The Value of Information in Technology Adoption*

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Abstract

We study the role of information in promoting technology adoption and diffusion using a repeated field experiment over two years in Bangladesh. We develop a simple model to understand how information received by untreated farmers from fellow treated farmers about the quality of a new technology predicts their decisions about technology adoption. We use a randomized saturation design in selecting farmers for the provision of the new agricultural technology and then randomize villages with some farmers receiving repeated training. Our results show that the share of treated farmers who receive better training in technology have a high positive impact on the adoption rate of untreated farmers. Further evidence indicates that treated farmers who are more influential or more knowledgeable or socially connected with other farmers in their village generate stronger spillover effects. Also, untreated farmers who are more risk-averse tend to adopt the technology less and are less influenced by their treated peers. Our results thus indicate that information transmission about the quality of the technology matters.

Keywords: Technology adoption, information, peers, risk attitude.

JEL Classification: D80, Q16, C93.

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1 Introduction

Policymakers and practitioners often need to provide information to educate, explain or disseminate new knowledge, practices, or technologies to help people make informed decisions that will improve their well-being. An important challenge to promote adoption and diffusion of a new technology is the accuracy and the reliability of information about the product. This is particularly challenging in rural areas in developing countries because of the difficulty to reach farmers, the lack of information, and also the possible misinformation about new technologies such as seed varieties or new cultivation methods. Further, farmers in these rural areas are more reluctant to adopt a new technology because of their risk aversion.

Previous research[1] has documented that the lack of information, difficulties about learning, and risk aversion are important barriers for adoption and diffusion of new and improved technologies. Hence, improving the accuracy and reliability of information on yield and on the profitability of the new agricultural system or technologies could play an important role in mitigating farmers' risk-aversion and in promoting the adoption and diffusion of new technologies.

In this study, we examine the role of the quality and accuracy of information from peers on the individual adoption of a new technology. In collaboration with BRAC, the world's largest NGO, we implemented a randomized controlled trial where we disseminated a new technology named System of Rice intensification (SRI) to farmers in rural Bangladesh. We investigate whether farmers who obtained information of a new technology generate spillover effects to other farmers, and whether the strength of spillover effects depends on the quality of information. We randomly vary the number of treated farmers across villages, and the intensity of their training to examine the transmission of SRI among those untreated in the same villages.

Though a new technology such as SRI is relatively simple, previous studies (e.g., Barrett et al., 2022) document that it is difficult to promote adoption of such new method. Farmers are confronted with barriers such as lack of adequate information, risk aversion, uncertainty and social norms. In order to understand better, we develop a simple model explaining the adoption decisions of untreated farmers when they receive better quality of information from peers who are treated. We test our theoretical prediction that untreated farmers are more likely to adopt the technology when they receive more precise signals from their peers regarding benefits and costs of adopting the technology.

[1] See, for example, Barrett et al. (2004); Ashraf et al. (2009); Conley and Udry (2010); Jack (2011, 2013); Hanna et al. (2014); Emerick et al. (2016); Fafchamps et al. (2020), and Barrett et al. (2022). Conley and Udry (2010), for example, found that a farmer tends to adjust his input level towards his neighbors with whom he communicates with advice about farming because he obtains knowledge about the value of the product. Jack (2011) explored information inefficiencies and technology adoption and pointed out that, despite a profitable technology, if it is complicated and required precise implementation, then there is great barrier for adoption. Barrett et al. (2004) found that yields risk associated with a new rice cultivation method could make it unattractive to many farmers in Madagascar. Emerick et al. (2016) show that risk is an important aspect in adoption of new seeds or technologies and improved technologies that reduce risk have the potential to increase agricultural productivity.

We disseminate the SRI technology by providing training using a two-stage randomization. In the first stage, we implement village-level randomization where villages are randomly allocated into two treatment groups and a control group. In the second stage, we randomly vary the number of treated farmers who will receive a SRI training within each treatment village. More importantly, we vary the doses of the treatments. Farmers in a randomly selected set of villages receive two-time training in the beginning of each year before the main rice cultivating season, while farmers in other treatment villages received just a one-time training in the beginning of year 1. Thus, our field experiment generates exogenous variations in the degree to which farmers who were not themselves trained (untreated farmers) were indirectly exposed to this technology by varying the intensity of treated training.

Our results show that an increase of 10% in treated farmers in a village increases the average rate of the adoption of SRI technology among untreated farmers in the same village by 2.36%. We show that only treated farmers with a two-time training have a significant impact on the adoption rate of untreated farmers. According to our theoretical model, this is because $T2-$ treated farmers who received repeated training provide untreated farmers with accurate and precise information on SRI technology. Furthermore, the more trained a farmer is, the lower is the variance in the noise of technology quality, the more accurate is the information transmitted to an untreated farmer, and the more likely the latter adopts SRI technology.

We then investigate why farmers with repeated training generate stronger spillover effects by testing if accuracy of information was the main mechanism. We start by a straightforward comparison of knowledge of SRI between $T1$ (farmers received one-time training) and $T2$ (farmers received repeated training over two successive years) farmers before and after they were trained. We find that the accuracy of information about SRI increased after training for all farmers and it particularly increased significantly more for $T2$ farmers than $T1$ farmers. In addition, when we differentiate between midline assessment (where both $T1$ and $T2$ received the same training) and endline assessment (where $T2$ farmers received the training twice while $T1$ received it only once), we show that, in the midline assessment, there is no significant difference in adopting or following correctly the different SRI principles while, in the endline assessment, $T2$ farmers not only increase their adoption rate but also implemented SRI principles more precisely than $T1$ farmers. These indicate that $T2$ farmers have a more accurate and precise information about the different principles of SRI technology and they themselves also implemented the technology more efficiently than $T1$ farmers.

To further document that information matters, we utilized our network survey collected before the start of training. We asked each farmer to nominate one role model farmer in his village and calculated the number of times a farmer is nominated as role models by his peers. We find evidence that role models do generate significant influence on their untreated peers. In that survey, farmers were also asked to rate the level of agriculture knowledge of other farmers from the same village. We find evidence that more knowledgeable farmers generate significant

effects on their peers. We also collected whether farmers discuss agriculture or financial issues with their friends. We find that spillovers are higher when we consider treated farmers who discuss agriculture or financial issues with their untreated friends.

Lastly, we check if our results are really because farmers with two years of training provide *better* and *more accurate information* about SRI technology to their peers and not because they produce more rice than farmers with one year of training so that their peers just *imitate* them. We rule out the latter by showing that there are no differences in rice production and yields between $T1$ and $T2$ villages, even though farmers in $T2$ villages have received more training on SRI technology. In fact, we show that there are differences in rice production and yields only between adopters and non-adopters, confirming the benefits of SRI technology. These results support the mechanism highlighted by our theoretical model that spillover effects mainly operate through information transmission rather than imitating more productive farmers. This is because the SRI is not a complex technology to adopt but it is based on certain principles that justify particular practices, which are expected to be adapted empirically to local conditions. The information involved in following SRI principles and practices needs to be followed carefully. Hence, there is a real "cost" of adopting the SRI for farmers because it is a totally new way of thinking and the crop fields look visibly different, thereby leading to some resistance. In our framework, farmers with two years of training are much more able to explain and convince their untreated peers to adopt the SRI than those with less training because they provide them with accurate information on how to implement the different principles and practices of the SRI.

When we extend our simple model to include risk-averse rather than risk-neutral farmers, we obtain two new predictions: risk-averse farmers adopt less than risk-loving farmers (direct effect) and the higher is the degree of risk aversion, the lower is the impact of the proportion of treated farmers on the adoption rate of untreated farmers (cross-effect). We then test these theoretical results using a direct measure of the degree of riskiness of all farmers in a village. We find that our empirical results confirm the predictions of the theoretical model. In particular, we show that *risk-averse untreated farmers* are less sensitive to the influence of *treated peers* from $T2$ villages than *risk-neutral untreated farmers*. This is again consistent with the way the SRI is adopted and the difficulty for farmers to implement the principles that underlie the different practices of the SRI. As a result, it is not surprising that more risk-averse untreated farmers are more reluctant to adopt the SRI and are less influenced by the treated farmers residing in the same village.

Barrett et al. (2022) also evaluate the impact of this SRI intervention on a range of outcomes. They find large and positive treatment effect of SRI training on rice yields and profits, and a number of household well-being indicators for both trained and untrained farmers. They also find spillover effects. The focus of our paper different. First, we examine the impact of the *quality or accuracy of information* on the probability of adopting SRI technology among untreated farmers. To do so, we exploit the intertemporal intensity of indirect training exposure to SRI by

examining the differences between one-time and two-time training villages. Second, we examine information-based spillovers by differentiating between treated peers who are "influential" versus those who are "knowledgeable". Third, we look at friendship-based spillovers using the effect of frequency of communication and financial relationships among farmers. Finally, we study the importance of farmers' risk aversion in technology adoption and provide a theoretical model highlighting the possible mechanism behind our results.

A large body of the empirical literature has demonstrated the importance of social and network effects on technology adoption and diffusion (Foster and Rosenzweig, 1995; Bandiera and Rasul, 2006; Conley and Udry, 2001; Oster and Thornton, 2012; Banerjee et al., 2013; Cai et al., 2015; Bonan et al., 2021; Fafchamps et al., 2020; Carter et al., 2021). Beaman et al. (2021) study social learning in diffusion by targeting seed farmers in Malawi and show that targeting central farmers induce social learning and thus increase technology diffusion. Banerjee et al. (2013) find that targeting individuals with the highest eigenvector and diffusion centrality will increase the diffusion of the microfinance program the most. They also show that learning effects dominate peer effects. BenYishay et al. (2020) document large spillover effects by both men and women farmers as communicators to diffuse new technology. Lerva (2022) finds that farmers anticipate large externalities from others receiving the training. Dar et al. (2019) show that inducing conversation between farmers can be just as effective as seeding central farmers. Carter et al. (2021) find important role of social networks with significant spillover effects from subsidized farmers to their social networks.

However, a very few studies uncover the drivers of spillovers beyond documenting the existence of spillovers. Effectively disseminate the information is a challenging issue. For example, Chandrasekhar et al. (2018) find that individuals are often reluctant to seek information from peers given communications may signal their true abilities to others. Banerjee et al. (2018) find that the success of information dissemination depends on common knowledge and how endogenous communication is affected. Targeted seedling increases conversations but broadcasting declined conversations holding common knowledge fixed. We differentiate the number of trainings provided to farmers to test the dissemination strategy of new technology. Our results show that repeated trainings improved farmers' knowledge of the new technology significantly and they generated stronger influence to their peers.[2]

The contributions of our study to this large literature are as follows. First, we show how by varying the treatment doses across different time periods one can examine the importance of quality and accuracy of information about the new technology in promoting technology adoption and diffusion.[3] Our approach of randomizing villages into one-time and two-time trainings is

[2]Studies in the literature on social diffusion have also considered the quality and accuracy of the information being diffused. For example, Kondylis et al. (2017) and BenYishay and Mobarak (2019) distinguish between learning via communication and observational learning. Maertens (2017) also finds that both acquiring knowledge and imitating others are important for adoption.

[3]Cai et al. (2015) also vary the information available about peers' decisions but study very short-term

new in the context of technology adoption and in the context of a program evaluation using an RCT. Second, we show that social network represented by interactions among farmers and financial relationships are important drivers of spillover effects. We also provide a theoretical model highlighting the importance of the quality and accuracy of information on the adoption and diffusion of a new technology. Finally, we also show how risk attitude affects this diffusion, and the cross-effect of peers and risk attitude.[4]

The rest of the paper is organized as follows. Section 2 develops the baseline theoretical model when farmers are risk-neutral. Section 3 describes the background of the study and explains the experimental design. Sections 4 and 5 describe the data and econometric model, which tests the prediction of the theoretical model. Section 6 presents the main empirical results and a robustness check. In Section 7, we investigate the possible the mechanisms of adoption behind our results. Section 8 explains the role of risk aversion in technology adoption, both from theoretical and from empirical viewpoints. Finally, Section 9 concludes. Appendix A provides all the mathematical proofs of the theoretical model. Appendix B supplies additional figures and tables. Appendix C provides another way of defining adoption based on the different principles of SRI technology.

2 Theoretical Framework

2.1 Model and notations

Consider a finite number of locations, which we call villages. Each village is populated by a continuum of agents, which we call farmers. As in our empirical analysis, there are three types of farmers: those *not treated*, those who received *one year of training* in SRI technology, and those who received *two years of training* in the SRI. Accordingly, we define a farmer's type θ as follows: $\theta \in \{NT, T\}$, where NT and T stand, respectively for "Non-Treated" and "Treated" and where $T = \{T1, T2\}$, where $T1$ and $T2$ stand for "Treated One Year" and "Treated Two Years."

In each village v, there are treated and untreated farmers. There are two types of villages: those in which treated farmers received one year of training, $v = T1$, and those in which treated farmers received two years of training, $v = T2$. We want to study how, in each village, the decision to adopt the SRI of an *untreated farmer* is affected by the percentage of *treated farmers* residing in the same village. Let $p \equiv \mathbb{P}\{\theta = T\}$ be the share of treated individuals in a given village.[5] We refer to p as the *exposure rate*. An untreated farmer, which we also refer to as

effects (three days). We use both cross-sectional and intertemporal intensity of indirect training exposure over a two year period and examine the spillover effects.

[4]To the best of our knowledge, few studies have investigated the effect of risk attitude on technology adoption (exceptions include Ghadim et al., 2005; Koundouri et al., 2006; Genius et al., 2014; Bonan et al., 2020) and none has examined the cross-effect of both risk and peers on technology adoption.

[5]Since we assumed a continuum of farmers in each village, from the law of large numbers, p $(1-p)$ can be interpreted as the probability that an untreated farmer randomly meets a treated (untreated)

an *uninformed* agent, does not precisely know the true benefit b (or rather, the quality of the technology) of adopting SRI technology, while treated farmers, referred to as *informed* agents, have received training that gives them some knowledge about the technology. The quality or the benefit of the technology b is a random variable, which follows a normal distribution, that is,

$$b \sim \mathcal{N}\left(\beta, \sigma_b^2\right), \tag{1}$$

where $\beta > 0$ is the mean and $\sigma_b^2 > 0$ is the variance. In other words, the average or expected benefit of adopting SRI technology is equal to β. Importantly, when an untreated (uninformed) farmer meets a $\theta-$type (informed) farmer, he receives a noisy signal s_θ about the benefit of adopting the new technology. This signal has the following standard structure:

$$s_\theta = b + \varepsilon_\theta, \tag{2}$$

where b satisfies (1), while ε_θ is an error term that follows a normal distribution,

$$\varepsilon_\theta \sim \mathcal{N}\left(0, \sigma_\theta^2\right), \qquad \text{with} \quad \text{Cov}(b, \varepsilon_\theta) = 0. \tag{3}$$

The key idea of our model is that better trained farmers are better informed and thus send less noisy signals. We capture this by imposing the following assumption:

$$\sigma_{NT}^2 > \sigma_{T1}^2 > \sigma_{T2}^2. \tag{4}$$

Indeed, because of their training, treated farmers have more information about the new technology than do untreated farmers. Furthermore, farmers with two years of training have better knowledge of the SRI than those with one year of training; hence, they send less noisy signals.

We now describe the adoption behavior of an untreated farmer. Define A as a binary variable, where $A = 1$ means that an untreated individual adopts the new technology, while $A = 0$ implies non-adoption. Then, the probability of an untreated individual of adopting the new technology is as follows:

$$\mathbb{P}\{A = 1\} = p\,\mathbb{P}\{A = 1 \,|\, \theta = T\} + (1 - p)\,\mathbb{P}\{A = 1 \,|\, \theta = NT\}, \tag{5}$$

where $\mathbb{P}\{A = 1 \,|\, \theta = T\}$ is the probability of adopting the new technology conditional on meeting a treated individual, while $\mathbb{P}\{A = 1 \,|\, \theta = NT\}$ is the probability of adopting the new technology conditional on meeting an untreated individual. We can easily verify that

$$\frac{\partial \mathbb{P}\{A = 1\}}{\partial p} > 0 \quad \Longleftrightarrow \quad \mathbb{P}\{A = 1 \,|\, \theta = T\} > \mathbb{P}\{A = 1 \,|\, \theta = NT\}. \tag{6}$$

farmer in the village.

In other words, there is a positive relationship between p, the proportion of treated farmers in a village, and $\mathbb{P}\{A = 1\}$, the individual probability of an untreated farmer adopting the new technology if and only if interacting with a treated farmer is more beneficial for adoption than interacting with an untreated farmer.

To proceed, we must structure the problem further by making assumptions about individual behavior and the utility function.

2.2 Model predictions with risk-neutral farmers

Assume that all farmers are risk-neutral.[6] Define z, the net payoff, as follows:

$$z := \begin{cases} b - c, & \text{if } A = 1, \\ 0, & \text{if } A = 0, \end{cases} \tag{7}$$

where $c > 0$ is the fixed cost of adopting the new technology. We have the following utility function:

$$U_\theta(A) := \mathbb{E}\left[z \mid s_\theta\right] = \begin{cases} \mathbb{E}\left(b \mid s_\theta\right) - c, & \text{if } A = 1, \\ 0, & \text{if } A = 0. \end{cases} \tag{8}$$

Risk neutrality implies that only the expected difference between the benefit and cost of adoption matters. Throughout this section, we assume that $c > \beta$, otherwise, the problem would be uninteresting. This assumption means that in the absence of interactions with treated (informed) farmers, a risk-neutral untreated farmer will never adopt the technology. Indeed, looking at the formula (12) of the probability of adopting the new technology conditional on meeting an individual of type $\theta = \{T, NT\}$, we see that if $c < \beta$, the quantity in parenthesis will always be negative and thus individuals will always adopt the technology. This is not what we observe in our data, since the SRI technology is sufficiently difficult to implement that most individuals would not adopt it on their own. For example, Table 2 below shows that even when influenced by treated farmers, only 8% of untreated farmers adopt SRI technology.

For $\theta = \{T, NT\}$, using (8), the conditional probabilities defined in equation (5) are given by

$$\mathbb{P}\{A = 1 \mid \theta\} = \mathbb{P}\{\mathbb{E}\left(b \mid s_\theta\right) > c\}, \tag{9}$$

where $\mathbb{E}\left(b \mid s_\theta\right)$ is the expected benefit of adopting the new technology for an untreated individual conditional on receiving signal s_θ. Owing to the normality assumptions in (1) and (3), we have

[6] We consider risk-averse farmers in Section 8.

(e.g., DeGroot (2005), Theorem 1, p. 167):

$$\mathbb{E}\left(b \,|\, s_\theta\right) = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_b^2}\beta + \frac{\sigma_b^2}{\sigma_\theta^2 + \sigma_b^2} s_\theta. \tag{10}$$

Combining (1) and (3) with (10), we can readily verify that

$$\mathbb{E}\left(b \,|\, s_\theta\right) \sim \mathcal{N}\left(\beta, \frac{\sigma_b^4}{\sigma_\theta^2 + \sigma_b^2}\right). \tag{11}$$

Using (11), (9) can be written as follows:

$$\mathbb{P}\{A = 1 \,|\, \theta\} = 1 - \Phi\left(\frac{(c-\beta)}{\sigma_b^2}\sqrt{\sigma_b^2 + \sigma_\theta^2}\right), \tag{12}$$

where

$$\Phi(x) := \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} \exp\left(-\frac{y^2}{2}\right) \mathrm{d}y$$

is the cumulative distribution function of the standard univariate normal distribution. Hence,

$$\mathbb{P}\{A = 1 \,|\, \theta = T\} - \mathbb{P}\{A = 1 \,|\, \theta = NT\} = \Phi\left(\frac{(c-\beta)}{\sigma_b^2}\sqrt{\sigma_b^2 + \sigma_{NT}^2}\right) - \Phi\left(\frac{(c-\beta)}{\sigma_b^2}\sqrt{\sigma_b^2 + \sigma_T^2}\right). \tag{13}$$

We have the following results.

Proposition 1 *Assume that (4) holds and that agents are risk-neutral. Then,*

(i) In each village, the adoption rate of untreated farmers increases with the exposure rate, i.e.,

$$\frac{\partial \mathbb{P}\{A = 1\}}{\partial p} > 0.$$

(ii) In a $T2$-treated village, the impact of the exposure rate on the adoption rate of untreated farmers is higher than that in a $T1$-treated village, i.e.,

$$\frac{\partial \mathbb{P}\{A = 1 \,|\, v = T2\}}{\partial p} > \frac{\partial \mathbb{P}\{A = 1 \,|\, v = T1\}}{\partial p}.$$

Part (i) of Proposition 1 shows that the larger the quantity and better the precision of information about the quality of the technology, the more likely an untreated farmer will adopt SRI technology. Indeed, when p increases, the untreated farmer is more likely to meet a treated farmer, who has more precise information about the technology, since $\sigma_{NT}^2 > \sigma_T^2$. Part (ii) of Proposition 1 compares different villages with different treatments. If an untreated farmer resides in a village in which treated farmers received two years of training, then, for the same

p, the precision of information on the quality of the technology is higher than that in a village in which treated farmers received one year of training. Therefore, the untreated farmer is more likely to adopt the new technology.[7]

3 Background and experimental design

3.1 The Technology: System of Rice Intensification (SRI)

SRI technology is a climate-smart, agro-ecological methodology aimed at increasing the yield of rice by changing the management of plants, soil, water, and nutrients (Uphoff, 2003; Africare, 2008). Specifically, the SRI involves early careful planting of single seedlings with wide spacing in fields that are not continuously flooded and have optimum water management, with actively aerated soil containing a higher proportion of organic matter. Over time, the expansion of the SRI occurs with much more flexibility, promoting a package of practices for farmers to test, modify, and adopt as they see fit. While a number of specific practices are associated with the SRI, these should always be tested and varied according to the local conditions rather than being simply adopted (Uphoff, 2003). Proponents of the SRI claim that its use increases yields, saves water, reduces production costs, and increases income and that its benefits have been observed in 40 countries (Africare et al., 2010).

To be more precise, the SRI is a *management strategy for crop improvement* (Stoop et al., 2002). As Uphoff (2015) puts it, "it is a set of ideas and insights for beneficially modifying agronomic practices that are based on validated knowledge for increasing the production of irrigated rice." Although the SRI is not complex, many farmers have found it difficult to adopt because it implies a drastic change in the way they cultivate rice. In some sense, it is not a new technology because the SRI does not require or depend on the use of improved or new varieties or on the use of synthetic fertilizers and agrochemical crop protection to raise output. These inputs can be used with SRI *management practices*, but they are not necessary to improve crop productivity. For this reason, the SRI offers an exceptional candidate for studying the spillover effects of technology diffusion.

Despite these clear benefits, the adoption of the SRI has been slow and farmers rarely implement SRI technology on more than half of their land (Fafchamps et al., 2020). There are various reasons for this sluggish adoption of the SRI. First, the SRI is a methodology for growing rice that differs from traditional practices. There is evidence that farmers are constrained by the information and skills necessary for local adaptation and must bear greater risks under the SRI than when using traditional cultivation methods (Barrett et al., 2022). Second, SRI fields

[7] Observe that we can easily extend the results of Proposition 1 when untreated farmers have heterogeneous costs c, namely if $c \sim G(\cdot)$, where $G(\cdot)$ is a cumulative distribution function. In this case, the condition $c > \beta$ can be replaced by the assumption that the share $G(\beta)$ of highly productive agents (i.e., for whom the adoption cost is lower than the expected value of the adoption benefit) is sufficiently low.

visibly differ from traditional rice fields; hence, social norms and conformity pressures could also discourage the ultimate adoption decision.

The SRI is new among most farmers in Bangladesh, with only limited scale experimentation by BRAC. The pilot study by Islam et al. (2012) finds higher yields of around 50% among those who adopt the SRI in Bangladesh.[8] The SRI has been widely practiced in many developing countries, and studies based on observational data show significant yield gains and increased profits associated with its adoption (Stoop et al., 2002; Sinha and Talati, 2007; Styger et al., 2011).

3.2 Measuring SRI adoption in our study

As stated above, SRI does not require innovative fertilizers nor seedlings. It is the modification of management practice that contributes to high yields. SRI is more appropriate for use during Boro season in Bangladesh, as irrigation management is easier during this period.[9] For the purpose of this study, we follow the following interdependent *six key principles* adopted by BRAC on SRI practices in Boro season:

(1) *Early transplanting of seedlings*: It is preferable to have 15-20 days old seedlings. (2) *Shallow planting*: Shallow planting (1–2 cm) of one or two seedlings, i.e., planting single seedling, per hill. (3) *Transplanting in wider spacing*: Seedlings should be planted singly and in square pattern (25 $\times$ 20 cm). This method gives plants more room to grow and spread, obtaining more sunlight and nutrients. (4) *Intermittent irrigation*: Soil in the field is kept moist but not continuously flooded, intermittently wetted and dried, so that the soil is mostly aerobic, never hypoxic. (5) *Nutrient management*: Enhance soil organic as much as possible, adding compost or other biomass to the soil. That is, feed the soil system so that it can feed the plant and reduce the use of synthetic chemical fertilizers (6) *Complementary weed and pest control*: Control weeds with repeated use of a mechanical hand weeder. This will aerate the soil better than possible with hand weeding or use of herbicides.

Given these six principles, which are applied at different stages of the rice cultivation, we have various measures of adoption.

First of all, the first round of information collection about adoption situation occurred in transplantation period in order to figure out the extent of adoption. BRAC staff visited the rice field to check if the first three principles (seedling age, number of seedling and spacing of plantation) were properly followed by farmers. In this early transplantation stage, BRAC enumerators only checked these three principles because the next three principles could only be

[8] These results are not surprising. Sinha and Talati (2007) find that average yields increase by 32% among farmers who partially adopt the SRI in West Bengal, India. Styger et al. (2011) show a 66% increase in SRI yields relative to experimentally controlled plots when using farming methods similar to local rice farmers in Mali.

[9] Boro season is the dry season in Bangladesh from October to March. The word "Boro" in Bengali means rice cultivation on residual or stored water in low-lying areas (Singh and Singh, 2000).

observed during the harvest period. Therefore, a second round of adoption check occurred in the harvest season. The aim was to observe whether farmers followed the next three principles including irrigation, nutrient and weed management.

As a result, there are different ways of measuring SRI adoption: one following immediately after transplantation, another following harvest. In terms of assessment, we have two ways of assessing whether farmers adopt SRI. The first is enumerator assessment. That is, enumerator visit the field and observe whether farmers applied each principle. A second assessment method is self report. Farmer have their own assessment about whether they follow each principle.

As the SRI adoption requires following certain principles and practices, we measured the SRI adoption using verification in the planting and pre-harvesting periods by *enumerators' field visits*.[10] The research team hired enumerators who worked with BRAC field staff to verify the SRI adoption. Enumerators, supported by BRAC field staff, identified farmers in the villages as well as went to the rice fields to observe the adoption. Specifically, we conducted a field survey to observe compliance with SRI practices and principles. We then determined the SRI adoption on the basis of plot visits by enumerators and BRAC field officers, who helped verify visually whether the farmer adopted SRI techniques on any of his cultivable rice plots during Boro season.

In this paper, we measure SRI adoption by having a dummy variable, $A = 1, 0$ in the theoretical model, which is equal to 1, i.e., a farmer is considered to be an SRI adopter, if both the enumerator and the BRAC field officer observed that the farmer practiced at least three out of the six principles described above on at least one plot of land. Indeed, we surveyed information only for their three plots of land. If farmers had more than three plots, we randomly picked three plots at the baseline (before SRI was known to the farmers) and followed them. As a result, as long as a farmer has followed at least three principles in *any of his three plots of land*, he will then be considered as an SRI adopter.

As a robustness check, in Section 6.2 below, we will use another measure of adoption, denoted by A^{PR}. It is not a $\{0, 1\}$ variable, but a percentage, which is equal to the proportion of principles that a famer has adopted in the plot of land that has adopted the highest number of principles. Since there are six principles, $A^{PR} = \left\{0, \frac{1}{6}, \frac{2}{6}, \cdots, 1\right\}$, where, for ex ample, $\frac{2}{6}$ is the fraction of principles adopted in the plot of land for which the farmer has adopted the highest number of principles, here 2 principles. This means that the farmer has not adopted more than 2 principles in any of his plots of land. In this definition, A^{PR} is an *effort of adoption*.

3.3 Experimental Design

In collaboration with BRAC, our RCT was conducted over two years (2014/15 and 2015/16) in 182 villages across five districts in rural Bangladesh: Kishoreganj, Pabna, Lalmonirat, Gopalgonj,

[10] This is because it is a more objective and unbiased evaluation. Our analysis have also been conducted using farmers' self-reported evaluation and the results are similar. They are available upon request.

and Shirajgonj. The blue areas in Figure B.1 in Online Appendix B depict the location of these districts in Bangladesh.

3.3.1 Selection of villages

Out of the five districts described above, we selected a total of 182 villages for our experiment. These villages were chosen based on their suitability of implementing the SRI technology according to the following three criteria: (*i*) Farmers needed to grow rice during the Boro season; (*ii*) BRAC had to operate in this village; (*iii*) SRI was not previously practiced in the village.

3.3.2 Farmers' selection

A census was conducted by BRAC local offices in 2014 before Boro season to generate a list of all farmers in these villages satisfying the following eligibility criteria: (*i*) each farmer cultivated rice in the previous Boro season; (*ii*) the farmer owned at least half an acre but not more than 10 acres of land.[11] Among the full list of all farmers in each village that satisfy these requirements, we randomly selected 29 to 36 farmers as participants from this list. We ended up with 5,486 participants in 182 villages.

Following the selection of farmers for training, local BRAC staff members and enumerators visited farmers' homes and invited them to SRI training with a letter from BRAC. Farmers were also briefly informed about the purpose of the training. All farmers received a fee (BDT 300) for their participation in the training. This fee is slightly more than the rural agricultural daily wage. Trainers were existing BRAC agricultural officers at the field level. Agricultural scientists who had previously worked on the SRI elsewhere in Bangladesh trained these trainers. Enumerators and field workers supported the trainers in conducting the training sessions and the pre- and post-training interviews.

To encourage treated farmers to take up the training, free lunch, refreshments and snacks was provided for the day. A certificate was also given to all farmers who attended the training to recognize their participation. We ended up with 99% take up rate and thus did not suffer from partial or non-compliance issues.

3.3.3 Randomization and saturation process

We use a two-stage randomization. The first-stage involves randomizing villages into treatment and control groups. In the second-stage, we randomly selected farmers from each of the treatment villages where we also vary randomly the number and proportion of farmers selected for the training. We describe the process below.

[11] Farmers with less than half an acre of land were excluded, as they are usually seasonal farmers. Similarly, farmers with more than 10 acres were not considered for SRI training, as they are land-rich farmers in Bangladesh.

Village-level randomization Out of the 182 villages, we randomly allocated 120 villages into *treated groups* and 62 villages into *control groups*. Within the 120 treated villages, we further divided them into 60 $T1-$villages (one year of training) and 60 $T2-$villages (two years of training). We used stratification based on village-level characteristics to randomize villages into $T1$, $T2$ and control villages. We checked the village-level characteristics including transportation, electricity, population, crops, etc, and they are balanced across different treatment groups as shown in Table B.1 in Online Appendix B.

Farmer-level randomization Out of the 120 treated villages, in each village, we randomly selected a different number of farmers to receive SRI training using a stratified random sampling. This stratification is based on the age of the farmers (i.e., whether or not they are older than 45 years old) and their land and farm size (i.e., whether or not they hold more than the median size farm land of 1.2 acres).

3.3.4 Training in $T1$ versus $T2$ villages

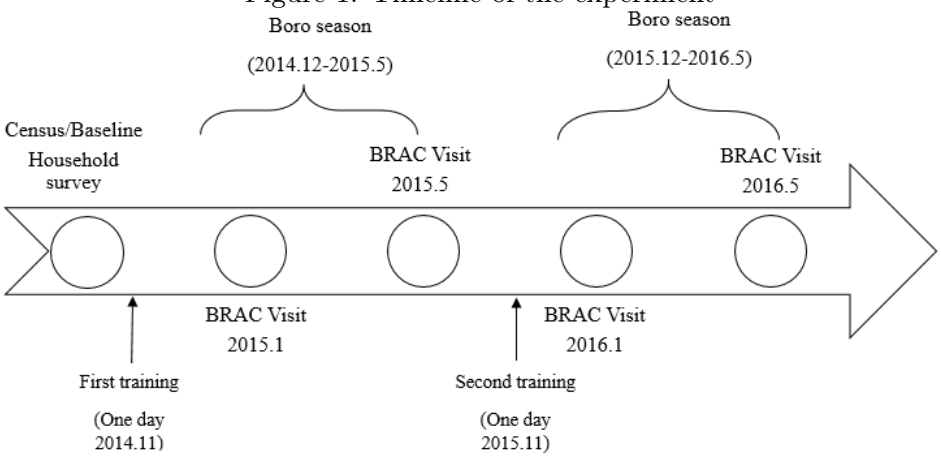
We divided 120 treatment villages into one year and two years of training. 60 villages were randomly allocated to one year of training (referred to as $T1-$villages) and treated farmers only received one-time training in year 1. This training lasted for a day, and was disseminated via a media presentation and video demonstration to teach farmers about the principles of SRI technology. The training was delivered by existing BRAC agricultural officers who were trained by agricultural scientists who had previously worked on SRI elsewhere in Bangladesh.[12] For the other 60 villages (referred to as $T2-$villages), treated farmers received the same training twice, namely they received training in both the first and the second years. There were two training sessions in year 2. In the first session, the topics of discussion were case studies of successful adoption from the first year of the intervention. The session also included discussions with local farmers about the training in year 1 and rice cultivation practices as well as constraints that affected their decision to adopt the SRI in year 1. In the second session, BRAC trainers provided the same training as in year 1 and attempted to ensure that farmers had a *clear understanding* of the key principles and practices of the SRI. Hence, farmers who were trained twice in $T2-$villages had a much better understanding of the rules and principles of the SRI, which imply changing practices for irrigated rice cultivation.

In Figure 1, we describe the timeline of our experiment. The Census was conducted at the beginning of 2014 to get a full list of all farmers in the villages. Then, we applied our eligibility criteria (Section 3.3.2) to select the participating farmers from whom we collected the baseline survey. The first and second training were conducted in November 2014 and 2015, respectively, both before the Boro season started. Finally, to collect farmer's adoption decisions, BRAC

[12] These scientists previously worked at the Bangladesh Rice Research Institute where they have working experience on SRI.

enumerators visited these villages twice a year: at the beginning of the Boro season and at the end of the Boro season. The reason we introduced different times of information collection is due to the different phases of growing rice as explained in Section 3.2.

Figure 1: Timeline of the experiment



3.3.5 The randomization of farmers into training

The farmers in each villages were randomly divided into two groups: treated (one year $T1$ or two-year $T2$) and untreated (NT). On average, 10 farmers out of 30 in each of the 120 villages received the SRI training. The number of treated farmers randomly selected in each village was different, varying between 13% to 50% of total farmers in a village. These randomly selected farmers (referred to as *Batch 1 farmers*) received SRI training in the first week. After two days of training, we asked each of these farmers to nominate one farmer in the same village. This second batch of farmers account for another one third of total farmers (referred to as *Batch 2 farmers*). These referred farmers were compensated or incentivized and received exactly the same SRI training in the second week. Given that each initially treated farmer referred exactly one farmer, the number of referred farmers is the same as the initially treated farmers. Finally, the remaining one third of farmers were referred to as *untreated* farmers because they did not receive any training but reside in the same village as the treated farmers.[13] The randomization process and different groups of farmers as described could be found in Figure B.2 in Online Appendix B.

[13]The selection of farmers was based on geographical location; thus, we usually surveyed one neighborhood from each village to guarantee that farmers are geographically close to each other. As farmers are invited to attend training sessions on the SRI, their proximity makes it easier to organize and collect responses from participants.

3.3.6 Referral process of treated farmers

To guarantee a clean exogeneity of the treatment, we have *excluded* the referred *Batch 2 farmers* from our sample of treated farmers. We conducted various analysis to support that our results are robust to including or excluding these referred farmers.

First, we performed the same spillover analysis as in our main analysis by including the referred Batch 2 farmers in the treated sample. The results are similar and thus robust to this inclusion (see Islam et al. (2019)). Second, when comparing the observable characteristics of non-referred (Batch 1) and referred (Batch 2) treated farmers, we show that they are *not* significantly different (see Table B.2 in Online Appendix B). Finally, Fafchamps et al. (2020), who only focus on the *direct* effect of this experiment, show that the main effect of introducing the referral process is that referred trainees are only 4.2% more likely to adopt SRI technology than randomly selected trainees. Here, we focus on the spillover effects of the initially *non-referred* trained farmers on untrained farmers.

Table 1 displays the number of farmers randomized into the treated and untreated groups within the treatment villages. Panel A describes the full sample by including treated farmers who are randomly selected (Batch 1) and referred farmers (Batch 2), as well as untreated farmers. Panel B displays our sample where we exclude referred farmers. Among the 2,157 farmers in these 120 villages, 1,006 were (initially) treated (480 for one year of training, i.e., $T1$ villages, and 526 for two years of training, i.e., $T2$ villages) and 1,151 were untreated (608 in $T1$ villages and 543 in $T2$ villages).

Table 1: Sample distribution of all farmers

Panel A: Original sample	T1	T2	Control	Total
Treated (Batch 1)	480	526	0	1,006
Treated (Batch 2)	445	474	0	919
Untreated	608	543	1,623	2774
Total	1,533	1,543	1,623	4,699
No. of villages	60	60	62	182
Panel B: Sample in our analysis	**T1**	**T2**	**Control**	**Total**
Treated (Batch 1)	480	526	0	1,006
Untreated	608	543	1,623	2774
Total	1,088	1,069	1,623	3,780
No. of villages	60	60	62	182

Notes: Batch 1 farmers are randomly selected to receive training in the first week, Batch 2 farmers are referred by Batch 1 farmers to receive training in the second week. Untreated farmers receive no training.

Consequently, our sample consists of only (Batch 1) treated farmers, referred to as *treated farmers* in $T1$ villages or $T2$ villages, and untreated farmers.

4 Data

We collected data at different times to support our analysis. As described in Figure 1, we first collected a baseline survey asking questions on demographics, income, assets and rice production, including current yield, cost and profit to understand pre-treatment household characteristics and agricultural conditions. Next, we collected farmers' adoption of SRI principles twice, one in the midline (one year after training) and the other one in the endline (two years after training) to observe how adoption decisions vary across time. We also collected farmers knowledge on SRI in the midline and endline consisting of questionnaires of SRI principles as well as social network data among farmers at baseline. Details of these two additional data collections are discussed in Section 7.

4.1 Balance checks

In this study, we mainly use data from 120 SRI treatment villages for our analysis as our focus is on understanding spillover effects from treated farmers to untreated farmers within the treatment villages. To start with, we did various balance checks to support our randomization strategy is valid. Table B.3 in Online Appendix B reports the balance checks of the observable characteristics between treated and untreated farmers, while Table B.4 reports the same results but between $T1-$ and $T2-$treated farmers. We observe no significant differences in the observable characteristics between these different treatments. Overall, treated and untreated farmers are observationally similar within the treatment villages and treated farmers are observationally similar between $T1$ and $T2$ villages.

To further buttress our randomization strategy, we split farmers in T1 and T2 villages. First, we compare treated farmers in T1 and treated farmers in T2 to confirm that farmers are randomly allocated between these two treatments. Second, we compare untreated farmers in T1, T2, and in control villages to show that untreated farmers are similar across these villages. Table B.5 displays the results and shows that there are no differences in terms of demographic and agricultural characteristics of farmers between these different groups.

4.2 Outcome variable

Our outcome variable is the adoption decision of untreated farmers, which we denoted by the binary variable $A = 1, 0$ in the theoretical model. In the econometric model, we denote it by $y^{NT}_{i,v,t}$. This is a dummy variable that takes a value of 1 if untreated (NT) farmer i, residing in village $v = T1, T2$, decides to adopt SRI technology in year $t = 1, 2$ and 0 otherwise. As stated

in Section 3.2, $y^{NT}_{i,v,t} = 1$ if the untreated farmer i, v, t has adopted at least three SRI principles in one of his plots of land, and $y^{NT}_{i,v,t} = 0$, otherwise. In Section 6.2, we will conduct some robustness checks by using an alternative definition of adoption, which is not a $\{0, 1\}$ variable but an effort variable.

Observe that we use time t as a subscript because we want to compare the adoption rate of untreated farmers residing in $T1-$treated villages (in which treated farmers received one year of training) and in $T2-$treated villages (in which treated farmers received two years of training). Consequently, in both $T1-$ and $T2-$treated villages, $y^{NT}_{i,v,t}$ takes two values, one at $t = 1$ and one at $t = 2$. Thus, given that the random allocation of training of farmers occurred either once in year 1 (treatment $T1$) or twice in years 1 and 2 (treatment $T2$), we have a panel in which the same 3,630 farmers are observed for two years.

Table 2 reports the average adoption rate by treatment groups and time. First, on average, significantly more treated farmers adopt SRI technology (between 37% and 47%) than untreated farmers (between 8% and 12%). This difference means that training has a direct impact on adoption. Second, at the end of year 2, farmers with two years of training adopt more than those with one year of training (47.53% versus 37.29%). Note there is no such significant difference in adoption after after one year, as in that case, both farmers received the same training. Third, and more importantly for our analysis, untreated farmers do not adopt more when residing in $T2-$treated villages than $T1-$treated villages after one year. However, they do significantly adopt more after two years (on average, $y^{NT}_{i,T2,2} = 12.15\% > 10.03\% = y^{NT}_{i,T1,2}$). This suggests that exposure to farmers receiving more training makes an untreated farmer more likely to adopt SRI technology.

Table 2: Adoption rate of farmers by treatment group and time

	End of year 1	End of year 2	T-statistic	p-value
Treated farmers in $T1$ villages	46.04%	37.29%	2.75	0.006
	(0.023)	(0.022)		
Treated farmers in $T2$ villages	45.63%	47.53%	-0.62	0.537
	(0.022)	(0.217)		
Untreated farmers in $T1$ villages	8.22%	10.03%	-1.09	0.274
	(0.011)	(0.012)		
Untreated farmers in $T2$ villages	8.65%	12.15%	1.89	0.059
	(0.121)	(0.140)		
Farmers in control villages	0.43%	0	2.49	0.013
	(0.001)	(0)		

Notes: Reported p-values are for a two-tailed test of the null hypothesis that group means are equal. Means are reported with standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1

Finally, many treated farmers in $T1-$villages in year 2 *dis-adopt*. This does not contradict our mechanism since we are explaining the adoption rate of the *untreated* farmers and not the

treated ones. Indeed, Table 2 shows that there is no statistical difference in the *untreated* farmers' adoption rate between years 1 and 2 for $T1-$villages while, in $T2-$villages, they increase their adoption rate from 8.65% and 12.15%. This is in accordance with our mechanism that untreated farmers benefit more from treated farmers' spillover effects in $T2$ than in $T1-$villages and this is why their adoption rate increases between years 1 and 2. However, one may wonder why 8.75% of *treated* farmers in $T1-$villages dis-adopt at the end of year 1. To understand this, we need a more detailed definition of adoption based on the percentage of principles adopted rather than a $\{0, 1\}$ adoption variable as it is here. We will explicitly address this issue in Section 6.2 below.

4.3 What farmers receive from adopting SRI

To show the benefit of adopting SRI technology, we compared the average rice yield between SRI adopter farmers in treatment villages and farmers in control villages (Non-adopters). [14] Table 3 shows that there is a significant positive difference in terms of yields between the adopters in 120 treatment villages and non-adopters in the 62 control village. This means that SRI technology is, indeed, beneficial for farmers in terms of yields. This direct evidence that SRI technology is beneficial for farmers has also been shown by Islam et al. (2012) for Bangladesh and by others for different countries (see footnote 8).[15]

Table 3: Yield difference between adopters and non-adopters

	Adopters Mean	Non-Adopters Mean	T-stat	P-value
Yield (kg per decimal of land)	25.60	21.73	29.42	0.000
	(0.009)	(0.091)		
Observations	774	1,616		
No. of villages	120	62		

Notes: The sample includes all adopters in treatment villages and non-adopters in control villages. A farmer is defined as an adopter if he is in a treatment village and adopted at least three principles in year 1, year 2, or both. Non-adopters in control villages are those who adopted less than three principles. Yield is defined as the amount of rice cultivated in one decimal of land, measured in kg. It is the total amount of rice cultivated (kg) divided by the total amount of land (decimal). We take the average of yield of a farmer over two years and report it. Means are reported with standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1.

[14] A farmer is defined to be an adopter if he adopted at least three principles in any year 1, year 2 or both. On average, farmers in control group adopted 0.8 principles in year 1 and 0.79 principles in year 2. Adoption rate of control farmers in both years are less than 1%.

[15] Similar figures were obtained when looking at profits instead of yields.

5 Econometric Model

5.1 Exposure rate

Following our theoretical model, our main explanatory variable is the *exposure rate* p measured as the percentage of treated farmers in a village. For untreated farmer i living in village $v = T1, T2$, his exposure rate is defined as[16]

$$p := p_{i,v}^T = \frac{N_{i,v}^T}{N_{i,v}^T + N_{i,v}^{NT}} \times 100\%, \tag{14}$$

where $N_{i,v}^T$ and $N_{i,v}^{NT}$ refer, respectively to the number of treated farmers and untreated farmers in village v in which untreated farmer i resides. Thus, $p_{i,v}^T$ is the percentage of treated farmers in village v. According to our experimental setting, there are two key properties of $p := p_{i,v}^T$. First, $p_{i,v}^T$ is not indexed by time because the randomization is implemented only once; therefore, the exposure rate does not change over time. As a result, $p_{i,v}^T$ is a time-invariant variable that is the same for a given untreated farmer for two years. Second, according to the questionnaire results, 99.99% of our farmers know each other in the same village because we select them from the same neighborhood. Therefore, for all untreated farmers residing in village v, their exposure rate $p_{i,v}^T$ should be the same.

Figure B.3 in Online Appendix B shows the distribution of p_v^T between $T1$ villages (blue dashed curve) and $T2$ villages (red solid curve) to see if they are the same across villages. We observe that they look similar and (roughly) normally distributed. To test this similarity, in Table B.6, we perform a $t-$test and the Kolmogorov–Smirnov (K-S) test.[17] We see that there is no significant difference in p_v^T between $T1$ and $T2$ villages and that the $p-$value of each test is greater than 0.05. As a result, we can conclude that the two distributions of p_v^T between $T1$ and $T2$ villages are similar. Finally, we perform a simple correlation test between $p_{i,v}^T$ and the baseline characteristics of farmers. Table B.7 reports the results. We find that there is no statistically significant relationship between $p_{i,v}^T$ and any of the baseline characteristics of the farmers. All these results seem to confirm the exogeneity of $p_{i,v}^T$.

[16] In our experiment, we define a treated farmer to be a farmer who was selected to receive training, regardless of whether or not he actually received the training. Since the (training) take-up rate was extremely high (99.8%), farmers did not self-select into whether or not receiving training.

[17] The K-S test is a non-parametric test of the equality of continuous, one-dimensional probability distributions that can be used to compare two samples.

5.2 Econometric model

We now empirically test parts (i) and (ii) of Proposition 1. The econometric equivalent of these two results can be written as a pooled OLS model, which is given by[18]

$$y_{i,v,t}^{NT} = \alpha_0 + \alpha_1 p_{i,v}^{T} + X_{i,v}^{'}\beta + \theta_t + \epsilon_{i,v,t}, \tag{15}$$

where $y_{i,v,t}^{NT}$ is a dummy variable equal to 1 if untreated farmer i residing in village $v = T1, T2$ adopts SRI technology in year $t = 1, 2$ and 0 otherwise. This corresponds to $A \in \{0, 1\}$ in the theoretical model and captures the binary choice of untreated farmer i residing in village v who decides whether to adopt SRI technology in year t. Moreover, $p_{i,v}^{T}$ is defined in (14), $X_{i,v}^{'}$ are the exogenous characteristics of farmer i residing in village v,[19] including age, income, land size, household size, occupation, and education. We also control for the *total number of farmers* in a village because it may vary between villages.[20] Finally, $\epsilon_{i,v,t}$ is an error term, and θ_t are the year fixed effects. Indeed, to account for a year-specific aggregate shock, we use a year dummy such that $t = 0$ corresponds to year 1 and $t = 1$ represents year 2. In all our regressions, standard errors are clustered at the village level.

According to part (i) of Proposition 1, we expect that $\alpha_1 > 0$. Second, according to part (ii) of Proposition 1, if we run (15) separately for the two samples of treated villages, we expect the α_1 obtained for the 60 $T2-$treated villages to be larger and more significant than the α_1 obtained for the 60 $T1-$treated villages.

6 Empirical results

6.1 Main Results

Table 4 displays the results of the estimation of equation (15). Columns (1) and (2) report these results for the 120 villages by increasing the number of control variables. We see that the main coefficient of interest, α_1 in (15), is highly significant (at the 1% level), does not really change when we add controls, and is equal to 0.236. Thus, an increase of 10% in treated farmers in a village increases the average adoption rate for an untreated farmer residing in the same village by 2.36%. According to our model, this means that untreated farmers tend to adopt more when they receive reliable information about SRI technology from treated farmers who have received either one or two years of training.

[18] All our results remain the same if we estimate a pooled *probit* model instead of the pooled OLS model (15). These results are available upon request.

[19] As stated in footnote 7, we can easily extend our theoretical model by including farmers with heterogeneous costs of adopting c. In that case, this heterogeneity captures the heterogeneity in characteristics $X_{i,v}$ described in (15).

[20] Figure B.4 in Online Appendix B displays the distribution of farmers, showing that it differs between $T1$ and $T2$ villages.

Next, we split the 120 villages into two groups, namely $T1-$treated villages in which farmers received one year of training and $T2-$treated villages in which farmers received two years of training, and estimate equation (15) separately for each sample of 60 villages. As predicted by part (ii) of Proposition 1, α_1 becomes insignificant for $T1-$treated villages (columns (3) and (4)) and is positive and significant at the 1% level for $T2-$treated villages (columns (5) and (6)). In fact, the coefficient α_1 is larger in magnitude than for the general regression, since an increase of 10% in $T2-$treated farmers in a village now increases the rate of adopting SRI technology for an untreated farmer residing in the same village by 3.96%.

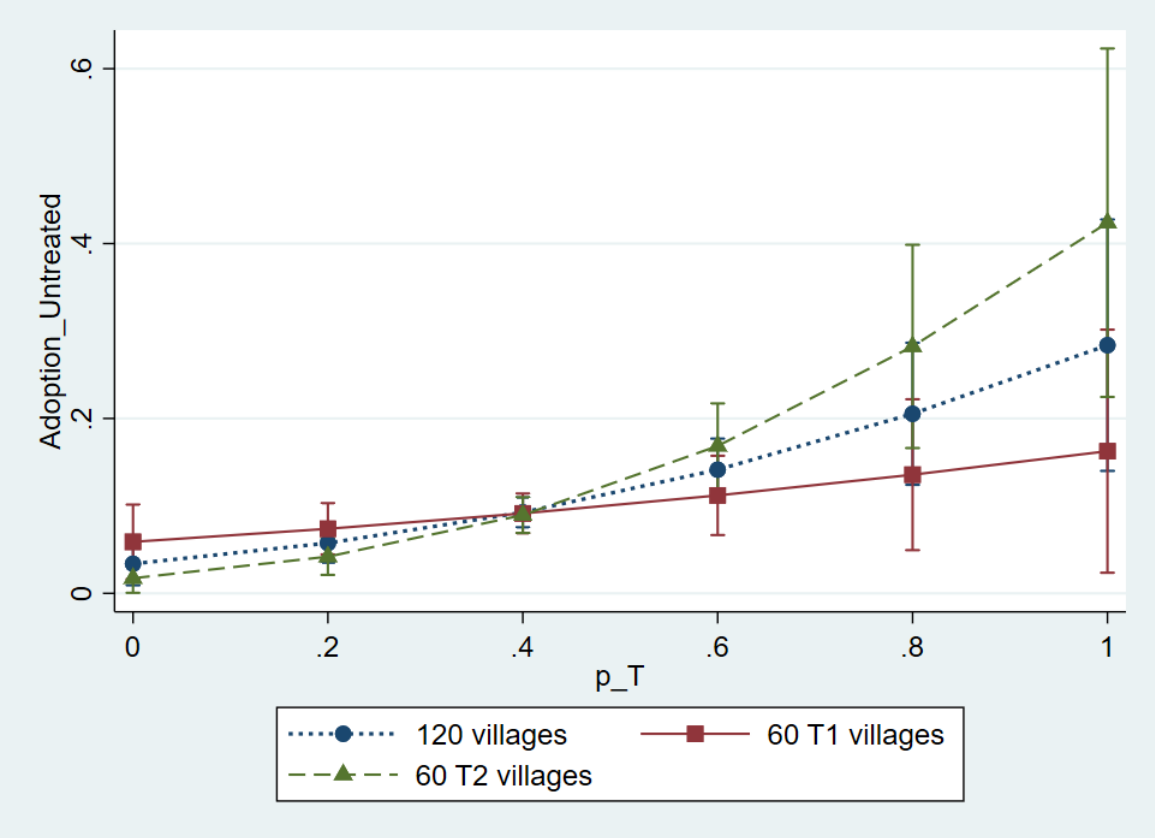
Table 4: The impact of trained farmers on the adoption rate of untreated farmers

	120 villages		60 villages (T1)		60 villages (T2)	
	(1)	(2)	(3)	(4)	(5)	(6)
$p^T_{i,v}$	0.244***	0.236***	0.0972	0.101	0.399***	0.396***
	(0.0758)	(0.0746)	(0.0945)	(0.0870)	(0.105)	(0.103)
Year dummy	0.0261**	0.0261**	0.0181	0.0181	0.0350*	0.0350*
	(0.0125)	(0.0125)	(0.0154)	(0.0155)	(0.0202)	(0.0203)
Age/10		-0.00692		-0.0130*		-0.00170
		(0.00566)		(0.00747)		(0.00815)
log(Income)		-0.0197		-0.0200		-0.0205
		(0.0134)		(0.0186)		(0.0178)
log(Land)		0.0196		-0.00617		0.0471***
		(0.0153)		(0.0215)		(0.0157)
Education		0.000790		0.000655		0.000890
		(0.00186)		(0.00266)		(0.00247)
Household size		-0.000994		0.00279		-0.00404
		(0.00434)		(0.00654)		(0.00552)
Occupation		0.00317		-0.0274		0.0535**
		(0.0228)		(0.0356)		(0.0239)
Total farmers/1000		0.186		0.400**		-0.0890
		(0.136)		(0.176)		(0.165)
Observations	2,302	2,300	1,216	1,214	1,086	1,086
No. of villages	120	120	60	60	60	60

Notes: The dependent variable is the adoption decision of an untreated farmer across two years. It is a dummy variable that equals 1 if an untreated farmer adopted in year t ($t = 1, 2$) and 0 if he did not. Standard errors are clustered at the village level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

To visualize these results, we report the 95% confidence intervals of each regression for the whole distribution of $p^T_{i,v}$. Figure 2 displays this distribution for the 120 villages (blue curve), 60 $T1$ villages (red curve), and 60 $T2$ villages (green curve). If we consider this distribution for the 120 villages, we see that in villages in which $p^T_{i,v}$, the percentage of treated farmers is 40%, the (predicted) adoption rate of untreated farmers is 10%, and when $p^T_{i,v}$ is equal to 80%, the (predicted) adoption rate is close to 20%. For $T1$ villages, these numbers are, respectively 10% and 14%, while for $T2$ villages, we obtain 10% and 30%. In other words, the effect of increasing $p^T_{i,v}$ on the adoption rate is small and the curve is flat for $T1$ villages, while the effect is large and the curve is steep for $T2$ villages.

Figure 2: Distribution of $p^T_{i,v,t}$ between different villages



To prove the robustness of our finding, we measure the effect at different points in time, that is, we report our main results year by year (and not only pooled as in Table 4). Tables B.8 and B.9 in Online Appendix B display the results after one year (end of year 1) and after two years (end of year 2), respectively. We see that by the end of year 1 (Table B.8), there is *no* significant spillover effect for any village, since treated farmers in $T1$ and $T2$ villages receive

the same one-time training at this point of time. However, at the end of year 2 (Table B.9), significant spillover effects are found only for the $T2$ villages and with a larger magnitude than in $T1$ villages.

Remember (see Section 3.1) that although SRI technology is not complex, the practices for using it differ from those of traditional methods. As a result, many farmers have found it difficult to adopt because it implies a drastic change in the way farmers are used to cultivate rice. Therefore, farmers are naturally reluctant to adopt SRI technology. Remember also that we are studying the behavior of farmers in the neighborhood of a village; therefore, these farmers know each other (treated and untreated) and form close-knit communities. Table 4 (and also Tables B.8 and B.9) show that providing *longer training* on the SRI has not only a direct impact on trained farmers but also spills over to other farmers in the village who did not receive any training (untreated). This effect is important. The more an untreated farmer is "exposed" to farmers with two years of training, the more likely he is to adopt SRI technology.[21]

According to our model, this is because $T2-$treated farmers provide untreated farmers with more *accurate* and more *precise* information on the SRI since the lower is the variance σ_θ^2 in the "noise" ε_θ of the quality of the technology, the more accurate is the information transmitted to the untreated farmer and the more likely the latter is to adopt SRI technology. Indeed, when farmers are trained two years in a row, they are more able to explain the principles involved in SRI practices, which need to be followed carefully because, unlike most current agricultural technologies, the SRI is not based on material inputs. Instead, it involves mostly mental changes and new ways of thinking.

6.2 Robustness check: Understanding adoption behavior

So far, we have measured adoption by having a dummy variable, $y_{i,v,t}^{NT}$, which takes a value of 1 if an untreated (NT) farmer i, residing in village $v = T1, T2$, has adopted at least three SRI principles in one of his plots of land in year $t = 1, 2$, and 0 otherwise. As a robustness check, we use another measure of adoption, which has been defined in Section 3.2 by A^{PR}. It is an "effort" variable, which is equal to the proportion of principles that a farmer has adopted in the plot of land that has adopted the highest number of principles. Since there are six principles, $A^{PR} = \left\{0, \frac{1}{6}, \frac{2}{6}, \cdots, 1\right\}$. To use the same notation as in econometric model, we denote this variable by $y_{i,v,t}^{PR,NT}$. This measure, which provides more detailed information about adoption will help us understand some aspects of the results and the mechanisms.

As stated above, Table 2 in Section 4.2 shows a (puzzling) difference between year 1 and year 2 between T1 and T2 villages: many *treated* farmers from $T1-$villages (15%) in year 2

[21] Recall that our RCT was conducted in five poor rural districts of Bangladesh (Kishoreganj, Pabna, Lalmonirat, Gopalgonj, and Shirajgonj), where the main farming activity is rice cultivation. Consequently, when SRI technology was introduced in these districts, farmers could not switch to cultivating other crops.

dis-adopt. We would now like to check if this result is due to our definition of adoption based on the dummy variable $y_{i,v,t}^{NT}$ instead of $y_{i,v,t}^{PR,NT}$. Indeed, it may be that many $T1-$farmers "adopt" in the first year because they have adopted at least three SRI principles in one of their plot of land but still use some of the principles (less than three) in the second year but we consider them as non-adopters.

In Tables C.1 and C.2 in Appendix C, we provide information on the percentage of principles adopted in the three first-ranked plots (in terms of principles adopted) on *treated* farmers $A_{1,0}$, who are farmers who adopt in year 1 and dis-adopt in year 2, and *treated* farmers $A_{1,1}$, who are farmers who adopt in both years 1 and 2 for $T1-$villages (Table C.1) and for $T2-$villages (Table C.2). Denote by $A^{1,PR}$, $A^{2,PR}$ and $A^{3,PR}$, the percentage of principles adopted in, respectively, first-ranked plot, second-ranked plot and third-ranked plot. Consider, for example, Table C.1 for $T1-$villages. We see that, for $A_{1,0}-$farmers, even though in year 2 they are considered as non-adopters since the average value in year 2 of A^{PR} is below 0.5, we still have $A^{1,PR} = 0.17$, $A^{2,PR} = 0.16$ and $A^{3,PR} = 0.14$. This means that they are still adopting, on average, between 1 ($1/6 = 0.167$) and 2 ($2/6 = 0.333$) principles in the second year in their three highest-ranked plots. These figures are a little higher for $A_{1,0}-$ farmers in $T2-$villages. Consider now $A_{1,1}-$ farmers in both villages. We see that the number of principles adopted in the first-ranking plot do not change between years 1 and 2 in $T1-$villages but increase in $T2-$villages. So, going back to Table 2, we see that mostly $T1-$farmers reduce the number of principles adopted (roughly 15%) but still keep some SRI principles in year 2 (Table C.2). For $T2-$farmers, less than 2% of them dis-adopt (Table 2) but also keep some SRI principles in year 2 (Table C.2). As a result, this shows that training twice make *treated* farmers trusting more the SRI principles adopted while, when *treated* farmers are only trained once, they tend to reduce the number of principles adopted but not dis-adopt totally.

In order to better understand these issues, we look at the observable baseline differences (before our intervention) between $A_{1,0}-$farmers and $A_{1,1}-$ farmers in all villages. Table C.3 in Appendix C reports the results by performing a $t-$test between these different variables. Compared to $A_{1,1}-$ farmers, $A_{1,0}-$farmers have significantly higher income, do other activities than farming activities, are more risk averse, have higher profit and higher yields before our intervention. So the result in Table 2 showing that some *treated* farmers dis-adopt in year 2 could be explained by the fact that they have different characteristics that may negatively affect their adoption behavior.

To summarize, despite the fact that Table 2 showed that 15% of $T1-$farmers dis-adopt in the second year, we have seen that, in fact, these farmers just reduce the number of SRI principles adopted (from 3 to 2 or 1 in their three highest-ranked plots). We have also seen that the reason of this reduction in the number of principles is not due to the fact that their yields and rice production decrease after adopting the SRI principles (see Tables 3 and B.12), but to the fact that they have higher income, are more risk-averse and have higher profits and yields before

our intervention. Finally, observe that, we explain the adoption rate of *untreated* farmers and not of *treated* farmers, and the former do not dis-adopt after one year. Also, *treated* farmers in $T2-$villages do not dis-adopt after one year and thus can transmit accurate information to *untreated* farmers in their villages.

As a robustness check, in Table C.4 in Appendix C, we reproduce the results of Table 4 using as a dependent variable $y_{i,v,t}^{PR,NT}$ instead of $y_{i,v,t}^{NT}$, which is defined as the percentage of principles adopted in the first-ranked plot. The results are similar, showing that the effect of $p_{i,v}^{T}$ on $y_{i,v,t}^{PR,NT}$ is positive and significant for all the 120 villages and for the 60 $T2-$villages only.

7 Understanding the mechanisms of adoption

Our primary results show that the more an untreated farmer is "exposed" to well-trained farmers in the village in which he lives, the more likely he is to adopt SRI technology. Thus, the accuracy of information transmission regarding SRI technology could be an important channel through which this occurs. In this section, we provide more evidence on this mechanism.

7.1 The role of information in SRI adoption

7.1.1 Do $T2-$farmers have more accurate information on SRI technology than $T1-$farmers?

The model in Section 2 postulates that there are more spillovers to untreated farmers from $T2$ rather than $T1-$farmers because the former have better information on how to use and implement the SRI technology. We can actually test this because we have conducted a survey on the SRI technology before the treatment (i.e., at $t = 0$) but also two years after the treatment (i.e., at $t = 2$).

Indeed, at $t = 0$, before they were treated but were already allocated to different treatments, we asked both $T1$ and $T2-$ farmers six questions about different practices of SRI, which correspond to the principles described in Section 3.2.[22] Table 5 compares the farmers' answers by treatment group at $t = 0$, i.e., before each farmer receives any training. We see that there are *no* (statistically significant) differences between $T1$ and $T2-$ farmers, which means that, before they were treated, their knowledge of the principles of SRI technology were the same.

We conducted a similar survey two years after (at $t = 2$) where both types of farmers were trained on the SRI technology. We asked both $T1$ and $T2-$ farmers eight questions about

[22]The questions are: (1) What are the days of the plant before they are moving from seedbed to soil? (principle 1); (2) how many seedlings should you plant together in the same hill? (principle 2); (3) what is the distance between plant to plant in cm? (principle 3); (4) what type of fertilizer should you use more in SRI fields? (principle 5) (principle 5); (5) after transplanting and before flowering, should the surface of the field be allowed to dry out at any time? (principle 4); (6) how many times do you need to remove weeds during the season? (principle 6).

Table 5: Knowledge test on SRI principles of treated farmers by treatment group at $t = 0$

Question	Accuracy rate		p-value
	$T1$	$T2$	
(1)	0.4%	0.2%	0.36
	(0.06)	(0.04)	
(2)	14%	13%	0.28
	(0.35)	(0.34)	
(3)	3.3%	1.5%	0.14
	(0.17)	(0.12)	
(4)	15.3%	15.8%	0.75
	(0.36)	(0.36)	
(5)	44.7%	42.8%	0.38
	(0.50)	(0.49)	
(6)	12%	15%	0.50
	(0.32)	(0.35)	
Average accuracy	14%	14%	0.62
	(0.15)	(0.15)	
Observations	1,088	1,069	
No. of villages	60	60	

Notes: The knowledge test was performed at $t = 0$. The "accuracy rate" is the percentage of farmers that answer a given question correctly. The "average accuracy" is the average percentage of questions that is answered correctly in each treatment group. It is equal to the number of questions answered correctly divided by 6, the total number of questions. The reported p values are from the two-tailed test with the null hypothesis being that group accuracy means are equal, while the reject rule is $p < 0.05$. Standard deviations are reported in parentheses.

different practices of SRI, which correspond to the principles described in Section 3.2. This includes exactly the same six questions as in $t = 0$ (Table 5), numbered from (1) to (6) as above, plus two extra questions: (7) How deep should the seedlings be planted? (principle 2); (8) what should be the depth of water each time for irrigation? (principle 4).

Table 6 compares the farmers' answers by treatment group. First, in comparison to Table 5, we see a huge increase in the accuracy of the answers. In particular, before training, the average accuracy rate was 14% while, after training, it increases to 71% for $T1-$ farmers and to 75% for $T2-$ farmers. Second, and more importantly, contrary to Table 5, we see that, now, $T2-$farmers have a much more accurate knowledge of the SRI technology than $T1-$farmers. In most questions, their answer is more accurate and the difference is statistically significant. This evidence shows that $T2-$farmers have a more accurate information on the SRI technology than $T1-$farmers, and this is why they can provide untreated farmers with more accurate and more precise information on the SRI technology to untreated farmers.

Table 6: Knowledge test on SRI principles of treated farmers by treatment group at $t = 2$

Question	Accuracy rate		p-value
	$T1$	$T2$	
(1)	65%	70%	0.04
	(0.47)	(0.46)	
(2)	72%	75%	0.22
	(0.45)	(0.43)	
(3)	86%	91%	0.00
	(0.33)	(0.28)	
(4)	89%	95%	0.00
	(0.31)	(0.22)	
(5)	94%	96%	0.05
	(0.23)	(0.19)	
(6)	23%	30%	0.00
	(0.42)	(0.46)	
(7)	85%	91%	0.00
	(0.34)	(0.28)	
(8)	51%	54%	0.25
	(0.49)	(0.49)	
Average accuracy	71%	75%	0.01
	(0.16)	(0.14)	
Observations	1,088	1,069	
No. of villages	60	60	

Notes: The knowledge test was performed at $t = 2$. The "accuracy rate" is the percentage of farmers that answer a given question correctly. The "average accuracy" is the average percentage of questions that is answered correctly in each treatment group. It is equal to the number of questions answered correctly divided by 8, the total number of questions. The reported p values are from the two-tailed test with the null hypothesis being that group accuracy means are equal, while the reject rule is $p < 0.05$. Standard deviations are reported in parentheses.

7.1.2 Do $T2$ treated farmers adopt more SRI principles than $T1$ farmers?

To provide further evidence on the fact that $T2$ farmers have better accuracy of information about SRI than $T1$ farmers, we differentiate between the effect in the *midline assessment*, where both $T1$ and $T2$ farmers have received the training only once (Column 2 of Table 7), and in the *endline assessment* where $T2$ farmers have received the training twice while $T1$ farmers have received the training only once (Column 5 of Table 7).

According to column 2 of Table 7, one year after the training (midline assessment), there is no significant difference in adopting or following correctly different SRI principles between $T1$ and $T2$ treated farmers, since everyone received the same training. On the contrary, according to column 5 of Table 7, we show that after two years (endline assessment), $T2$ farmers, who receive a

second training, not only increase their adoption rate but also implemented the technology more precisely and more efficiently than $T1$ farmers. In particular, $T2$ farmers used more principles and follow them more correctly than $T1$ farmers.

Table 7: Adopting different principles at each period of time

Dependent variable: Whether a farmer adopt a SRI principle						
	Midline assessment			Endline assessment		
	T2		p-value	T2		p-value
$y_{i,v,t}^{NT}$	-0.00414	(0.0571)	0.897	0.141***	(0.0527)	0.008
$y_{i,v,t}^{PR,NT}$	-0.00288	(0.0296)	0.820	0.0629**	(0.0278)	0.025
Principle 1	-0.0138	(0.0343)	0.301	0.0369	(0.0343)	0.285
Principle 2	-0.0271	(0.0175)	0.304	0.0468*	(0.0242)	0.056
Principle 3	0.0269	(0.0563)	0.653	0.117**	(0.0541)	0.032
Principle 4	0.0296	(0.0461)	0.656	0.130***	(0.0491)	0.009
Principle 5	-0.0174	(0.0495)	0.929	0.117**	(0.0450)	0.010
Principle 6	-0.0163	(0.0558)	0.808	0.0931*	(0.0470)	0.050

Notes: The sample includes all treated farmers in T1 and T2 villages. T2 is a dummy indicator for T2 group. Principle 1 to 6 are dummy variables that equal to 1 if a farmer adopted this principle. $y_{i,v,t}^{NT}$ is the adoption decision using dummy definition and $y_{i,v,t}^{PR,NT}$ is the proportion of principles adopted. Standard errors are clustered in village level and reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

7.1.3 Do $T2$ farmers better transmit information about SRI adoption to untreated farmers than $T1$ farmers?

So far, we mainly proved that farmers who receive two-time training know the technology better and used more principles. Now, we are providing direct evidence of why farmers with repeated training spill over their knowledge about the new technology to their untreated peers while those with one-time training do not.

Role model farmers We explore whether farmers who are influential generated stronger spillovers to their peers. In our baseline survey, we asked every farmer to nominate "who is the most professional farmer in your village". Based on the nominations, we calculated for each farmer the total number of times he was nominated by as the most professional farmer in his village. We define a *role model* farmer in a village the farmer who has been nominated by at least one other farmer as the most professional farmer in farming in his village. Then, we determine

an exposure rate to these role-model farmers as

$$p_{i,v}^{T,RM} = \frac{N_{i,v}^{T,RM}}{N_{i,v}^{T}} \times 100\%, \tag{16}$$

where "RM" stands for "Role Model", $N_{i,v}^{T,RM}$ is the number of treated farmers who are role model farmers in the same village v as farmer i, and $N_{i,v}^{T}$ is the number of treated farmers in the same village v as farmer i. We then estimate equation (15) at the end of year 2 where we replace $p_{i,v}^{T}$ by $p_{i,v}^{T,RM}$. Table 8 displays the results. We see that only farmers in $T2-$villages have a significant impact on the adoption rate of the untreated farmers in their village. This indicates that role model farmers are able to transmit efficiently information about SRI technology only if they have received sufficient training.

Table 8: The effect of the most professional farmers on adoption rate of untreated farmers at the end of year 2

	All villages	T1 villages	T2 villages
	(1)	(2)	(3)
$p_{i,v}^{T,RM}$	0.0178	-0.00920	0.0561***
	(0.0119)	(0.0119)	(0.0198)
Controls	Yes	Yes	Yes
Observations	1,387	732	654
No. of villages	119	60	59

Notes: The sample includes all untreated farmers in T1 and T2 villages. The dependent variable is the adoption rate of an untreated farmer at the end of year 2. $p_{i,v}^{T,RM}$ is the fraction of role-model farmers in a village. A farmer is a role-model farmer if he is nominated by at least one other farmer as the most professional farmer in farming in his village.

Knowledgeable farmers We also ask farmers to answer the following question: "How knowledgeable about farming is this person?" (rated 1-5). We define a *knowledgeable farmer* as a farmer whose level of knowledge is above the average knowledge (determined by his peers) in his village. Then we calculate the number of treated farmers who are nominated as knowledgeable in a village. As above, we can construct an exposure rate to knowledgeable farmers as

$$p_{i,v}^{T,K} = \frac{N_{i,v}^{T,K}}{N_{i,v}^{T}} \times 100\%, \tag{17}$$

where "K" stands for "Knowledgeable", $N_{i,v}^{T,K}$ is the number of treated farmers who are knowledgeable in the same village v as farmer i, and $N_{i,v}^{T}$ is the number of treated farmers in the same village v as farmer i. We again estimate equation (15) at the end of year 2 where we replace $p_{i,v}^{T}$

by $p_{i,v}^{T,K}$. Table 9 displays the results. As in Table 8, we see that only farmers in $T2-$villages have a significant impact on the adoption rate of the untreated farmers in their village. Thus, only knowledgeable farmers in T2 villages are able to transmit efficiently information about SRI technology.

Table 9: The effect of knowledgeable farmers on adoption rate of untreated farmers at the end of year 2

	All villages	T1 villages	T2 villages
	(1)	(2)	(3)
$p_{i,v}^{T,K}$	0.0212	-0.0109	0.0461***
	(0.0132)	(0.0167)	(0.0170)
Controls	Yes	Yes	Yes
Observations	1,387	732	654
No. of villages	119	60	59

Notes: The sample includes all untreated farmers in T1 and T2 villages. The dependent variable is the adoption rate of an untreated farmer in the end of year 2. $p_{i,v}^{T,RM}$ is the fraction of knowledgeable farmers in a village. A farmer is a knowledgeable farmer if his knowledge level is voted as above the average.

Farmers who share information with others Finally, we also collected data on every farmer where we ask the question: "How many farmers do you regularly share information with". We define a farmer to be an *informed farmer* if he shares information with at least 3 farmers in his village (3 is the median). We can again construct an exposure rate to informed farmers as

$$p_{i,v}^{T,I} = \frac{N_{i,v}^{T,I}}{N_{i,v}^{T}} \times 100\%, \tag{18}$$

where "I" stands for "Informed", $N_{i,v}^{T,I}$ is the number of treated farmers who are "informed" in the same village v as farmer i, and $N_{i,v}^{T}$ is the number of treated farmers in the same village v as farmer i. We again estimate equation (15) at the end of year 2 where we replace $p_{i,v}^{T}$ by $p_{i,v}^{T,I}$. Table 10 displays the results. They are similar to the ones obtained in Tables 8 and 9, that is, only informed farmers in T2 villages are able to transmit efficiently information about SRI technology.

Table 10: The effect of informed farmers on the adoption rate of untreated farmers at the end of year 2

	All villages	T1 villages	T2 villages
	(1)	(2)	(3)
$p_{i,v}^{T,I}$	0.0252**	0.00283	0.0485**
	(0.0123)	(0.0134)	(0.0208)
Controls	Yes	Yes	Yes
Observations	1,387	732	654
No. of villages	119	60	59

Notes: The sample includes all untreated farmers in T1 and T2 villages. The dependent variable is the adoption rate of an untreated farmer in the end of year 2. $p_{i,v}^{T,I}$ is the fraction of informed farmers in a village. A farmer is informed if he shares information with at least 3 farmers.

7.2 The role of social interactions in SRI adoption

We would like to study how *social interactions* among farmers promote adoption. To measure social interactions between farmers, we will use the frequency of communication among *friends* and their financial relationship.

7.2.1 Effect of frequency of communication

In our baseline survey, we collected data on the frequency of communication among farmers. Specifically, we asked if they interact daily, weekly, monthly, yearly, or never. The discussion involves communicating crop experience (which includes the price and type of crop) or other agricultural issues (which include weather, agricultural inputs, and field practices). Table B.10 in Online Appendix B provides the interactions between farmers in the 120 villages. We find that 63% of farmers discuss agricultural issues at least once a month and 35% discuss them daily or weekly. Therefore, unsurprisingly, there is much interaction between farmers, as they all belong to the same neighborhood.

We now estimate equation (15) using a different definition of $p_{i,v}^{T}$ than the one in (14). We define the exposure rate as follows:

$$p_{i,v,d}^{T,Friend} = \frac{N_{i,v,d}^{T,Friend}}{N_{i,v}^{T}} \times 100\%,$$

where $d = \{daily, weekly, myn\}$ (myn means either monthly, yearly, or never) is the frequency of discussion between farmers, $N_{i,v,d}^{T,Friend}$ is the number of treated farmers who are friends[23] and who interact at frequency d with untreated farmer i residing in village v and $N_{i,v}^{T}$ is the

[23]Friends of i are farmers who have been nominated by i as friends.

total number of treated farmers residing in village v. Thus, $p_{i,v,d}^{T,Friend}$ is the percentage of treated farmers who interact at frequency d with untreated farmer i. We estimate (15) but with $p_{i,v,d}^{T,Friend}$ instead of $p_{i,v}^{T}$. Table 11 presents the results.

First, in comparison to Table 4, we find that the general effect of exposure (columns (1), (2), and (3)) is highly significant only when farmers interact either daily or weekly but less when they interact monthly, yearly, or never. In addition, the coefficient is much larger for $p_{i,v,daily}^{T,Friend}$ than for $p_{i,v,weekly}^{T,Friend}$. Second, distinguishing between one year and two years of training, we find that compared with Table 4, even in $T1-$treated villages, there is a significant effect of $p_{i,v,d}^{T,Friend}$ on the adoption rate of an untreated farmer for weekly interactions. Finally, the magnitude of the coefficient α_1 always decreases when farmers interact less frequently.

All this evidence seems to confirm our information story, as formally modeled in Section 2. Indeed, when untreated farmers obtain accurate information from treated friend farmers through frequent interactions, they are more likely to adopt the SRI methodology. Interestingly, even if treated farmers only receive one year of training, they may still have a positive and significant impact on the adoption rate of those untreated farmers if they are *friends* and discuss with them at a sufficiently *high frequency*.

Table 11: Impact of frequency discussion on the adoption rate of untreated farmers

	All villages			T1 villages			T2 villages		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$p_{i,v,daily}^{T,Friend}$	0.178***			0.134**			0.202**		
	(0.0555)			(0.0576)			(0.0811)		
$p_{i,v,weekly}^{T,Friend}$		0.133***			0.144***			0.118*	
		(0.0377)			(0.0485)			(0.0590)	
$p_{i,v,myn}^{T,Friend}$			0.0981**			0.0544			0.149**
			(0.0384)			(0.0448)			(0.0647)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,151	1,151	1,151	608	608	608	543	543	543
No. of villages	120	120	120	60	60	60	60	60	60

Notes: The dependent variable is the adoption decision of untreated farmers across two years. Each regression includes year dummies and all seven control variables in Table 4. Standard errors are clustered at the village level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1..

7.2.2 Effect of financial relationships

In our baseline survey, we also collected information on another important social interaction between farmers in a village, that is, the financial relationship. We suppose that two farmers have a financial relationship if they have borrowed or lent money to each other or have discussed financial issues in the last six months. Table B.11 in Online Appendix B supplies some summary statistics. On average, each untreated farmer has 3 peers with whom he has borrowed or lent money or discussed financial issues. Furthermore, 70% of farmers have lent or borrowed money

from each other and 52% have at least two finance-related peers. Therefore, most farmers in these villages have some kind of financial relationship with each other.

We now define the exposure level as follows:

$$p^{T,Friend}_{i,v,finance} = \frac{N^{T,Friend}_{i,v,finance}}{N^{T}_{i,v}} \times 100\%,$$

where $N^{T,Friend}_{i,v,finance}$ is the number of *treated* farmers who are friends with i and borrowed or lent money or discussed financial issues in the last six months with farmer i residing in village v and $N^{T}_{i,v}$ is the total number of treated farmers residing in village v. Thus, $p^{T,Friend}_{i,v,finance}$ measures the fraction of treated farmers who borrowed or lent money or discussed financial issues in the last six months with farmer i. As above, we estimate (15) but with $p^{T,Friend}_{i,v,finance}$ instead of $p^{T}_{i,v}$. Table 12 presents the results. We obtain similar results to that of the previous tables, that is, the effect is significant and its magnitude is much bigger for farmers in $T2$ compared to $T1$ villages.

Table 12: Impact of finance-related friends on adoption rate of untreated farmers

	120 villages	60 villages (T1)	60 villages (T2)
	(1)	(2)	(3)
$p^{T,Friend}_{i,v,finance}$	0.0172**	0.0104**	0.0228*
	(0.00701)	(0.00411)	(0.0119)
Controls	Yes	Yes	Yes
Observations	1,096	569	527
No. of villages	120	60	60

Notes: The dependent variable is the adoption decision of untreated farmers across two years. This is a dummy variable that equals 1 if an untreated farmer adopted in year t ($t = 1, 2$) and 0 if he did not. Each regression includes year dummies and all seven control variables in Table 4. $n_{i,v,finance}$ is the total number of friends that a farmer i talks about finance with. Standard errors are clustered at the village level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

To summarize, the strength of spillover effects depends on the network characteristics of treated farmers. When they are socially connected with their untreated peers (e.g., they discuss frequently or financially linked with untreated farmers), providing treated farmers with an one-time training can generate significant influence, making untreated farmers willing to try the new technology. On the other hand, to spread accurate information about SRI technology from farmers who are influential, knowledgeable or informed in a village, it is important to introduce a two-time training in order to trigger significant spillover effects.

7.3 Alternative mechanism

So far, we have shown that the quality of information is crucial in encouraging untreated farmers to adopt SRI technology. There may be another mechanism. For example, farmers who have two years of training ($T2$ villages) may produce more rice and have higher yields than farmers

with one year of training ($T1$ villages). In that case, untreated farmers would adopt more in $T2$ villages than in $T1$ villages not because of better information quality about SRI technology but because they observe higher rice production. Let us rule out this possibility.

To exclude this possibility, table 13 shows *no* difference in *two-year average* rice production (yields) between $T1$ and $T2$ villages. Table B.12 in Online Appendix B displays the same table *by year* and also shows no difference. This confirms the idea that spillover effects operate mainly through *information* transmission rather than imitating more productive farmers. This is intuitive since the training only helps farmers understand SRI technology and decide whether to adopt it. However, once someone adopts, independently of his training, the production of rice using SRI technology is the same. It is also higher than the rice production of farmers who did not adopt SRI technology (Table 3). In other words, farmers with two years of training in $T2$ villages are not better at using the SRI than farmers with one year of training in $T1$ villages but are better at explaining how to use it to their untrained peers by providing more accurate information about the technology and thus convincing their peers to adopt it.

Table 13: Average yield difference between T1 and T2 villages

Yield (kg)	T1	T2	p-value
All farmers	25.47	25.50	0.315
	(0.32)	(0.31)	
Treated farmers	25.69	25.70	0.709
	(0.18)	(0.18)	
Adopters	25.60	25.60	0.974
	(0.258)	(0.824)	
Treated adopters	25.68	25.70	0.612
	(0.18)	(0.18)	

Note: Yield is defined as the amount of rice cultivated in one decimal of land, measured in kg. It is calculated as the total amount of rice cultivated (kg) divided by total amount of cultivable land (decimal). The yield reported in this table is the average yield of years 1 and 2. Means are reported with standard deviations in parentheses. ***p<0.01, **p<0.05, *p<0.1.

8 The role of risk aversion in technology adoption

Thus far, our analysis has explained how and why untreated farmers adopt SRI technology. However, the analysis has lacked one crucial element: the degree of risk aversion of untreated farmers. Risk aversion plays an important role in technology adoption (Ghadim et al., 2005; Genius et al., 2014), especially in the poor districts in Bangladesh in which we conduct our experiment. This is what we want to investigate both theoretically and empirically.

8.1 Extending the theory

Let us extend our model presented in Section 2 by considering risk-averse instead of risk-neutral farmers. For simplicity, we assume that conditional on meeting a $\theta-$type agent ($\theta = \{T, NT\}$), all individuals share the same constant von Neumann–Morgenstern utility function with constant absolute risk aversion:

$$U(A \,|\, \theta) := \mathbb{E}\left[u(z) \,|\, s_T\right], \qquad u(z) := \frac{1 - \exp(-\delta z)}{\delta}, \tag{19}$$

where z is defined by (7), while $\delta > 0$ is the risk aversion parameter.[24] As each farmer faces a conditional distribution, $b \,|\, s_T$, of the benefit of adoption, the utility level $U(. \,|\, \theta)$ is a *random variable*, and its value depends on the type of farmer (treated or untreated) with whom an untreated farmer interacts.

Since payoffs are normally distributed, we can show (Sargent, 2009, p.154-155) that preferences (19) can be equivalently represented by the following utility function:

$$\mathcal{U}(A \,|\, \theta) = \begin{cases} \mathbb{E}(b \,|\, s_\theta) - c - \frac{\delta}{2}\mathrm{Var}\left(b \,|\, s_\theta\right), & \text{if } A = 1, \\ 0, & \text{if } A = 0. \end{cases} \tag{20}$$

Equation (20) implies that the expected utility $\mathcal{U}(A \,|\, \theta)$ of adoption conditional on meeting a $\theta-$type agent is *mean-variance* utility, namely it only depends on the conditional mean and conditional variance in the uncertain adoption benefit b. Throughout this section, we assume that

$$\delta > \underline{\delta} := \max\{0, 2(\beta - c)/\sigma_b^2\}, \tag{21}$$

which becomes $c < \beta$ in the limit case of risk-neutral agents ($\delta \to 1$). (21) is less demanding than $c < \beta$, since the latter implies the former. This is because, now, a farmer who has other information than the distribution of the benefits will not adopt if he is sufficiently risk-averse. In particular, if $c > \beta$, a risk-neutral farmer will not adopt, and a fortiori, a risk-averse farmer will be even less willing to adopt.

For $\theta = \{T, NT\}$, the conditional probabilities of adoption are now given by

$$\mathbb{P}\{A = 1 \,|\, \theta\} = \mathbb{P}\left\{\mathbb{E}(b \,|\, s_\theta) > c + \frac{\delta}{2}\mathrm{Var}\left(b \,|\, s_\theta\right)\right\}. \tag{22}$$

The following proposition shows how taking risk aversion into account affects the main predictions of the model.

[24] In the limit case when $\delta \to 0$, we fall back to the case of risk-neutral agents. Indeed, as $\delta \to 0$, the Bernoulli function $u(z)$ becomes linear: $\lim_{\delta \to 0} u(z) = z$, which is equivalent to risk neutrality.

Proposition 2 *Assume that* (4) *and* (21) *hold and that all farmers exhibit risk aversion captured by mean-variance utility* (20).

(i) In each village, the adoption rate of untreated farmers increases with the exposure rate.

(ii) In each village, the adoption rate of untreated farmers decreases with δ, the degree of risk aversion.

(iii) In a $T2$-treated village, the impact of the exposure rate on the adoption rate of untreated farmers is higher than that in a $T1$-treated village.

(iv) When farmers are sufficiently risk-averse, the higher the degree of risk aversion, the lower is the impact of the exposure rate on the adoption rate of untreated farmers,

$$\frac{\partial^2 \mathbb{P}\{A = 1\}}{\partial p \, \partial \delta} < 0. \tag{23}$$

Parts (i) and (iii) of Proposition 2 share the same intuition as parts (i) and (ii) of Proposition 1. With risk aversion, we have two new results. First, according to part (iii), when agents become more risk-averse, they are less likely to adopt the new technology. This is because since the outcome is uncertain, more risk-averse farmers prefer the "safe" lottery, which is to not adopt.[25] In part (iv), we investigate the cross-effect of p and δ on the adoption rate of an untreated farmer. Indeed, if farmers are sufficiently risk-averse, when risk aversion increases, the impact of the proportion of treated farmers (the exposure rate) on the adoption rate of untreated farmers is lower. This is because when a farmer is very risk-averse, his treated peers in the village do not have a large impact on his adoption rate and therefore the marginal effect is smaller.

8.2 Empirical test and results

Let us now test these theoretical results, especially parts (ii) and (iv) of Proposition 2, which are new.

8.2.1 Measuring risk attitude of farmers

We asked all farmers in our field experiment to answer two questions about their risk-taking attitudes.[26] The *first question* is: "In daily life how much risk do you like to take?" The answers

[25] Formally speaking, the higher the risk aversion δ, the lower is the certainty equivalent of the lottery associated with the adoption tradeoff.

[26] Contrary to the literature that shows that risk aversion has a negative effect on technology adoption (Ghadim et al., 2005; Koundouri et al., 2006; Genius et al., 2014; Bonan et al., 2020), where risk is *indirectly* measured through the variation in each farmer's production or profit, we here *directly* measure the risk attitudes of farmers through a survey. For example, Koundouri et al. (2006) measure the "production" risk of each farmer by calculating the variance in each farmer's profit and by assuming that farmers who experience high variance in their current profits face higher production risk.

range from 1 to 10. If a farmer answers 1, it indicates that his risk attitude is low and he is willing to take little risk in his daily life. On the contrary , if a farmer answers 10, it means that his risk attitude is high and he is ready to take risk in his daily life. The *second question* is: "When cultivating, how much risk do you like to take?" The answers also range from 1 to 10, where a higher number means more risk-taking.

Figure B.5 in Online Appendix B provides the distribution of the 2,157 farmers' risk attitudes in the 120 treatment villages. We see that 28% of farmers report a 9 or 10 for their risk-taking in daily life. On average, they report taking a risk of 7.6 in daily life. Figure B.6 shows a similar figure but for risk attitudes in cultivation activity. The numbers are relatively similar even though 31% of farmers report a 9 or 10. Figures B.7 and B.8 display the same distributions but for the 1,404 untreated farmers only. The numbers are similar but the percentages of (untreated) farmers with high risk attitudes are lower.

8.2.2 Defining risk attitudes

We say that a farmer has a higher level of risk tolerance if he answered a 9 or 10 to both questions. Table B.13 in Online Appendix B shows that the percentage of farmers with high risk-tolerance level is slightly smaller for untreated farmers (22%) than for treated farmers (25%).

We also run another analysis in which we defined a farmer with a high level of risk tolerance as someone who answered a 10 to both questions. In this more extreme definition, only 10.83% and 12.04% of untreated and treated farmers are risk-loving, respectively. Using this definition, the results of the empirical analysis are qualitatively the same as in Table 14 and can be found in Table B.16 in Online Appendix B.

In order to show that our measure of risk attitude is meaningful, let us show that it correlates with some characteristics of the farmers. By using our definition of risk attitude, that is, a farmer has a higher level of risk tolerance if he answers 9 or 10 in both questionnaires, we examine the correlation between these risk attitudes and four measures that capture different dimensions of farmers' charateristics, that is their well-being status, their personality, their ability and their confidence. Each of these characteristics is constructed as an index that stems from several questions, which are listed in Table B.14 in Online Appendix B. The results are reported in Table B.15.[27]

It is found that farmers with higher level of risk tolerance have better well-being status, are more outgoing, have open personality, have higher ability and are more confident than farmers with lower level of risk tolerance. Even though these results are just correlations, they show that our measure of risk attitude makes sense.

[27]Note that all four indexes have been standardized so the coefficients in Table B.15 are comparable.

8.2.3 Econometric model

We can now test Proposition 2 by extending our pooled OLS model (15) to

$$y_{i,v,t}^{NT} = \alpha_0 + \alpha_1 p_{i,v}^{T} + \alpha_2 \delta_{i,v}^{NT} + \alpha_3 (\delta_{i,v}^{NT} \times p_{i,v}^{T}) + X_{i,v}^{'}\beta + \theta_t + \epsilon_{i,v,t}, \tag{24}$$

where $\delta_{i,v}^{NT}$ indicates the risk attitude of untreated farmer i in village $v = T1, T2$. $\delta_{i,v}^{NT}$ is a dummy variable: it is equal to 0 ($\delta_{i,v}^{NT} = 0$) if the farmer has a high level of risk tolerance (i.e., if he answered a 9 or 10 to both questions) and 1 ($\delta_{i,v}^{NT} = 1$) if the farmer has a low level of risk tolerance (i.e., if he answered otherwise). All the other variables are defined as in (15). According to Proposition 2, we should expect $\alpha_1 > 0$, $\alpha_2 < 0$, $\alpha_3 < 0$ and a higher value of α_1 when comparing the 60 $T2-$treated villages with the 60 $T1-$treated villages.

8.2.4 Empirical results

Table 14 displays the results of the estimation of equation (24), which has the same structure as Table 4 in terms of dividing the total sample into the 60 $T1$ villages and 60 $T2$ villages. There are two columns for each regression. The first columns (i.e., columns (1), (3), and (5)) report the results without the cross effect while the second columns (i.e., columns (2), (4), and (6)) report the results with the cross effect.

Table 14: The effect of risk on the adoption rate of untreated farmers

	All villages		T1 villages		T2 villages	
	(1)	(2)	(3)	(4)	(5)	(6)
$p_{i,v}^{T}$	0.235***	0.345***	0.0883	0.130	0.396***	0.532***
	(0.0753)	(0.104)	(0.0927)	(0.136)	(0.105)	(0.126)
$\delta_{i,v}^{NT}$	-0.0649***	0.0991*	-0.0680***	-0.0160	-0.0623***	0.200*
	(0.0149)	(0.0592)	(0.0203)	(0.0841)	(0.0218)	(0.0768)
$\delta_{i,v}^{NT} \times p_{i,v}^{T}$		-0.302***		-0.0986		-0.464***
		(0.111)		(0.162)		(0.140)
Observations	2,300	2,300	1,214	1,214	1,086	1,086
No. of villages	120	120	60	60	60	60

Notes: The dependent variable is the adoption decision of an untreated farmer. This is a dummy variable that takes the value of 1 if an untreated farmer adopted the technology at time t ($t = 1, 2$) and 0 if he did not. A farmer has a relatively higher tolerance in risk ($\delta_{i,v}^{NT} = 0$) if he answered a 9 or 10 to both risk questions in terms of daily life and rice activities. A farmer a has lower level of risk tolerance ($\delta_{i,v}^{NT} = 1$) otherwise. Each regression includes year dummies and all seven control variables in Table 4. Standard errors are clustered at the village level and reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

We see that there is a significant negative direct effect of $\delta_{i,v}^{NT}$, the degree of the risk tolerance of an untreated farmer, on $y_{i,v,t}^{NT}$. As predicted by Proposition 2, the lower is the level of risk tolerance of an untreated farmer (i.e., higher $\delta_{i,v}^{NT}$), the less likely he is to adopt SRI technology. This is because adopting the SRI is risky, as it involves mostly mental changes and new ways of

thinking. When looking at the cross-effect $\delta_{i,v}^{NT} \times p_{i,v}^{T}$, as predicted by Proposition 2, we find a significant and negative effect. That is, when the proportion of treated farmers increases, more untreated farmers adopt SRI technology; however, the lower is level of risk tolerance, the *lower* is this impact on the adoption rate of untreated farmers.

More generally, our results show that risk aversion deters untreated farmers from adopting SRI technology and can reduce the impact of the information transmission of treated farmers on the adoption rate of untreated farmers. As stated above, this is because the SRI imposes a certain set of rules and practices (e.g., planting young seedlings, having wider spacing between plants, having the soil in the field kept moist but not continuously flooded; see Section 3.2) that are not standard and thus involves mental changes and new ways of thinking. Risk-averse farmers or, more exactly, farmers with a lower level of risk tolerance, are therefore reluctant to adopt it and are also less likely to listen to other farmers, even if the latter have been trained on the SRI.

9 Conclusion

Uphoff (2015) tells the story of farmer Miyatty Jannah from Crawuk village in East Java, Indonesia. When Miyatty first learned about the SRI in 2004, she invited SRI trainers to her village and personally covered the costs of their stay to provide four days of training. Of the 25 farmers they trained, only 10 were willing to try out the methods and there was a lot of resistance initially, even abuse. She told Norman Uphoff in 2008 the following: "The whole village was against us at first. 'You are stupid,' they said when they saw the tiny planted SRI seedlings: 'You will get nothing.' But when harvesting was done, people came and said, 'Wow. How did that happen from such small seedlings?' All the people were surprised. With less water and less money, we had 40–50% more paddy."

This story by Miyatty Jannah is typical of the SRI adoption. Because it is so unusual and involves a different way of thinking, most farmers are initially reluctant to adopt the technology. However, when exposed to well-trained farmers who can explain them the benefits of the SRI and how to implement it, they tend to change their opinions and adopt the SRI. Moreover, when some farmers adopt, other farmers also tend to adopt because of effects and social norms.

In this study, we investigate this issue both theoretically and empirically in rural Bangladesh. This is an important issue in a country in which rice cultivation accounts for 48% of rural employment, provides two–thirds of the caloric needs of the nation along with half the protein consumed, and its contribution to agricultural GDP is about 70%, while its share of national income is one–sixth (Sayeed and Yunus, 2018).

We provide a simple theoretical model in which risk-neutral untreated farmers adopt this new technology when they are "exposed" to trained (treated) farmers who can provide accurate and reliable information about SRI technology. Further, we consider risk-averse untreated farmers

who were also influenced by trained farmers but whose degree of risk aversion has both a direct negative effect on their adoption rate and a cross-effect by reducing the effect of peers on the adoption decision.

We test these predictions by conducting a field experiment on 2,157 farmers in 120 villages in rural Bangladesh, where rice is the main crop. We consider two types of treatments: farmers trained only once ($T1$ villages) and those trained twice ($T2$ villages). We expect that farmers with two years of training (i.e., repeated training) could provide more accurate and reliable information about SRI technology than those with one year of training. We use the exogenous variation across villages in terms of both the treatment and the percentage of treated farmers by studying how the exposure rate (i.e., the proportion of treated farmers in each village) of an untreated farmer affects his decision to adopt SRI technology.

We find that the percentage of farmers with two years of training in a village has a significant and positive impact on the adoption rate of untreated farmers living in the same village, while those with one year of training have no significant impact. We firstly checked if the accuracy of information is the main mechanism behind our results by conducting surveys on the different principles of SRI before and after the farmers have been trained. We find that the accuracy of information about SRI increases after training but it increases significantly more for $T2-$farmers compared to $T1-$farmers. We also show in the endline assessment, where $T2-$farmers received more training than $T1-$farmers, the former increase their adoption rate and implement the technology more precisely and more efficiently than the latter. This finding supports our mechanism story that more accurate and reliable information disseminated by farmers with repeated training could be an important reason to promote spillovers.

Furthermore, we consider the role of social networks as an alternative mechanism in promoting spillover effects. We find that treated farmers who are influential or knowledgeable in his village only generate significant influence to their peers if they receive a two-time training. Despite of being influential and professional in farming, a one-time training is insufficient to make their peers adopt the technology. On the other hand, when there is a friendship link (discussing agricultural or financial issues)between farmers, farmers are easier to be convinced and the length of training becomes less important: both one-year- and two-year-trained farmers have a significant and positive impact on the adoption rate of untreated farmers, although we observe higher effects for two years of training.

Finally, we examine the effect of risk aversion on the adoption rate of untreated farmers and find that more risk-averse untreated farmers are less likely to adopt SRI technology. We also find that for more risk-averse farmers, the effect of two-year-trained farmers on the adoption rate of untreated farmers is smaller than that for less risk-averse untreated farmers.

As in the story of Miyatty Jannah, we believe that the primary incentive for untreated farmers in rural Bangladesh to adopt SRI technology is "exposure" to farmers who have received sufficient training in this technology. The more they trust these farmers, the more they believe

the accuracy and reliability of information on the quality of SRI technology and its ease of adoption. Moreover, given the risk and cost in terms of new ways of thinking about the SRI, it is not surprising that more risk-averse farmers are less likely to adopt the SRI and are less "influenced" by their peers who have been trained and/or have adopted this technology.

In terms of policy implications, when a new technology is as different as the SRI is from standard rice technologies, most farmers would be reluctant to adopt it. This study finds that information and training policies on the new technology are the easiest ways to help farmers decide to adopt it.

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Online Appendix

Appendix A Proofs of the propositions in the theoretical model

Proof of Proposition 1

(i) Combining (13) with (4) and (6) and taking into account that $\Phi(\cdot)$ is an increasing function, we find that

$$\frac{\partial \mathbb{P}\{A=1\}}{\partial p} = \mathbb{P}\{A=1\,|\,\theta=T\} - \mathbb{P}\{A=1\,|\,\theta=NT\} > 0 \quad \Longleftrightarrow \quad c > \beta.$$

(ii) We need to show that

$$\mathbb{P}\{A=1\,|\,\theta=T2\} > \mathbb{P}\{A=1\,|\,\theta=T1\},$$

which is equivalent to

$$\Phi\left(\frac{(c-\beta)}{\sigma_b^2}\sqrt{\sigma_b^2+\sigma_{T2}^2}\right) < \Phi\left(\frac{(c-\beta)}{\sigma_b^2}\sqrt{\sigma_b^2+\sigma_{T1}^2}\right).$$

If $c > \beta$, this is true since $\sigma_{T2}^2 < \sigma_{T1}^2$. ■

Proof of Proposition 2

(i) Because (b, s_θ) follow a bivariate normal distribution, one can show that

$$\mathrm{Var}\,(b\,|\,s_\theta) = \frac{\sigma_\theta^2\,\sigma_b^2}{\sigma_\theta^2+\sigma_b^2}.$$

Combining this with (11) yields

$$\mathbb{P}\{A=1\,|\,\theta\} = \frac{1}{\sqrt{2\pi}} \int\limits_{\Delta(\delta,\sigma_\theta)}^{\infty} \exp\left(-\frac{x^2}{2}\right)\,\mathrm{d}x, \tag{A.1}$$

where

$$\Delta(\delta,\sigma_\theta) := (c-\beta)\frac{\sqrt{\sigma_b^2+\sigma_\theta^2}}{\sigma_b^2} + \frac{\delta}{2}\frac{\sigma_\theta^2}{\sqrt{\sigma_b^2+\sigma_\theta^2}}. \tag{A.2}$$

Hence,

$$\mathbb{P}\{A=1\,|\,\theta=T\}-\mathbb{P}\{A=1\,|\,\theta=NT\} \;=\; \frac{1}{\sqrt{2\pi}}\int\limits_{\Delta(\delta,\sigma_T)}^{\Delta(\delta,\sigma_{NT})} \exp\left(-\frac{x^2}{2}\right)\mathrm{d}x.$$

Combining this with (4) and (6), we obtain

$$\frac{\partial\mathbb{P}\{A=1\}}{\partial p}>0 \quad\Longleftrightarrow\quad \Delta(\delta,\sigma_{NT})>\Delta(\delta,\sigma_T). \tag{A.3}$$

Since $\sigma_{NT}>\sigma_T$, a sufficient condition for $\Delta(\delta,\sigma_{NT})>\Delta(\delta,\sigma_T)$ to hold is that $\Delta(\delta,\sigma_\theta)$ increases with σ_θ. Differentiating $\Delta(\delta,\sigma_\theta)$ w.r.t. σ_θ yields after simplifications:

$$\frac{\partial\Delta(\delta,\sigma_\theta)}{\partial\sigma_\theta}=\frac{\sigma_\theta}{2\sqrt{\sigma_\theta^2+\sigma_b^2}}\left[\delta\left(1+\frac{\sigma_b^2}{\sigma_\theta^2+\sigma_b^2}\right)-\frac{2(\beta-c)}{\sigma_b^2}\right]>\frac{\sigma_\theta}{2\sqrt{\sigma_\theta^2+\sigma_b^2}}\left[\delta-\frac{2(\beta-c)}{\sigma_b^2}\right].$$

Setting $\underline{\delta}:=\max\{0,2(\beta-c)/\sigma_b^2\}$, we find that

$$\delta>\underline{\delta} \quad\Longrightarrow\quad \frac{\partial\Delta(\delta,\sigma_T)}{\partial\sigma_T}>0.$$

(ii) We now show that when risk aversion is higher, untreated individuals adopt less:

$$\frac{\partial\,\mathbb{P}\{A\}}{\partial\,\delta}<0. \tag{A.4}$$

Using (5), (A.1), and (A.2), we obtain

$$\frac{\partial\,\mathbb{P}\{A=1\}}{\partial\,\delta}=-\frac{1}{2}\left[\varphi\left(\Delta(\delta,\sigma_T)\right)\frac{p\,\sigma_T^2}{\sqrt{\sigma_b^2+\sigma_T^2}}+\varphi\left(\Delta(\delta,\sigma_{NT})\right)\frac{(1-p)\,\sigma_{NT}^2}{\sqrt{\sigma_b^2+\sigma_{NT}^2}}\right], \tag{A.5}$$

where $\varphi(\cdot)$ is the standard normal distribution density:

$$\varphi(x):=\frac{1}{\sqrt{2\pi}}\exp\left(-\frac{x^2}{2}\right).$$

Since the expression in squared brackets is strictly positive, we obtain (A.4).

(iii) Let us show that residing in a $T2-$treated village has a larger impact on the adoption probability of an untreated farmer than residing in a $T1-$treated village. This situation can be captured in the model as a reduction in the variance in the noise: farmers exposed to $T2-$treated farmers receive a more precise signal about the quality of the technology than those exposed to $T1-$treated farmers. When $\delta>\underline{\delta}$, where $\underline{\delta}$ is defined in (21), we have

$$\frac{\partial\,\mathbb{P}\{A=1\}}{\partial\,\sigma_T}=-\varphi\left(\Delta(\delta,\sigma_T)\right)\frac{\partial\Delta(\delta,\sigma_T)}{\partial\sigma_T}<0.$$

Hence, more training (i.e., a lower σ_T) implies more adoption.

(iv) We now study the cross-effect of stronger risk aversion (higher δ) and more exposure to treated individuals (higher p). Differentiating both sides of (A.5) with respect to p, we obtain

$$\frac{\partial^2 \mathbb{P}\{A=1\}}{\partial\delta\,\partial p} = -\frac{1}{2}\left[\varphi\left(\Delta(\delta,\sigma_T)\right)\frac{\sigma_T^2}{\sqrt{\sigma_b^2+\sigma_T^2}} - \varphi\left(\Delta(\delta,\sigma_{NT})\right)\frac{\sigma_{NT}^2}{\sqrt{\sigma_b^2+\sigma_{NT}^2}}\right]. \tag{A.6}$$

Factorizing $\varphi\left(\Delta(\delta,\sigma_T)\right)$ on the right-hand side of (A.6), we find that (23) holds if and only if the following inequality holds:

$$\frac{\sigma_T^2}{\sqrt{\sigma_b^2+\sigma_T^2}} - \frac{\sigma_{NT}^2}{\sqrt{\sigma_b^2+\sigma_{NT}^2}}\frac{\varphi\left(\Delta(\delta,\sigma_{NT})\right)}{\varphi\left(\Delta(\delta,\sigma_T)\right)} > 0. \tag{A.7}$$

From the definition of standard normal density, we have

$$\frac{\varphi\left(\Delta(\delta,\sigma_{NT})\right)}{\varphi\left(\Delta(\delta,\sigma_T)\right)} = \exp\left\{-\frac{1}{2}\left[\Delta^2(\delta,\sigma_{NT}) - \Delta^2(\delta,\sigma_T)\right]\right\}.$$

Combining this with (A.7), we find that (23) is equivalent to

$$\Delta^2(\delta,\sigma_{NT}) - \Delta^2(\delta,\sigma_T) > \ln\left(\frac{\sigma_{NT}^4}{\sigma_T^4}\frac{\sigma_b^2+\sigma_T^2}{\sigma_b^2+\sigma_{NT}^2}\right). \tag{A.8}$$

Using (4) and (A.2), it is readily verified that the left-hand side of (A.8) is a strictly convex quadratic function. Thus, there must exist a threshold value $\delta_0 \geq 0$ of risk aversion such that (A.8), and hence (23) holds true for all $\delta > \delta_0$. This completes the proof. ■

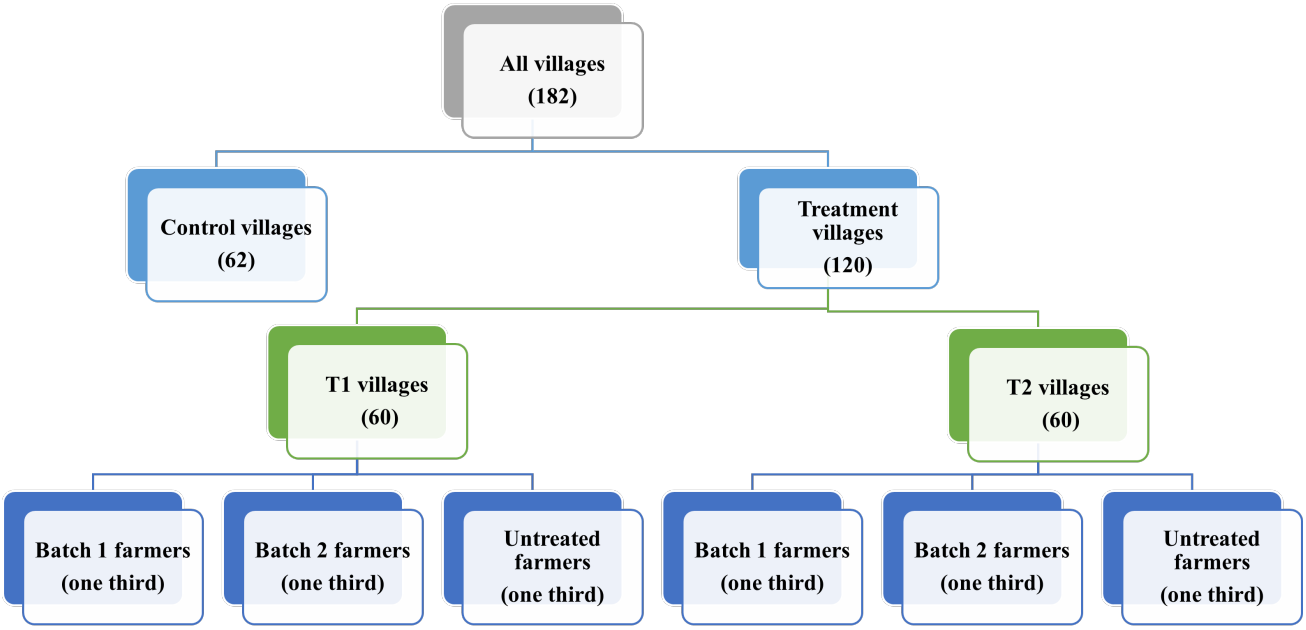
Appendix B Additional Figures and Tables

B.1 Map, timing, randomization process and other figures

Figure B.1: Districts in the field experiment

Notes: The five blue areas are the districts in which the RCT experiments were conducted.

Figure B.2: Randomization process



Notes: Batch 1 farmers refer to the group of farmers who are randomly selected to receive training in the first week. Batch 2 farmers refer to the group of farmers who are nominated by Batch 1 farmers to receive training in the second week. Untreated farmers are remaining farmers who did not receive any training but reside in the same treatment village with treated farmers. Each group accounts for one third of all participants on average in a village.

Figure B.3: Density distribution of p_v^T

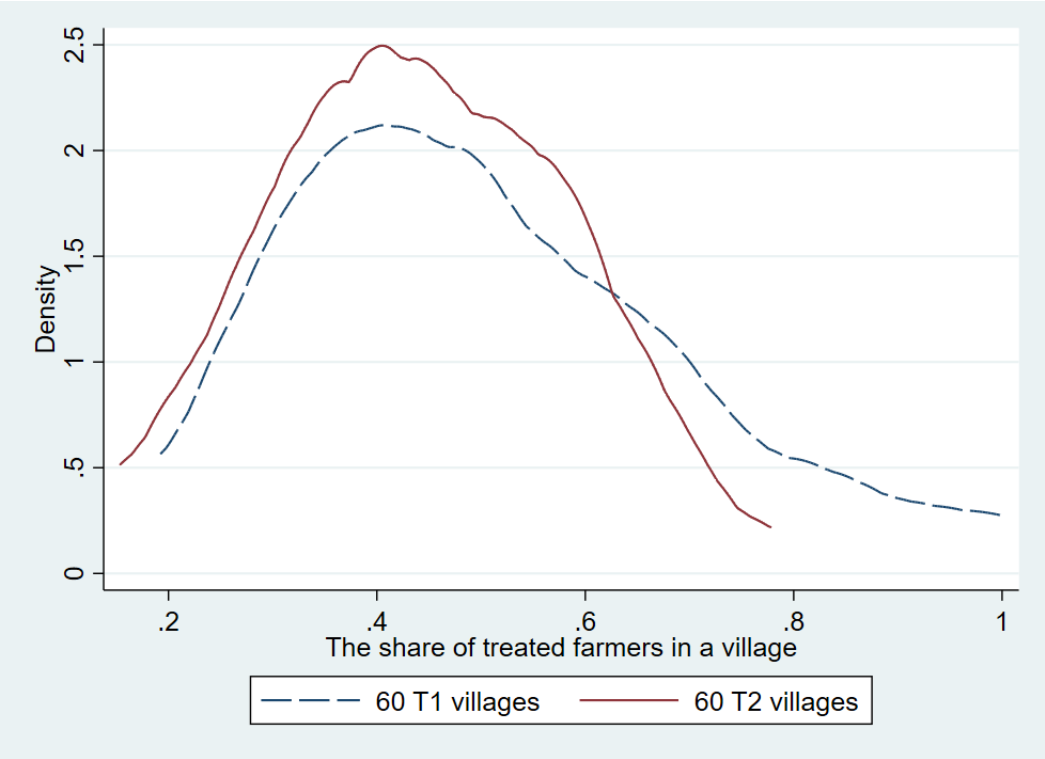
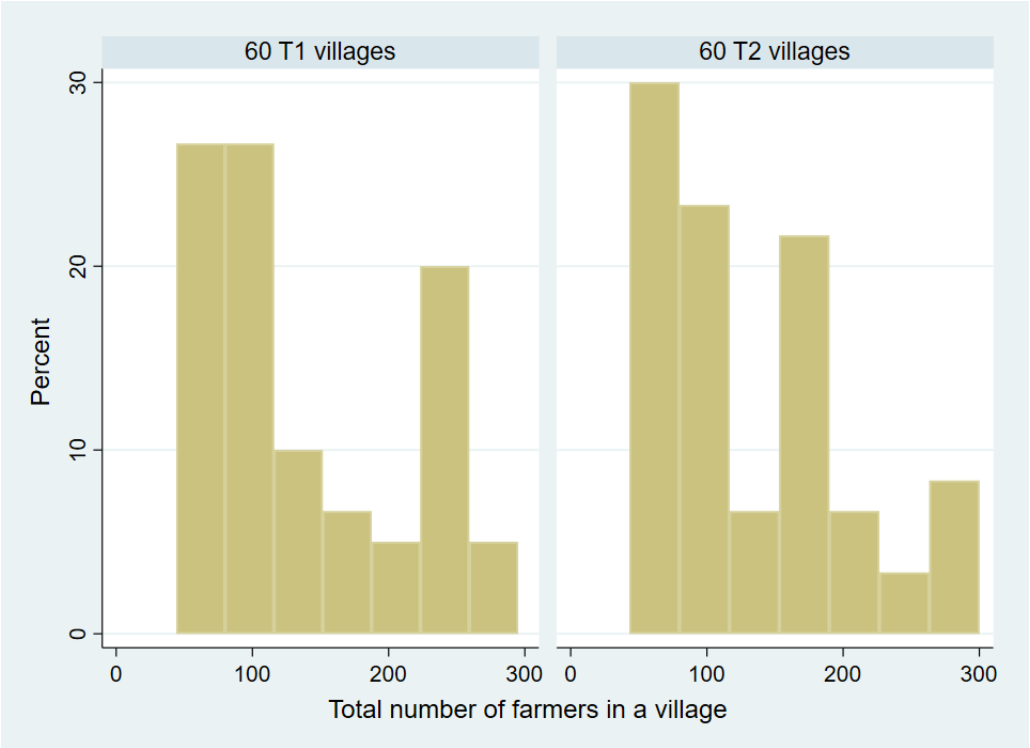
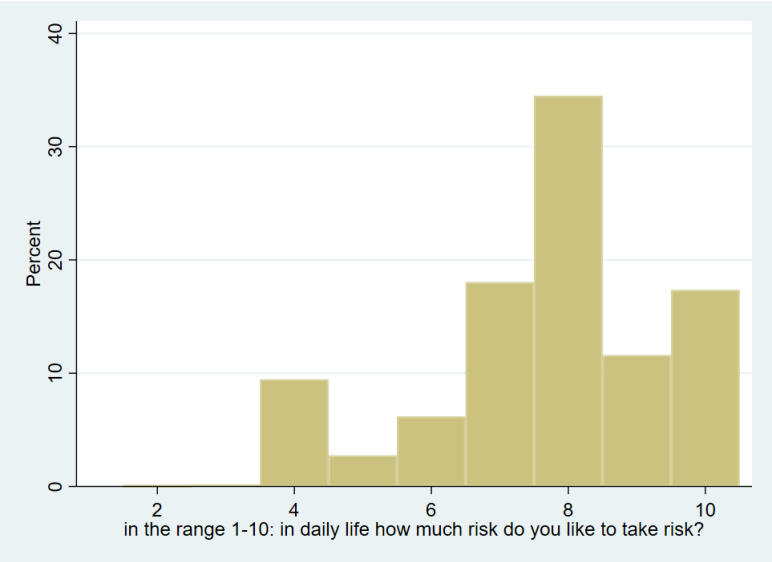


Figure B.4: Distribution of total number of farmers between villages



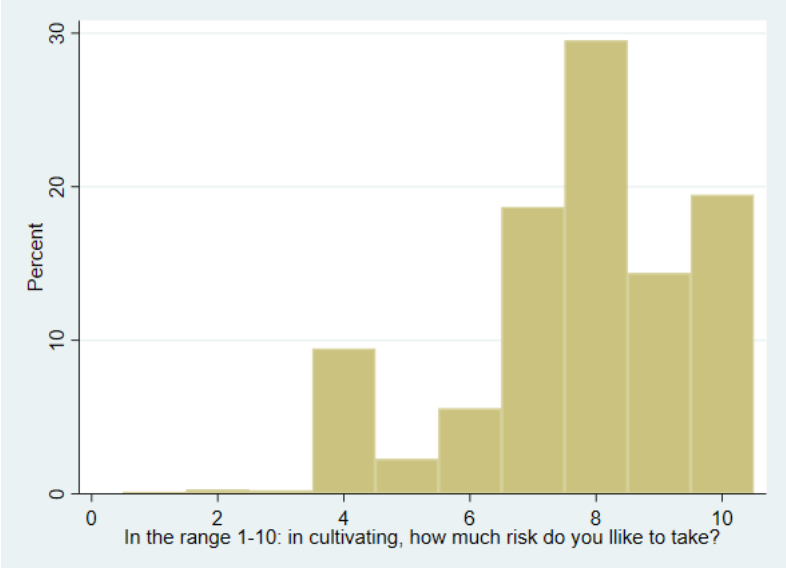
Notes: Total number of farmers refers to all farmers who naturally reside in the village, and it is not total participants of our experiment.

Figure B.5: Distribution of risk taking attitudes in daily life for *all* farmers



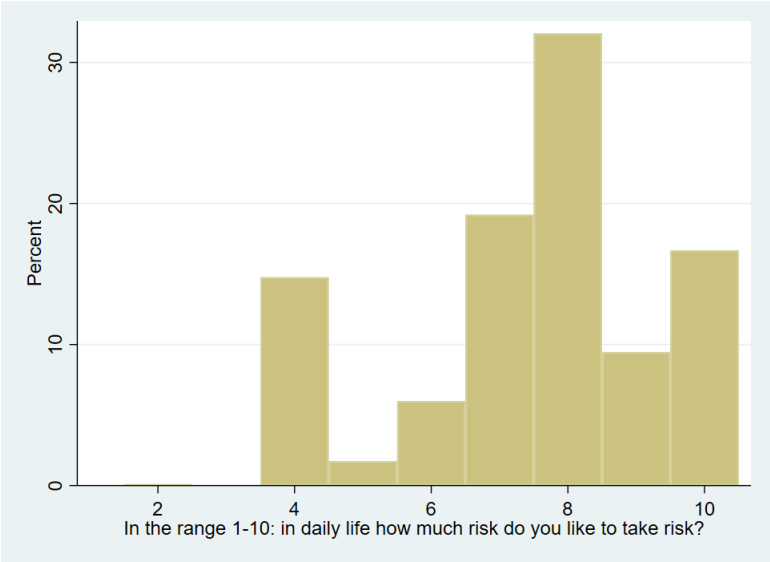
Notes: The sample includes all 2,157 farmers in the 120 treatment villages. The risk-taking attitude measure ranges from 1 to 10, where 1 indicates the lowest degree of risk and 10 implies the highest degree of risk.

Figure B.6: Distribution of risk taking attitudes in cultivation activity for *all* farmers



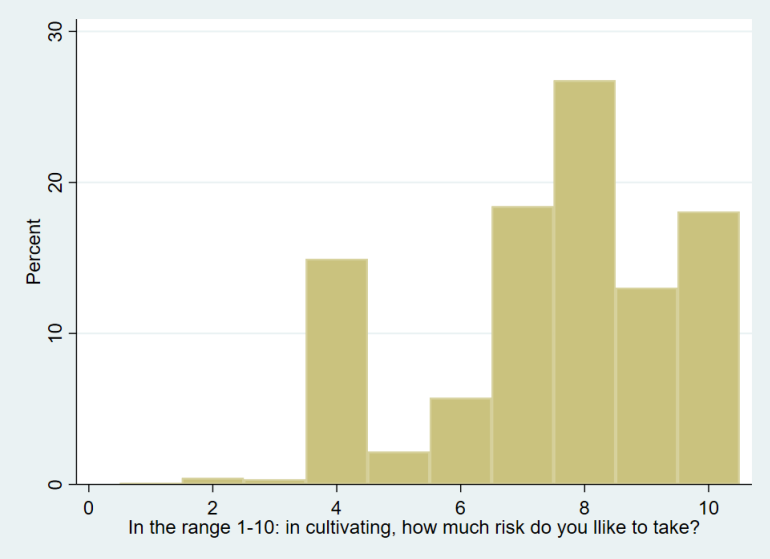
Notes: The sample includes all 2,157 farmers in the 120 treatment villages. The risk-taking attitude measure ranges from 1 to 10, where 1 indicates the lowest degree of risk and 10 implies the highest degree of risk.

Figure B.7: Distribution of risk attitudes in daily activities for *untreated* farmers



Notes: The sample includes all 1,151 untreated farmers in the 120 treated villages. The risk-taking attitude ranges from 1 to 10, where 1 indicates the lowest degree of risk and 10 implies the highest degree of risk.

Figure B.8: Distribution of risk attitudes in cultivating activities for *untreated* farmers



Notes: The sample include all the 1,151 untreated farmers in the 120 treated villages. The risk taking attitude is ranging from 1 to 10, where 1 indicates the lowest degree of risk and 10 implies the highest degree of risk.

B.2 Tables

Table B.1: Balance check of village-level characteristics

Village-level characteristics (Baseline)	T1	T2	Control	p-value
Transport	0.30	0.35	0.40	0.490
	(0.46)	(0.48)	(0.49)	
Road	0.75	0.65	0.65	0.378
	(0.44)	(0.48)	(0.48)	
Electricity	0.88	0,92	0.92	0.750
	(0.32)	(0.28)	(0.27)	
Electricity-population	0.63	0.61	0.64	0.826
	(0.31)	(0.31)	(0.27)	
Population	2419.67	2415.58	2383.39	0.775
	(2290.06)	(1879.98)	(2597.03)	
Total farmer	142.51	133.32	135.96	0.919
	(76.90)	(73.54)	(188.96)	
Crop	0.95	0.97	0.92	0.507
	(0.22)	(0.18)	(0.27)	
Rain	61.53	56.67	60.16	0.478
	(27.98)	(17.45)	(21.19)	
Observations	60	60	62	

Notes: Transport is a dummy that equals to 1 if transport system in a village is good, and 0 if bad. Road is a dummy that equals to 1 if village road is made of mud, 0 for other materials. Electricity equals to 1 if electricity is available in a village, and 0 if not. Electricity-population is the percentage of people in a village that have electricity connection. Population is the total number of people living in a village. Total farmer is the total number of farmers living in a village. Crop is a dummy that equals to 1 if rice is the primary crop in a village, 0 if other crops. Rain is the average rainy days in a village. Chi square tests are conducted for dummy variables to compare the group means across T1, T2 and control groups. One way ANOVA tests are conducted for continuous variables to compare the means across T1, T2 and control groups. Means are reported with standard deviations in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table B.2: Balance check of random selected farmers, referred farmers, and untreated farmers

Treated villages only				
	Batch 1	Batch 2	Untreated	p-values
Household Characteristics (Baseline)	Mean	Mean	Mean	
Age (years)	46.01	46.08	45.04	0.117
	(11.07)	(13.11)	(13.94)	
Household Income (Taka)	12440.79	11764.23	13115.64	0.189
	(13189.37)	(9399.14)	(22977.37)	
Amount of cultivable land (Decimal)	162.09	172.77	172.01	0.296
	(139.06)	(167.89)	(198.86)	
Education (years)	4.11	4.24	4.41	0.270
	(4.09)	(4.10)	(4.31)	
Household size	5.16	5.16	5.20	0.875
	(1.88)	(1.94)	(1.89)	
Occupation	0.88	0.89	0.86	0.471
	(0.32)	(0.31)	(0.35)	
Agricultural characteristics (Baseline)				
Production cost (Taka)	409.19	409.71	410.10	0.995
	(214.78)	(217.50)	(210.76)	
Profit (Taka)	440.57	437.97	436.99	0.949
	(266.86)	(263.07)	(263.36)	
Yield (kg per decimal of land)	23.08	23.08	23.23	0.799
	(6.05)	(5.95)	(6.08)	
Observations	1,006	919	1,151	
No. of villages	120	120	120	

Notes: Taka is the unit of Bangladesh currency. Occupation equals to 1 if the participant's primary occupation is agriculture related, and 0 if his primary occupation is not related to agriculture. The reported p-values are from the two tailed test with the null hypothesis that group means are equal. Standard errors are clustered at village level and reported in parentheses.

Table B.3: Balance checks between treated and untreated farmers

Treated villages only			
Household Characteristics (Baseline)	Treated	Untreated	p-value
	(1)	(2)	(1)=(2)
Age (years)	46.02	45.04	0.123
	(11.70)	(13.94)	
Household Income (Taka)	12440.79	13115.64	0.423
	(13189.37)	(22977.38)	
Amount of cultivable land (Decimal)	162.09	172.07	0.170
	(139.06)	(198.86)	
Education (Years)	4.11	4.40	0.138
	(4.08)	(4.31)	
Household size	5.16	5.20	0.664
	(1.88)	(1.89)	
Occupation	0.88	0.86	0.193
	(0.32)	(0.35)	
Agricultural Characteristics (Baseline)			
Production cost (Taka)	409.19	410.10	0.936
	(214.78)	(210.76)	
Profit (Taka)	440.56	436.98	0.792
	(266.86)	(263.36)	
Yield (kg per decimal of land)	23.08	23.23	0.607
	(6.05)	(6.08)	
Observations	1,006	1,151	
No. of villages	120	120	

Notes: Taka is the unit of Bangladesh currency. Occupation equals to 1 if the participant's primary occupation is agriculture related, and 0 if his primary occupation is not related to agriculture. The reported p-values are from the two tailed test with the null hypothesis that group means are equal. Standard errors are clustered at village level and reported in parentheses.

Table B.4: Balance checks between $T1-$and $T2-$treated farmers

Treated villages only			
	T1	T2	p-value
Household Characteristics (Baseline)	(1)	(2)	(1)=(2)
Age (years)	45.19	45.80	0.429
	(12.86)	(13.04)	
Household Income (Taka)	12416.49	13192.14	0.472
	(11818.4)	(24289.1)	
Amount of cultivable land (Decimal)	165.31	169.56	0.725
	(159.28)	(187.08)	
Education (Years)	4.33	4.20	0.624
	(4.26)	(4.16)	
Household size	5.22	5.14	0.461
	(1.87)	(1.90)	
Occupation	0.86	0.87	0.515
	(0.34)	(0.33)	
Agricultural Characteristics (Baseline)			
Production cost (Taka)	401.09	418.44	0.419
	(202.41)	(222.24)	
Profit (Taka)	444.20	433.02	0.617
	(252.84)	(276.72)	
Yield (kg per decimal of land)	23.16	23.16	0.995
	(5.99)	(6.13)	
Observations	1,088	1,069	

Notes: Taka is the unit of Bangladesh currency.Occupation equals to 1 if the participant's primary occupation is agriculture related, and 0 if his primary occupation is not related to agriculture. The reported p-values are from the two tailed test with the null hypothesis that group means are equal. Standard errors are clustered at village level and reported in parentheses.

Table B.5: Balance check across different groups

	T1		T2		Control	p-values	
	Treated	Untreated	Treated	Untreated		p1	p2
Household	(1)	(2)	(3)	(4)	(5)	(1)=(3)	(2)=(4)=(5)
Age	45.72	44.76	46.27	45.35	45.24	0.455	0.703
	(11.80)	(13.63)	(11.61)	(14.28)	(12.71)		
Income	12749	12153	12159	12192	11465	0.479	0.608
	(15150)	(8296)	(11108)	(32263)	(14264)		
Land	163.77	166.52	160.56	178.28	169.02	0.715	0.415
	(151.75)	(165.11)	(126.51)	(230.87)	(128.84)		
Education	4.26	(4.40)	3.98	4.42	4.07	0.289	0.109
	(4.22)	(4.29)	(3.97)	(4.34)	(4.02)		
Household size	5.22	5.21	5.10	5.18	5.24	0.280	0.801
	(1.96)	(1.80)	(1.80)	(1.99)	(2.01)		
Occupation	0.881	0.847	0.880	0.847	0.861	0.960	0.399
	(0.323)	(0.360)	(0.325)	(0.331)	(0.346)		
Agricultural							
Production cost	406.22	402.34	412.41	418.78	403.57	0.172	0.253
	(209.27)	(202.28)	(222.16)	(219.73)	(185.83)		
Profit (Taka)	450.47	439.25	431.53	434.45	465.99	0.261	0.348
	(259.57)	(247.51)	(273.28)	(280.25)	(317.29)		
Yield	23.19	23.15	22.98	23.33	22.71	0.587	0.372
	(6.16)	(5.87)	(5.95)	(6.31)	(5.90)		
Observations	480	608	526	543	1,623		

Notes: Taka is the unit of Bangladesh currency. Occupation equals to 1 if the participant's primary occupation is agriculture related, and 0 if his primary occupation is not related to agriculture. The reported p-values are from the two tailed test with the null hypothesis that group means are equal. Standard errors are clustered at village level and reported in parentheses. p1 test the difference between treated in T1 and treated in T2, and p2 tests the difference across untreated in T1, untreated in T2 and control farmers. ***p<0.01, **p<0.05, *p<0.1.

Table B.6: Test of p_v^T between $T1$ and $T2$ villages

Treatment Group	Means
T1	0.44
	(0.14)
T2	0.50
	(0.19)
P-value of the t-test	0.16
P-value of the K-S test	0.38

Notes: A t-test examines the difference in the mean p_v^T between $T1$ and $T2$ villages. A K-S test tests the equality of the distributions between $T1$ and $T2$ villages. The rejection criteria of both tests is p<0.05.

Table B.7: Balancing test of exposure rate ($p_{i,v}^{T}$)

	(1)	p-values
Age	-0.151	0.745
	(0.463)	
Education	1.542	0.198
	(1.190)	
Occupation	19.45	0.251
	(16.87)	
Income	0.00003	0.844
	(0.000158)	
Land size	0.0194	0.498
	(0.0286)	
Total farmers	0.123	0.539
	(0.200)	
Training	23.04	0.412
	(27.96)	
Yield	0.885	0.520
	(1.371)	
Cost	-0.0261	0.482
	(0.0370)	
Profit	5.643	0.478
	(7.672)	
Observations	1,151	
No. of villages	120	

Notes: The table reports coefficients from a regression of exposure rate $p_{i,v}^{T}$ on each of the baseline characteristics reported in the rows.Training is a dummy that equals to 1 if this farmer belongs to a T2 village, and it is 0 if he is in a T1 village. Yield is thhe amount of rice yield in baseline per decimal of land. Cost is the cost of producing rice in baseline year. Plots of land is the number of plots of land that a farmer grows rice. Education is the years of education a farmer receives. Occupation is a dummy that equals to 1 if the primary occupation of him is farmer, and 0 if not. Income is the monthly household income in taka. Land size is the amount of cultivable land that a farmer grow rice measured in decimals. Total farmer is the total number of farmer reside in this village (not only participants in our experiment, it corresponds to total population of farmers living in a village). All results are clustered in village level. Standard errors are clustered in village level and reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table B.8: The impact of trained farmers on the adoption rate of untreated farmers at the end of year 1

	120 villages		60 villages (T1)		60 villages (T2)	
	(1)	(2)	(3)	(4)	(5)	(6)
$p_{i,v}^{T}$	0.157	0.166	0.143	0.167	0.169	0.201
	(0.0787)	(0.0787)	(0.107)	(0.111)	(0.137)	(0.135)
Age/10		-0.0124*		-0.00897		-0.0173*
		(0.00662)		(0.00862)		(0.00997)
log(Income)		-0.0170		-0.0265		0.00478
		(0.0185)		(0.0258)		(0.0236)
log(Land)		-0.00547		0.00516		-0.0213
		(0.0183)		(0.0281)		(0.0247)
Education		0.000766		-0.00121		0.00190
		(0.00218)		(0.00281)		(0.00339)
Household size		0.0110**		0.0139		0.00608
		(0.00539)		(0.00854)		(0.00690)
Occupation		0.00877		-0.0265		0.0440
		(0.0274)		(0.0510)		(0.0301)
Total farmers/1000		0.201		0.102		0.314
		(0.129)		(0.159)		(0.202)
Observations	1,151	1,151	608	608	543	543
No. of villages	120	120	60	60	60	60

Notes: The dependent variable is the adoption decision of an untreated farmer in the end of year 1. It is a dummy variable that equals 1 if an untreated farmer adopted in year 1 and 0 if he did not. Standard errors are clustered at the village level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B.9: The impact of trained farmers on the adoption rate of untreated farmers at the end of year 2

	120 villages		60 villages (T1)		60 villages (T2)	
	(1)	(2)	(3)	(4)	(5)	(6)
$p_{i,v}^T$	0.331***	0.306***	0.149	0.138	0.521***	0.503***
	(0.104)	(0.102)	(0.126)	(0.110)	(0.149)	(0.150)
Age/10		-0.00150		-0.0119		0.00767
		(0.00858)		(0.0103)		(0.0132)
log(Income)		-0.0224		-0.00652		-0.0348
		(0.0172)		(0.0232)		(0.0228)
log(Land)		0.0447**		0.0123		0.0763***
		(0.0191)		(0.0222)		(0.0273)
Education		0.000814		0.000727		0.000830
		(0.00249)		(0.00315)		(0.00370)
Household size		-0.0130**		-0.00920		-0.0162**
		(0.00524)		(0.00795)		(0.00629)
Occupation		-0.00243		-0.0289		0.0526
		(0.0290)		(0.0447)		(0.0335)
Total farmers/1000		0.170		0.522**		-0.256
		(0.184)		(0.228)		(0.225)
Observations	1,151	1,150	608	607	543	543

Notes: The dependent variable is the adoption decision of an untreated farmer in the end of year 2. It is a dummy variable that equals 1 if an untreated farmer adopted in year 2 and 0 if he did not. Standard errors are clustered at the village level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B.10: Percentage of farmers who discuss by type of frequency

Category	% of farmers
Daily	8.15
Weekly	27.16
Monthly	27.98
Yearly	32.52
Never	4.19
Sum	100
Observations	1,151

Table B.11: Number of finance-related peers for untreated farmers

Category	Value
Mean	3
Median	2
Mode	0
Standard deviation	3.83
Observations	1,151

Table B.12: Yield difference between T1 and T2 villages by year

	End of year 1			End of year 2		
	$T1$	$T2$	p-value	$T1$	$T2$	p-value
All farmers	25.65	25.70	0.164	25.28	25.30	0.773
	(0.42)	(0.44)		(0.41)	(0.39)	
Farmers who receive training	26.07	26.09	0.732	25.30	25.31	0.793
	(0.29)	(0.30)		(0.13)	(0.12)	
Farmers who adopt	25.93	25.97	0.293	25.31	25.28	0.262
	(0.39)	(0.40)		(0.29)	(0.26)	
Farmers who are trained and adopt	26.07	26.10	0.721	25.30	25.31	0.763
	(0.29)	(0.31)		(0.14)	(0.12)	

Notes: Yield is defined as the amount of rice cultivated in one decimal of land, measured in kg. It is calculated as the total amount of rice cultivated (kg) divided by total amount of cultivable land (decimal). Yield is reported by year. Means are reported with standard deviations in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Table B.13: The share of farmers with different risk attitudes

Percentage	High level of risk tolerance
Treated farmers	25%
Untreated farmers	22%
Total farmers	23%

Notes: We define a farmer to have higher risk tolerance if he answers a 9 or 10 in his risk-taking attitude to both daily life and cultivating activities than farmers who answer 1-8 in his risk taking attitude of daily life and cultivating activities.

Table B.14: The construction of each index that correlates with risk aversion

Well-being (Range 1 to 10)
How much happy do you think you are in your life?
How much happy you are about your livelihood?
How much happy you are about your life's achievement
How much satisfied you are about your future security?
Ability (Range 1 to 5)
Everyone says that I am good at farming
I don't have any problem using new cultivation technique
I can successfully solve any cultivation related problem
I can produce more crop than other farmer
No one can defeat me in producing crop
Whether rain or drought, I can produce crop
I deeply think about how can I produce more crops
Personality (Range 1 to 7)
Strong imagination power
Does everything with skill and successful
Respondent is hard working
Can start communicating with people easily and likes to talk
Likes to travel and very social
Respondent often has new ideas
Confidence (Range 1 to 10)
Respondent's confidence in himself
Respondent confidence in cultivation

Notes: This is the list of questions that we collected in order to construct the four indexes that describe a farmer's characteristics. It includes wellbeing, personality, ability and confidence. Each index is calculated as the average score of the questions. Then, we standardize each index by substracting it from the mean of the distribution and dividing it by the standard deviation of the distribution.

Table B.15: The impact of risk attitude on farmer's characteristics

	120 villages			
	(1)	(2)	(3)	(4)
	Well-being	Personality	Ability	Confidence
$\delta_{i,v}$	-0.0887***	-0.193***	-0.201***	-0.589***
	(0.0218)	(0.0113)	(0.0105)	(0.0143)
Observations	2,157	2,157	2,157	2,157

Notes: Each dependent variable captures an aspect of the farmer's characteristics, which include well-being, personality, ability and confidence. The questions measuring these variables can be found in Table B.14. A farmer has a high level of risk tolerance ($\delta_{i,v} = 0$) if he answered a 9 or 10 to both risk questions in terms of daily life and rice activities. A farmer has low level of risk tolerance ($\delta_{i,v} = 1$) otherwise. ***p<0.01, **p<0.05, *p<0.1.

Table B.16: The effect of risk on adoption for extreme risk-loving farmers

	120 villages			60 T1 villages			60 T2 villages		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$p^T_{i,v}$	0.241***	0.238***	0.340**	0.105	0.100	0.0382	0.390***	0.389***	0.600***
	(0.0756)	(0.0748)	(0.139)	(0.0929)	(0.0935)	(0.177)	(0.103)	(0.100)	(0.155)
$\delta^{NT}_{i,v}$		-0.0366**	0.0524		-0.0234	-0.0734		-0.0598**	0.140
		(0.0169)	(0.0717)		(0.0227)	(0.0925)		(0.0247)	(0.0867)
$p^T_{i,v} \times \delta^{NT}_{i,v}$			-0.161			0.0928			-0.353**
			(0.128)			(0.170)			(0.152)
Observations	2,300	2,300	2,300	1,214	1,214	1,214	1,086	1,086	1,086

Notes: The dependent variable is the adoption decision of an untreated farmer. This is a dummy variable that takes the value of 1 if an untreated farmer adopted the technology at time t ($t = 1, 2$) and 0 if he did not. A farmer has a relatively higher level of risk tolerance ($\delta^{NT}_{i,v} = 0$) if he answered a 10 to both risk questions in terms of daily life and rice activities. A farmer's risk tolerance is lower ($\delta^{NT}_{i,v} = 1$) otherwise. Each regression includes year dummies and all six control variables in Table 4. Standard errors are clustered at the village level and reported in parentheses. ***p<0.01, **p<0.05, *p<0.1.

Appendix C Another way of defining adoption

So far, we have measured adoption by having a dummy variable, $y^{NT}_{i,v,t}$, which takes a value of 1 if an untreated (NT) farmer i, residing in village $v = T1, T2$, has adopted at least three SRI principles in one of his plots of land in year $t = 1, 2$, and 0 otherwise. As a robustness check, we use another measure of adoption, which has been defined in Section 3.2 by A^{PR}. It is an "effort" variable which is equal to the proportion of principles that a farmer has adopted in the plot of land that has adopted the highest number of principles. Since there are six principles, $A^{PR} = \{0, \frac{1}{6}, \frac{2}{6}, \cdots, 1\}$. To use the same notation as in econometric model, we denote this variable by $y^{PR,NT}_{i,v,t}$. This measure, which provides more detailed information about adoption will help us understand some aspects of the results and the mechanisms.

C.1 Differences between adopters in both years and adopters in year 1 only

Table C.1: Extent of applying SRI principles for 60 T1 villages

	60 T1 villages					
	First-ranked plot		Second-ranked plot		Third-ranked plot	
	2014	2015	2014	2015	2014	2015
$A_{1,0}$	0.36	0.20	0.19	0.15	0.17	0.14
	(0.21)	(0.15)	(0.17)	(0.14)	(0.14)	(0.13)
$A_{1,1}$	0.48	0.57	0.24	0.32	0.22	0.32
	(0.21)	(0.18)	(0.21)	(0.26)	(0.17)	(0.21)
Observations	221		201		158	

Notes: The extent of applying SRI principles is defined as the number of principles they applied on this plot of land divided by total number of applicable principles, which is six. $A_{1,0}$ farmers refer to the adopters who adopted in year 1 only but terminated in year 2. $A_{1,1}$ farmers refer to adopters who adopted in both years. The total number of $A_{1,0}$ and $A_{1,1}$ adopters is 221, each of them has at least one plot of land land. 201 of them has at least two plots of land, and 158 of them has three plots of land. For each farmer, we rank their plots of land according to the extent of applying SRI principles; first-ranked plot refers to the plot of land that they applied most principles, and third-ranked plot is the plot of land for which they adopted the least number of principles. Standard errors are reported in parentheses.

Table C.2: Extent of applying SRI principles for 60 T2 villages

	60 T2 villages					
	First-ranked plot		Second-ranked plot		Third-ranked plot	
	2014	2015	2014	2015	2014	2015
$A_{1,0}$	0.32	0.25	0.15	0.20	0.13	0.18
	(0.22)	(0.16)	(0.19)	(0.15)	(0.14)	(0.14)
$A_{1,1}$	0.45	0.56	0.22	0.30	0.20	0.27
	(0.21)	(0.18)	(0.21)	(0.23)	(0.18)	(0.16)
Observations	240		218		171	

Notes: The extent of applying SRI principles is defined as the number of principles they applied on this plot of land divided by total number of applicable principles, which is six. $A_{1,0}$ farmers refer to the adopters who adopted in year 1 only but terminated in year 2. $A_{1,1}$ farmers refer to adopters who adopted in both years. The total number of $A_{1,0}$ and $A_{1,1}$ adopter is 240, each of them has at least one plot of land land. 218 of them has at least two plots of land, and 171 of them has three plots of land. For each farmer, we rank their plots of land according to the extent of applying SRI principles; first-ranked plot refers to the plot of land that they applied most principles, and third-ranked plot is the plot of land for which they adopted the least number of principles. Standard errors are reported in parentheses.

Table C.3: Baseline characteristics of adopters

120 treatment villages			
	$A_{1,1}$	$A_{1,0}$	p-value
Age	45.79	46.34	0.641
	(11.37)	(11.00)	
Household Income	10717.94	13582.28	0.028
	(6541.91)	(14753.34)	
Education (years)	4.43	4.30	0.746
	(3.96)	(4.15)	
Amount of cultivable land(decimals)	168.29	186.56	0.224
	(115.65)	(177.55)	
Household size	5.37	5.12	0.208
	(1.86)	(1.83)	
Occupation	0.93	0.90	0.298
	(0.26)	(0.30)	
Risk aversion (Cultivation activity)	3.53	4.01	0.02
	(1.15)	(1.76)	
Production cost	574.50	601.85	0.441
	(305.75)	(310.17)	
Profit	396.24	442.85	0.097
	(289.49)	(279.07)	
Yield	22.71	24.48	0.005
	(6.42)	(5.87)	

Notes: All farmer's characteristics are baseline data. Education is the maximum years of education in a household. Occupation is a dummy that equals to 1 if the primary occupation of this participant is farmer or agricultural related, and 0 otherwise. Risk aversion is a number ranging from 1 to 10 to capture farmer's risk attitudes, a higher number implies that he is more risk averse. The reported p-values are from the two-tailed test with the null hypothesis that the group means are equal. Means are reported with standard deviations in parentheses. ***p<0.01, **p<0.05, *p<0.1.

C.2 Reproducing the main regressions with a different definition of adoption

Table C.4: The impact of trained farmers on the adoption rate (based on principles) of untreated farmers

	120 villages	60 $T1$ villages	60 $T2$ villages
	(1)	(2)	(3)
$p^T_{i,v}$	0.101**	0.0267	0.187***
	(0.0433)	(0.0499)	(0.0637)
Constant	0.123	0.180*	0.0412
	(0.0744)	(0.0919)	(0.0915)
Observations	2,300	1,214	1,086

Note: The dependent variable is the percentage of principles that an untreated farmer adopted on the first ranking plot at time t (t=1,2). First ranking plot is defined as the plot where a farmer used most principles. Percentage of principles equals to the number of principles a farmer used on this first ranking plot divided by total number of principles, which is 6. All regressions control for year fixed effect, baseline characteristics including age, years of education, occupation, land size, household size and household income. Standard errors are clustered at village level, standard errors are reported in parentheses. *** p<0.01, **p<0.05, *p<0.1.