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ABSTRACT

The Value of Information in Technology Adoption*

We develop a theoretical model in which technology adoption decisions are based on the information received from others about the quality of a new technology and on their risk attitudes. We test the predictions of this model using a randomized field experiment in Bangladesh. We show that the share of treated farmers who receive better training in System of Rice Intensification (SRI) technology have a high positive impact on the adoption rate of untreated farmers. We also find that untreated farmers who are more risk-averse tend to adopt the technology less and are less influenced by their treated peers. Finally, a trained farmer's impact on his untrained peers increases if he himself adopts SRI technology. Our results indicate that the crucial determinants of technology adoption for untreated farmers are the accuracy and reliability of information transmission about the quality of the technology circulated among farmers as well as their degree of risk aversion.

JEL Classification: O13, Z13

Keywords: Bayesian model, technology adoption, peers, risk attitude, RCT, Bangladesh

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1 Introduction

In many developing countries, especially in South Asia and Sub-Saharan Africa, agricultural productivity has remained low due to the sluggish adoption and diffusion of new efficient cultivation methods, which are critical for food security and economic growth. Although most frictions impeding the adoption of new agricultural technologies are rooted in imperfect information (i.e., they stem from farmers' uncertainty), the costs of learning, and the limited knowledge of these new technologies (Moser and Barrett, 2006; Barrett et al., 2010; Conley and Udry, 2010; Jack, 2013; Barrett et al., 2019), we still know little about the role of information transmission and risk attitudes in technology adoption decisions. Moreover, existing policy evaluations of technology adoption programs mostly focus on the direct impact of "the treatment" on those who are treated, ignoring the indirect spillover effects on the technology adoption behavior of the untreated.

In this study, we address these issues by examining from a theoretical and empirical perspective the importance of farmers' risk attitudes and role of the quality and accuracy of information on a new technology transmitted by treated farmers on the adoption rate of untreated farmers in rural Bangladesh.

We first develop a theoretical model in which each farmer makes an adoption decision based on a noisy signal received from his peers about the uncertain quality of a new technology. The key assumption of the model is that individuals possessing better knowledge about the new technology (because of better training) send less noisy signals about its quality.

When farmers are assumed to be risk-neutral, we show that the adoption rate of untreated (uninformed) farmers increases with the proportion of treated (informed) farmers residing in the same village. Indeed, the higher is the proportion of treated farmers in a village in which an untreated farmer lives, the higher is the probability of meeting a treated (informed) farmer. This, in turn, implies a higher quality of information about the new technology transmitted to untreated farmers. We also show that when treated farmers receive longer training and thus send more precise signals about the quality of the technology, the impact of treated farmers on the adoption rate of untreated farmers is higher. We use the variance in the noisy component of a signal as an inverse measure of its accuracy.

We then test these predictions of the theoretical model by randomly varying the number of trainees (treated farmers) in each village, thereby generating exogenous variation in the degree to which farmers who were not themselves trained (untreated farmers) on the System of Rice Intensification (SRI) were indirectly exposed to this technology. Moreover, in a random subset of the villages, farmers were trained for two years in a row, improving knowledge and sustaining adoption among these farmers and exploring the implications for social diffusion.

We find 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 2.2%. We then split the 120 villages into two groups: $T2-$treated villages in which treated farmers received two years of training and $T1-$treated villages in which treated farmers received one year of training and estimate the model separately. We show that only treated farmers with two years of training have a significant impact on the adoption rate of untreated farmers. According to our theoretical model, this is because $T2-$treated farmers 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 also show that our results are stronger if we include a subset of treated farmers such as those who discuss agricultural and financial issues with untreated farmers.

One may wonder 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, 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.

We then extend our theoretical 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 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 farmers are more reluctant to adopt the SRI and are less influenced by their peers.

Finally, to better understand the mechanisms behind our results, we estimate a peer effects model in which we examine the impact of treated farmers who *adopt* SRI technology on the adoption rate of untreated farmers residing in the same village. Because the percentage of treated farmers who adopt SRI technology is an endogenous variable, we instrument it by the percentage of treated farmers, which is clearly exogenous. We show that the results are similar albeit larger. Now, an increase of 10% in treated farmers who adopt SRI technology increases the adoption rate of untreated farmers by 3.61% instead of 2.2%. Therefore, we believe that the key aspect of the SRI adoption is the transmission of information about the quality of the SRI but also peer pressure. This is because the SRI is a methodology for growing rice, which 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 traditional cultivation methods (Barrett et al., 2019). In addition, SRI fields visibly differ from traditional rice fields; hence, social norms and conformity pressures affect the adoption decision.

A large body of the empirical literature has demonstrated the importance of peer and network effects[1] on technology adoption (see Foster and Rosenzweig, 1995; Bandiera and Rasul, 2006; Conley and Udry, 2001, 2010; Banerjee et al. 2013; Fafchamps et al. 2018).[2] Prior studies have utilized data from farmers in Northern Mozambique (Bandiera and Rasul, 2006), pineapple plantation farmers in Ghana (Conley and Udry, 2010), and olive plantation farmers in Greece (Genius et al., 2013). Peer influence and imitation effects within a social network have also been applied to the effectiveness and transmission of information in relation to health initiatives in studies of menstrual cup usage in Nepal (Oster and Thornton, 2012), malaria prevention in Sub-Saharan Africa (Apouey and Picone, 2014), and fighting cases of intestinal worms in Kenya (Miguel and Kremer, 2004).

One important channel for technology adoption is learning and peer effects. In Ghana, Conley and Udry (2010) investigate how farmers' input decisions change when they observe the actions and outcomes of other farmers in their information network.[3] The results show that farmers are more likely to increase input use when their neighbors achieve higher than expected profits using more input than before. Cai et al. (2015) use a randomized experiment in rural China to study the influence of social networks on weather insurance adoption. Varying the information available about peers' decisions and randomizing the default options, they show that the network effect is driven by the diffusion of insurance knowledge rather than purchase decisions. Bonan et al. (2017) evaluate the role of social interactions in technology adoption and find a positive and direct peer influence, demonstrating that consumers are more willing to buy an improved cook stove if their close

[1]Network economics is a growing field. For overviews, see Jackson (2008) and Jackson et al. (2017).

[2]See Munshi (2008), Maertens and Barrett (2013), Chuang and Schechter (2015), and Breza (2016) for overviews of this literature.

[3]An information neighbor is a farmer who gives advice to another.

peers purchased the same product. Similarly, Oster and Thornton (2012) study the role of peer effects in adopting a type of sanitary technology in Nepal. They find strong peer effects; a girl whose friend uses a menstrual cup increases her use of this device by 18.6%.

Beaman et al. (2018) also study social learning in diffusion by targeting seed farmers in Malawi and show their effectiveness in promoting technology diffusion.[4] Banerjee et al. (2018) further examine social learning by comparing the diffusion outcomes between broadcasting and seedling. They find that if information dissemination occurs in the scope of common knowledge (i.e., publicizing information), seedling improves learning more than broadcasting does. Finally, social reinforcement, or peer effects, may motivate individuals to reproduce the behavior of others. Banerjee et al. (2013) analyze the role of peer effects by exploring the diffusion process of microfinance programs. They find that diffusion is independent of the number of adopters surrounded by an agent. In other words, learning effects dominate peer effects.[5]

How do peer effects operate? What is it that farmers have learned from their informed friends that influenced their take-up decisions? Generally speaking, peers may influence the adoption of a new technology or a financial product for three reasons: (*i*) people gain knowledge from their friends about the value of the product (Conley and Udry, 2010; Kremer and Miguel, 2007), (*ii*) people learn from their friends how to use the product (Munshi and Myaux 2006; Oster and Thornton, 2012), or (*iii*) people are influenced by other individuals' decisions (Bandiera and Rasul, 2006; Banerjee, 1992; Bursztyn et al., 2014; Golub and Jackson, 2012; Campbell et al., 2017). In the last case, this could be social learning/imitation or the social utility effect.

The contributions of our study to this large literature are as follows. First, we are the first to provide a new theoretical model highlighting the importance of the quality and accuracy of information on the adoption rate of a new technology. Second, we not only examine the effect of peers on technology adoption but also how risk attitude affects this adoption, and the cross-effect of peers and risk attitude.[6] Third, to test this theory, we conduct different randomized controlled trials (RCTs) using distinct treatments (in terms of the duration of training) that provide farmers with different knowledge and accuracy

[4]See also Dar et al. (2019), who show that inducing conversation between farmers can be just as effective as seeding central farmers.

[5]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, while Carter et al. (2018) shed light on how the availability and use of formal savings services may affect the dynamic impacts of subsidies for agricultural technology adoption.

[6]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., 2013) and none has examined the cross-effect of both risk and peers on technology adoption.

of information about the new technology.[7] Fourth, instead of directly testing the effect of the treatment (technology training) on the adoption rate of treated farmers compared with the control group (untreated farmers), we investigate how untreated farmers are positively affected by the proportion of treated farmers in the village in which they live. Indeed, spillover effects can be identified by varying the treatment intensity across space and time. Our results show large spillover effects from treated to untreated farmers. This implies that the total effect of an intervention is usually underestimated because it takes into account the impact of treated individuals on untreated ones (see also Miguel and Kremer, 2004; List et al., 2019).

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. Section 4 describes the data and econometric model, which tests the prediction of the theoretical model. Section 5 presents the main empirical results and robustness checks. Section 6 explains the role of risk aversion in technology adoption, both from theoretical and from empirical viewpoints. Section 7 empirically studies peer effects in technology adoption. Section 8 concludes. Appendix A provides all the mathematical proofs. Appendix B supplies additional figures and tables. Appendix C provides an additional way of measuring farmers' risk attitudes.

2 Theory

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.[8] We refer to p as the *exposure rate*. An

[7] Cai et al. (2015) also vary the information available about peers' decisions but study very short-term effects (three days), do not use a theoretical model, and do not investigate how risk aversion affects technology adoption.

[8] Since we assumed a continuum of farmers in each village, from the law of large numbers, p

untreated farmer, which we also refer to as 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,

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

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

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

$(1 - p)$ can be interpreted as the probability that an untreated farmer randomly meets a treated (untreated) 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.[9] 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:

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

Risk neutrality implies that only the expected difference between the benefit and cost of adoption matters. Throughout this section, we assume that

$$c > \beta; \tag{9}$$

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. Clearly, if $c < \beta$, the technology will be easy to adopt, without the need for information transmission. In our data, the SRI technology is sufficiently difficult to implement that most individuals would not adopt it on their own. For example, Table 1 below shows that even when influenced by treated farmers, only 7–10% of untreated farmers adopt SRI technology.

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

$$\mathbb{P}\{A = 1 \,|\, \theta\} = \mathbb{P}\{\mathbb{E}\left(b \,|\, s_\theta\right) > c\}, \tag{10}$$

where $\mathbb{E}\left(b \,|\, s_\theta\right)$ 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 (e.g., DeGroot, 2004, Theorem 1, p. 167):

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

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

Combining (1) and (3) with (11), we can readily verify that

$$\mathbb{E}\left(b \,|\, s_\theta\right) \sim \mathcal{N}\left(\beta, \frac{\sigma_b^4}{\sigma_\theta^2 + \sigma_b^2}\right). \tag{12}$$

Using (12), (10) can be written as follows:

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

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) *and* (9) *hold 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 if $c > \beta$, 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.[10]

[10] Observe that we can easily extend the results of Proposition 1 when untreated farmers have

3 Background and experimental design

We now empirically test parts (*i*) and (*ii*) of Proposition 1. This section describes the specific features of Bangladesh that make it particularly suitable for our empirical exercise and experimental design.

3.1 Background

In Bangladesh, improving agricultural productivity has been critical to facilitating poverty alleviation and food security. Rice is Bangladesh's largest crop and the main staple food for the 180 million people in the country. Furthermore, rice cultivation accounts for 48% of all rural employment (Sayeed and Yunus, 2018). It also provides two–thirds of the caloric needs of the nation, along with half the protein consumed. Its contribution to agricultural GDP is about 70%, while its share of national income is one–sixth. In other words, rice plays a critical role in Bangladesh (Faruqee, 2012).

Moreover, demand for rice has been constantly rising in recent years due to the rising population. Despite sustained rice production, flood, drought, and high population density are creating challenges for the rice production sector in Bangladesh. In 2010, of the 180 million inhabitants in Bangladesh, 33 million were classified as lacking food security. By 2020, this number is estimated to have increased to 37 million. Crop yields in Bangladesh remain low because of the limited adoption of new innovations by farmers.

3.2 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, Oxfam America, WWF-ICRISAT Project, 2010).

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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.

To be more precise, the SRI is a *management strategy for crop improvement* (Stoop et al., 2002). As Uphoff (2016) 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.

In our experiment, we adopt the approach taken by BRAC in Bangladesh through experimentation over the past few years. The SRI is more appropriate for use during Boro season in Bangladesh, as irrigation management is easier during this period.[11] However, as Boro season coincides with winter season when plants grow slowly, BRAC recommends comparatively older (about 20 days) seedlings in Bangladesh than that recommended in Africa (10–15 days). For the purpose of this study, we follow the basic principles adopted by BRAC on SRI practices in Boro season: planting younger seedlings (20-day-old seedlings), planting single seedling, per hill, planting in wider spacing (25×20 cm), providing organic matter as much as possible, following the alternate wetting and drying method of irrigation, and practicing mechanical weeding at regular intervals.

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 (Moser and Barrett, 2006; Fafchamps et al., 2018). There are various reasons for this sluggish adoption of the SRI. First, the SRI is a system rather than a technology, as it contains a set of principles and guidelines. In other words, it 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., 2019). Second, SRI fields 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.[12] The SRI has been widely practiced in many

[11]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).

[12]These results are not surprising. In a study in Indonesia, Takahashi and Barrett (2014) estimate that the SRI generates average yield gains of 64% relative to conventional cultivation methods. Sinha and Talati (2007) find that average yields increase by 32% among farmers who partially adopt the SRI in West Bengal, India. Stygler et al. (2011) show a 66% increase in SRI yields relative to experimentally controlled plots when using farming methods similar to local rice farmers

developing countries, and studies based on observational data show significant yield gains and increased profits associated with its adoption (e.g., Stoop et al., 2002; Barrett et al., 2004; Sinha and Talati, 2007; Stygler et al., 2011; Takahashi and Barrett, 2014).

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, and Shirajgonj. The blue areas in Figure B1 in Online Appendix B depict the location of these districts in Bangladesh. The 182 villages were randomized into 62 villages randomly assigned to a control treatment without training and 120 villages randomly assigned to each of the two treatments ($T1$ and $T2$).

Among the 120 villages randomly selected for SRI training, we randomly selected about 30 farmers (28–35 farmers) from each village. A census was conducted by BRAC local offices in 2014 before Boro season to generate a list of all farmers in these villages who cultivated rice in the previous Boro season and owned at least half an acre but not more than 10 acres of land.[13] 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.

The 120 villages were randomly divided into one year and two years of training. Sixty 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. 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

in Mali. Barrett et al. (2004) find that SRI yields are 84% higher than traditional practices by the same farmers on other plots in Madagascar.

[13]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.

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.

As the objective of this study is to analyze how treated farmers influence untreated farmers, in each village, the 30 farmers were randomly divided into two groups: treated (one year $T1$ or two-year $T2$) and untreated (NT). To guarantee that the variation in the number of treated farmers across villages was purely random, the number of treated farmers randomly selected in each village was different, varying between 10 and 30. Although untreated farmers did not receive any training, they live in the same villages as their treated peers.[14] On average, there were 18 treated farmers and 12 untreated farmers in each village. Table B1 in Online Appendix B displays the number of farmers randomized into the treated and untreated groups. Among the 3,630 farmers in these 120 villages, 2,226 were treated (1,060 for one year of training and 1,166 for two years of training) and 1,404 were untreated.

4 Data and econometric model

4.1 Data and balance checks

Initially, a baseline survey was conducted among the 3,630 farmers in the 120 villages, focusing on collecting individual characteristics such as age, income, education, amount of cultivable land, household size, and occupation. Table B2 in Online Appendix B presents the different characteristics of treated and untreated farmers. We see that the level of education is low (on average, farmers attend school up to year 4), household size is relatively high (five members on average), and farmers tend to work on their own farms.

To check if the randomization between treated and untreated farmers is successful, we examine whether their characteristics are the same for treated and untreated farmers within villages and for $T1$ and $T2$ farmers between villages. As is standard, we conduct a $t-$test to compare the group means of these characteristics.

Table B2 reports the balance checks of the observable characteristics between treated and untreated farmers, while Table B3 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.

[14]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.

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 $y_{i,v,t}^{NT}$. 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. 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, $y_{i,v,t}^{NT}$ 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.

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 field visits. 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. A farmer was considered to be an SRI adopter if both the enumerator and the BRAC field officer observed that the farmer practiced any of the three key SRI practices (early planting, using single seedling plants, and wide spacing) on at least one plot of land. We used the mid-season verified observations of SRI practices rather than *farmer self-reports*. As a robustness check, we also used several other definitions of adoption, but found no qualitative differences between these measures.

Table 1 reports the average adoption rate by treatment group and time. First, on average, significantly more treated farmers adopt SRI technology (between 32% and 48%) than untreated farmers (between 7% and 10%). 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 (45.8% versus 32.6%), even if this difference is not significant after one year, as in that case, both farmers received the same training. Finally, 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, $y_{i,T2,2}^{NT} = 9.53\% > 6.89\% = y_{i,T1,2}^{NT}$). This suggests that exposure to farmers receiving more training makes an untreated farmer more likely to adopt SRI technology.

Table 1: Adoption rates of farmers by treatment group and time

	End of year 1	End of year 2	Observations
Treated farmers in $T1$ villages	47.98%	32.6%	1,060
Treated farmers in $T2$ villages	47.25%	45.8%	1,166
Untreated farmers in $T1$ villages	7.03%	6.89%	745
Untreated farmers in $T2$ villages	7.59%	9.53%	659

Table 1 also indicates that the adoption rates are relatively high, especially for treated farmers. Let us now show that SRI technology is, indeed, beneficial for farmers in terms of yields. Table 2 shows that there is a significant positive difference in terms of yields between the 120 villages that were treated ($T1$ or $T2$) and the 62 villages that were not (control villages).

Table 2: Yield difference between treated (T1 and T2) and control villages

	Treated		Control		T-statistic	P-value
	Mean	S.D	Mean	S.D		
Yield (kg per decimal of land)	25.38	(6.01)	22.13	(4.95)	26.33	0.000
Observations	3,630		1,856			

Notes: 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).

Within the 120 treated villages, Table 3 reports that the farmers who adopt the SRI do produce higher yields than the farmers who do not. As a result, SRI technology does provide more rice production and yield to adopters. This is direct evidence that SRI technology is beneficial for farmers, which has also been shown by Islam et al. (2012) for Bangladesh and by others for different countries (see footnote 12).

Table 3: Yield difference between adopters and non-adopters in treated villages

	Adopters		Non-Adopters		T-stat	P-value
	Mean	S.D	Mean	S.D		
Yield (kg per decimal of land)	25.84	(6.16)	25.16	(5.96)	4.23	0.000
Observations	1,615		2,015			

Notes: 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). A farmer is defined as an adopter if he adopted in year 1, year 2, or both.

4.3 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

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

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 B2 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 B4, we perform a $t-$test and the Kolmogorov–Smirnov (K-S) test.[15] 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.

4.4 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[16]

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

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,[17] including

[15] 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.

[16] 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.

[17] As stated in footnote 10, 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).

age, income, land size, household size, occupation, and education, $\epsilon_{i,v,t}$ 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.

5 Empirical results

5.1 Main Results

Table 4 displays the results of the estimation of equation (15). Columns (1), (2), and (3) 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 change when we add controls, and is equal to 0.22. 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 2.2%. 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.

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 (4), (5), and (6)) and is positive and significant at the 1% level for $T2-$treated villages (columns (7), (8), and (9)). 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 4.21%.[18]

To visualize these results, we report the 95% confidence intervals of each regression for the whole distribution of $p^T_{i,v}$. Figure 1 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

[18] In Table 4, we do not control for the total number of farmers (treated plus untreated plus other farmers) in each village. Indeed, the number of farmers does vary from village to village. Figure B3 in Online Appendix B displays the distribution of farmers, showing that it differs between $T1$ and $T2$ villages. As a result, we estimate equation (15) but control for the total number of farmers in each village. Table B5 in Online Appendix B displays the results, which are basically the same as those in Table 4.

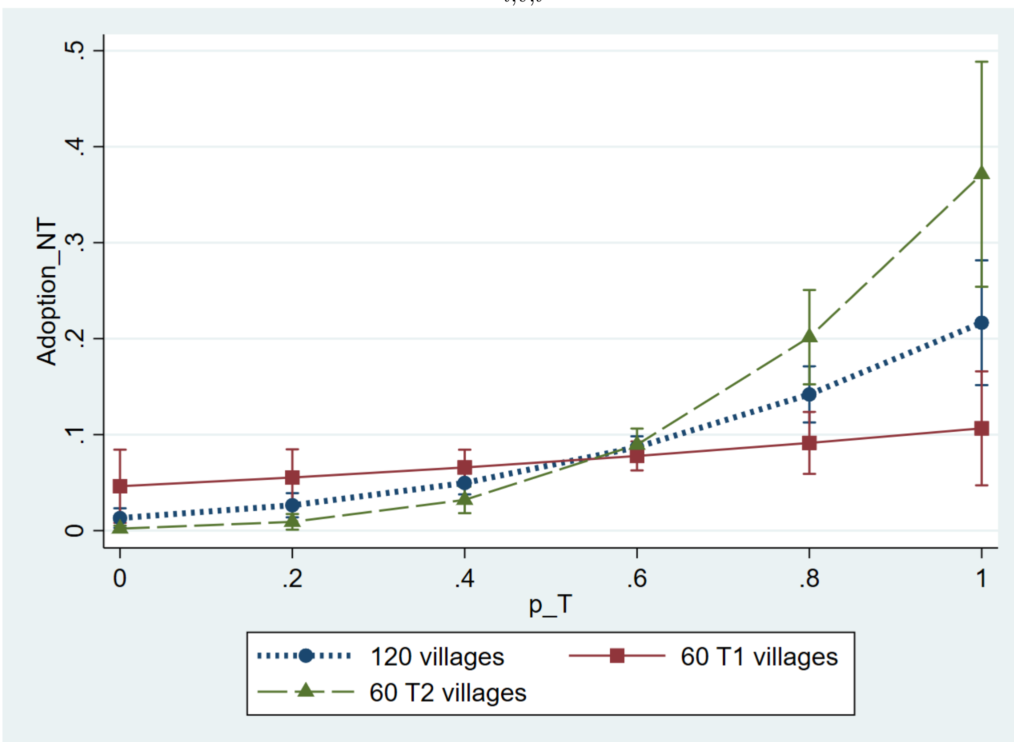
Table 4: The impact of trained farmers on the adoption rate of untreated farmers

	120 villages			60 villages (T1)			60 villages (T2)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$p^T_{i,v}$	0.222***	0.222***	0.229***	0.0641	0.0644	0.0713	0.404***	0.404***	0.421***
	(0.073)	(0.073)	(0.0736)	(0.0910)	(0.0911)	(0.0888)	(0.0982)	(0.0985)	(0.0975)
Year dummy		0.0025	0.0011		-0.0042	-0.0055		0.0111	0.0088
		(0.0115)	(0.0115)		(0.0135)	(0.0136)		(0.0195)	(0.0192)
Age/10			-0.0094*			-0.0196***			0.0002
			(0.0048)			(0.0061)			(0.0071)
log(Income)			-0.0299**			-0.0418**			-0.0202
			(0.0122)			(0.0173)			(0.0173)
log(Land)			0.0206**			0.0125			0.0365**
			(0.0091)			(0.0105)			(0.0153)
Education			0.001			0.0008			0.001
			(0.0016)			(0.0023)			(0.0021)
Household size			0.0057			0.0088			0.0036
			(0.0037)			(0.0055)			(0.005)
Occupation			0.0164			0.0038			0.0367*
			(0.0166)			(0.0238)			(0.0208)
Observations	2,808	2,808	2,808	1,490	1,490	1,490	1,318	1,318	1,318

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.

treated farmers is 40%, the (predicted) adoption rate of untreated farmers is 5%, and when $p_{i,v}^T$ is equal to 80%, the (predicted) adoption rate is close to 22%. For $T1$ villages, these numbers are, respectively 6% and 10%, while for $T2$ villages, we obtain 3% and 36%. In other words, the effect of increasing $p_{i,v}^T$ 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 1: Distribution of $p_{i,v,t}^T$ between different villages



Remember (see Section 3.2) 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 shows that providing *longer training* on the SRI has not only a direct impact on trained farmers (Fafchamps et al., 2018), 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.[19]

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.

5.2 Understanding the mechanism 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. The accuracy of information transmission regarding SRI technology is the primary channel through which this occurs. In this section, we therefore investigate this mechanism further by running regressions on different subsamples and ruling out other possible mechanisms.

5.2.1 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 B6 in Online Appendix B provides the interactions between farmers in the 120 villages. We find that 69% of farmers discuss agricultural issues at least once a month and 39.8% 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:

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

where $d = \{daily, weekly, myn\}$ (myn means either monthly, yearly, or never) is the frequency of discussion between farmers, so that $p_{i,v,d}^T$ is the percentage of treated farmers in village v who interact at frequency d with untreated farmer i who also resides in village

[19] 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.

Table 5: Impact of the frequency of interactions on the adoption rate of untreated farmers

	120 villages			60 villages (T1)			60 villages (T2)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$p^T_{i,v,daily}$	0.234*			0.108			0.359*		
	(0.120)			(0.116)			(0.200)		
$p^T_{i,v,weekly}$		0.185***			0.220***			0.169***	
		(0.0412)			(0.0573)			(0.0586)	
$p^T_{i,v,myn}$			0.0442			0.0209			0.0963
			(0.0496)			(0.0629)			(0.0682)
Observations	2,808	2,808	2,808	1,490	1,490	1,490	1,318	1,318	1,318

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 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.

v. Clearly, $N_{i,v,d} \leq N^T_{i,v}$, since among all treated farmers residing in village v as i (i.e., $N^T_{i,v}$), $N_{i,v,d}$ is the number of farmers who discuss with i at frequency d. This implies that $p^T_{i,v,d} \leq p^T_{i,v,d}$. We estimate (15) but with $p^T_{i,v,d}$ instead of $p^T_{i,v}$. Table 5 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 not when they interact monthly, yearly, or never. In addition, the coefficient is much larger for $p^T_{i,v,daily}$ than for $p^T_{i,v,weekly}$. 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 $p^T_{i,v,d}$ 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 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 who discuss with their peers at a sufficiently high frequency.

These results can be interpreted as follows: the more treated farmers interact with untreated farmers and/or the more trained are treated farmers, the lower is the variance σ^2_θ in the "noise" ε_θ of the quality of the technology and the more accurate is the information transmitted to the untreated farmer. In particular, they are more able to explain the advantages of the SRI technology and how to implement it.

5.2.2 Effect of financial relationships

In our baseline survey, we 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 B7 in Online Appendix B supplies some summary statistics. On average, each untreated farmer has 4.5 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:

$$p^T_{i,v,finance} = \frac{N^T_{i,v,finance}}{N^T_{i,v} + N^{NT}_{i,v}} \times 100\%,$$

where $N^T_{i,v,finance}$ is the number of treated farmers who borrowed or lent money or discussed financial issues in the last six months with farmer i residing in village v. As above, we estimate (15) but with $p^T_{i,v,finance}$ instead of $p^T_{i,v}$. Table 6 presents the results.

We obtain similar results to the case of farmers who frequently discuss agricultural issues with untreated farmers (Table 5). Indeed, contrary to Table 4, famers with one year of training have a significant impact on the adoption rate of untreated farmers. In addition, the magnitude of the effect is larger than that in the general case (Table 4) because untreated farmers focus more on farmers with whom they interact than a "random" farmer in the village. Consequently, when a farmer with one year of training, who discusses financial issues with untreated farmers, provides information about SRI technology to an untreated farmer, the latter considers this information to be accurate and is therefore more likely to adopt SRI technology.

Table 6: Impact of finance-related peers on adoption rate of untreated farmers

	120 villages	60 villages ($T1$)	60 villages ($T2$)
$p^T_{i,v,finance}$	0.296***	0.196***	0.433**
Observations	2,808	1,490	1,318

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 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.

5.2.3 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.

Tables 7 and 8 show *no* difference in rice production and yields between $T1$ and $T2$ villages, even though $T2$ villages have received more training on SRI technology. 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 7: Rice production difference between T1 and T2 villages

Amount of cultivated rice (kg)	T1		T2		T-statistic	P-value
	Mean	S.D	Mean	S.D		
All farmers	1736	(1344)	1763	(1357)	-0.81	0.79
Farmers who receive training	1759	(1286)	1750	(1284)	0.23	0.40
Farmers who adopt	1955	(1166)	1883	(1149)	1.38	0.08
Farmers who are trained and adopted	1909	(1172)	1838	(1088)	1.33	0.02

Notes: The amount of cultivated rice is the total rice crop (kg) that a farmer obtains from all his cultivated land. This is the sum of rice crops for all plots of land for each farmer.

Table 8: Yield difference between T1 and T2 villages

Amount of cultivated rice (kg)	T1		T2		T-statistic	P-value
	Mean	S.D	Mean	S.D		
All farmers	25.34	(6.15)	25.42	(5.87)	-0.52	0.7
Farmers who receive training	25.51	(5.94)	25.63	(6.21)	-0.57	0.28
Farmers who adopt	25.66	(0.18)	26.02	(6.17)	-1.31	0.09
Farmers who are trained and adopted	25.63	(6.13)	26	(6.26)	-1.26	0.10

Notes: Yield is defined as the amount of rice cultivated in one decimal of land, measured in kg. This is the total amount of rice cultivated (kg) divided by the total amount of land (decimal).

To summarize, the different analyses in this section seem to confirm our information mechanism from the theoretical model: untreated farmers are more likely to adopt if they obtain more precise and accurate information about SRI technology from their treated peers. In particular, we have shown that the *source* and *reliability* of information is important because untreated farmers will be more likely to adopt SRI technology if they *trust* the person transmitting this information. In the general case (Table 4), in the absence of a special relationship between treated and untreated farmers, only those with two years of training provide accurate information about the quality of SRI technology. However, as soon as we focus on peers with whom the untreated farmer discusses agricultural or financial issues, the duration of the training seems to become less important, as untreated farmers tend to trust farmers with whom they have professional contact on agricultural or financial issues. We have also shown that this is not because more trained farmers produce more rice than less trained ones.

6 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 (e.g., Ghadim et al., 2005; Koundouri et al., 2006; Genius et al., 2013), especially in the poor districts in Bangladesh in which we conduct our experiment. This is what we want to investigate both theoretically and empirically.

6.1 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:

$$U(A \,|\, \theta) := \mathbb{E}\left[u(z) \,|\, s_T\right], \qquad u(z) := \frac{1 - \exp(-\delta z)}{\delta}, \tag{16}$$

where z is defined by (7), while $\delta > 0$ is the risk aversion parameter.[20] 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 (e.g., Sargent, 1987, pp. 154–155) that preferences (16) can be equivalently represented by the following utility function:

$$\mathcal{U}(A \,|\, \theta) = \begin{cases} \mathbb{E}(b \,|\, s_\theta) - c - \frac{\delta}{2}\mathrm{Var}\left(b \,|\, s_\theta\right), & \text{if } A = 1, \\ 0, & \text{if } A = 0. \end{cases} \tag{17}$$

[20] 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.

Equation (17) implies that the expected utility $\mathcal{U}(A \mid \theta)$ 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

$$\delta > \underline{\delta} := \max\{0, 2(\beta - c)/\sigma_b^2\}, \tag{18}$$

which becomes (9) in the limit case of risk-neutral agents ($\delta \to 1$). (18) is less demanding than (9) 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

$$\mathbb{P}\{A = 1 \mid \theta\} = \mathbb{P}\left\{\mathbb{E}(b \mid s_\theta) > c + \frac{\delta}{2}\mathrm{Var}\,(b \mid s_\theta)\right\}. \tag{19}$$

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

Proposition 2 *Assume that* (4) *and* (18) *hold and that all farmers exhibit risk aversion captured by mean-variance utility* (17)*.*

(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,

$$\frac{\partial^2 \mathbb{P}\{A = 1\}}{\partial p \, \partial \delta} < 0. \tag{20}$$

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.[21] 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.

6.2 Empirical test and results

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

6.2.1 Measuring risk attitude of farmers

We asked all farmers in our field experiment to answer two questions about their risk-taking attitudes.[22] The *first question* is: "In daily life how much risk do you like to take?" The answers 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 B4 in Appendix B provides the distribution of the 3,630 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 B5 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 B6 and B7 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.

6.2.2 Defining risk attitudes

We say that a farmer is *risk-loving* if he answered a 9 or 10 to both questions. Otherwise, he is considered to be *risk-averse*. Table B8 in Appendix B shows that the percentage of risk-

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

[22] Contrary to the literature that shows that risk aversion has a negative effect on technology adoption (e.g., Ghadim et al., 2005; Koundouri et al., 2006; Genius et al., 2013), 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.

loving farmers is slightly smaller for untreated farmers (19.66%) than for treated farmers (24.17%).[23]

6.2.3 Econometric model

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

$$y_{i,v,t}^{NT} = \alpha_0 + \alpha_1 p_{i,v}^{T} + \alpha_2 \delta_{i,v}^{NT} + \alpha_3(\delta_{i,v}^{NT} \times p_{i,v}^{T}) + X_{i,v}^{'}\beta + \theta_t + \epsilon_{i,v,t}, \tag{21}$$

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 is risk-loving (i.e., if he answered a 9 or 10 to both questions) and 1 ($\delta_{i,v}^{NT} = 1$) if the farmer is risk-averse (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.

6.2.4 Empirical results

Table 9 displays the results of the estimation of equation (21), which has the same structure as Table 4 in terms of dividing the total sample into the 60 $T1$ villages and 60 $T2$ villages.

[23] We also run another analysis in which we defined a risk-loving farmer 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. However, using this definition, the results of the empirical analysis are qualitatively the same as in Table 9. They can be found in Table B9 in Appendix B.

Table 9: The effect of risk on the adoption rate of untreated farmers

	120 villages				60 T1 villages				60 T2 villages			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$p_{i,v}^{T}$	0.229***		0.221***	0.245***	0.0713		0.0628	0.158***	0.421***		0.412***	0.352***
	(0.0382)		(0.0382)	(0.0421)	(0.0504)		(0.0505)	(0.0551)	(0.0583)		(0.0581)	(0.0642)
$\delta_{i,v}^{NT}$		-0.0526***	-0.0478***	-0.124**		-0.0404**	-0.0388**	-0.347***		-0.0733***	-0.0664***	-0.123
		(0.0134)	(0.0133)	(0.0578)		(0.0172)	(0.0172)	(0.0758)		(0.0212)	(0.0208)	(0.0884)
$\delta_{i,v}^{NT} \times \mathrm{p}_{i,v}^{T}$				-0.341***				-0.551***				-0.328**
				(0.0992)				(0.132)				(0.149)
Observations	2,808	2,808	2,808	2,808	1,490	1,490	1,490	1,490	1,318	1,318	1,318	1,318

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 is risk-loving ($\delta_{i,v}^{NT} = 0$) if he answered a 9 or 10 to both risk questions in terms of daily life and rice activities. A farmer is risk-averse ($\delta_{i,v}^{NT} = 1$) 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.

There are four columns for each regression. The first columns (i.e., columns (1), (5), and (9)) report the direct effect of $p^T_{i,v}$ on $y^{NT}_{i,v,t}$ and correspond to columns (3), (6), and (9) in Table 4. As in the latter, in the 120 and 60 $T2$ villages, we find that $p^T_{i,v}$, the percentage of untreated farmers, has a positive and significant impact on $y^{NT}_{i,v,t}$, the probability of adopting SRI technology for untreated farmers residing in the same village.

The second columns (i.e., columns (2), (6), and (10)) report the direct effect of $\delta^{NT}_{i,v}$, the degree of the risk aversion of an untreated farmer, on $y^{NT}_{i,v,t}$. As predicted by Proposition 2, we observe that the more risk-averse is an untreated farmer (i.e., higher $\delta^{NT}_{i,v}$), 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. The third columns (i.e., columns (3), (7), and (11)) combine $p^T_{i,v}$ and $\delta^{NT}_{i,v}$ in the same regression. The results are robust.

The last columns (i.e., columns (4), (8), and (12)) introduce the cross-effect $\delta^{NT}_{i,v} \times p^T_{i,v}$ into the regression. As predicted by Proposition 2, this is always significant and negative. Hence, when the proportion of treated farmers increases, more untreated farmers adopt SRI technology; however, the more risk-averse they are, the *lower* is this impact on the adoption rate of untreated farmers.

As a robustness check, in Appendix C, we measure farmers' risk attitudes by making them play a lottery game similar to that of Binswanger (1980). Unfortunately, as only treated farmers played this game, we could directly measure risk attitudes only for treated farmers. However, because untreated and treated farmers were randomly assigned and the distribution of their observable characteristics is similar, we could then predict the risk attitudes of untreated farmers by matching their observable characteristics with those of treated farmers. The estimation results in Table C4 in Appendix C show that the results are relatively similar to those in Table 9. In particular, there is still a direct negative effect of risk aversion and a negative cross-effect of risk aversion and peers 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 Uphoff, 2016) that are not standard and thus involves mental changes and new ways of thinking. Risk-averse farmers 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.

7 Impact of social norms and peers on adopting the SRI

We have thus far tested the models developed in Sections 2 and 6 in which we highlighted the importance of the quality and reliability of information about SRI technology transmitted from treated farmers to untreated farmers. However, as mentioned in Section 3.2, SRI fields visibly differ from traditional rice fields; hence, there is additional pressure from peers not to adopt this norm in the village. To better understand this issue, we next investigate how the *adoption decision* of treated farmers (and not the percentage of treated farmers, as above) affects the *adoption decision* of untreated farmers.

Essentially, we now estimate the following pooled OLS equation:

$$y^{NT}_{i,v,t} = \alpha_0 + \alpha_1 p^T_{i,v,t,A} + X'_{i,v}\beta + \theta_t + \epsilon_{i,v,t}, \tag{22}$$

where, as before, $y^{NT}_{i,v,t}$ is a dummy variable equal to 1 if untreated farmer i residing in village v adopts SRI technology at time t and 0 otherwise. However, now,

$$p^T_{i,v,t,A} = \frac{N^T_{i,v,t,A}}{N^T_{i,v} + N^{NT}_{i,v}} \times 100\%$$

is the proportion of treated farmers living in village v who *adopt* SRI technology at time t (the subscript A stands for "Adoption") and $N^T_{i,v,t,A}$ is the number of treated farmers living in village v who adopt SRI technology at time t. The problem of estimating (22) with OLS is that $p^T_{i,v,t,A}$ is endogenous; hence, the OLS estimation would be biased. Therefore, we instrument $p^T_{i,v,t,A}$ by $p^T_{i,v}$, the proportion of treated farmers in village v, which is exogenous, and run a 2SLS estimation.

Precisely, in the first stage, we estimate the following equation:

$$p^T_{i,v,t,A} = \omega_0 + \omega_1 p^T_{i,v} + X'_{i,v}\beta + \theta_t + \mu_{i,v,t}. \tag{23}$$

From the estimation of equation (23), we obtain $\widehat{p}^T_{i,v,t,A}$. In the second stage, we estimate the following equation:

$$y^{NT}_{i,v,t} = \alpha_0 + \alpha_1 \widehat{p}^T_{i,v,t,A} + X'_{i,v}\beta + \theta_t + \epsilon_{i,v,t}. \tag{24}$$

Table 10 presents the results of the first stage.[24] We find that independently of which villages are treated, the first stage is strong, as there is a positive and significant impact of $p^T_{i,v}$, the proportion of treated farmers, on $p^T_{i,v,t,A}$, the proportion of treated farmers living in village v who adopt SRI technology at time t. This should not come as a surprise, as Table 1 showed that treated farmers are much more likely to adopt than untreated farmers.

[24]The complete table with all the control variables can be found in Table B10 in Appendix B.

Table 10: First stage: Peer effects

	120 villages	60 villages ($T1$)	60 villages ($T2$)
$p^T_{i,v}$	0.634***	0.533***	0.748***
Observations	2,808	1,490	1,318

Notes: The dependent variable is the proportion of treated farmers who adopt SRI technology. 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.

Table 11 reports the results of the second stage.[25] As in our baseline econometric specification (Table 4), even when farmers with only one year of training adopt the new technology, they have no impact on the adoption rate of untreated farmers. This gives us additional confidence that the mechanism at work is the one highlighted in the theoretical model; therefore, the adoption rate of untreated farmers is driven by the transmission of information about the quality and cost of SRI technology but also by social norms and peer effects. Indeed, farmers with *two years of training* and who *adopt* SRI technology have the most accurate and reliable information. Moreover, as stated in Section 3.1, SRI fields visibly differ from traditional rice fields; hence, social norms and conformity pressures could also discourage the ultimate adoption decision. The results in this section show that peer effects and social norms do indeed matter: an increase of 10% in treated farmers who *adopt* SRI technology increases the adoption rate of untreated farmers by 3.61%, while, when we assess the impact of treated farmers only (who did not necessarily adopt), this number is 2.2% (Table 4).

Table 11: Second stage: Peer effects

	120 villages	60 villages ($T1$)	60 villages ($T2$)
$\widehat{p}^T_{i,v,t,A}$	0.361***	0.119	0.661***
Observations	2,808	1,490	1,318

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 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.

8 Conclusion

Uphoff (2016) 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.

[25] The complete table with all the control variables can be found in Table B11 in Appendix B.

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 peer 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 also influenced by trained farmers residing in the same village 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 3,630 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). Clearly, farmers with two years of training (i.e., repeated training) should 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. When we consider treated farmers who have a professional relationship (discussing agricultural or financial issues) with untreated farmers, 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. We also consider the impact of treated farmers who adopt SRI technology on the adoption rate of untreated farmers and find similar results: only two-year-trained farmers who adopt have a significant and positive influence on the adoption rate of untreated farmers.

We then 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 but also 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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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 (12) 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 (18), 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 (20) 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

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

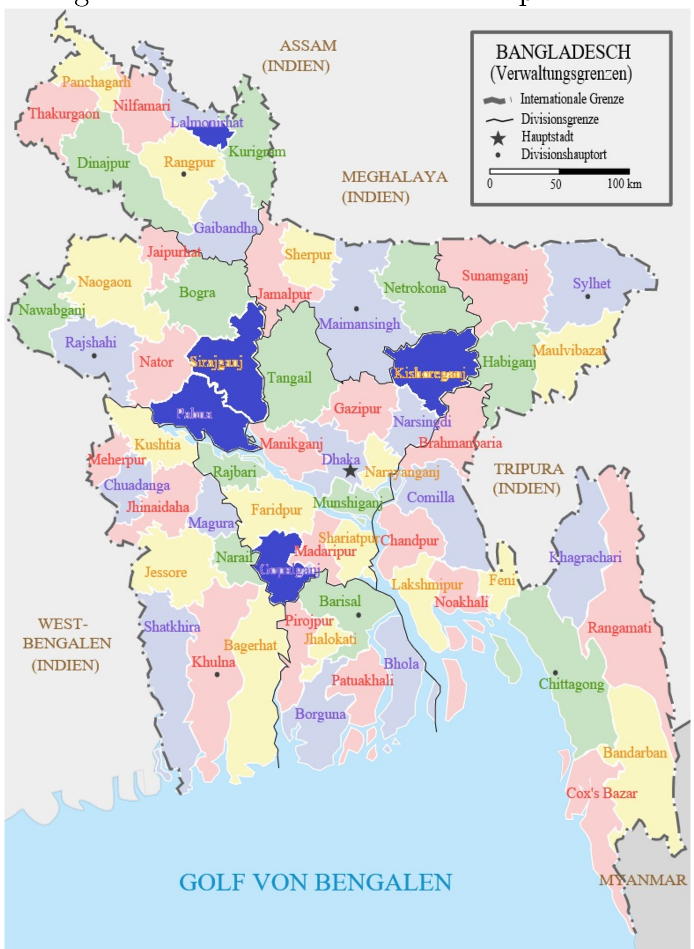
Combining this with (A.7), we find that (20) is equivalent to

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

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 (20) holds true for all $\delta > \delta_0$. This completes the proof. ■

B Additional figures and tables

Figure B1: Districts in the field experiment



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

Figure B2: Density distribution of p_v^T

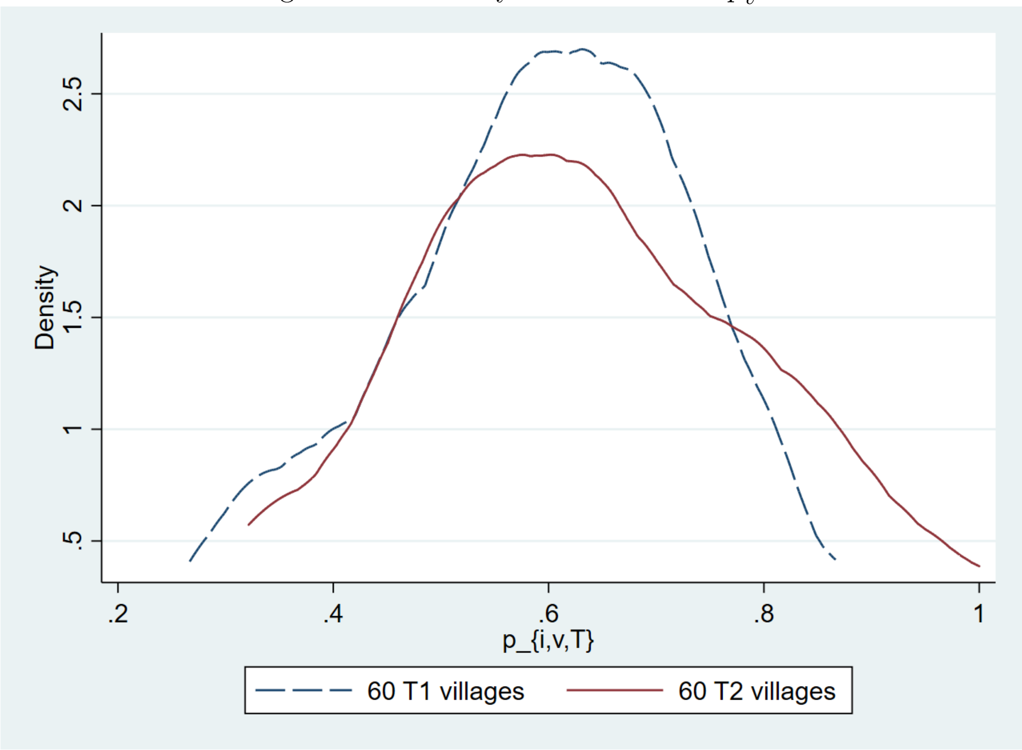


Figure B3: Distribution of total number of farmers between villages

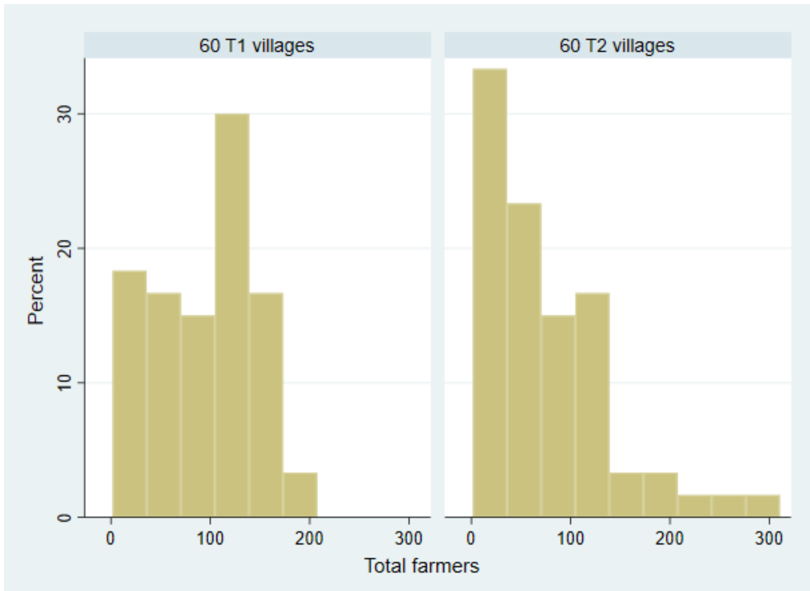
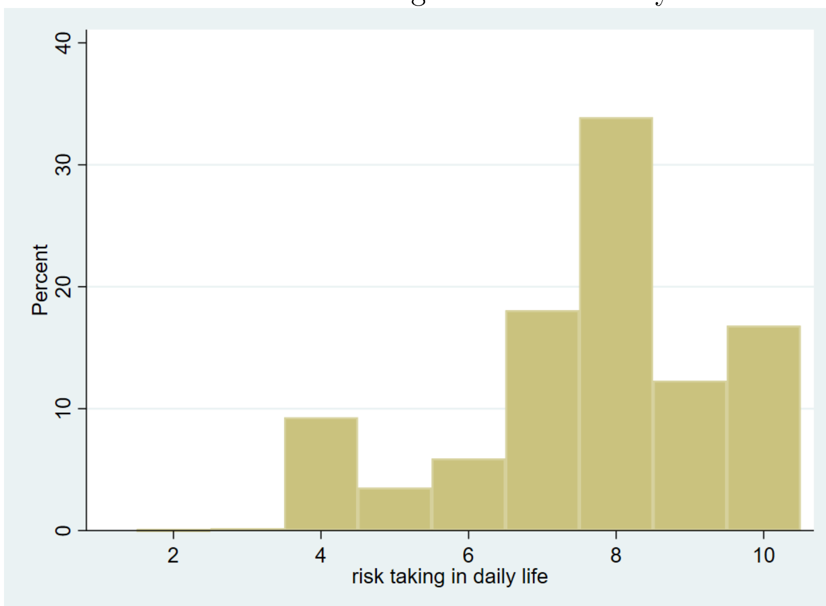
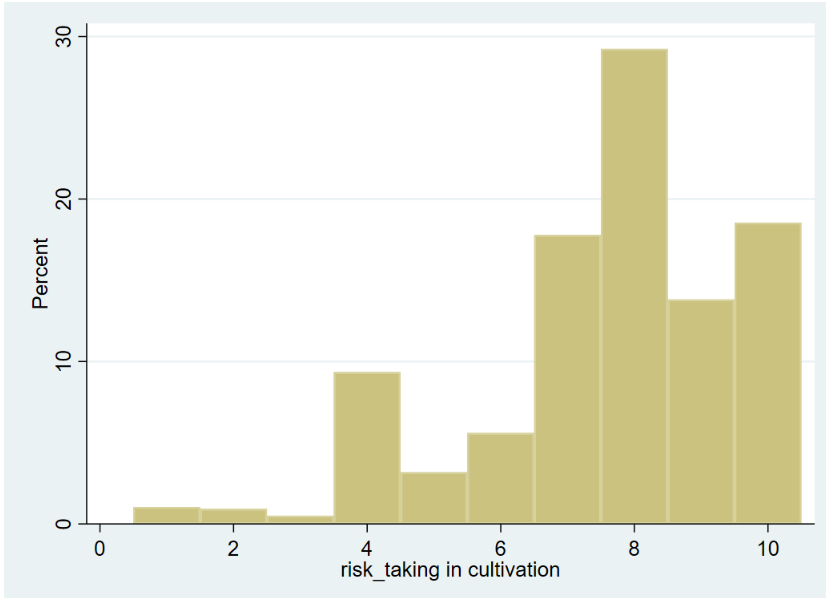


Figure B4: Distribution of risk taking attitudes in daily life for *all* farmers



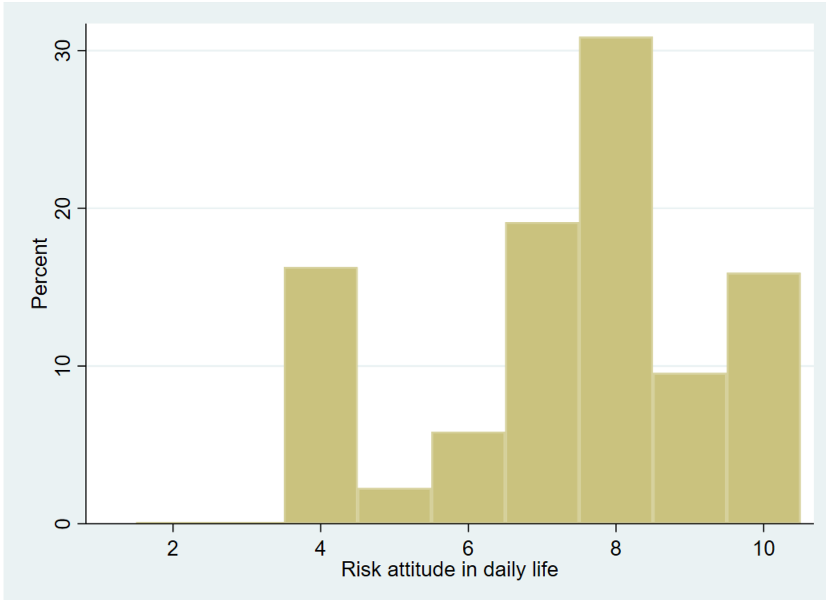
Note: Notes: The sample includes all 3,630 farmers in the 120 treatment villages. The risk-taking attitude measure ranges from 1 to 10, where 1 indicates the lowest degree of risk and 10 implies the highest degree of risk.

Figure B5: Distribution of risk taking attitudes in cultivation activity for *all* farmers



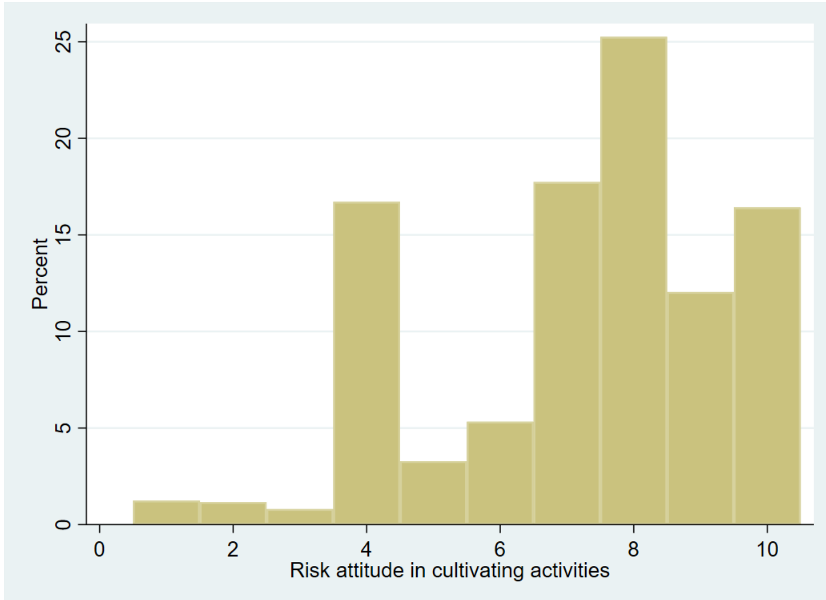
Notes: The sample includes all 3,630 farmers in the 120 treatment villages. The risk-taking attitude measure ranges from 1 to 10, where 1 indicates the lowest degree of risk and 10 implies the highest degree of risk.

Figure B6: Distribution of risk attitudes in daily activities for *untreated* farmers



Notes: The sample includes all 1,404 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 B7: Distribution of risk attitudes in cultivating activities for *untreated* farmers



Notes: The sample include all the 1,404 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.

Table B1: Sample distribution of treatment villages

	Treatment	Villages	Total farmers	Treated farmers	Untreated farmers
Year 1 (2014-15)	T1	60	1,805	1,060	745
	T2	60	1,825	1,166	659
Year 2 (2015-16)	T1	60	1,805	No training	
	T2	60	1,825	1,166	659

Table B2: Balance checks between treated and untreated farmers

Treated villages only			
	Treated	Untreated	t-statistic
Household Characteristics (Baseline)	Mean	Mean	
Age (years)	45.85	44.95	1.68
	(0.38)	(0.53)	
Household income (takas)	12385.99	13313.48	-1.36
	(399.23)	(693.17)	
Amount of cultivable land (decimals)	163.49	168.74	-0.85
	(5.46)	(6.7)	
Education (years)	4.26	4.46	-1.19
	(0.13)	(0.17)	
Household size	5.11	5.18	-1.09
	(0.06)	(0.06)	
Occupation	0.89	0.87	1.67
	(0.01)	(0.001)	
Observations	2,226	1,404	

Notes: The reported t-statistics are from the two-tailed test with the null hypothesis that the group means are equal. Standard errors are clustered at the village level and reported in parentheses. Occupation equals 1 if the participant's primary occupation is a farmer and 0 if his primary occupation is not a farmer.

Table B3: Balance checks between $T1-$ and $T2-$treated farmers

	Treated villages only					
	One-year training villages(T1)			Two-year training villages(T2)		
	Treated	Untreated	t-statistic	Treated	Untreated	t-statistic
Household Characteristics (Baseline)	Mean			Mean		
Age	46.39	44.70	0.93	45.36	45.23	0.17
	(0.51)	(0.76)		(0.55)	(0.75)	
Household income (takas)	12372.68	12565.59	−0.36	12398.03	14163.47	−1.33
	(536.30)	(473.58)		(589.75)	(1373.04)	
Education	4.38	4.47	−0.37	4.15	4.45	−1.25
	(0.18)	(0.24)		(0.19)	(0.23)	
Amount of cultivable land (decimals)	166.17	167.25	−0.15	161.06	170.45	−0.91
	(8.46)	(8.92)		(7.06)	(10.19)	
Household size	5.2	5.17	0.32	5.02	5.19	−1.77
	(0.08)	(0.08)		(0.08)	(0.08)	
Occupation	0.89	0.86	1.96	0.89	0.88	0.95
	(0.01)	(0.01)		(0.01)	(0.01)	
Observations	1,060	745		1,166	659	

Notes: The reported t-statistics are from the two-tailed test with the null hypothesis that the group means are equal. Standard errors are clustered at the village level and reported in parentheses.

Table B4: Test of p_v^T between $T1$ and $T2$ villages

Treatment Group	Means
T1	0.59
	(0.02)
T2	0.63
	(0.02)
t-statistic of the t-test	-1.54
P-value of the K-S test	0.18

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 B5: 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)	(7)	(8)	(9)
$p^T_{i,v}$	0.222***	0.222***	0.231***	0.0641	0.0644	0.0709	0.404***	0.404***	0.423***
	(0.0730)	(0.0730)	(0.0732)	(0.0910)	(0.0911)	(0.0866)	(0.0982)	(0.0985)	(0.0984)
Year dummy		0.00252	0.00119		-0.00418	-0.00528		0.0111	0.00886
		(0.0115)	(0.0115)		(0.0135)	(0.0136)		(0.0195)	(0.0192)
Age/10			-0.00933*			-0.0195***			0.000243
			(0.00475)			(0.00601)			(0.00710)
log(Income)			-0.0300**			-0.0428**			-0.0203
			(0.0121)			(0.0174)			(0.0172)
log(Land)			0.0208**			0.0136			0.0368**
			(0.00907)			(0.0107)			(0.0155)
Education			0.000952			0.000652			0.000971
			(0.00160)			(0.00227)			(0.00205)
Household size			0.00574			0.00900			0.00357
			(0.00371)			(0.00549)			(0.00501)
Occupation			0.0162			0.00176			0.0367*
			(0.0167)			(0.0244)			(0.0207)
Total farmers/1000			0.0344			0.191			0.0300
			(0.101)			(0.141)			(0.164)
Observations	2,808	2,808	2,808	1,490	1,490	1,490	1,318	1,318	1,318

Notes: The dependent variable is the adoption decision of an untreated farmer 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. Standard errors are clustered at the village level and reported in parentheses.
***p<0.01, **p<0.05, *p<0.1.

Table B6: Percentage of farmers who discuss by type of frequency

Category	% of farmers
Daily	8.82
Weekly	31.02
Monthly	29.26
Yearly	25.9
Never	5
Observations	1,404

Table B7: Number of finance-related peers for untreated farmers

Category	Value
Mean	4.5
Median	2
Mode	0
Standard deviation	5.4
Observations	1,404

Table B8: Percentage of risk-loving farmers

Percentage	Risk loving
Treated farmers	24.17%
Untreated farmers	19.66%
Total farmers	22.42%

Notes: We define a farmer as risk-loving if he answers a 9 or 10 in his risk-taking attitude to both daily life and cultivating activities.

Table B9: 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)	(10)	(11)	(12)
$p^T_{i,v}$	0.229***		0.229***	0.273***	0.0713		0.0708	0.130**	0.421***		0.421***	0.441***
	(0.0382)		(0.0382)	(0.0405)	(0.0504)		(0.0504)	(0.0536)	(0.0583)		(0.0583)	(0.0615)
$\hat{\delta}^{NT}_{i,v}$		-0.00835	-0.00657	-0.224***		-0.00726	-0.00636	-0.274***		-0.0135	-0.0129	-0.127
		(0.0156)	(0.0155)	(0.0684)		(0.0200)	(0.0200)	(0.0863)		(0.0246)	(0.0241)	(0.110)
$p^T_{i,v} \times \hat{\delta}^{NT}_{i,v}$				-0.387***				-0.484***				-0.200
				(0.119)				(0.152)				(0.189)
Observations	2,808	2,808	2,808	2,808	1,490	1,490	1,490	1,490	1,318	1,318	1,318	1,318

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 is risk-loving ($\delta^{NT}_{i,v} = 0$) if he answered a 10 to both risk questions in terms of daily life and rice activities. A farmer is risk-averse ($\delta^{NT}_{i,v} = 1$) 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.

Table B10: First stage: Peer effects

	120 villages			60 villages (T1)			60 villages (T2)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$p^T_{i,v}$	0.613***	0.613***	0.634***	0.526***	0.526***	0.533***	0.709***	0.709***	0.748***
	(0.109)	(0.109)	(0.1000)	(0.145)	(0.145)	(0.133)	(0.167)	(0.167)	(0.147)
Year dummy		-0.108***	-0.114***		-0.151***	-0.158***		-0.0605***	-0.0648***
		(0.0185)	(0.0190)		(0.0290)	(0.0295)		(0.0209)	(0.0219)
Age/10			-0.0134***			-0.0172***			-0.0099
			(0.0043)			(0.0051)			(0.0066)
log(Income)			-0.0861***			-0.0744***			-0.0974***
			(0.0132)			(0.0202)			(0.0160)
log(Land)			0.0301***			0.0295***			0.0292**
			(0.008)			(0.0101)			(0.0126)
Education			0.0026			0.005**			-0.0006
			(0.0016)			(0.0022)			(0.0021)
Household size			0.0085***			0.0099**			0.0089***
			(0.0028)			(0.0046)			(0.0031)
Occupation			0.0313*			0.0345*			0.0348
			(0.0163)			(0.0178)			(0.0263)
Observations	2,808	2,808	2,808	1,490	1,490	1,490	1,318	1,318	1,318

Notes: The dependent variable is the proportion of treated farmers who adopt SRI technology. Standard errors are clustered at the village level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B11: Second stage: Peer effects

	120 villages			60 village (T1)			60 villages (T2)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$p^T_{i,v,t,A}$	0.246***	0.373***	0.361***	0.156*	0.227**	0.119	0.368***	0.545***	0.661***
	(0.0697)	(0.0915)	(0.116)	(0.0857)	(0.113)	(0.141)	(0.108)	(0.136)	(0.153)
Year dummy		0.0457***	0.0436**		0.0222	0.0091		0.0731***	0.0850***
		(0.0159)	(0.0173)		(0.0181)	(0.0194)		(0.0263)	(0.0275)
Age/10			-0.0035			-0.0154**			0.0092
			(0.005)			(0.0063)			(0.0072)
log(Income)			0.0015			-0.0314			0.0368**
			(0.0150)			(0.0212)			(0.0183)
log(Land)			0.0093			0.0083			0.0164
			(0.008)			(0.0087)			(0.0141)
Education			0.0006			0.0007			-0.0007
			(0.0016)			(0.0023)			(0.002)
Household size			0.0027			0.0082			-0.0021
			(0.0036)			(0.0052)			(0.005)
Occupation			0.006			-0.0001			0.0168
			(0.0170)			(0.0250)			(0.0216)
Observations	2,808	2,808	2,808	1,490	1,490	1490	1,318	1,318	1,318

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. Standard errors are clustered at the village level and reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

C Another way of measuring risk attitudes

C.1 Measuring risk

To capture the risk attitudes of farmers, in the baseline survey, a simple *gamble choice task* was introduced to all *treated* farmers across the 120 villages. The design of the lottery game was similar to that of Binswanger (1980). Specifically, this gamble game was a one-period incentivized game that involved assigning different payoffs to each option. Table C1 summarizes the payoffs and risk classification. In the baseline survey, each treated farmer was given a form with the first three columns of the payoffs in Table C1. They were then asked to choose from alternatives 1 to 6. Once this choice was made, a coin toss decided if farmers received the low payoff (heads) or the high payoff (tails). In other words, in each option, a farmer had a 50/50 chance of winning a high or low payoff.

Table C1: Payoffs and corresponding risk classification

Choice	Heads (low payoff)	Tails (high payoff)	Expected payoff	Risk aversion	Proportion
1	100	100	100	Extreme	13.84%
2	80	200	140	Severe	8.80%
3	70	250	160	Moderate	11.13%
4	60	300	180	Inefficient	14.03%
5	50	350	200	Slight to Neutral	21.45%
6	0	400	200	Negative	30.77%

As shown in Table C1, farmers could be classified into different risk attitudes according to their choices. For example, farmers who chose option 1 were classified as extremely risk-averse people. Indeed, choosing option 1 gave a 100-taka payoff with probability 1. Although this payoff was the lowest across of six alternatives, it was a guaranteed payment (i.e., it was risk-free). On the contrary, farmers who chose option 6 were classified as risk-loving, or having negative risk aversion. In option 6, they had a 50% chance of earning an extremely high payoff of 400 taka or getting nothing. Although options 5 and 6 had the same expected payoff, option 6 had a higher payoff variance; therefore, only risk-loving farmers would choose option 6.

A (treated) farmer was described as risk-loving if he chose option 6 and risk-averse otherwise. We find that 30.77% of farmers are risk-loving, while the rest (69.23%) are risk-averse. This is higher than the percentage of risk-loving farmers when we used the survey (see Table B8 in Appendix B, where the percentage of risk-loving treated farmers was 24.17%.

However, *untreated* farmers did *not* participate in this game; therefore, we do not know their risk attitudes. To predict the risk attitudes of untreated farmers, we rely on our randomization process by assuming that the distribution of risk preferences is the same between treated and untreated farmers (as they were chosen at random). Indeed, Table B2 in Appendix B shows that treated and untreated farmers have on average similar observable characteristics such as education, age, income, amount of cultivable land, household size, and occupation. Therefore, it is reasonable to conclude that the distribution of risk attitude is also similar between these two groups. To predict the risk attitudes of untreated farmers, we thus run a regression on the risk attitudes of treated farmers, as a function of their observable characteristics, as follows:

$$\delta^T_{i,v} = \gamma_0 + X'_{i,v}\beta + \theta_v + \epsilon_{i,v}, \tag{C.1}$$

where $\delta^T_{i,v}$ is a dummy variable that takes the value of 1 if the treated farmer is risk-averse (i.e., chose options 1–5 in Table C1) and 0 if he is risk-loving (i.e., chose option 6 in Table C1). The vector X_i includes all the household- and individual-level characteristics likely to be predictors of risk-taking behavior (i.e., education, age, income, amount of cultivable land, household size, and occupation), while $\epsilon_{i,v}$ and θ_v are defined as in equation (15).

Table C2 displays the results of the estimation of equation (C.1). The signs obtained are intuitive: older farmers are more risk-averse, while farmers that are more educated and farmers with larger families are less risk-averse.

Let $\widehat{\gamma_0}$ and $\widehat{\beta}$ be the OLS estimates of γ_0 and β in equation (C.1). Then, untreated farmer i's risk attitude, $\widehat{\delta}^{NT}_{i,v}$, is estimated as follows:

$$\widehat{\delta}^{NT}_{i,v} = \widehat{\gamma_0} + X'_{i,v}\widehat{\beta}. \tag{C.2}$$

Equation (C.2) relies on our assumption that farmers who have similar individual characteristics (e.g., age, income, household size, amount of cultivable land, education, and occupation) have similar risk attitudes. In Table C3 in Appendix B, we check the number of farmers predicted correctly, according to (C.1), where $\widehat{\delta}^T_{i,v}$ gives the *estimated* value of the risk attitude of treated farmers from the estimation of (C.2), while $\delta^T_{i,v}$ gives the "real" value of the risk attitude of treated farmers. Remember that $\delta^T_{i,v}$ equal to 1 means risk-averse, while $\delta^T_{i,v} = 0$ means risk-loving. All the values on the diagonal of Table C3 mean that the prediction is correct. Specifically, of the 1,612 risk-averse farmers, the model predicts that 966 are risk-averse, with a hit rate of 60%. Moreover, of the 614 risk-loving farmers, the model predicts 438 correctly, with a hit rate of 71.3%. The overall hit rate is 63.1%, which is high, providing us with confidence in our measure of the risk attitudes of untreated farmers.

Figure C1 displays the distribution of (predicted) risk preferences for treated (dashed curve) and untreated (solid curve) farmers. Overall, the risk preferences for both groups

Table C2: Relationship between risk attitude and the characteristics of treated farmers

Age	0.0026***
	(0.0009)
log(Income)	-0.0372*
	(0.0202)
log(Land)	-0.005*
	(0.0141)
Education	-0.0065
	(0.0072)
Household size	0.0014
	(0.0059)
Occupation	0.0076
	(0.0338)
Education^2	-0.0013**
	(0.0006)
Observations	2,226

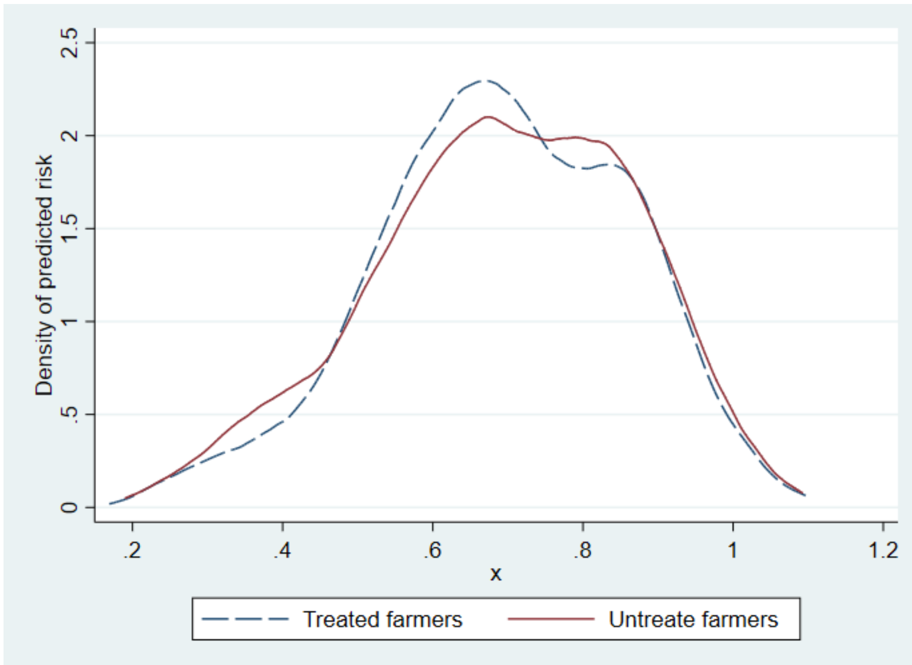
Notes: The dependent variable is the dummy variable, which is 1 if a farmer is risk-averse, namely who chose options 1–5 in Table C1, and 0 if a farmer is risk-loving, who chose option 6. Education ^{2} is the squared value of education. The regression contains village dummies to capture the village-level fixed effects. Standard errors are clustered at the village level and reported in parentheses.

Table C3: Predicted and real values of risk attitude

		$\hat{\delta}_{i,v}^T$		
		0	1	Total
$\delta_{i,v}^T$	0	438	176	614
	1	646	966	1612
	Total	1,084	1,042	2,226

Notes: $\delta_{i,v}^T = 1$ means risk-averse and $\delta_{i,v}^T = 0$ means risk-loving

Figure C1: Density distribution of the predicted riskiness of treated and untreated farmers



are similar.[1] This suggests that there is no difference in risk preference between treated and untreated farmers in the villages.

After we calculate the predicted riskiness of the attitude $\widehat{\delta}_{i,v}^{NT}$ for all 1,330 untreated farmers, we rank this riskiness index from low to high. Given that the share of risk-loving people among treated farmers is 30.77%, we define the first 69.23% untreated farmers as risk-averse and assign them a value of 1, with the remaining 30.77% of untreated farmers categorized as risk-loving and assigned a value of 0.[2]

C.2 Econometric model and empirical results

As in the main text, we estimate the following model:

$$y_{i,v,t}^{NT} = \alpha_0 + \alpha_1 p_{i,v}^{T} + \alpha_2 \widehat{\delta}_{i,v}^{NT} + \alpha_3 (\widehat{\delta}_{i,v}^{NT} \times p_{i,v}^{T}) + X_{i,v}^{'} \beta + \theta_t + \epsilon_{i,v,t}. \tag{C.3}$$

[1] A K-S test is conducted to compare whether the distribution of estimated riskiness is identical between treated and untreated farmers. We find that the combined difference is 0.0303 and is insignificant at the 95% confidence level. Therefore, the distribution of $\widehat{\delta}_{i,v}$ for treated farmers is similar to that for untreated farmers.

[2] This is higher than the percentage of risk-loving farmers when we used the survey (see Table B8 in Appendix B, where the percentage of risk-loving *untreated* farmers was 19.66%.

The difference between equations (21) and (C.3) is that in the former the risk attitude is directly measured by the survey and thus denoted by $\delta_{i,v}^{NT}$, while in the latter it is indirectly measured and thus denoted by $\widehat{\delta}_{i,v}^{NT}$.

Table C4 displays the results of the estimation of equation (C.3). We see that the direct and cross-effects of risk aversion on the adoption rate of untreated farmers are roughly similar to those in Table 9 where we measured risk using the survey.[3]

[3]In the columns in which $\widehat{\delta}_{i,v}^{NT}$ has a positive sign, the net effect of risk aversion on adoption is negative, since the negative cross-effect of $\widehat{\delta}_{i,v}^{NT} \times p_{i,v}^{T}$ is much higher than the direct effect of $\widehat{\delta}_{i,v}^{NT}$.

Table C4: The effect of risk on the adoption rate of untreated farmers

	120 villages				60 $T1$ villages				60 $T2$ villages			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$p^T_{i,v}$	0.229***			0.365***	0.0713			0.268**	0.421***			0.467***
	(0.0382)			(0.101)	(0.0504)			(0.126)	(0.0583)			(0.148)
$\widehat{\delta}^{NT}_{i,v}$		-0.0288**		0.121*		-0.0133		0.172**		-0.0446**		0.0289
		(0.0127)		(0.0683)		(0.0173)		(0.0834)		(0.0207)		(0.105)
$\widehat{\delta}^{NT}_{i,v} \times p^T_{i,v}$				-0.193*				-0.291**				-0.0158
				(0.116)				(0.142)				(0.177)
Observations	2,808	2,808	2,808	2,808	1,490	1,490	1,490	1,490	1,318	1,318	1,318	1,318

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. We determine the risk attitudes of treated farmers through a lottery game and then predict the risk attitudes of untreated farmers. A farmer is risk-loving when $\widehat{\delta}^{NT}_{i,v} = 0$) and risk-averse when $\widehat{\delta}^{NT}_{i,v} = 1$. 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.