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THE VALUE OF INFORMATION IN TECHNOLOGY ADOPTION: THEORY AND EVIDENCE FROM BANGLADESH

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JEL Classification: O13, Z13

Keywords: Technology adoption, risk attitude, randomized controlled trial (RCT)

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The Value of Information in Technology Adoption: Theory and Evidence from Bangladesh*

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

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Keywords: Bayesian model, information, technology adoption, risk attitude, RCT, Bangladesh.

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1 Introduction

The adoption of new agricultural technologies is critical for improving labor productivity, food security, and economic growth in developing countries. In particular, agricultural productivity in South Asia and Sub-Saharan Africa remain very low, and the adoption and diffusion of new efficient cultivation methods have been sluggish. This can be explained by farmers' (lack of) knowledge, uncertainty, and costs of learning (Moser and Barrett 2006; Barrett et al., 2010; Conley and Udry, 2010; Jack, 2013; Barrett et al., 2018).

However, we know little about risk attitude and the role of information transmission between treatment and control groups 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 paper, we address these issues by examining from a theoretical and empirical perspective, the importance of risk attitude, and the quality and accuracy of 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 farmers make adoption decisions based on noisy signals about the uncertain quality of a new technology they receive from their peers. The key assumption of the model is that individuals possessing better knowledge about the new technology (because of some training) send less noisy signals. More precisely, there are two types of individuals: *uninformed* or *untreated* agents (i.e., farmers who did not receive any training) and *informed* or *treated* agents (i.e., trained farmers residing in the same village). Because the outcomes of adopting a complex new technology are usually uncertain, we assume that the benefit of technology adoption for a farmer is a random variable.

In the absence of interactions with treated farmers, untreated farmers will not adopt the new technology because it costs much more than its expected benefit. However, when an untreated farmer meets a treated farmer, that is, a farmer who has received one-year or two-year training in the new technology, the latter provides a noisy signal about the benefit of adopting the new technology. The more trained (in terms of years of training) the treated farmer, the more accurate is his signal, and smaller is the variance in the noise of the signal.

When farmers are assumed to be risk-neutral, we show that the adoption rate of untreated (uninformed) farmers increases with the fraction of treated (informed) farmers residing in the same village. Indeed, higher the fraction of treated farmers in a village where an untreated farmer lives, 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 send precise signals about the quality of technology, the impact of treated farmers on the adoption rate of untreated farmers is higher. We use the variance of the noisy component of a signal as an inverse measure of its accuracy.

We then test these two predictions of the theoretical model by randomly selecting farmers and exogenously varying the number of farmers receiving treatment across different villages. We use a repeated randomized controlled trial to examine the spillover effects of the SRI technology in rural Bangladesh. We randomly assign villages to receive one-year or two-year training and examine the spillover effects among farmers by observing the adoption decisions of untreated farmers, for whom the only channel of learning about the new technology is treated farmers.

We find that an increase of 10% in treated farmers in a village, increases the average rate of 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 where treated farmers received two-year training and the $T1-$treated villages where treated farmers received one-year training, and estimate the model separately. We show that only treated farmers with two-year 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, the lower the variance in the noise of technology quality, the more accurate 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.

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-lover farmers (direct effect) and higher the degree of risk aversion, the lower the impact of the fraction of treated farmers on the adoption rate of untreated farmers (cross effect). We test these theoretical results using a 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.

Finally, to better understand the mechanisms behind our results, we estimate a peer-effect 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 in 10% of treated farmers who adopt the SRI technology increases the adoption rate of untreated farmers by 3.4% instead of 2.2%. This gives us confidence that the mechanism at work is indeed the one highlighted in the theoretical model. Therefore, the key aspect of technology adoption for untreated farmers is the transmission of information about the quality of SRI technology.

A large body of empirical literature on technology adoption demonstrates the importance of peer and network effects[1] (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, through studies on menstrual cup usage in Nepal (Oster and Thorton, 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 or imitation. In Ghana, Conley and Udry (2010) investigate how farmer's input decisions change when they observe the actions and outcomes of other farmers in their information network.[3] Indeed, since the 1990s, farmers living in Ghana are experiencing a transformation in terms of the intensive production of pineapple for export. This transformation involves the adoption of a set of new technologies, such as fertilizers and agricultural chemicals. It shows that farmers are more likely to increase input use when their neighbors achieve higher than expected profits using more input than before. Bonan et al. (2017) evaluated the role of social interactions in technology adoption, and found positive and direct peer influence, demonstrating that consumers are more willing to buy an improved cook stove if their close peers purchased the same product. Similarly, Oster and Thornton (2012) study the role of peer effects in adopting the "menstrual cup" (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%.

[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.

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

Our study contributes to this literature in different ways. First, we are the first to provide a new theoretical model highlighting the importance of 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.[4] Third, to test this theory, we conduct different RCTs using distinct treatments (in terms of duration of training) that provide farmers with different knowledge and accuracy of information about the new technology. Fourth, instead of directly testing the effect of the treatment (technology training) on the adoption rate of the treated farmers compared to the control group (untreated farmers), we investigate how untreated farmers are positively affected by the fraction of treated farmers in the village where 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 under-estimated because it does take into account the impact of the treated individuals on the untreated ones (see also Miguel and Kremer, 2004, and List et al., 2018).

The rest of the paper is organized as follows. Section 2 develops the main 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 the econometric model, which tests the prediction of the theoretical model. Section 5 presents the main empirical results and some robustness checks. Section 6 explains the role of risk aversion in technology adoption, both from theoretical and empirical viewpoints. Section 7 empirically studies peer effects in technology adoption. Finally,

[4] To the best of our knowledge, very 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 have examined the cross-effect of both risk and peers on technology adoption.

Section 8 concludes. Appendix A provides all the proofs of the propositions in the theoretical model. Appendix B supplies additional figures and tables.

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: *not treated*, who received *one-year training* in SRI technology, and those who received *two-year training* in SRI. Accordingly, we define a farmer's type θ as follows: $\theta \in \{NT, T\}$, where NT and T stands, 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: where treated farmers received one-year training, $v = T1$, and where treated farmers received two-year training, $v = T2$. We want to study how, in each village, the decision to adopt SRI of an *untreated farmer* is affected by the percentage of *treated farmers* residing in the same village. Let $p \equiv \mathbb{P}\{\theta = T\}$ be the share of treated individuals in a given village.[5] We refer to p as the *exposure rate*. An untreated farmer, which we also refer to as 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 of the technology (or benefit) 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 while $\sigma_b^2 > 0$ is the variance. In other words, the average or expected benefit of adopting the 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:

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

[5]Since we assumed a continuum of farmers in each village, by the Law of Large Number, p $(1-p)$ can be interpreted as the probability that an untreated farmer randomly meets a treated (untreated) farmer in the village.

where b satisfies (1) while ε_θ is an error term that follows a Normal distribution, i.e.,

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

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 SRI than those with one-year 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 for 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

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

In words, there is a positive relationship between p, the fraction 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 utility function.

2.2 Model predictions with risk-neutral farmers

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

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

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

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

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

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

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

otherwise, the problem will 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 very easy to adopt, without the need for information transmission. In our data, the technology is sufficiently complex that most individuals would not adopt it on their own. For example, Table 2 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

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

where $\mathbb{E}\left(b \mid s_\theta\right)$ is the expected benefit of adopting the new technology for an untreated individual, conditional on receiving signal s_θ. Owing to the normality assumptions in (1) and (3), we have (see e.g., DeGroot, 2004, Theorem 1, page 167):

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

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

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

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

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

where

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

is the cdf (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 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 where treated farmers received two-year training, then, for the same p, the precision of information on the quality of technology is higher than in a village where treated farmers received one-year training. Therefore, the untreated farmer is more likely to adopt the new technology.[7]

3 Background and experimental design

We would now like to 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 our experimental design.

[7] Observe that we can easily extend the results of Proposition 1 when untreated farmers are heterogeneous in costs c, i.e., 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.

3.1 Background

In Bangladesh, improving agricultural productivity has been critical in facilitating poverty alleviation and food security. Rice is Bangladesh's largest crop and the main staple food for the 180 million people of the country. Furthermore, rice cultivation accounts for 48 percent of total 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 percent, while its share of national income is one–sixth. In other words, rice plays a critical role in Bangladesh (Faruqee, 2012).

Moreover, the demand for rice has been constantly rising in recent years due to the rising population. Despite sustained rice production in recent years, 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 increase to 37 million.

Crop yields in Bangladesh remain low because of limited adoption of new innovations by farmers. The SRI is a climate-smart, agro-ecological methodology aimed at increasing the yield of rice by changing the management of plants, soil, water, and nutrients (see Uphoff, 2003; Africare, 2008). Specifically, SRI involves early, careful transplanting of single seedlings with wider spacing, in fields that are not continuously flooded and have optimum water management, with actively aerated soil containing a higher proportion of organic matter. Proponents of SRI claim its use increases yield, 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).

Despite these clear benefits, the adoption of SRI has been slow and farmers rarely implement SRI on more than half their land (Moser and Barrett, 2006; Fafchamps et al., 2018). There are various reasons for this sluggish adoption of SRI. First, SRI is a system rather than a technology, as it contains a set of principles and guidelines. In other words, SRI is a methodology for growing rice, which differs from traditional practices. There is evidence that farmers are constrained by information and skills necessary for local adaptation, and must bear greater risks under SRI than traditional cultivation methods (Barrett et al., 2018). Second, SRI fields visibly differ from traditional rice fields; hence, social norms and conformity pressures could also discourage the ultimate adoption decision.

SRI is new among most farmers in Bangladesh, with only limited scale experimentation by BRAC. A pilot study by Islam et al. (2012) finds higher yields of around 50%

among those who adopt SRI in Bangladesh.[8] SRI has been widely practiced in many developing countries, and studies based on observational data show significant yield gains and increased profits associated with the adoption of SRI (see, for example, Stoop et al., 2002; Barret et al., 2004; Sinha and Talati, 2007; Stygler, et al., 2011; Takahashi and Barrett, 2014).

3.2 Experimental Design

In collaboration with BRAC, our Randomized Controlled Trial (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 1 depict the location of these districts in Bangladesh. The 182 villages were randomized into 62 villages, which were randomly assigned to a control treatment without training, and 120 villages, which were randomly assigned to each of the two treatments ($T1$ and $T2$). In the current paper, we do not use the information of these 62 control villages, and thus, focus on the 120 "treated" villages.

[*Insert Figure* 1 *here*]

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 the Boro season[9] to generate a list of all farmers in these villages who cultivated rice in the previous Boro season, and owned at least 0.5 acre but not more than 10 acres of land.[10] 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. The farmers were also briefly informed about the purpose of the training. All farmers received a fee (BDT

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

[9] The 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).

[10] Farmers with less than 0.5 acres of land are excluded, as they are usually seasonal farmers. Similarly, farmers with more than 10 acres were not considered for SRI training, as they were land-rich farmers in the context of Bangladesh.

300) for their participation in the training. This fee is slightly more than the rural agricultural daily wage. The trainers were existing BRAC agricultural officers at the field level. Agricultural scientists who had previously worked on 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-year training. A set of 60 villages were randomly allocated to one-year training (referred to as $T1-$ villages) and treated farmers only received one-time training in year 1. This training lasts for a day, and is disseminated via 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, i.e., they received training in both the first and second year. There were two training sessions in year 2. In the first session, the topics of discussion were the case studies on successful adoption from first year of 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 SRI in year 1. In the second session, BRAC trainers provided the same training as in year 1, and attempted to ensure that farmers have a clear understanding of the key principles and practices of SRI.

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.[11] On average, there are 18 treated farmers and 12 untreated farmers in each village. Table 1 displays the number of farmers who were randomized into treated and untreated groups. Among the 3,630 farmers in these 120 villages, 2,226 were treated (1,060 for one-year training and 1,166 for two-year training) and 1,404 were untreated (745 reside in $T1-$ villages and 659 in $T1-$ villages).

[*Insert Table* 1 *here*]

[11] The selection of farmers was based on geographical locations, and 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 SRI, their proximity makes it easier to organize and collect responses from participants.

4 Data and econometric model

4.1 Data and balance checks

Initially, a baseline survey was conducted among 3,630 farmers in 120 villages, focusing on collecting individual characteristics, such as average education, cultivable land, household size, and occupation. Table B1 in Appendix B presents the different characteristics of treated and untreated farmers. We see that the level of education is quite low (on average, farmers attend school up to year 4), household size is relatively high (5 members on average), and on average, farmers work on their own farms.

Let us now check if the randomization between the treated and untreated farmers has been successful. We want to see if farmers' characteristics, namely, age, income, education, occupation, land size, and household size, 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.

In Appendix B, Table B1 reports the balance checks in terms of observable characteristics between treated and untreated farmers and Table B2 reports the same results but between $T1-$ and $T2-$treated farmers. We see no differences in observable characteristics between these different treatments. Overall, treated and untreated farmers are observationally similar within the treatment villages and $T1-$ and $T2-$treated farmers are observationally similar between villages.

4.2 Outcome variable

Our outcome variable is the adoption decision of untreated farmers, which we denoted by the binary variable A in the theoretical model. In the econometric model, we denote it by $y^{NT}_{i,v,t}$. It is a dummy variable that takes the value of 1 if an untreated 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 (where treated farmers received one-year training) and in $T2-$treated villages (where treated farmers received two-year training). Consequently, in both $T1-$ and $T2-$treated villages, $y^{NT}_{i,v,t}$ will take two values, one at $t = 1$ and one at $t = 2$. Thus, given that the random allocation of training of farmers occurred either once in year 1 (treatment $T1$) or twice in years 1 and 2 (treatment $T2$), we have a panel in which the same 3,630 farmers are observed for two years.

Table 2 reports the average adoption rate by treatment 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, as shown by Fafchamps et al. (2018). Second, at the end of year 2, farmers with two-year training adopt more than those with one-year 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, $y^{NT}_{i,T2,2} = 9.53\% > 6.89\% = y^{NT}_{i,T1,2}$). This suggests that exposure to farmers receiving more training makes an untreated farmer more likely to adopt SRI technology.

[*Insert Table* 2 *here*]

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 an untreated farmer i living in village $v = T1, T2$, his exposure rate is defined as

$$p := p^T_{i,v} = \frac{N^T_{i,v}}{N^T_{i,v} + N^{NT}_{i,v}} \times 100\% \tag{14}$$

where $N^T_{i,v}$ and $N^{NT}_{i,v}$ refer, respectively, to the number of treated farmers and untreated farmers in village v, where the untreated farmer i resides. Thus, $p^T_{i,v}$ is the percentage of treated farmers in village v, where the untreated farmer i resides. According to our experimental setting, there are two key properties of $p := p^T_{i,v}$. First, $p^T_{i,v}$ is not indexed by time because the randomization is implemented only once; therefore, the exposure rate does not change over time. As a result, $p^T_{i,v}$ is a time-invariant variable, which 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 the same village v, their exposure rate $p^T_{i,v}$ should be the same.

In Figure B1 in Appendix B, we examine the distribution of p^T_v between $T1-$villages (blue dashed curve) and $T2-$villages (red solid curve) to see if they are the same across different villages. We observe that they look very similar and (roughly) normally distributed. To test this similarity, in Table B3 in Appendix B, we perform a $t-$test and the Kolmogorov–Smirnov (K-S) test.[12] We see that there is no significant

[12] The Kolmogorov–Smirnov test (K–S test) is a nonparametric test of the equality of continuous, one-dimensional probability distributions that can be used to compare two samples.

difference in p_v^T between $T1-$ and $T2-$villages, and 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 very 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:[13]

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

where $y_{i,v,t}^{NT}$ is a dummy variable equal to 1 if the untreated farmer i, residing in village $v = T1, T2$ adopts SRI technology in year $t = 1, 2$, and 0 otherwise. It corresponds to $A \in \{0, 1\}$ in the theoretical model, and captures the binary choice of an untreated farmer i, residing in village v, who decides whether to adopt SRI technology in year t or not. Moreover, $p_{i,v}^T$ is defined in (14), $X_{i,v}^{'}$ are the exogenous characteristics of farmer i, residing in village v,[14] including 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 different 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 3 displays the results of the estimation of equation (15). In columns (1), (2), and (3), we 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

[13] 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.

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

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 training of either one or two years.

[*Insert Table* 3 *here*]

Next, we split the 120 villages into two groups: $T1-$treated villages where farmers received one-year training and $T2-$treated villages where farmers received two-year training, and estimate equation (15) separately for each sample of 60 villages. As predicted by part (*ii*) of Proposition 1, we see that 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%.

To visualize these results, we report the 95% confidence intervals of each regression for the whole distribution of $p_{i,v}^T$. Figure 2 displays this distribution for the 120 villages (blue curve), the 60 $T1-$ villages (red curve), and the 60 $T2-$ villages (green curve). If we consider this distribution for the 120 villages, we see that in villages where $p_{i,v}^T$, the percentage of treated farmers is 40%, the (predicted) adoption rate of untreated farmers is 5% while, 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 very small and the curve is very flat for $T1-$villages, while the effect is large and the curve is very steep for $T2-$villages.

[*Insert Figure* 2 *here*]

Remember (see Section 3.1) that SRI technology is very complex, as it requires changing the management of plants, soil, water, and nutrients. In addition, SRI is a low-input-intensity approach to rice cultivation, which increases yield but requires more time and attention from the farmer (Uphoff, 2003). Despite the prevalence of rice cultivation and the abundance of labor in Bangladesh, its requirement of superior management skills makes it unsuitable for all farmers(Moser and Barrett, 2006). Furthermore, it is a new technique among farmers in Bangladesh. Therefore, naturally, farmers are 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 3 shows that providing longer training in SRI technology has not only a direct impact on the trained farmers themselves (Fafchamps et al., 2018), but also spillovers to other farmers in the village who did not receive any training (the untreated). The effect is relatively important. The more an untreated farmer is "exposed" to farmers with two-year training, the more likely that he will adopt SRI technology.[15]

According to our model, this is because the $T2-$treated farmers provide the untreated farmers with *accurate* and *precise* information on SRI technology. Indeed, in our model, lower the variance σ_θ^2 of the "noise" ε_θ of the quality of technology, the more accurate the information transmitted to the untreated farmer, and the more likely that the latter adopts SRI technology.

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 where he lives, the more likely he is to adopt SRI technology. We believe that the accuracy of information transmission regarding SRI technology the primary channel through which this occurs. In this section, we investigate this mechanism further by running regressions on different sub-samples.

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 B4 in Appendix B provides the interactions between farmers in the 120 villages. We find that 69% farmers discuss agricultural issues at least once a month and 39.84% 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

[15] Observe that our RCT was conducted in five districts of Bangladesh: Kishoreganj, Pabna, Lalmonirat, Gopalgonj, and Shirajgonj, which are mainly rural and poor, and 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.

(14). We define the exposure rate as follows:

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

where $d = \{daily, weekly, monthly, yearly, never\}$ is the frequency of discussion between farmers, so that $p^T_{i,v,d}$ is the percentage of treated farmers in village v who interact at a frequency d with the untreated farmer i who also resides in village v. Clearly, $N_{i,v,d} \leq N^T_{i,v}$, since among all treated farmers residing in the same 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 $p^T_{i,v}$. The results are presented in Table 4.

First, in comparison to Table 3, 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-year training, we find that compared to Table 3, 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 either daily or 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 the treated farmers only receive one-year training, they 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 the treated farmers, the lower is the variance σ^2_θ of the "noise" ε_θ of the quality of technology and the more accurate is the information transmitted to the untreated farmer.

[*Insert Table* 4 *here*]

5.2.2 Effect of financial relationships

In our baseline survey, we collect 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 B5 in Appendix

B supplies some summary statistics. On average, each untreated farmer has 4.5 peers with whom he/she has borrowed or lent money or discussed financial issues. Furthermore, 70% of farmers have lent or borrowed money from each other and 52% of them 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 have 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 $p^T_{i,v}$. The results are presented in Table 5.

We obtain similar results to the case of farmers who frequently discussed agricultural issues with untreated farmers (Table 4). Indeed, contrary to Table 3, famers with one-year training have a significant impact on the adoption rate of untreated farmers. In addition, the magnitude of the effect is larger than in the general case (Table 3). This is 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 training, who discusses financial issues with untreated farmers, provides information about SRI technology to an untreated farmer, the latter considers this information as accurate, and is therefore, more likely to adopt SRI technology.

[*Insert Table* 5 *here*]

5.2.3 Effect of relatives

Finally, we examine another important social relationship of untreated farmers, that of relatives, to understand if they are effective in diffusing information about SRI technology. In our baseline survey, of the 30 farmers in each village, each untreated farmer has two relatives, on average. We now define the exposure level as follows:

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

where $N^T_{i,v,relative}$ is the number of treated farmers who are related (by blood or marriage) to farmer i residing in village v. As above, we estimate (15) but with $p^T_{i,v,relative}$ instead of $p^T_{i,v}$. Table 6 presents the results.

In comparison to Tables 4 and 5, we obtain a different result here; one-year trained farmers have no significant impact on the adoption rate of treated farmers. Although untreated farmers may discuss agricultural or financial issues with other farmers, they do not trust their relatives to have accurate information about the quality of SRI technology, and thus, only the duration of training matters in this case. It could also be that relatives do not discuss any new information but focus on family issues, or other matters.

[*Insert Table* 6 *here*]

To summarize, our three analyses (treated farmers, either relatives or with whom the untreated farmer discusses agricultural or financial issues) 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. In particular, we have shown that the *source* and the *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 3), in the absence of a special relationship between treated and untreated farmers, only those with two years of training were providing accurate information about the quality of SRI technology. This is also true for relatives. 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 regarding agricultural or financial issues.

6 Role of risk aversion in technology adoption

Thus far, our analysis has provided a clear explanation of how and why untreated farmers adopt SRI technology. However, the analysis lacked one crucial element: the degree of risk aversion of untreated farmers. It is well-known that risk aversion plays an important role in technology adoption (see, e.g. Ghadim et al., 2005; Koundouri et al., 2006; Genius et al., 2013), especially in poor districts in Bangladesh, where 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 of Section 2 to consider when farmers are risk-averse instead of risk-neutral. For simplicity, we assume that conditional on meeting a $\theta-$type agent, all individuals share the same constant von Neumann-Morgenstern utility function with constant absolute risk aversion (CARA):

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

where z is defined by (7) while $\delta > 0$ is the risk-aversion parameter.[16] As each farmer faces a conditional distribution, $b \mid s_T$, of the benefit of adoption, the utility level $U(. \mid \theta)$ 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 (see, e.g., Sargent, 1987, pp. 154-155) that preferences (16) can be equivalently represented by the following utility function:

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

Equation (17) implies that the expected utility $\mathcal{U}(A \mid \theta)$ of adoption conditional on meeting a $\theta-$type agent is a *mean-variance* utility, i.e., it only depends on the conditional mean and conditional variance of 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 ($\delta \to 1$). Observe that (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 she 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

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

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

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

Proposition 2 *Assume that* (4) *and* (18) *hold and that all farmers exhibit risk aversion captured by the 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, higher the degree of risk aversion, the lower is the impact of the exposure rate on the adoption rate of untreated farmers, i.e.,

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

Parts (*i*) and (*iii*) of Proposition 2 have exactly 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.[17] 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 fraction 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 big 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.

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

6.2.1 Measuring risk

To capture the risk attitude of farmers, in the baseline survey, a simple gamble-choice task was introduced to all *treated* farmers across 120 villages.[18] The design of the lottery game is similar to that of Binswanger (1980). Specifically, this gamble game is a one-period incentivized game that involves assigning different payoffs in each option. The payoffs and risk classification are summarized in Table B6 in Appendix B. In the baseline survey, each treated farmer was given a form with the first three columns of payoffs in Table B6. They were 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 has a 50-50 chance to win a high or low payoff.

From Table B6, farmers could be classified into different risk attitude according to their choices. For example, farmers who choose option 1 are classified as extremely risk averse people. Indeed, choosing option 1 will give a 100-taka payoff with probability 1. Although the payoff is the lowest across all six alternatives, it is a guaranteed payment, which involves no risk. On the other hand, farmers who choose option 6 are classified as risk lovers, or negative risk averse. In option 6, they have a 50% chance of earning an extremely high payoff of 400 taka, or get nothing. Although options 5 and 6 have the same expected payoff, option 6 has a higher payoff variance; therefore, only risk-loving farmers would choose option 6.

We say that a (treated) farmer is a risk lover if he chooses option 6, and risk-averse otherwise. We find that 30.77% of farmers are risk lovers while the rest (69.23%) are risk averse.

However, *untreated* farmers did not participate in this game; therefore, we do not know their risk attitude. To predict the risk attitude 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, in Table B1 in Appendix B, we see that treated and untreated farmers are, on average, similar in terms of 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 attitude of untreated farmers, we run a regression on the

[18] Contrary to the literature that shows risk aversion has a negative effect on technology adoption (see, 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 *directly* measure the risk attitude of farmers through a lottery game. For example, Koundouri et al. (2006) measure the "production" risk of each farmer by calculating the variance of each farmer's profit and by assuming that farmers who experience high variance in their current profits face higher production risk.

risk attitude of treated farmers, as a function of their observable characteristics, as follows:

$$\delta^T_{i,v} = \gamma_0 + X'_{i,v}\beta + \theta_v + \epsilon_{i,v} \tag{21}$$

where $\delta^T_{i,v}$ is a dummy variable that takes the value of 1 if the treated farmer is risk averse (i.e., chooses option 1-5 in Table B6) and 0 if he is a risk lover (i.e., chooses option 6 in Table B6). The vector X_i includes all household and individual level characteristics that are likely 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 B7 in Appendix B displays the results of the estimation of equation (21). The signs obtained are intuitive: older farmers are more risk averse while farmers that are more educated and farmers with bigger families are less risk averse.

Let $\widehat{\gamma_0}$ and $\widehat{\beta}$ be the OLS estimates of γ_0 and β in equation (21). Then, an untreated farmer i's risk attitude, $\widehat{\delta}^{NT}_{i,v}$, is estimated as follows:

$$\widehat{\delta}^{NT}_{i,v} = \widehat{\gamma_0} + X'_{i,v}\widehat{\beta} \tag{22}$$

Equation 22 relies on our assumption that farmers who have similar individual characteristics (in terms of age, income, household size, cultivable land, education, and occupation) have similar risk attitudes. In Table B8 in Appendix B, we check the number of farmers predicted correctly, according to (21) where $\widehat{\delta}^T_{i,v}$ gives the *estimated* value of risk attitude for treated farmers from the estimation of (22) while $\delta^T_{i,v}$ gives the "real" value of risk attitude of the treated farmers. Remember that a $\delta^T_{i,v}$ equal to 1 means risk aversion, while $\delta^T_{i,v} = 0$ means risk loving. All the values on the diagonal of Table B8 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 71.34%. The overall hit rate is 63.1%, which is quite high, and thus, gives us confidence in our measure of risk attitude of untreated farmers.

Figure B2 in Appendix B displays the distribution of (predicted) risk preferences for treated (dashed curve) and untreated (solid curve) farmers. Overall, the risk preferences for both groups are similar.[19] This suggests that there is no difference in risk preference between treated and untreated farmers in the villages.

[19] A Kolmogorov-Smirnov test (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 under the 95% confidence level. Therefore, the distribution of $\widehat{\delta}_{i,v}$ for treated farmers is very similar to that for untreated farmers.

After we calculate the predicted riskiness 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 the treated farmers is 30.77%, we define the first 69.23% untreated farmers as risk averse, and assign them a value of 1, and the remaining 30.77% of untreated farmers as risk lovers, and assign them a value of 0.

6.2.2 Econometric model

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

$$y_{i,v,t}^{NT} = 1 = \alpha_0 + \alpha_1 p_{i,v}^T + \alpha_2 \widehat{\delta}_{i,v}^{NT} + \alpha_3 (\widehat{\delta}_{i,v}^{NT} \times p_{i,v}^T) + X_{i,v}^{'} \beta + \theta_t + \epsilon_{i,v,t} \tag{23}$$

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.

6.2.3 Empirical results

Table 7 displays the results of the estimation of equation (23), which has the same structure as Table 3.

[*Insert Table* 7 *here*]

Focusing on column (3), in which the estimation has been performed for the 120 villages, we find that $p_{i,v}^T$, which is the percentage of untreated farmers, has a positive and significant impact on the probability of adopting SRI technology for the untreated farmers residing in the same village. Moreover, as predicted by Proposition 2, in column (1),[20] we find that risk-averse untreated farmers are less likely to adopt than risk-lover untreated farmers. Finally, in column (3), we see that the cross effect $\widehat{\delta}_{i,v}^{NT} \times p_{i,v}^T$ is significant and negative, as predicted by Proposition 2. This means that when the fraction 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.

Let us now focus on the effect of the different treatments $T1$ and $T2$ in columns (4)-(9). We see that the results are similar to that of columns (1)-(3), although

[20] We use column (1) to measure the direct effect of risk aversion on adoption because, in columns (2) and (3), the cross effect $\widehat{\delta}_{i,v}^{NT} \times p_{i,v}^T$ affects this. Indeed, even though, in columns (2) and (3), $\widehat{\delta}_{i,v}^{NT}$ has a positive sign, the net effect of risk aversion on adoption is negative, since $\widehat{\alpha}_3$ is much higher than $\widehat{\alpha}_2$.

the effect of risk aversion on the adoption rate is not significant in the $T1-$treated villages. Furthermore, the effect of $p^T_{i,v}$ on the adoption rate of untreated farmers is now positive and significant in both $T1$ and $T2$ treatments. This is different to the results obtained in the case of risk neutrality (Table 3) in which this effect was significant in only $T2-$treated villages. This may indicate that when controlling for risk aversion, even less-trained farmers have an impact on the adoption rate of untreated farmers, highlighting the importance of risk attitude in the adoption rate.

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.

7 Peer effects

Thus far, we have tested the models developed in Sections 2 and 6 in which we highlight the importance of the quality and reliability of information about SRI technology, transmitted from treated farmers to untreated farmers. To better understand these results, we now investigate how the *adoption decision* of treated farmers (and not the percentage of treated farmers, as above) affects the *adoption decision* of untreated farmers. In other words, we would like to test a peer-effect model.

7.1 General results with risk-neutral agents

Essentially, we estimate the following pooled OLS equation:

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

where, as before, $y^{NT}_{i,v,t}$ is a dummy variable equal to 1 if the 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 fraction of treated farmers living in the same 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 the same village v who adopt SRI technology at time t. The problem of estimating (24) with OLS is that $p^T_{i,v,t,A}$ is endogenous; hence, the OLS estimation would be biased. Therefore, we will instrument $p^T_{i,v,t,A}$ by $p^T_{i,v}$, the fraction of treated farmers in village v, which is exogenous, and run a 2SLS estimation.

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

$$p^T_{i,v,t,A} = \omega_0 + \omega_1 p^T_{i,v} + X'_{i,v}\beta + \theta_t + \mu_{i,v,t} \tag{25}$$

From the estimation of equation (25), we obtain $\widehat{p}^T_{i,v,t,A}$. In the second stage, we estimate the following equation:

$$y^{NT}_{i,v,t} = \alpha_0 + \alpha_1 \widehat{p}^T_{i,v,t,A} + X'_{i,v}\beta + \theta_t + \epsilon_{i,v,t}. \tag{26}$$

Thus far, we have shown that information (and beliefs) is crucial in understanding the adoption rate of untreated farmers. An alternative mechanism could be the greater importance of cost, that is, untreated farmers do not adopt SRI technology because it is too costly. If our information explanation holds true, α_1 should be positive and significant (or more exactly, if we use $\widehat{p}^T_{i,v,t,NA}$, the share of treated farmers who do *not* adopt instead of $\widehat{p}^T_{i,v,t,A}$, then α_1 should be negative and significant). If adoption decisions are driven by the cost of SRI technology, then α_1 should be insignificant, since the share of treated farmers who do not adopt should not have any impact on the individual adoption rate of untreated farmers.

Table 8 presents the results of the first stage. We find that, independently of which villages are treated, the first stage is very strong, as there is a positive and very significant impact of $p^T_{i,v}$, the fraction of treated farmers on $p^T_{i,v,t,A}$, the fraction of treated farmers living in the same village v who adopt SRI technology at time t.

[*Insert Table* 8 *here*]

Table 9 reports the results of the second stage. We find that the results are relatively similar to that of Table 3, where the peer effects are only significant for the 120 villages and for the $T2-$treated villages. More importantly, we find that α_1 is positive and significant, or if we had used $\widehat{p}^T_{i,v,t,NA}$, the share of treated farmers who do *not* adopt instead of $\widehat{p}^T_{i,v,t,A}$, we would have obtained α_1, which would be negative and significant. This confirms our mechanism that information transmission(and beliefs)has a key impact on the adoption rate of untreated farmers. Moreover, if the treated farmers have adopted SRI technology, their impact on the adoption probability of untreated farmers is even higher than when they have not adopted. For example, an increase of 10% in the exposure rate in a village leads to an increase in the average adoption rate of SRI technology for an untreated farmer residing in the same village by 2.2% (Table 3). If we now consider an increase of 10% in *treated farmers who have adopted SRI technology* in a village, the resulting increase in the adoption rate of the untreated farmers is 3.61% (Table 9).

As in our baseline econometric specification (Table 3), even when farmers with only one-year 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 the untreated farmers is driven by the transmission of information about the quality and cost of SRI technology. Indeed, farmers, with *two-year training* and who *adopt* SRI technology have the most accurate and reliable information about this (complex) SRI technology.

[*Insert Table* 9 *here*]

7.2 General results with risk-averse agents

Our final empirical exercise is analyzing how including farmers' risk aversion affects our peer-effect results. The first stage is exactly the same as in (25). In the second stage, we estimate the following equation:

$$y^{NT}_{i,v,t} = \gamma_0 + \gamma_1 \widehat{p}^{T}_{i,v,t,A} + \gamma_2 \widehat{\delta}^{NT}_{i,v} + \gamma_3 (\widehat{\delta}^{NT}_{i,v} \times \widehat{p}^{T}_{i,v,t,A}) + X'_{i,v}\beta + \theta_t + \epsilon_{i,v,t}. \tag{27}$$

where, both for the direct effect and the cross-effect, we instrument $p^T_{i,v,t,A}$ by $p^T_{i,v}$. Table 10 reports the results of the second stage regression. We find that the results are qualitatively similar to those reported in Tables 9 and 7.

[*Insert Table* 10 *here*]

8 Conclusion

This study aimed to understand how poor rural farmers in Bangladesh adopt SRI technology, which is a complex and risky technology and differs from traditional rice cultivation practices. This is an important issue in a country where rice cultivation accounts for 48 percent of total 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 percent, 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. We also consider risk-averse untreated farmers who are 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 adoption.

We test these predictions by conducting a field experiment for 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 (repeated) two-year training should provide more accurate and reliable information about SRI technology than those with (one-time) one-year training. We use the exogenous variation across villages both in terms of treatment and percentage of treated farmers, by studying how the "exposure" rate (i.e., the fraction of treated farmers in each village) of an untreated farmer affects his decision to adopt SRI technology.

We find that the percentage of two-year trained farmers 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 training have no significant impact on the adoption rate of untreated farmers. 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 of the two-year training program. We also consider the impact of treated farmers who adopt SRI technology on the adoption rate of untreated farmers (peer effects) 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 the two-year trained farmers on the adoption rate of untreated farmers is smaller than for less risk-averse untreated farmers.

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 complexity of this technology, more risk-averse farmers are not only less likely to adopt it, but also are less "influenced" by their peers who have been trained, and/or have adopted this technology.

In terms of policy implications, we believe that when a new technology is as complex as the SRI, 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 adopt it. Indeed, these policies have not only a direct positive effect on farmers' adoption rate (Barrett et al., 2018; Fafchamps et al., 2018) but also an indirect positive effect on untreated farmers who live nearby, through spillover effects.

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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:

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

(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:

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

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,

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

By 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 will now show that, when risk aversion is higher, non-treated individuals adopt less, i.e:

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

Using (5), (A.1), and (A.2), we get:

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

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 of the noise: farmers who are exposed to $T2-$treated farmers receive a more precise signal on 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 get:

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

Factorizing $\varphi\left(\Delta(\delta, \sigma_T)\right)$ in the right-hand side of (A.6), we find that (20) holds if and only if the following inequality holds:

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

By definition of the 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: Density distribution of p_v^T

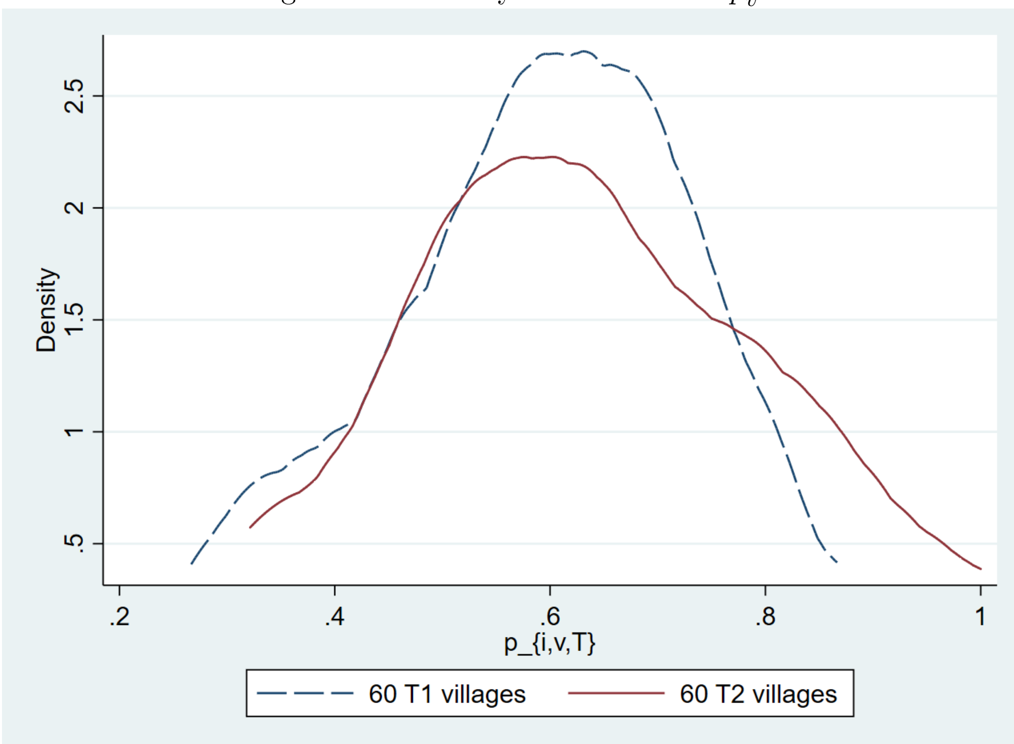


Figure B2: Density distribution of predicted riskiness of treated and untreated farmers

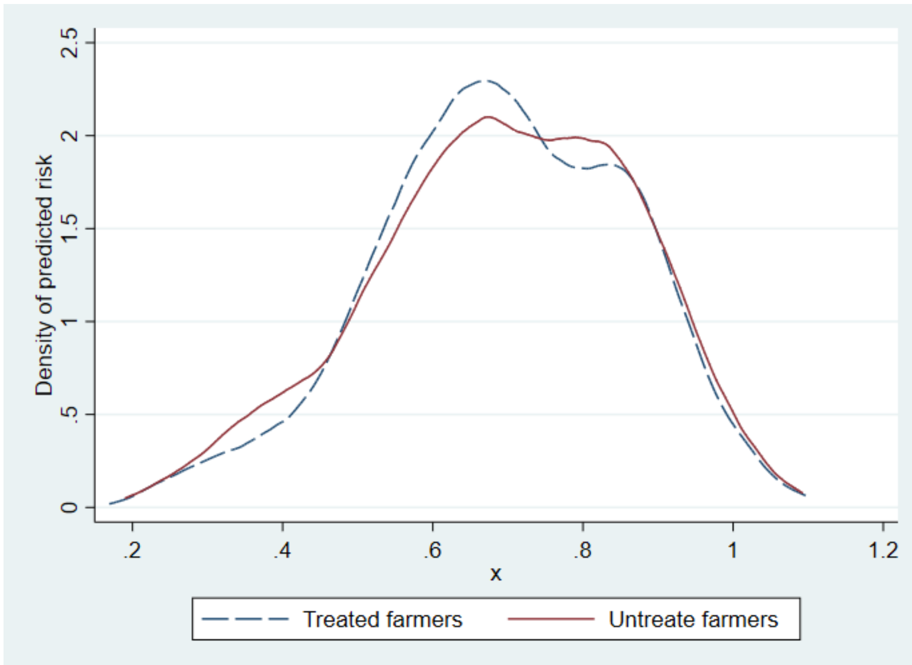


Table B1: Balance checks between treated and untreated farmers

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	

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

Table B2: 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	

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

Table B3: 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

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

Table B4: 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 B5: 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 B6: The 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%

Table B7: 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

Note: 1. The dependent variable is the dummy variable, it is 1 if a farmer is risk averse, who chooses option 1-5 in Table B6. It is 0 if a farmer is risk loving, who chooses option 6 in Table B6.

2. Education^2 is the squared value of education

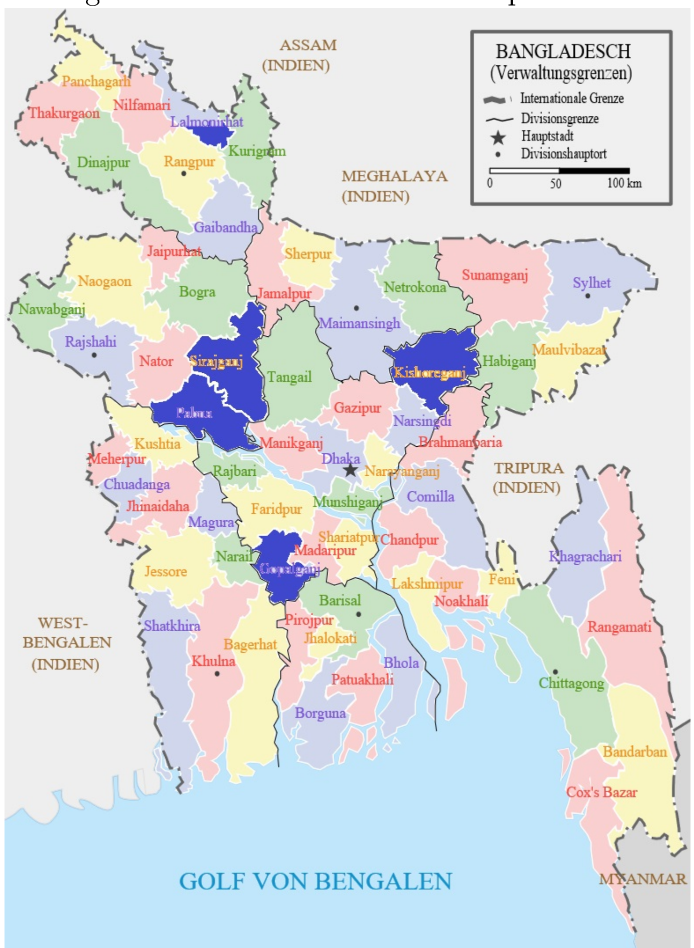
3.The regression contains village dummies to capture village-level fixed effects. Standard errors are reported in parentheses. Standard errors are clustered at the village level.

Table B8: Predicted versus real value of risk attitude

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

Note: $\delta^T_{i,v} = 1$ means risk aversion and $\delta^T_{i,v} = 0$ means risk loving

Figure 1: Districts in the field experiment



Note: The five blue areas are the districts where the RCT experiments were conducted

Figure 2: Distribution of $p^T_{i,v,t}$ for the 120 villages and the 60 $T1-$ and $T2-$villages

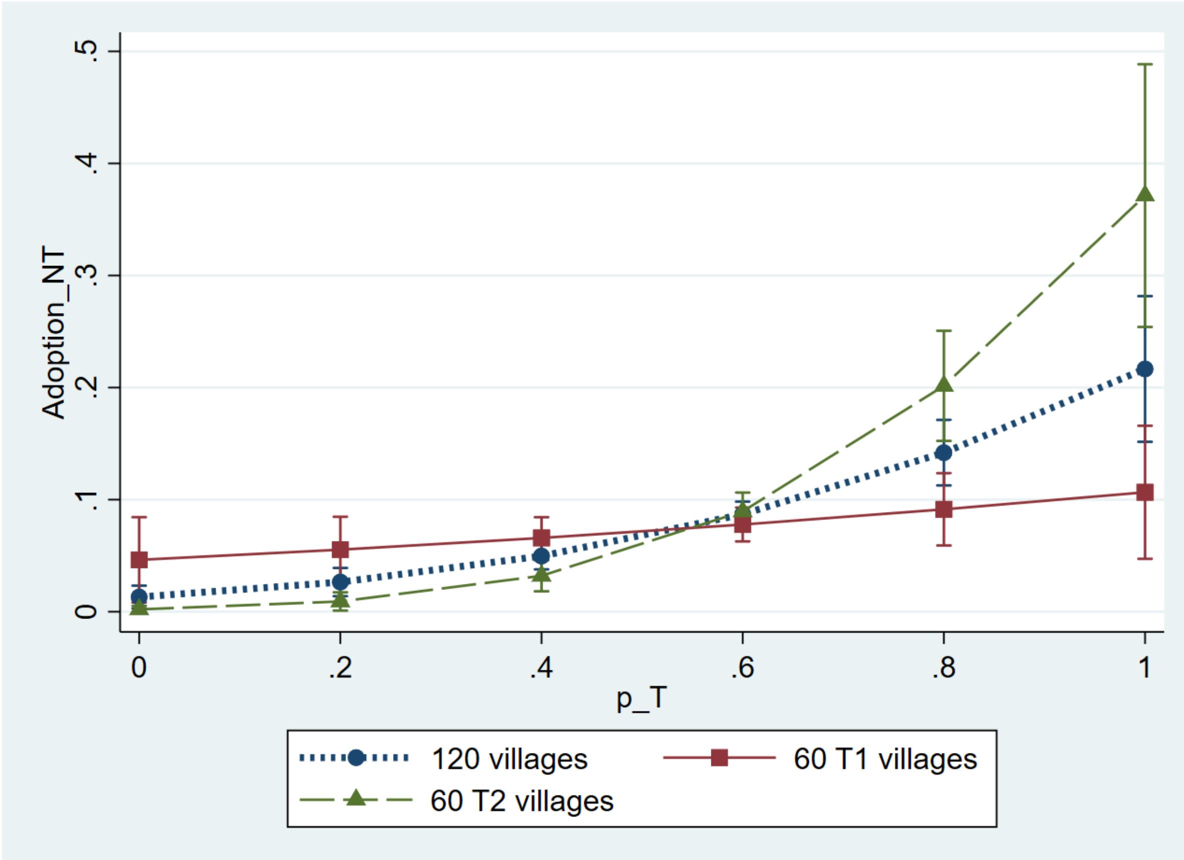


Table 1: Sample distribution of treatment villages

	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 2: Adoption rates of farmers by treatment group and time

Category	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 farmersin T1 villages	7.03%	6.89%	745
Untreated farmers in T2 villages	7.59%	9.53%	659

Table 3: 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)
$p_{i,v}^T$	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 to 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. Standard errors are reported in parentheses.
*** p<0.01, ** p<0.05, * p<0.1.

Table 4: The 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 year. It is a dummy variable that equals to 1 if an untreated farmer adopted in year t ($t = 1, 2$), and 0 if he did not. $p^T_{i,v,myn}$ is the share of treated farmers to whom a farmer discussed either monthly (m), yearly (y) or never (n). Each regression includes year dummies and all the six control variables that are in Table 3. Standard errors are clustered at the village level. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Impact of finance-related peers on adoption rate of untreated farmers

	120 villages			60 villages (T1)			60 villages (T2)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$p^T_{i,v,finance}$	0.318***	0.318***	0.296***	0.218***	0.218***	0.196***	0.422**	0.422**	0.433**
	(0.103)	(0.103)	(0.104)	(0.0602)	(0.0603)	(0.0538)	(0.182)	(0.182)	(0.185)
Year dummy		0.0051	0.004		-0.0055	-0.0062		0.0165	0.0139
		(0.0121)	(0.0121)		(0.0139)	(0.0139)		(0.0203)	(0.0200)
Age/10			-0.0087*			-0.0213***			0.0032
			(0.005)			(0.0063)			(0.0071)
log(Income)			-0.0161			-0.0301*			-0.0043
			(0.0123)			(0.0167)			(0.0179)
log(Land)			0.0153			0.0063			0.0356**
			(0.0094)			(0.0115)			(0.0166)
Education			0.0006			0.0002			0.0006
			(0.0016)			(0.0023)			(0.0024)
Household size			0.0022			0.0052			-0.0013
			(0.0037)			(0.005)			(0.0052)
Occupation			0.0181			0.006			0.0353
			(0.0168)			(0.0240)			(0.0218)
Observations	2,808	2,808	2,808	1,490	1,490	1,490	1,238	1,238	1,2138

Note: The dependent variable is the adoption decision of an untreated farmer. It is a dummy variable that takes the value of 1 if an untreated farmers adopted the technology at time t ($t = 1, 2$), and it is 0 if he did not adopt. Standard errors are clustered at the village level.
Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Impact of relatives on adoption rate of untreated farmers

	120 villages			60 villages (T1)			60 villages (T2)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$p^T_{i,v,relative}$	0.159	0.158	0.179*	0.0916	0.0917	0.101	0.232	0.232	0.273*
	(0.0981)	(0.0982)	(0.0943)	(0.0928)	(0.0928)	(0.0880)	(0.167)	(0.167)	(0.161)
Year dummy		0.0048	0.0033		-0.0056	-0.0067		0.0164	0.0131
		(0.0121)	(0.0121)		(0.0139)	(0.0138)		(0.0203)	(0.0201)
Age/10			-0.0093*			-0.0213***			0.0014
			(0.0051)			(0.0063)			(0.0075)
log(Income)			-0.0292**			-0.0376**			-0.0247
			(0.0127)			(0.0174)			(0.0179)
log(Land)			0.0214**			0.0109			0.0417**
			(0.0097)			(0.0113)			(0.0175)
Education			0.0009			0.0002			0.0014
			(0.0017)			(0.0023)			(0.0025)
Household size			0.0034			0.0058			0.0006
			(0.0037)			(0.0053)			(0.0051)
Occupation			0.0191			0.0099			0.0287
			(0.0175)			(0.0241)			(0.0258)
Observations	2,808	2,808	2,808	1,490	1,490	1,490	1,318	1,318	1,318

Note: The dependent variable is the adoption decision of an untreated farmer. It is a dummy variable that takes the value of 1 if an untreated farmers adopted the technology at time t ($t = 1, 2$), and it is 0 if he did not adopt. Standard errors are clustered at the village level. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Effect of risk on adoption

	120 villages			60 village (T1)			60 villages (T2)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{\delta}_{i,v}^{NT}$	-0.0288**	0.118*	0.121*	-0.0133	0.161*	0.172**	-0.0446**	-0.0103	0.0289
	(0.0127)	(0.0684)	(0.0683)	(0.0173)	(0.0846)	(0.0834)	(0.0207)	(0.105)	(0.105)
$\widehat{\delta}_{i,v}^{NT} \times p_{i,v}^{T}$		-0.196*	-0.193*		-0.285**	-0.291**		0.0396	-0.0158
		(0.116)	(0.116)		(0.145)	(0.142)		(0.177)	(0.177)
$p_{i,v}^{T}$		0.356***	0.365***		0.249*	0.268**		0.408***	0.467***
		(0.100)	(0.101)		(0.127)	(0.126)		(0.148)	(0.148)
Year dummy		0.0042	0.0026		-0.0052	-0.0057		0.0145	0.0113
		(0.0114)	(0.0113)		(0.0150)	(0.0148)		(0.0172)	(0.0171)
Age/10			-0.0095**			-0.0219***			-0.0001
			(0.0044)			(0.0053)			(0.0069)
log(Income)			-0.0285***			-0.0356***			-0.0179
			(0.0105)			(0.0134)			(0.0166)
log(Land)			0.0206**			0.0057			0.0406***
			(0.0085)			(0.001)			(0.0139)
Education			0.0009			0.0003			0.0009
			(0.0014)			(0.0019)			(0.0022)
Household size			0.0045			0.0056			0.0044
			(0.0031)			(0.0036)			(0.0048)
Occupation			0.0153			0.0065			0.0315
			(0.0153)			(0.0209)			(0.0221)
Observations	2,808	2,808	2,808	1,490	1,490	1,490	1,318	1,318	1,318

Note: The dependent variable is the adoption decision of an untreated farmer. It is a dummy variable that takes the value of 1 if an untreated farmers adopted the technology at time t ($t = 1, 2$), and it is 0 if he did not adopt. Standard errors are clustered at the village level. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: 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

Note: The dependent variable is the adoption decision of an untreated farmer. It is a dummy variable that takes the value of 1 if an untreated farmers adopted the technology at time t ($t = 1, 2$), and it is 0 if he did not adopt. Standard errors are clustered at the village level.Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 9: Second stage of peer effects for risk-neutral farmer

	120 villages			60 village (T1)			60 villages (T2)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{p}^{T}_{i,v,t,A}$	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

Note: The dependent variable is the adoption decision of an untreated farmer. It is a dummy variable that takes the value of 1 if an untreated farmers adopted the technology at time t ($t = 1, 2$), and it is 0 if he did not adopt. Standard errors are clustered at the village level.Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Second stage of peer effects for risk averse farmer

	120 villages			60 villages (T1)			60 villages (T2)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\widehat{\delta}_{i,v}^{NT}$	-0.0280**	0.0510	0.0509	-0.0130	0.0924*	0.0785	-0.0436**	-0.0093	0.0027
	(0.0141)	(0.0373)	(0.0377)	(0.0192)	(0.0486)	(0.0498)	(0.0208)	(0.0571)	(0.0570)
$\widehat{\delta}_{i,v}^{NT} \times \widehat{p}_{i,v,t,A}^{T}$		-0.172	-0.166		-0.327**	-0.291*		0.0509	0.0570
		(0.119)	(0.119)		(0.157)	(0.159)		(0.178)	(0.179)
$\widehat{p}_{i,v,t,A}^{T}$		0.483***	0.468***		0.426***	0.282*		0.518***	0.677***
		(0.110)	(0.119)		(0.148)	(0.164)		(0.162)	(0.172)
Year dummy		0.0457***	0.0436***		0.0178	0.0043		0.0778***	0.0938***
		(0.0123)	(0.0133)		(0.0156)	(0.0170)		(0.0192)	(0.0207)
Age/10			-0.0042			-0.0196***			0.0097
			(0.0048)			(0.0066)			(0.0067)
log(Income)			0.0012			-0.0279			0.0445**
			(0.0134)			(0.0184)			(0.0198)
log(Land)			0.0091			0.0026			0.0183
			(0.0099)			(0.0131)			(0.0150)
Education			-0.0006			0.0002			-0.001
			(0.0016)			(0.002)			(0.0024)
Household size			0.0016			0.0047			-0.0019
			(0.0037)			(0.0053)			(0.005)
Occupation			0.0053			0.0059			0.0101
Observations	2,808	2,808	2,808	1,490	1,490	1,490	1,318	1,318	1,318

Note: The dependent variable is the adoption decision of an untreated farmer. It is a dummy variable that takes the value of 1 if an untreated farmers adopted the technology at time t ($t = 1, 2$), and it is 0 if he did not adopt. Standard errors are clustered at the village level. Standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.