As Good as the Networks They Keep?: Improving Farmers' Social Networks via Randomized Information Exchange in Rural Uganda

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Abstract

We examine an intervention randomized at the village level in which women were encouraged to add other (randomly assigned) women farmers to their existing social networks. We show that the intervention significantly increased the productivity of women except for individuals who were already in the highest quartile of productivity, and that there were significant spillovers to male farmers as well. Importantly, the net benefits to women were higher than in a concurrently-run conventional agricultural training program. Examining the mechanisms by which the program was successful, we focus on the importance of adding weak links to women's networks.

JEL: O, Q

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1 Introduction

Programs aimed at increasing agricultural productivity are regarded as some of the most powerful means to reduce poverty (Asfaw et al., 2011; Thirtle et al., 2001). Essential elements in the early stages of such programs are the dissemination of information from centers of science and research to farmers and the subsequent diffusion of this new knowledge among farmers. Thus, the effectiveness of agricultural extension depends not only on the technical merits of a new technology, but on the quality of the interactions between extension agents and the farmers they train, as well as the subsequent interactions between trained and untrained farmers (Anderson and Feder, 2007, pp. 2346). However, despite the expectation that trained farmers will disseminate information to the remainder of the village, many studies over the past forty years have documented a poor retention of learned information and even poorer diffusion of information across farmers (Feder et al., 2004; Leonard, 1977; Sinha and Mehta, 1972). For example, Sinha and Mehta (1972) report that farmers who learned about a new innovation passed on only 28% of what they had learned to the farmers they spoke to directly. In contrast, Conley and Udry (2010), report that Ghanian pineapple farmers were able to improve yields through contact with farmers in their own network, suggesting that diffusion is not a broad social phenomenon but, a more narrow, network–based phenomenon. Indeed, belonging to strong social networks is correlated with earlier adoption and better outcomes (see Isham, 2002; Munshi, 2004, for example).

Unfortunately, although the poorest farmers often stand to benefit the most from new technologies, they are often outside of the very networks that would allow them to learn about these new technologies. This is particularly true of women who provide a significant amount of labor to African agriculture, are responsible for most food crop production, and typically experience significantly lower yields than men, even for the same crops (Quisumbing, 2003; Udry, 1996; Udry and Goldstein, 2006). At the same time, there is evidence that female networks are typically less oriented towards cash crops than those of males' (Edmeades et al., 2008; Katungi et al., 2006). Thus, women—who provide significant inputs into agriculture—

are among the poorest people in most communities, are relatively less productive than men, and may suffer from large "structural holes" in their production networks (Hoang et al., 2006). This suggests that agricultural extension programs could be augmented by attempts to improve the dissemination of information to women and the dissemination of information within women's production networks.

This paper examines an intervention, the Social Network Intervention (SNI), to study the impact of new network links combined with information designed to improve the yields of female cotton farmers in rural Uganda. Specifically, we look at the impact of weak links in spreading information within a network that is not complete. In this setting, women and men are growing a new crop (cotton); average productivity is low and female farmers are significantly less productive than male farmers (Baffes, 2008). We compare the impact of our intervention to a standard training program, also randomized at the village level. Both interventions aimed to introduce the same agricultural information but through different methodologies.[1] The standard training (TR) disseminated information via biweekly visits during critical stages of the season: pre-planting, planting, pesticide use, harvesting, marketing, while the SNI intervention disseminated information through one information session involving peer learning.

In each village in the sample we randomly selected 7 women and 7 male farmers to be surveyed in two crop years. In villages that received the TR intervention, each of the surveyed farmers received biweekly visits during the critical stages of the season. In villages that received the SNI intervention, the 7 sampled female farmers and an additional 7 female farmers were invited to one information training session. In this session women participated in games in which incentives were given for learning and remembering new cotton farming facts that they learned from their peers. At the conclusion of the session, women were paired with a randomly chosen female grower from the list of invited women. Each paired woman was given a picture of her partner, and reminded to talk to her partner throughout the season. Importantly, although women were randomly paired, we randomly re-paired women when the women in the pair already knew one another well. Thus, our intervention combined information on productive cotton farming techniques and exogenously–assigned *new* network links. Men were not directly trained via the SNI method, but, as they also belong to social networks, we examine the indirect impact of the SNI intervention on males' outcomes. Furthermore, because the two interventions were randomized orthogonally, we can examine the impact of the social network intervention, the standard training, and the cumulative impact of the two training programs.

Difference in difference estimates of cotton yields show that cotton farmers in villages that received the SNI experienced large gains over the baseline compared to cotton farmers in control villages for all farmers other than the highest performing farmers (namely, those with starting yields greater than 400 kilograms per hectare, where the average starting yield is 180 kilograms per hectare). The gains are not solely the result of a direct treatment effect, because men in the treated villages also saw significant increases in their yields. The TR intervention also increased yields, but conversely, men gained significantly *more* than women with traditional agricultural extension training. Because we provided information and new links to every female farmer in our intervention, we cannot perfectly identify the separate effect of information versus network effects, however, the structure of the data do allow us to investigate the mechanisms by which the intervention worked including: new links, changing network composition, new knowledge, and learning from others.

We show that our intervention was successful in creating new links between female cotton growers, who, prior to the SNI intervention, did not know one another, but following the intervention, reported sharing of cotton growing information. Despite the success of these new links, we do not see a significant impact in the total network size of women after the SNI treatment. However, we do observe a change in the composition of females' networks: the proportion of women in females' networks increased. This suggests that the SNI affected network structures rather than network size. Additionally, when we asked women to list both the individuals they interact with as well as a list of key cotton growers (with whom they may or may not interact), we see a greater overlap between the two lists after the SNI intervention. We also see an increase in the percentage of female cotton growers in the "key" growers list after the intervention.

Knowledge about cotton farming (as measured by a quiz in the second year) also improved among treated women, but the gains appear to account for only about a quarter of the total gains in yields. And finally, for a small subsample of women in which we observe yields for both of the paired members at the base– and end–line, we find that being paired with a higher–yielding farmers led to significant increases in yields, whereas being paired with a worse farmer had no impact on yields. This suggests that the pairing may have led to additional learning beyond the initial information that we disseminated.

This is one of two recent research studies on social networks in the development literature that uses a randomized encouragement design aimed at exogenously changing the actual social networks of females in an agricultural network.[2] Field et al. (2013) is another current study that exogenously perturbs new microfinance groups in Bangladeshi villages by varying the meeting frequency of these groups to understand the impact of network effects on loan repayment. Where our study and Field et al. (2013) attempt to alter the structure of the network, other studies, such as Leonard (2007), Duflo and Saez (2014) and Marmaros and Sacerdote (2002) use natural variation in networks to identify network effects, and still others use other sources of variation to understand when and how networks can affect decisions. Breza (2014) use natural variation in loan repayment incentives to study the impact of a peers' repayment on an individual's timing of payments, and show evidence of network effects. Banerjee et al. (2013) exploit the natural random variation found in the network centrality of each individual who was initially exposed to their micro finance program to identify network effects. BenYishay and Mobarak (2014) aslo examine information flows in agriculture and alter which member of the network received an incentive to spread information. They find that peer farmers (average village members selected by a local focus group), when provided with a small incentive, are more effective at promoting adoption than lead farmers (leaders identified by the same community focus group) or government-employed extension workers.

Recent literature on networks suggests that the structure of a network and the roles of individuals within that network can have important implications (Bramoullé et al., 2014; Jackson and Golub, 2012). We focus on weak links: individuals who do not know each other well, but who may have different sources of valuable information. These nascent and weaker links are also more likely to propagate new information (Granovetter, 1974, 2005; Santos and Barrett, 2005), and may therefore be more useful to individuals and the network as a whole than expanding the raw size of the network.

This paper is organized as follows: the following section provides a background on the research context and describes the data collection and randomization. Section 3 outlines a simple model to motivate the empirical estimation of the SNI program in Section 4. Section 5 tests the potential channels by which the SNI is affecting outcomes. Section 6 concludes.

2 Data

This setting in Uganda is a perfect place to study the role of social networks and social learning for a variety of reasons. First, farmers are growing a crop that was only recently reintroduced. Due to civil war and political unrest, cotton production ceased under Idi Amin's regime when the majority of the Indians who managed Uganda's businesses were persecuted and expelled. As a result, at least one generation passed in which no transfer of knowledge occurred for many cash crops. It is precisely in these circumstances, where technologies are nascent, that social networks and social learning should have their greatest impacts. Second, since reintroduction, the government and ginners have tried to improve productivity using various extension services, but none of these education campaigns were targeted to women. Baffes (2008) shows that male-heads of households yields are three to four times that of female-head of households' yields in Uganda. Thus, formal sources of information have not circumscribed the opportunities for social learning. Third, women who grow cotton undoubtedly belong to social networks, but the chances that their existing networks include optimal numbers of women cotton farmers are low. In general, female networks are typically less oriented to cash crops than those of men (Edmeades et al., 2008; Katungi et al., 2006). While males' days are delineated by morning work and afternoon discussion with other males, women's days are often a simultaneous combination of work, child-care, and household responsibilities. A wider range of household responsibilities raises the cost and reduces the availability of acquiring new production techniques. Responsibilities close to the home also restrict females from participating in geographically dispersed social networks and community projects, and force their relationships to be dependent on the collaborative tasks that they perform with other females, i.e. collecting water, fuel, and harvesting crops (Maluccio et al., 2003). Thus, existing social networks for women may not be optimally designed for learning about cotton.

As females supply 70-80% of agricultural labor in rural Uganda and are responsible for up to 80% of food crop production (Tanzarn, 2005), low female productivity is a tremendous loss to national welfare. Other studies have looked at possible reasons for these productivity differentials (Quisumbing, 2003; Udry, 1996; Udry and Goldstein, 2006). They have tested the impact of lower quality inputs, time constraints, disparate production functions, and property rights, where ownership of one's property seemed to be a significant explanation for gender differentials in productivity.

To investigate the role of networks we introduced two randomized interventions in cotton farming villages in the North and Northeast of Uganda. A household survey was administered in randomly selected villages in the two major cotton growing regions of Uganda: North (13 villages) and Northeast (13 villages). The baseline data was collected from February through May 2009. The second round was collected in March through May 2010. We interviewed randomly selected households that grew cotton in 2008 stratified by headship gender.[3] The household survey consisted of questions on household demographics, input use and outputs for cotton and other crops grown, household controls for financial assets, including sales from cotton, and a separate survey instrument on farmers' social networks regarding adoption, cultivation and marketing of cotton.

In order to capture the effect of the social network intervention (SNI) and training intervention (TR), we randomly assigned these treatments by village. By randomizing the SNI and TR programs across villages, we are able to measure the effect of the SNI treatment, the TR treatment, and the complimentary effect of both treatments against a control group. The SNI was targeted to all female cotton farmers who were surveyed in SNI villages and the TR was targeted to all surveyed farmers (men and women) in TR villages. A total of 13 villages received SNI, and 17 villages received TR. Table 1 represents the sample sizes across the two treatments. While only some villages were selected to receive one of the two programs, every village in our sample was visited by our team. Therefore, the effects from our results cannot be attributed purely to a behavioral response to our visits.

The SNI was directed at female-headed households who were invited to participate in an information meeting and were paired with a "buddy" in their village area with whom they were encouraged to develop an agricultural link. All female-headed cotton farmers were invited to participate in the games and included in the pairing exercise (not only the female–headed households randomly selected for our survey). The pairing occurred by first stratifying the cotton growing participants into distinct geographic areas of the village,[4] and then randomly pairing individuals within these areas.[5] The goal was to add a network link, and, therefore, we re-selected a pair if the individuals were already neighbors or if both women were to receive training in training villages. Thus, in villages that received the training intervention, each pair consisted of at least one female who would receive training and one female who would not receive training. Each pair received a Polaroid photo of themselves and their partner, identified cultivation issues, chose a collaborative goal, and set potential times when they would meet to exchange information. They then presented this to their peers at the group information meeting. In this way they were strongly encouraged to build a relationship to discuss cotton growing. Individual participants appeared to take the pairing exercise seriously. Since the new link is not someone with whom the woman previously had a strong link, the new links can be seen as weak links, potentially changing the composition of the network, not just the size.

For the training intervention (TR), all households selected for the survey were visited by a local agronomist for five training stages in 2009:[6] pre-planting in March through April; planting in May; pesticides use in July through August; harvesting in October through November; and marketing in December and January. All farmers in the village, including women, were invited to the training sessions, and care was taken to make sure that female participation was encouraged and welcomed.

Table 3 summarizes the cotton data for the sample, both in the baseline and follow-up, and Table 2 shows the yields in the baseline by treatment group. The yields are well balanced in the baseline. The average Ugandan cotton farmer in our sample produces between 100 and 200 kilograms per year.[7] Standard deviations for the yield of cotton (kilograms per acre) and level of cotton (total kilograms produced) are particularly high. This is due to the stark drop-off in production from 2009 to 2010, as well as to yields being right-skewed, as seen in Figure 1. The number of acres used to grow cotton is between one-half to one acre on average. Though land is not seen as scarce, the labor required to clear and prepare the land renders yield per acre a more accurate measure of productivity than total production. Also of note is that output per kilogram of seed was 52 kilograms in 2009 and fell to 37 kilograms in 2010. In 2010, both the Northern and Eastern parts of Uganda suffered from rain deficits drought. Average rainfall was below average for approximately 11 months 57% of the time (Namara and Bitekerezo, 2010).

3 Model

Households in this setting are growing cotton without the benefit of significant previous experience due to the interruption caused by civil war. We expect households to learn by doing (learning from their own experiences) as well as from the experiences of others in their community. In addition, they can learn from agricultural extension agents. Female-headed households experience lower yields in part because they have fewer opportunities to learn from others, and they may not be able to take full advantage of the training offered by extension officers. To illustrate the potential impact of our interventions, we use the standard target-input model (Foster and Rosenzweig, 1995; Jovanovic and Nyarko, 1996) with a simple addition as a way of framing our hypotheses about the role of learning by doing, extension programs and learning from others in this setting. The conventional exposition of the model focuses on the choice of input levels (such as fertilizer). However, in this context, the greatest opportunities for learning are on issues of timing. Farmers are learning *when* to prepare, plant, thin, weed, apply pesticides and harvest.[8]

In the target-input model, the farmer chooses an input level (or in our case a time to apply inputs), θ_{it}, in order to maximize profits. Profits are larger when the farmer's chosen input is closer to the target, $\tilde{\theta}_{it}$. Profit q for farmer i in period t is:

$$q_{it} = 1 - (\theta_{it} - \tilde{\theta}_{it})^2 \tag{1}$$

$\tilde{\theta}_{it}$ is determined by $\tilde{\theta}_{it} = \theta^* + \mu_{it}$, where μ_{it} is i.i.d. normally distributed with variance σ_μ, and θ^* is the optimal target. To maximize expected profit, the farmer will seek to learn θ^*. After choosing the input, given the best available information, the farmer can observe the output and infer the correct level for that time period. In other words, by farming in period $t-1$, the farmer observes output $q_{i,t-1}$, infers $\tilde{\theta}_{i,t-1}$, uses this noisy observation of θ^* to update his or her beliefs over θ^* to θ_t and then chooses θ_t as the input in period t.

The precision of the farmer's estimate of the target (θ_t) improves as the farmer observes more outcomes and updates the estimate with each new outcome. The number of outcomes observed at time period t is S_{t-1} and, applying Bayes' rule, the variance of the farmer's estimate can be shown to evolve as follows:

$$\sigma_\theta^2 = \frac{1}{\rho_{i0} + \rho_\mu S_{t-1}} \tag{2}$$

where ρ_{i0} is the precision (inverse of the variance) of a farmer's estimate in the initial period and ρ_μ is the precision of the observations of the target input ($\rho_\mu = \frac{1}{\sigma_\mu^2}$). Maximization of expected outputs implies $E_t(q_{it}) = 1 - \sigma_\theta^2 - \sigma_\mu^2$. σ_μ^2 does not change over time, but the variance of the farmer's estimate (σ_θ^2) falls over time, resulting in increased expected profits.

In the above model, the farmer cannot experiment over time or within his or her own plots; each period yields exactly one observation on the target, and the usefulness of that observation is independent of the input chosen (the farmer learns the same amount if he or she is close as if he or she is far from the best guess).[9] However, if the farmer can observe the outcome of other farmers, that information can be used to update the prior. Assume that the farmer can observe his or her neighbor's target level in period t, $\tilde{\theta}_{jt} = \theta^* + \mu_{jt}$ with additional noise ξ_{jt}. The precision of this new information is an inverse function of the variance of the signal $\rho_v = \frac{1}{\sigma_\mu + \sigma_\xi}$. The variance of the farmer's guess evolves as follows:

$$\sigma_\theta^2 = \frac{1}{\rho_{i0} + \rho_\mu S_{t-1} + \rho_v N_{t-1}} \tag{3}$$

where N_{t-1} is the total number of trials of other farmers observed before period t. Expected output is now a function of learning by doing (S_t) and learning from others (N_t). The standard result on the value of learning by doing and learning from others is that the expected profit increases at a decreasing rate with the number of own trials and with the number of other trials observed:

$$\frac{\partial Eq_{it}\left(S_{t-1}, N_{t-1}\right)}{\partial S_{t-1}} > 0 \tag{4}$$

$$\frac{\partial^2 Eq_{it}\left(S_{t-1}, N_{t-1}\right)}{\partial S_{t-1}^2} < 0 \tag{5}$$

$$\frac{\partial Eq_{it}\left(S_{t-1}, N_{t-1}\right)}{\partial N_{t-1}} > 0 \tag{6}$$

$$\frac{\partial^2 Eq_{it}\left(S_{t-1}, N_{t-1}\right)}{\partial N_{t-1}^2} < 0 \tag{7}$$

This model is parsimonious and gives some intuition in situations where farmers do not experiment within their own plots during a season. In situations where farmers have small plots and the random draws of natural events are the same across the whole plot, it makes little sense to experiment within a plot during a season. In our setting, 80% of female farmers grow cotton on only one parcel, which is, on average three quarters of an acre. In addition, because pests spread easily within a plot, spillovers would reduce the value of any within plot experiments (Harper and Zilberman, 1989; Regev et al., 1976). Thus, dividing the plot in half does not provide twice the information, but the farmer can learn from the observations from his or her neighbors' plots if the random draws are independently distributed across farmers.[10] Naturally, if two plots are next to each other, pests can move as easily as they would within a plot and this later assumption may not strictly hold. Thus, we suggest that the error term μ_{it} is correlated across farmers, where $\gamma_{ij} = 2COV(\mu_i, \mu_j)$.[11] The error of the signal learned from a neighboring farmer is $\sigma_\mu^2 + \sigma_\xi^2 + \gamma_{ij}$ and the precision is a function of the covariance of the error term for farmers i and j.

The variance of the farmer's guess now evolves in the following manner:

$$\sigma_\theta^2 = \frac{1}{\rho_{i0} + \rho_\mu S_{t-1} + \sum_{t=0}^{t-1} \sum_J \frac{1}{\sigma_\mu^2 + \sigma_\xi^2 + \gamma_{ij}}} \tag{8}$$

Thus:

$$\frac{\partial E q_{it}\left(S_{t-1}, N_{t-1}\right)}{\partial \gamma} < 0 \tag{9}$$

$$\frac{\partial E q_{it}\left(S_{t-1}, N_{t-1}\right)}{\partial \sigma_{\mu}^{2}} < 0 \tag{10}$$

$$\frac{\partial^{2} E q_{it}\left(S_{t-1}, N_{t-1}\right)}{\partial \gamma \partial S} < 0 \tag{11}$$

$$\frac{\partial^{2} E q_{it}\left(S_{t-1}, N_{t-1}\right)}{\partial \sigma_{\mu}^{2} \partial S} < 0 \tag{12}$$

In other words, the value of accumulated and new learning from neighbors is smaller when the covariance in the error terms is higher (as would be the case between strong ties) and when the noise associated with observing neighbors' plots is higher.

Note that with these additional terms, N does not denote the size of the network nor the total number of observations. Rather, N is a function of the quality of each link in the network and the number of previous observations. Intuitively, we expect that the covariance of the error of the target input (γ_{ij}) is larger when farmers are closer together (strong links) and the variance of the observation error (σ_{μ}^{2}) is smaller. Thus, stronger links imply more precise information flows, however, following the intuition of Granovetter (1974), these links provide less information (compared to the farmer's own observations) than weak links.

Our experiment increased the precision of information flows between two weakly linked-individuals while leaving the level of communication between strongly-linked individuals unchanged. Importantly, we test this implication in a setting where accumulated learning levels are low, and therefore additional information should still have a high marginal value.

We test the above four hypotheses using the following reduced form regression:

$$q_t(SN_t, TR_t) = \alpha + \beta t + \rho SNI_t + \mu TR_t + \nu SNI \cdot TR_t + \eta SN \cdot TR \cdot t + \gamma SN_t \cdot t + \delta TR_t \cdot t + u_t \tag{13}$$

The estimated $\hat{\gamma}$ captures the average treatment effect (ATE) of the SNI, that is:

$$\gamma = [E(y|SNI = 1, t = 1, TR = 0) - E(y|SNI = 1, t = 0, TR = 0)]$$

$$-$$

$$[E(q|SNI = 0, t = 1, TR = 0) - E(q|SNI = 0, t = 0, TR = 0)]$$

$\hat{\delta}$ captures the effect of TR on yields, denoted by q. The estimation of η in Equation 13 is equivalent to a triple difference across both treatments and time, and γ captures the double difference across time and SNI. We expect both δ and γ to be greater than 0 and, in particular, we expect these coefficients to be larger for farmers with less effective pre-existing social networks: women and farmers with low yields in the baseline. Since both TR and SNI trained farmers from the same training modules, we expect η to be negative, suggesting that TR and SNI are not additive programs.

4 Empirical Estimation of Program Effects

We measure the impact of the SNI in two ways. First, we measure the impact that the SNI had on increasing the probability that a household maintained cotton as a cash crop despite the reported drought. Second, we estimate the impact that the SNI had on output, and intermediate input decisions for farmers.

4.1 Choice to Grow Cotton

We first look at the impact of the SNI and TR on farmers' decisions to grow cotton, clustering standard errors at the village level to account for within village correlations between households' error terms on outcomes. Table 4 estimates the effect of the SNI and TR on remaining a cotton grower between 2009 and 2010, despite the adverse weather shocks mentioned earlier. We use a Probit model to predict the probability that a grower continues to grow cotton. Column 1 indicates that the presence of the SNI in a village positively and significantly impacted a farmer's decision to continue to grow cotton, where the outcome variable is 0 if the individual ceased to grow cotton in 2010, and equals 1 if they planted cotton. The marginal effect of the program is an 18% increase in the probability of remaining a cotton grower. On the other hand, introducing training to a farmer increases the probability of remaining a cotton grower by only 11% and is statistically insignificant.

Table 4, Column 2, estimates an Ordered Probit model, where the ordered outcomes are: not planting, which is 0, planting but realizing no yields is assigned a 1,[12] and planting and realizing positive yields is assigned a 2. The estimates reveal the significance of the SNI and TR in affecting the outcome variable. The coefficients show that SNI and TR increased the probability that households choose to plant as well as the probability that they achieved a non-zero yield.

4.2 Cotton Output

Table 5 estimates the reduced form effect of SNI and TR on cotton yields (Equation 13). We run the estimations with yields in levels in Columns 1. We are interested in the coefficients on $SNI \cdot t$, and $SNI \cdot TR \cdot t$: that is, the pure impact of the SNI intervention over time on outcomes, and the interaction effect of SNI and TR. Note that we also check that the estimated coefficients on SNI and TR are insignificant, demonstrating the validity of the random selection. Similarly, the t variable measures whether there is a significant time trend in yields, which we expect to be negative given the drop in yields between 2009 and 2010. The estimated impacts of $SNI \cdot t$ and of $SNI \cdot TR \cdot t$ on total yield (Column 1) are insignificant. However, estimates are significant under the log yields specification in Column 2. The estimate of the interaction term between SNI on TR program is insignificant.

As Figure 1 indicates, yields are right skewed and the average producer, before and after the treatments, produces less that 400 kilograms per acre. We would not expect a significant impact from SNI or TR for the highest producers, who are already far above the mean yield and this is reflected in significance of the SNI treatment on log yields but not on yields. Columns 3, 4 and 5 examine those individuals who experienced yields of 400 kilograms per acre or less in 2009 (excluding the top 11% of our original sample). Column 3 of Table 5 estimates Equation 13, conditional on having grown 400 kilograms of cotton per acre or less in 2009. Columns 4 and 5 show the same sample divided into male and female–headed households.

Note that, despite the SNI being a randomly assigned program, in 2009, women who were selected for the SNI happened to be worse off than those who did not. With the small sample sizes to which our field experiment was constrained, the possibility that our treatment group is statistically different than our control as we continue to sub-divide groups is not surprising. This baseline difference is controlled for in the difference-in-difference framework.

The SNI treatment has a positive and significant impact on households who harvested less than 400 kilograms of cotton in 2009 as shown in Column 3. On average, females in the SNI groups gained a total 97 kilograms per acre, while men gained 64 kilograms per acre, conditional on their starting yields. Considering that the average yield across 2009 and 2010 was 160 kilograms per acre, the gains from SNI are economically significant for both men and women, but more so for women, while the reverse is true for TR. The interaction effect between SNI and TR is negative (though not significant) indicating that the joint effect of the SNI and TR is less than the sum of each intervention's independent effect. Note that, since 2010 was a bad year compared to 2009, most of the gains we observe from the two interventions are actually avoided losses, not net gains.

5 Network, Knowledge or Learning from Others?

The SNI had a significant and positive impact both for lower yielding female farmers and indirectly for males, and, as such, is a useful program for policy consideration. The social network intervention is significantly less expensive (one visit per year versus five) than the training intervention, achieves at least the same results for yields on average, and achieves better results for females than the standard training program.[13] However, it is also helpful to understand the mechanism through which the intervention affected yields.

There are three ways in which the SNI could have affected yields: changes in the size or structure of individuals' networks, knowledge expansion as a result of participation in the information meetings and knowledge expansion as a result of learning through new network links. We consider the evidence for these impacts.

5.1 Network Variables

We implemented a social network survey that asked respondents to state the size of their cotton growing network, to list individuals in their cotton growing network, and to state the status of those individuals. The responses to these questions were used as measures of an individual's social network. Recall that men in SNI villages experienced learning spillovers, but we only matched women with new network members, therefore, this section focuses on females in our sample.

We report seven measures of network size and quality, measured at the individual level: (1) stated network size, (2) actual size based on a count of names provided, (3) the proportion of people in the network who grew cotton in the previous season, (4) the proportion of the people in the network who are female, (5) the average age of members of the network, (6) the average education level of network members, (7) the proportion of members whose plots neighbor the respondents' plots.

Table 6 reports the effects of SNI on each of these network variables, where female is equal to 1 if the respondent is female and 0 if male. The stated size and actual size of women's networks increased in SNI villages, but the coefficients are not significantly different from zero, nor are they significantly different from the expected value of the intervention: one new link. (Note that the positive coefficient for networks in the baseline for treated villages applies only to men.) However, stated and actual size of network may be a poor indicators of network size, particularly because there is often listing fatigue when a survey asks for an open–ended list of names.

We do observe that the composition of females' networks changed as a result of the intervention. Table 6 shows that women's networks had a greater proportion of women and fewer educated individuals after the intervention. These are, essentially, equivalent findings, as women have 4.3 of years of education as opposed to males who have 5.1 (t–test=6.117).

The effect of the SNI on social networks is a natural first stage for an instrumented regression in which we use the predicted change in social networks as a dependent variable in the yield equation. However, the results in the second stage are not significant at the 5% level, both because our measures of social network size are noisy and because there was greater attrition on the social network survey than for the yields survey. The first stage estimation does suggest that increasing the proportion of women in a woman's social network by 10 percentage points leads to an increase in yields of 26 kilograms per acre.[14]

One other compositional shift that we see is in the connectedness of female participants. We looked at the percentage overlap between individuals listed as cotton contacts and names regarded as important for cotton growing but not necessarily as contacts. We find an increase in the overlap of these names from 26% to 31% between 2009 and 2010. In addition, we found that, in the second year, women were more likely to be listed as 'important growers.' We did not collect this list for individuals in the control villages and, therefore, we cannot compare these results to results in the control villages.

5.2 Knowledge Expansion

As part of the survey in the second round, we gave each farmer a quiz on the information taught in the meetings for the SNI. Using this quiz, we can devise a measure of information correctly learned and stated using the results from this quiz. We calculate the percentage of correctly answered questions out of 12 questions on the information points taught (see appendix). This data can only be analyzed in a cross sectional regression, taking advantage of the randomization to identify program impacts. As a check on our cross sectional results, we also examine the yield regressions in the same framework. Given that the assignment of programs is random, the impact of SNI and TR should not be statistically different whether we use panel or cross-sectional data for the full sample.

Table 7 shows that both the training and SNI improved the scores of participants by between 4 and 5%, or about half a question. Given that the initial score is about 40% (four and half questions correct out of twelve), this is not an unimportant improvement. However, it is not the case that farmers remembered everything that they learned in either the training or the networking games. Using quiz scores over the whole sample from 2010, we estimate that farmers who scored 10% higher on the test experienced 27 kg per acre greater yields (30 kg for a restricted sample of women). This suggests that an increase of 5% on the test would increase yields by around 15 kg per acre. In comparison, we estimate that female yields increased by between 60 and 90 kg, suggesting that improved knowledge is only directly responsible for a small proportion of the gains.

In addition, there is a subset of females who participated in the pairing meetings and the social network survey who were unable to attend the initial information games. These individuals were paired, but did not directly receive or learn the information taught via the games. We create another treatment variable, Information, which assumes a value of one if an individual attended the meetings and was paired, and assumes a value of zero if the individual did not attend the meetings but was paired with a new link in round two. If $SNI \cdot t$ is insignificant after controlling for Information, then we can conclude that the program's effect is operating via the information games, and not through the pairings. Of course, attendance in the information meetings is voluntary, and therefore, Information is endogenous. Women who attend may have had fewer time constraints, or had poorer yields and more reason to attend.

Table 8 includes the estimates of the Information variable in the panel model for females. Information is not a significant contributor to the gains in female yields while SNI remains significant. This suggests that attending the information sessions alone was not the only mechanism by which the SNI improved yields for females. Note that those who attended the meetings were, on average, better farmers before the intervention than those who missed the meeting.

Taken together, the results on test scores and attendance suggest that the meetings may have improved test scores, but that, at most, the increase in yields from this additional information explains only about a quarter to a fifth of the gains observed, as we found in the cross-sectional estimates of SNI's effect on information learned. Note that no men attended the information meetings and their gains in yield were still significant.

5.3 Learning from Pairs

While we know that the SNI works through information and through pairing, we cannot separate out the two effects with our RCT design. However, we can test whether individuals actually talked to their pair and if the pairing took hold. For a small subset of our data, we can also look at whether being paired with a higher yielding farmer had a differential impact as compared to being paired with a lower yielding farmer.

First, we look at whether individuals in the SNI intervention mentioned their pairs in the social network survey. We find that no participants mentioned talking to their pair in the 2009 baseline survey, confirming our strategy of forming weak links. However, in 2010, 26% of our SNI participants mentioned their pair, suggesting that the SNI pair did have an effect on networking. Women in the control villages added, on average, two and a half new names to their rosters in the second year. However, given that an average of 96 individual names were mentioned across all surveys within a village, there is only a 3% probability of selecting one individual name in a random process with two and a half draws out of sample of 96. Thus, the finding that 26% of households mentioned their pair is notably different from what we would expect from a random process.

In addition, we have a small subset of SNI recipients in which both individuals in a pair were surveyed about their agricultural production. Using these 23 pairs (20 individuals in 10 pairs and one triplet), we can look at whether being paired with a better farmer, as measured by yields in 2009, leads to an increase in yields. Namely, learning would suggest that, controlling for initial yields, a farmer's yield should increase if she is paired with a farmer who has higher yields than herself, but not if she is paired with a lower–yielding farmer.[15]

Column 1 of Table 9, is a regression of farmers' yield differentials over time on initial yield (Own Yield) and on the difference between a farmer and her pair's initial yields (Partner-Own.) In addition, we include an interaction term, Partner-Own*Low indicating that the farmer had a lower yield than their partner. This allows us to test that farmers' yields are increasing if paired with a better performing farmer but also that they are not decreasing if paired with a worse performing farmer. In Column 1, we see that the coefficient of Partner-Own*Low is positive, though insignificant, which suggests that it is poorer farmers who improve their yields when paired with better farmers. However, the effect of Pair-Own when Low=0, namely when the pair is a lower performing farmer, is negative but insignificant. We also estimate a model using a dichotomous explanatory variables for Partner-Own, Partner-Own>0. Partner-Own now assumes a value of one if the farmer's starting yield was less than her partner's, and Partner-Own<0 assumes a value of one if the farmer's starting yield was greater than her partner's. Column 2 shows a positive and significant effect of being paired with a higher yielding farmer, while being paired with a lower yielding farmer has a positive but insignificant effect on a farmer. This suggests that being paired with a better farmer is helpful, but the effect is not increasing in the pair's initial yield differential.

6 Conclusion

Our research estimates the effects of a social network–based agricultural training program for women and compares its effectiveness at increasing yields to a traditional extension training program. We find significant effects of the SNI intervention for all farmers with the exception of the highest yielding farmers. Our estimated impacts of the SNI are positive and significant for farmers who were producing up to 400 kilograms per acre in 2009, where the average Ugandan farmer produces between 100 and 200 kilograms per acre per year. In particular, the difference in difference estimates of SNI on yields show that pairing a female cotton grower with someone they do not know as well as providing pairs with new knowledge to share increased yields by about 74 kilograms per acre across all participants and 98 kilograms per acre for females. Furthermore, while the SNI had its greatest impact on females' yields, it also had positive and significant spillover effects for males.

Several mechanisms contributed to the effectiveness of the SNI. We consider both direct effects of the intervention: new links, and new knowledge, as well as indirect effects: the additional learning that may have transpired as a result of changes in network structure. The evidence suggests that the encouragement of new links was successful; we saw an increase in the number of new relationships discussing cotton production issues, particularly between women who were exogenously paired. The SNI did not affect females' overall network size but it did affect the composition of females' networks, increasing the percentage of females in an individual's network. In terms of knowledge, we find that the SNI expanded participants' agricultural knowledge (as seen on tests) and that these gains can account for about 20% of the increase in farmers' yields. More importantly, women appear to have learned directly from their new network links. Individuals paired with farmers who had comparatively better yields in the initial year (2009) had a statistically significantly higher yields in the subsequent year (2010), even after controlling for productivity in the first period.

Taken together, our research shows that there are large gains from a development approach that encourages the growth of local social networks. Thus, low-cost agricultural training is possible without a top-down training structure, and it can be more effective at improving outcomes for the poorest farmers, who are very often females. Women in this setting were effectively excluded from higher quality agricultural networks and have fewer opportunities to learn about better farming practices. Without integrating these individuals explicitly into male networks, we were able to improve their outcomes by increasing the number of weak links with women in their networks. Since women appear to learn from the better women farmers in their new networks, incorporating the best farmers in our intervention was important, even if the top performing farmers may not have been impacted directly. Interestingly, this addition of links to female networks improved outcomes experienced by males.

These results suggest a number of directions for future work including a greater understanding of how weak links facilitate information exchange, whether information transmission via weak links is sustainable, and whether this methodology extends to other domains such as the adoption of health practices or information communication technologies.

7 Acknowledgements

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References

Anderson, J. and G. Feder (2007). Agricultural extension. In R. Evenson and P. Pingali (Eds.), *Handbook of Agricultural Economics*, Volume 3. Elsevier.

Asfaw, S., M. Kassie, F. Simtowe, and L. Lipper (2011). Poverty reduction effects of agricultural technology: A micro-evidence from tanzania. *Food and Agricultural Organization of the United Nations, Agricultural Development Economics Division, Working Paper*.

Baffes, J. (2008). The 'full potential' of uganda's cotton industry. *Development Prospects Group, The World Bank. September 2008*.

Banerjee, A., A. Chandrasekhar, E. Duflo, and M. Ojackson (2013). Diffusion of microfinance. *Science 341*.

BenYishay, A. and A. M. Mobarak (2014). Social learning and communication. *NBER Working Paper No. 20139* (20139).

Bramoullé, Y., R. Kranton, and M. D'Amours (2014). Strategic interaction and networks. *American Economic Review 104*(3), 898–930.

Breza, E. (2014). Peer effects and loan repayment: Evidence from the krishna default crisis. *Working Paper, MIT*.

Conley, T. and C. Udry (2010). Learning about a new technology: Pineapple in ghana. *American Economics Review 100*(1), 35–69.

Conner Mullally, S. B. and M. Carter (2013). Encouraging development: Randomize encouragement designs in agriculture. *American Journal of Agricultural Economics 95*(5), 13521358.

Duflo, E. and E. Saez (2014). The role of information and social interactions in retirement plan decisions: Evidence from a randomized experiment. *The Quarterly Journal of Economics 118*(3), 815–842.

Edmeades, S., E. Katungi, and M. Smale (2008). Gender, social capital and information exchange in rural uganda. *Journal of International Development 20*(1), 35–52.

Feder, G., R. Murgai, and J. Quizon (2004). The acquisition and diffusion of knowledge: The case of pest management training in farmer field schools, indonesia. *Journal of Agricultural Economics 55*, 217–239.

Field, E., B. Feigenberg, and R. Pande (2013). The economic returns to social interaction: Experimental evidence from microfinance. *Review of Economic Studies 80*(4), 1459–1483.

Foster, A. and M. Rosenzweig (1995). Learning by going and learning from others: Human capital and technical change in agriculture. *Journal of Political Economy 103*(6), 1176–1209.

Granovetter, M. (1974). The strength of weak ties. *American Journal Sociology 78*(1), 1360–1380.

Granovetter, M. (2005). The impact of social structure on economic outcomes. *Journal of Economic Perspectives 19*(1), 33–50.

Harper, C. R. and D. Zilberman (1989). Pest externalities from agricultural inputs. *American Journal of Agricultural Economics 71*(3), 692–702.

Hoang, L. A., J.-C. Castella1, and P. Novosad (2006). Social networks and information access: Implications for agricultural extension in a rice farming community in northern vietnam. *Journal Agriculture and Human Values 23*(4), 1572–8366.

Isham, J. (2002). The effects of social capital on technology adoption: Evidence from rural tanzania. *Journal of African Economies 11*(1), 39–60.

Jackson, M. O. and B. Golub (2012). Does homophily predict consensus times, testing a model of network structure via a dynamic process. *Review of Network Economics 11*(978-1-4503-1229-5), 1–31.

Jovanovic, B. and Y. Nyarko (1996). Learning by doing and the choice of technology. *Econometrica 64*(6), 1299–1310.

Katungi, E., S. Edmeades, and M. Smale (2006). Gender, social capital and information exchange in rural uganda. *Collective Action and Property Rights Working Paper No. 5 December 5, 2006 International Food Policy Research Institute*.

Leonard, D. (1977). *Reaching the Peasant Farmer: Organization Theory and Practice in Kenya*. Chicago: University of Chicago Press.

Leonard, K. (2007). Learning in health care: Evidence of learning about clinician quality in tanzania. *Economic Development and Cultural Change 55*, 531–555.

Maluccio, J., L. Haddad, and J. May (2003). Social capital and gender in south africa. In A. Quisumbing (Ed.), *In Household Decisions, Gender and Development, A Synthesis of Recent Research*. Washington DC: International Food Policy Research Institute.

Marmaros, D. and B. Sacerdote (2002). Learning by doing and learning from others: Human capital and technical change in agriculture. *European Economic Review 46*, 870–879.

Munshi, K. (2004). Social learning in a heterogenous population: Technology diffusion in the indian green revolution. *Journal of Development Economics 73*, 185–213.

Namara, S. and M. Bitekerezo (2010). The 2010-2011 Integrated Rainfall Variability Impacts, Needs Assessment and Drought Risk Management Strategy. Technical report, Office of the Prime Minister, Uganda.

Quisumbing, A. (2003). Social capital, legal institutions, and property rights: Overview. In A. Quisumbing (Ed.), *Household Decisions, Gender and Development*, pp. 139–144. Washington DC: International Food and Policy Research Institute.

Regev, U., A. P. Gutierrez, and G. Feder (1976). Pests as a common property resource: A case study of alfalfa weevil control. *American Journal of Agricultural Economics 58*(2), 186–197.

Santos, P. and C. Barrett (2005). Interest and identity in network formation:who do smallholders seek out for information in rural ghana? *Unpublished, Cornell University*.

Sinha, B. and P. Mehta (1972). Farmer's need for achievement and change-proneness in acquisition of information from a farm-telecast. *Rural Sociology 37*(3).

Tanzarn, N. (2005). Revisiting the past, reflections on the future: Gender in science, technology and agricultural development. In N. Tanzarn (Ed.), *Gender in Agriculture and Technology*, pp. xvii–xxxii. Kampala, Uganda: Women and Gender Studies.

Thirtle, C., X. Irz, L. Lin, V. McKenzie-Hill, and S. Wiggins (2001). Relationship between changes in agricultural productivity and the incidence of poverty in developing countries. *Report commissioned by the Department for International Development: London, UK* (7946).

Udry, C. (1996). Gender, agricultural production,and the theory of the household. *Journal of Political Economy 104*(5), 1010–1046.

Udry, C. and M. Goldstein (2006). Addressing unequal economic opportunities, a case study of land tenure in ghana. *Development Outreach 8*(1), 7–9.

Notes

[1]For the SNI information sessions, we used the list of agricultural information points that the ginners provided to us, which they used as a guideline for their own training sessions.

[2]Conner Mullally and Carter (2013) indicate that "A review of the literature uncovered no published examples of randomized encouragement designs in agricultural economics."

[3]The head of the household was defined as the individual who made land, resource and income allocation decisions in the household.

[4]This was to ensure that females were not separated by large geographic constraints.

[5]We used numbers randomly drawn from a uniform distribution, $U[0, x]$, where x represents the number of individuals in the group. We would then pair individual "1" with the first listed number on the list of numbers drawn from U[0,14]. If the first number was "1" then we would select the next number in the list, perhaps "3". Now "1" and "3" would be paired, "3" would be crossed out, and we would continue down the list in this way until all 14 women were paired.

[6]This was part of the larger RCT that implemented a cotton training program under "Gender Dimension of Cotton Productivity in Uganda" led by Laoura Maratou (University of Maryland) and John Baffes (World Bank).

[7]One kilogram of seed cotton yields 0.30 kilograms of cotton lint—which could produce one to two t-shirts, for example—and return 30-40 US cents (600-900 shillings per kilogram) to a Ugandan farmer. Seed cotton refers to the harvested cotton lint and seed, where the seeds have not been filtered from the lint. Cotton seed refers to the actual seeds that the cotton plant produces.

[8]The monitoring reports from trainers in the TR intervention contain information on what farmers said they spoke to other farmers about. The most commonly reported conversations are focused on timing issues. Farmers complain about inadequate access to pesticides and fertilizers but they do not talk about application levels (see Conley and Udry, 2010, for more about typical farmer information exchanges).

[9] μ_{it} is identical across the whole plot, so varying θ across the plot, while changing q_{it}, does not provide new information. Dividing the plot gives multiple observations of one draw from a random variable, not multiple draws.

[10]Foster and Rosenzweig (1995) assume learning depends not on the number of neighbors but the hectares planted. Since hectares planted is not evolving in our model or data, we use the simplifying assumption that one farmer equals one observation.

[11]Munshi (2004) generates variability in the usefulness of a neighbors' information by assuming farmer characteristics are heterogeneous; different farmers may be seeking different target input levels. In our specification, there is only one target input level, but nearby neighbors provide less unique information.

[12]Realizing no yields means the farmer planted cotton, tended to the crop, but the crop did not produce any output.

[13]Ginners need high volumes of cotton to cover the expense of their infrastructure investment and will subsidize training, but their objective is to increase total quantity of cotton. The training intervention is clearly better for anyone with these goals.

[14]Results available upon request.

[15]The model developed earlier does not allow for higher quality learning from a better farmer, but such a prediction is not difficult to derive (see Conley and Udry, 2010, for an example).

Table 1: Treatment Sample Size (Villages)

	(1) TR	(2) No TR	(3) Totals
SNI	96	59	155
	(8)	(5)	(13)
No SNI	120	50	170
	(9)	(5)	(14)
Totals	216	109	325
	(17)	(10)	(27)

Table 2: Baseline Yields for Females (kg/acre)

	Un-Treated	Treated
SNI	165	190
	(182)	(284)
Training	138	185
	(163)	(251)

Mean of each variable with standard deviation in parentheses.

Table 3: Means in 2009 & 2010

	(1) 2009	(2) 2010	(3) Total
Social Network	0.475	0.475	0.478
Intervention (SNI)	(0.500)	(0.500)	(0.500)
Training	0.658	0.658	0.660
Intervention (TR)	(0.474)	(0.475)	(0.474)
Gender (Fem=1)	0.48	0.48	0.48
	(0.50)	(0.50)	(0.50)
Education (Yrs)	5.6	5.9	5.7
	(2.9)	(2.9)	(2.9)
Kg Cotton	140.8	79.54	109.9
	(201.5)	(129.2)	(171.6)
Acres	0.983	0.586	0.783
	(0.701)	(0.593)	(0.678)
Yield (Kg/Acre)	182.0	139.5	160.6
	(208.7)	(234.9)	(223.1)
Kg Seed	4.976	3.232	4.097
	(3.799)	(3.000)	(3.527)
Yield Per	52.83	36.96	44.83
Seed	(78.32)	(62.70)	(71.27)

Mean of each variable with standard deviation in parentheses.

Table 4: Probit, OProbit

	(1)	(2)
	Probit	Ordered Logit
	0=Did not Plant	0=Did not Plant
	1=Planted	1=Planted & 0 yield
	Planted & >0 yield	
SNI	0.565**	0.699***
	(2.272)	(3.115)
TRAINING	0.334	0.428**
	(1.579)	(2.286)
TR · SNI	0.0657	0.0159
	(0.207)	(0.0558)
Observations	325	325

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Difference in Differences

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Yield	LnYield	Yield less than 400	Males less than 400	Females less than 400
t	-97.84***	-3.127***	-76.74***	-66.58***	-100.5***
	(-4.275)	(-8.404)	(-3.685)	(-3.096)	(-4.063)
SNI	58.85	-0.0983	-8.464	22.48	-50.74**
	(1.569)	(-0.251)	(-0.359)	(0.738)	(-2.368)
TRAINING	26.98	0.124	8.357	15.08	-6.137
	(0.745)	(0.368)	(0.432)	(0.733)	(-0.265)
TR · SNI	-15.22	0.334	31.53	19.59	54.15
	(-0.256)	(0.725)	(1.050)	(0.522)	(1.549)
SNI · t	1.332	1.593**	74.69***	64.79*	98.18**
	(0.0457)	(2.699)	(2.899)	(1.878)	(2.374)
TR · t	75.83*	1.160	82.73*	134.7*	67.32*
	(1.791)	(1.645)	(1.881)	(1.752)	(1.928)
TR · SNI · t	17.20	-0.457	-48.27	-89.85	-42.77
	(0.352)	(-0.491)	(-0.909)	(-1.021)	(-0.707)
Constant	140.2***	4.534***	113.2***	107.0***	127.4***
	(7.076)	(17.07)	(8.307)	(6.479)	(10.09)
Observations	646	646	574	286	288
R-squared	0.047	0.238	0.045	0.066	0.057

Robust t-statistics in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: Impact of SNI on Average Social Network Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	stated size	actual size	grew (t-1)	gender	age	education	distance
female	-0.578	-0.0553	0.0349	0.145**	2.333	-0.477	0.00546
	(-1.011)	(-0.178)	(0.911)	(2.733)	(1.651)	(-1.161)	(0.136)
t	-0.643	-0.418	0.117**	-0.0379	0.352	0.0237	-0.229***
	(-0.558)	(-1.124)	(2.104)	(-1.316)	(0.207)	(0.0860)	(-2.997)
TRAINING	0.757	-0.0818	-0.0356	-0.0395	-2.194	0.216	0.0328
	(0.500)	(-0.291)	(-1.505)	(-1.074)	(-1.083)	(0.513)	(0.856)
TR · t	-0.334	0.205	0.000615	0.0381	1.576	-0.253	0.0591
	(-0.217)	(0.592)	(0.00983)	(0.941)	(1.069)	(-0.674)	(0.748)
SNI	4.887	2.079***	-0.0341	-0.0275	2.306	-0.209	-0.0386
	(0.832)	(2.787)	(-0.590)	(-0.292)	(0.496)	(-0.214)	(-0.393)
SNI · female	-2.326	-0.988*	-0.00248	0.00330	-3.015	0.426	-0.0327
	(-0.766)	(-1.987)	(-0.0641)	(0.0453)	(-1.092)	(0.754)	(-0.556)
SNI · t	-5.292	-0.896	-0.0215	-0.0866	-1.371	1.169	0.120
	(-0.841)	(-1.005)	(-0.274)	(-1.295)	(-0.433)	(1.406)	(0.929)
SNI· t · female	2.443	0.398	-0.0287	0.169***	0.454	-1.187*	0.00448
	(0.733)	(0.809)	(-1.120)	(3.470)	(0.195)	(-1.988)	(0.0575)
Constant	5.420***	3.812***	1.029***	0.973***	45.87***	6.687***	1.840***
	(4.123)	(8.466)	(20.49)	(14.55)	(20.12)	(9.881)	(28.27)
Observations	463	493	480	480	479	460	472
R-squared	0.017	0.062	0.066	0.149	0.031	0.039	0.057

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

stated size: stated size of network; actual size: number of names listed; grew(t-1): proportion who grew cotton last year; gender: proportion of network that is female; education: average years of education of network; distance: proportion who have plots adjacent to one another.

Table 7: Cross Sectional Impact

	(1) SNI on Yields	(2) SNI on Information Learned
SNI	60.18*	0.0483**
	(1.710)	(2.307)
TRAINING	102.8*	0.0406*
	(1.848)	(1.701)
TR · SNI	1.976	-0.0375
	(0.0262)	(-1.052)
Constant	42.33***	0.378***
	(2.854)	(25.95)
Observations	325	324
R-squared	0.057	0.021

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Impact of SNI Controlling for Attendance at the Information Meetings

VARIABLES	Yield (F)
t	-100.5***
	(-4.058)
SNI	-87.41***
	(-4.284)
TRAINING	-10.40
	(-0.457)
TR · SNI	72.26**
	(2.305)
SNI · t	96.02**
	(2.513)
TR · t	56.88
	(1.682)
TR · SNI · t	-58.10
	(-1.260)
Info	46.87***
	(3.838)
Info · t	-2.371
	(-0.0992)
Constant	127.4***
	(10.08)
Observations	288
R-squared	0.103

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Pair's Impact on Yields: Continuous and Discrete

	(1)	(2)
	Δ_t yield	Δ_t yield
(Own Yield)$_{t-1}$	-1.339	-1.118*
	(-1.162)	(-1.827)
(Partner-Own)$_{t-1}$	-0.346	
	(-0.238)	
(Partner-Own)$_{t-1}$*Low	1.061	
	(0.575)	
(Partner-Own)$_{t-1}$ >0		230.1**
		(2.656)
(Partner-Own)$_{t-1}$ <0		161.8
		(1.159)
Constant	161.7	
	(1.362)	
Observations	23	23
R-squared	0.303	0.286

t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

8 Appendix A: Game Points

1. Ladybirds are good insects (show picture).
2. Spacing between rows is 75 cm (demonstrate 3 sheets long).
3. Spacing between plants is 30 cm (demonstrate 1 sheet long)
4. Only plant 3-5 seeds per hole.
5. More than 2 seedlings in one place will reduce cotton yield.
6. First weeding occurs between the 2nd and 3rd week after planting.
7. Second weeding occurs between the 6th and 10th week after planting.
8. Bollworm (show picture) larvae appears between the 8th and 9th week after planting.
9. Cover mouth and hands with cloth while applying pesticides. It's harmful to your health.
10. Check germination after 5 days. Replant seeds at proper gaps to get even crop cover.
11. Prepare land several weeks in advance for cotton planting
12. Cotton is good as a mixed and as a rotational crop.

Figure 1: Non-Parametric Frequency of Yields