180)	(0.002)
Outcome 2018	0.361***	0.090*	0.153***
	(0.000)	(0.076)	(0.001)
Control mean	0.103	0.084	0.067
N	942	941	942
R-squared	0.154	0.044	0.100

Note: *** *p*<0.01, ** *p*<0.05, * *p*<0.1. Robust *p*-values (clustered at the village level) in parentheses. 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.

Table H2
Treatment effects over time (ITT): Manure

	(1) Manure 2019 (=1)	(3) Manure 2021 (=1)	(5) Manure 2023 (=1)
Treatment	0.091**	0.115***	0.102**
	(0.016)	(0.003)	(0.016)
Outcome 2018	0.362***	0.375***	0.344***
	(0.000)	(0.000)	(0.000)
Control mean	0.103	0.084	0.067
N	942	942	942
R-squared	0.194	0.181	0.163

Note: *** *p*<0.01, ** *p*<0.05, * *p*<0.1. Robust *p*-values (clustered at the village level) in parentheses. 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.

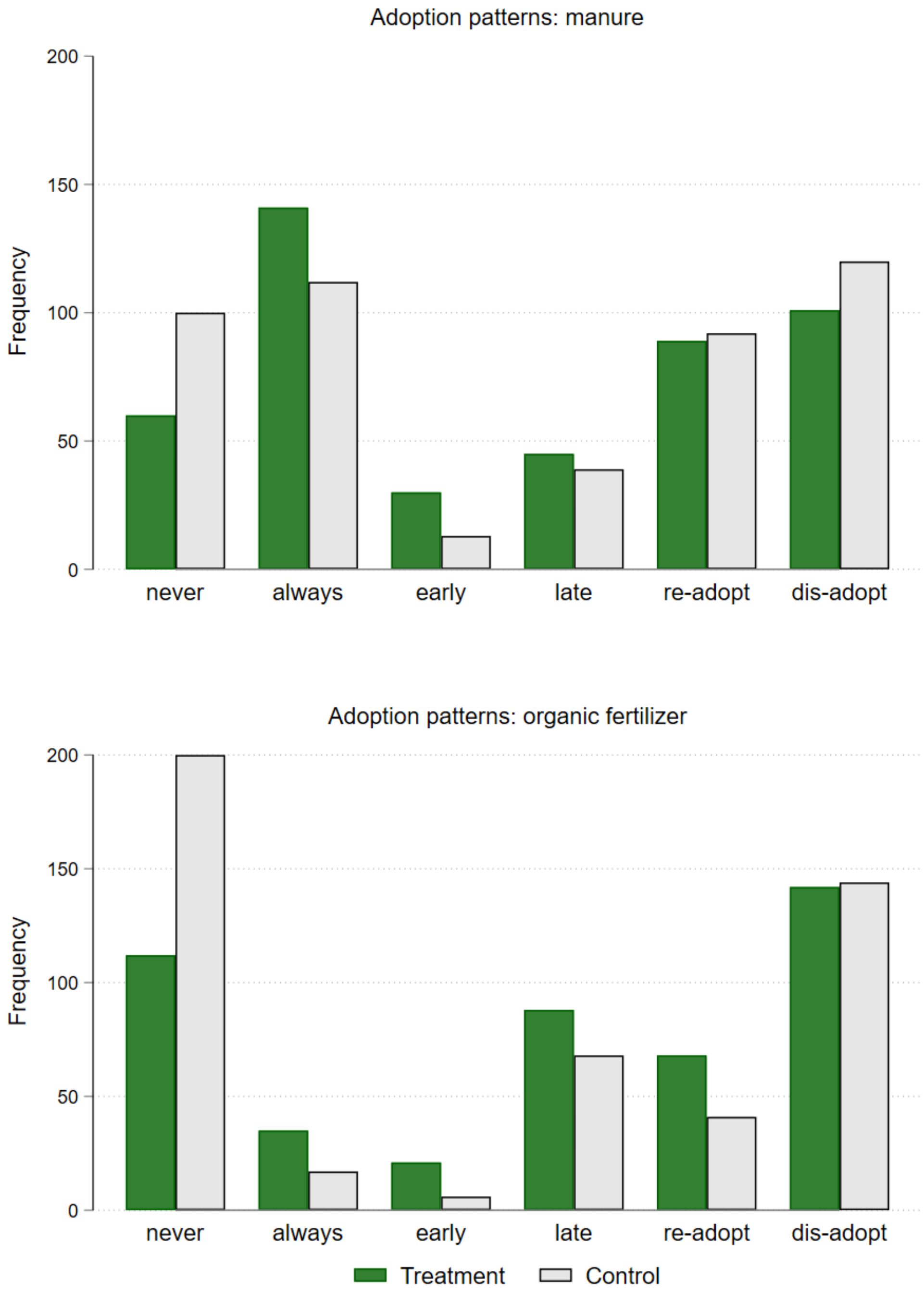

Figure H1: Comparison adoption patterns organic fertilizer and manure across treatment status (2018-2023)

Appendix I: Treatment effects on welfare outcomes

Table I1
Treatment effects (ITT): Satisfaction and perceptions of farming

	Satisfaction (score 1 - 10)			Perceptions of farming (agree=1)		
	(1) Job	(2) Income	(3) Free time	(4) Worthwhile youth	(5) Preserve nature	(6) Wealth opportunity
Treatment	0.171	0.048	-0.027	0.042**	0.002	0.021
	(0.227)	(0.752)	(0.824)	(0.027)	(0.820)	(0.292)
Control mean (2023)	6.916	6.611	7.209	0.893	0.966	0.876
Standard deviation	2.056	1.939	1.899			
N	942	942	942	942	942	942
R-squared	0.031	0.036	0.080	0.043	0.035	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. Perception is coded as "agree" if respondents reported to strongly agree or agree.

Table I2
Treatment effects (ITT): Farm outcomes (all plots)

			Expenditures details		
	(1) HH labor (h/week)	(2) Expenditures all (IDR 1,000 /ha)	(3) Chemicals inputs (IDR 1,000/ha)	(4) Organic inputs (IDR 1,000/ha)	(5) Hired labor (IDR 1,000/ha)
Treatment	-0.020	-392.506	-43.895	124.052	-519.558
	(0.992)	(0.614)	(0.866)	(0.234)	(0.275)
Control mean (2023)	24.038	7996.779	2246.236	237.424	5188.341
Standard deviation	17.198	6749.666	2082.720	820.964	4770.068
N	942	942	942	942	942
R-squared	0.109	0.086	0.086	0.092	0.082

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. Expenditure variables are top codded at 99%.

Table I3
Treatment effects (ITT): Farm outcomes rice plots

	(1) HH labor (h/week)	(2) Hired labor (IDR 1,000/ha)	(3) Chemicals inputs (IDR 1,000/ha)	(4) Rice harvest (ton/ha)
Treatment	0.407	-165.047	-264.717	0.021
	(0.565)	(0.627)	(0.270)	(0.924)
Control mean (2023)	4.634	4838.444	2574.182	4.558
Standard deviation	8.277	3728.335	2035.527	2.287
N	873	873	873	854
R-squared	0.075	0.072	0.124	0.079

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. Expenditure variables are top codded at 99%. Sample for harvest (Col. 4) is smaller because 20 respondents did not harvest anything by themselves and instead sold the "right to harvest" to someone else.

Appendix J: Deviations from the pre-analysis plan (PAP) and supplemental analysis

We registered two pre-analysis plans: one for adoption outcomes (AEARCTR-0011018) and another for welfare indicators (AEARCTR-0011004). Both plans are publicly available through the American Economic Association's registry for randomized controlled trials. In this paper, we combine results from both plans.

The pre-analysis plans pre-specified the outcomes for the ITT estimations detailed in Section 4.1. Table J1 reports deviations related to the analyses presented in Sections 4.1 and 5.1–5.5 and 5.7. While the focus of this paper is on adoption outcomes, we also report welfare outcomes. However, the welfare pre-analysis plan includes a broader set of outcomes. ITT results following the respective pre-analysis plans are published on the AEA registry. The analysis of long-term adoption (Section 5.6) is exploratory and not part of the pre-analysis plans.

Table J1
Deviations from the pre-analysis plan (PAP) and supplemental analysis

Pre-analysis plan (PAP)	**Deviation from plan**
(AEARCTR-0011018) – Adoption outcomes **Primary outcomes** Family 1: Adoption - Domain 1 1. Organic fertilizer *Fermented manure* (binary variable) =1 if the respondent applied fermented manure. Fermented manure may be produced by farmers themselves or bought. […] 4. Sum of organic practices used This outcome will be a count variable from 0 to 4 for the number of practices applied. It will be 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 will be considered for this variable.	Unlike the specification in the pre-analysis plan, our analysis focuses on manure in general rather than exclusively on fermented manure. This decision was made because opinions about what classifies as fermented manure differed across respondents. Additionally, the diversity of manure types, combinations of animal sources, use of fermentation speed-increasing add-ins, and varying other management practices complicated binary classification for enumerators. The results based on respondents' own classification of fermented manure and strictly following the pre-analysis plan that can be found on the American Economic Association's registry.
(AEARCTR-0011018) – Adoption outcomes **Secondary outcomes** 4. Residues: *Burnt plant residues (binary variable)* =1 if the respondent burned all or some part of the plant residues.	To keep conciseness, we do not report the results for the outcome "burnt plant residues" in the paper. Similar to the primary outcome "returned plant residues" (Table 2), we observe no statistically significant effect for this variable.
(AEARCTR-0011004) – Welfare outcomes **Primary outcomes** Agricultural yields, revenue, profits, labor • *Agricultural revenue* (per ha) during the last season measured at the respondent level & separately for rice	To keep conciseness, we focus on a subset of welfare outcomes. This selection provides sufficient evidence to support our conclusion that there is little quantitative indication of welfare effects.

Agricultural profits (per ha) during the last season measured at the respondent level & separately for rice (considering revenues, input costs, land rent costs and labor cost) - Rice yields (per ha) during the last season at the respondent level (for those respondents that grow rice) - Average respondent and family labor during the last season per ha	Specifically, we do not report results for revenue and profits. Given the absence of treatment effects on both expenditures and yields, there is limited reason to expect effects on revenues or profits, which is consistent with our empirical findings showing no statistically significant impacts on these outcomes. The complete set of results for all outcomes is available on the American Economic Association's registry.
(AEARCTR-0011004) – Welfare outcomes **Secondary outcomes** Income and wealth - Satisfaction with household income: measured on a scale from 1 (not satisfied at all) to 10 (very satisfied) *Asset ownership index* (motorcycle, car, fridge, washing machine, Laptop, TV) *Electricity expenditures* per HH member (in 000 IDR) *Financial distress*: Binary variable =1 if respondent answers that HH was in financial distress anytime during the last 6 months (financial distress: unable to fulfil usual daily expenditures) *Nutritional insecurity*: Binary variable =1 if respondent answers that HH faced with a situation when there has not been enough food to feed the HH during the last 6 months	Since we did not observe any quantifiable or statistically significant effects on yields, expenditures, or labor, there is little reason to expect impacts on farmers' economic welfare. Accordingly, we do not report results for the "asset ownership index," "electricity expenditures," "financial distress," or "nutritional insecurity." None of these outcomes show statistically significant treatment effects.
(AEARCTR-0011004) – Welfare outcomes **Secondary outcomes** Health *Health perception*: Respondents perception of own current health on a scale from 1 to 10. 1 means the worst health the respondent can imagine and 10 means the best health the respondent can imagine. *Perceived health complaints*: skin irritation (itchy), skin irritation (hurt), sore throat, cough, dizziness, diarrhea during the last 2 months. Binary variables=1 if respondent reports yes for the respective complaint. We will also measure this as an index variable ranging from 0 (no complaints) to 6 (suffered from all 6 complaints)	We do not report results on health outcomes in the paper; these are available on the American Economic Association's registry. The results suggest that farmers in the treatment group reported fewer health issues, which is consistent with the broader findings, i.e., reduced use of chemical pesticides. However, we find no statistically significant correlation between reported health complaints and indicators of chemical input use, which would constitute the main channel for a treatment effect on health and results must be interpreted with caution. For more details, see results available on the American Economic Association's registry.
	Supplemental analysis (not in PAP)
	Robustness checks using Lee Bounds (Table B1), spillover effects (Table C1), and FDR adjusted *p*-values which correct for multiple hypothesis testing (main outcomes presented in paper).

	An analysis of treatment effects on specific fertilizer types, specifically NPK and Urea, as cross-check for the Nitrogen decline that we observe (Table F1). Exploration of potential mechanisms for decline in nitrogen use, specifically correlation of nitrogen use with two measures of organic engagement (Table F2). Heterogeneity by age, gender, education, perception that agricultural pollution is problematic, financial difficulty, and land share owned (Table E1).