

ABSTRACT

Title of dissertation: DEVELOPMENT, TECHNOLOGY ADOPTION
AND SOCIAL NETWORKS

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Agriculture remains a key component of economic development, but the methodology for how development policies are determined has changed for developing countries. In the last decade, the focus of economic growth in developing countries has shifted from country-wide prescriptions to testable micro-development programs at the local level. As international development focuses in on local programs, social networks have been identified as a key component for their effective deployment.

This dissertation analyzes the effects of a social network-based intervention. It contributes to the economics literature on identifying social network effects by implementing a randomized encouragement design to develop social capital, while simultaneously introducing a new method of development training. The program implemented here is comprised of two parts, and was conducted with female-headed households in rural Uganda, that were growing a relatively new cash crop, cotton. The first part conducted social network-based information games in 20 sample villages, in which each participant was trained in one aspect of cultivating cotton, and

encouraged to attain a full set of knowledge on growing cotton through her assigned learning networks. They were presented with two different incentives schemes for accumulating information: competitive and team incentives.

The second portion of the program paired the surveyed individuals at random with other game participants. These pairs were encouraged to develop team goals across the growing season and a time schedule for networking as well as update and share their learned information from the games on a regular basis. The estimated effects of the SNI, which comprise this dissertation, include both the effects from the information games and the effects of the mentored pairing; that is, the impact of acquiring one information point and one new link. I compare the effects of this program to a standard agricultural training program that was concurrently conducted during this research, in which extension agents taught the same information that was presented in the information games but with a traditional classroom-based teaching method.

My games analysis shows that females learn more when presented with competitive incentives. The total number of learning points learned during competitive incentives first order stochastically dominates the total number of learning points learned during team incentives. However, for the dissemination of one specific information point, team incentives are better at ensuring that a unique information point reaches the entire group. Difference in difference estimates, controlling for the training program, show that the overall SNI program had significant effects on the

average farmer, with diminishing returns for higher yielding farmers. I find that these average effects are comparable to the effects of the conventional training program, but at a fifth of the implementation cost. A closer examination shows that the SNI program has its most significant effect for farmers growing around the average output when the program was started in 2009 (100-200 kgs/acre), while the Training program has its greatest and most significant impact for those yielding above the average output in 2009. Therefore, the two programs are not necessarily substitutes in how they effect change. My research shows that a competitive incentive structure coupled with social network-based learning serves as an effective paradigm for improving outcomes for the poorest producers.

DEVELOPMENT, TECHNOLOGY ADOPTION,
AND SOCIAL NETWORKS

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To Sean, for adamantly believing that my ideas and capabilities will take me down a path that I had not yet imagined.

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Chapter 1

Introduction

In the last decade, social network-based technologies have become an important tool for disseminating information. In the developed world, the average person spends a considerable amount of time remotely researching what others are doing and learning from neighbors, friends, and even friends-of-friends-of-friends. Expanding one's network can be as simple as clicking "accept." As a result, first-degree networks in the developed world can incorporate geographically distant individuals, with the irony that next-door neighbors may never interact.

In both of these worlds, networks are extremely powerful in initiating the flow of information. In the developing world, the idea of observing and learning through one's social networks is hardly an innovation, but rather a staple for survival. This is particularly true within agriculture, the primary source of livelihood in the rural developing world. While programs aimed at increasing agricultural productivity are regarded as a powerful means to reducing poverty, the dissemination of new techniques and technologies by agricultural extension agents and trainers is one of the

weakest links in the process.

One of the reasons for the lack of clear success in agricultural extension training is that trainers' success in reaching and affecting all individuals in a particular location relies on the effectiveness of social networks, which are often unknown to an outsider and difficult to identify. While extension agents may bring new technologies with each program, extension agents can often have a misconception as to what is important to local production and how to disseminate the new technology. It is through individuals' personal ties that external information is disseminated within a remote area, tested and localized, ultimately creating usable and believable knowledge. Thus, many welfare-improving technologies are never adopted because individuals are not connected to effective social networks.

This paper examines a research project that measures the impact of social capital for female subsistence farmers in rural Uganda. Identifying the impacts of social capital generally suffers from serious identification problems. Unobservable characteristics of an individual, such as networking ability and sociability, and/or unobservable weather shocks, confound the impact of network effects, and bias the estimated impact of social network measures. The novelty behind this study is that I am able to randomly perturb females' networks, creating a source of network identification. This was done by encouraging one new randomly assigned link for each participating female farmer, in addition to being taught about one new randomly assigned aspect of growing cotton. This random assignment of partners and in-

formation directly addresses the identification problem that plagues most network studies. In the context of the economics literature, my identification of network effects captures the net result of network's churning¹, and not the effect of any particular network structure, or the structural positioning of nodes.

There is a large body of literature that does detail the importance of a network's structure, and the impact of a node's position in that structure. For instance, Kranton and Bramoulle (2007) looks at how a node's position within a network structure affects its donation behavior to a public good. They show that central actors² are more likely to free ride in contributing to a public good. There is a large body of literature within sociology, entitled social network analysis, that evaluates network structure and nodes' characteristics, in terms of network characteristics such as centrality, density, and brokerage. Freeman (2007) and Granovetter (1974) are foundational texts in this area. Prell et al. (2009) utilizes social network analysis to determine what types of actors should be targeted for stakeholder selection. They find that choosing central stakeholders with high betweenness³ improves stakeholder representation, which is a finding that speaks to mechanisms at work in this research. Namely, I believe that incorporating individuals with high betweenness, as opposed to high degree centrality, in my social network intervention is a major reason for why I observe a positive effect of my social network interention. However, given my limited resources in mapping each village's complete network structure, in addition

¹Churning is the formation and breakup of new links.

²Degree centrality is how many others a node is connected to.

³Betweenness, or brokerage is how many times an actor rests between two other nodes. Brokers are those who can bring together disconnected segments of a network.

to the logistical constraints in assigning a unique name to each village member⁴, my main focus in this dissertation is to capture the overall impact of the intervention and not the effect of a node's placement within the network.

The impetus behind identifying the effects of social capital in this setting is to uncover the reasons for major productivity differentials between males and females. Baffes (2009) had discovered with a similar sampling of individuals in the Ugandan cotton growing sector that women's productivity lagged far behind that of men's. Productivity differentials across genders have been studied, but primarily with a focus on the tangible differences in inputs and ownership across males and females (Appleton et al., 1999; Quisumbing, 1999; Udry, 1996). Yet, if fluid social networks are a universal input for development, then their absence could be a reason for economic stagnation. This research tests that hypothesis.

Both my own and past research has discovered that social networks within rural Uganda remain topically specialized and segregated across gender. Females speak to one another about child care, health and family, but hardly about production. Males speak to one another about finances, spouses, and land. And there is little updating across the two, as witnessed by many focus group meetings as well as the work of Katungi et al. (2006). It was clear in my field work that even if some members of a village received new information, there was no guarantee that that

⁴Individuals in Uganda do not retain a unique last name within their family lineage. In addition, women are known by one of three names: their own first and second name, their own first and husband's first name, and their son's name.

information would diffuse to everyone in a village.

I realized that several institutional norms brought about the currently observed networks in Uganda: (1) Only a handful of locally recognized males frequently receive training; (2) Trainers have unrealistic expectations that the trainees will train additional individuals; (3) Women do not discuss production, especially not for the purposes of cash income; (4) Women and men do not mingle on a daily basis; (5) There is a stated and stigma-less acceptance that females have less capacity to learn, retain, and execute information ⁵.

In this research, I implemented a randomized control trial to test whether social capital has a causal effect on productivity. I designed a program that paired individuals to new links and provided them with exchangeable information as an incentive to learn and interact. The purpose was to observe whether an exogenous shift in a female's network, in addition to access to new information, would affect uptake of a new cash crop, as well as change productive outcomes. Working with females in particular was crucial, as I expected there to be large gains from providing them with new contacts and information.

By quantifying the latter, I am able to identify a bottleneck in development programs, as many development programs today are information-based training pro-

⁵This is something that I was repeatedly told in focus meetings. I say "stigma-less" because individuals were open to women demonstrating their potential in a male's domain, and subsequently respected as an authority, but the norm was that they were guilty of ignorance until they proved otherwise.

grams that rely on, and are overlaid onto, existing social networks. Yet, existing social structures may not be able to transmit the specific information that development agents expect them to as those networks developed for the purpose of transmitting other types of information. By developing a social network-based training program, I encouraged the formation of a new link for the purpose of transmitting new information, and have simultaneously created an exogenous source of variation in network formation from which I can identify the effects of social networks.

The next chapter presents a backdrop on gender and agriculture in development, and describes where females, and female-headed households, specifically, stand in terms of agricultural production, local institutions, and social norms. A historical perspective of Uganda and its commodities from pre-to post-colonial rule outlines the origins of government institutions under which subsistence farmers work today. The final section outlines the project design. Chapter 2 analyzes the results of the experimental games, while chapter 3 analyzes the results of the full social network program. Chapter 4 concludes.

1.1 Motivation: Gender and Agriculture

Much of the world's growth in land productivity, labor productivity, and real income has occurred over the past two centuries as agrarian economies transitioned to industrial economies. The modernization of agriculture has not yet occurred in developing nations such as Africa and Latin America. In SSA, agriculture comprises

30% of GDP, and utilizes 70% of the continent's labor force, yet productivity per unit of land and labor is low (Mangheni, 2007). In Uganda, for example, the agricultural sectors consist of small holder farmers, cultivating about 2 to 3 acres each, 70% of which is used to produce locally-consumed crops. This research addresses ways to improve the productivity of local agrarian systems as the first step in a transition to a modern agricultural system and long term economic growth.

If agriculture is the keystone to development, then women are the turnkeys of agricultural production in SSA. In Uganda, women supply 70-80 % of the agricultural labor force, are responsible for 80 % of food crop production, and provide 50-60 % of labor for cash crop production (J.R.Bibangambah, 1996). As women provide the bulk of agricultural labor in SSA, their contribution to both local and national economies is substantial. The food crops that females produce feed their country's future human capital. Females are thus often single-handedly responsible for the growth and development of their household's dependents, while their male counterparts often do not or cannot hedge their wives against adverse income shocks (Duflo, 2010).

While food crops fuel current and future human capital, they rarely are a sufficient source of capital for investments into new tools and inputs. Food crops rarely generate sufficient surplus that could be converted into a meaningful sum of disposable income. As such, there are barriers to entering the "virtuous cycle" of development and reinvestment (Duflo, 2010). To enable females the opportunity to dictate their own growth and investments, it is crucial that they be incorporated

into more lucrative production chains.

1.1.1 Female-headed Households

In most instances, the chance to cultivate cash crops is unlikely, even if females have the opportunity to do so. In more traditional male-headed households females receive the inputs that their husbands allocate to them, which are generally inferior in quality. Even if they have the opportunity to cultivate cash crops, women do not manage the cash flow that is generated from selling them.

This research does not delve into the issues of household bargaining and inequality that females face within male-headed households in SSA. Rather, it investigates a possible channel through which the stagnation in female productivity can be broken. The sample utilized in the thesis comprises of female-headed households, allowing us to abstract away from some of the consistently cited sources of gender productivity differentials, such as land tenure. Namely, female-headed households are in control of their own resources and resource allocation, and therefore, are not subject to the insecurity in land ownership that can be at the root of low yields (Udry, 1996).

Female-headed households are also often deemed more “at risk” to food insecurity than females who are privy to their spouses’ resources. Because they are often divorced, widowed, or separated, their social context, choices and outcomes will be atypical for females belonging to male-headed households. Although they may have acquired their own land, they are nevertheless on the periphery of local social

settings, and therefore socially and subsequently physically far from the density of information, information that their married counterparts may be privy to via their husbands. As such, this population of independent women is an excellent example of how marginalized groups can improve their outcomes.

1.2 Cotton Production in Uganda-Formal Institutions

This research focuses on one of Uganda's, and Sub Saharan Africa's major cash crops, cotton. Cotton was introduced to Uganda in 1903 while it was governed by the British Commonwealth, 1894-1964. Since the early 20th century, cotton has been one of the key export crops of 30 African countries. In Uganda, it employs more than 1 million households, where about half of the country's output is produced in the Northern and Eastern regions.

To understand the context and constraints that cotton farmers face today, it is important to look at the history and current standing of the country's institutions. The institutions at the government-level determine the incentives and contracts, or lack thereof, of ginners and traders, which ultimately affects the production of the subsistence farmer. From 1903 to 1930, cotton was a government-controlled crop, which led to the establishment of research and extension services, seed breeding, quality control, and seed input supplies. But by the 1930s privately owned ginneries sprang up, mostly owned by families resettled from India (J.R.Bibangambah, 1996).

To balance large-scale control, co-operative unions were formed in the 1950s to represent smallholder farmers, to help them maintain ownership of their cotton and to process the cotton into viable products rather than selling it in its raw form. But by the time Uganda gained independence in 1964, these co-operative unions had been subsumed into government boards such as the Cotton Growers Association (CGA), which were first designed by the colonial government. They were later converted into various other entities: the Lint Marketing Board (LMB), followed by the current Cotton Development Organization (CDO). The boards were created so that the state could maintain control over agricultural marketing.

Both the CGA and the LMB dictated lint prices, and controlled the potential output of cotton through the ginneries which were the sole providers of cotton seed and sole purchasers of seed cotton. Thus a relationship between ginner and farmer began with less than ideal incentives for efficient production. Because ginners determined how much seed would be sold and purchased from farmers' output at a fixed price, there was little incentive to improve upon growing techniques as compared to one's neighbor. Today, some residual disincentives for efficiency remain. Seed is in fact provided for free, and while prices are not fixed, they are foreshadowed by a new system called indicative prices. Indicative prices are announced prior to the growing season to allow farmers to predict their potential revenue from cotton, and allocate their resources across crops appropriately. Unfortunately, the predictive power in determining the market price is poor and prices are volatile. There are years when the indicative price falls short of the realized price and farmers over-produce, and

vice versa.

1.2.1 Local Institutions

Formalized property rights circumscribed what females could pursue with regards to agriculture, and agricultural extension training has allowed this disparity to persist. Agricultural extension training services began during colonial times, and have continued into the present through government funding and international aid in Uganda. The most prominent agricultural program since 2001, which provides training services in cotton, is led by Uganda's National Agricultural Advisory Services (NAADS) that relies on the participatory monitoring and evaluation design (PME). One of the failings that extension trainers cite in PME is, that it works best when groups are already organized and empowered. This type of program clearly presents a vicious circle for growers of new crops (Mangheni, 2007). As a result, NAADS, like many extension training programs default to training males, whose day- to -day livelihood is mainly structured around production. Furthermore, the dissemination of NAADS information depends upon a top down training structure, where the most able and literate males in a village are trained, often in a classroom-like setting, and then anticipated to share and propagate their knowledge informally. Males are very often selected for training because they are more likely to be literate. As a result, women are a minority in such training, and even if one is present, the female networks to which she belongs cannot support or reinforce her training (Mangheni,

2007). As such, females, and to a greater degree, female-headed households, which more recently had the opportunity to grow and invest in cash crops, had little formal and informal institutional support in their undertakings. This research will help us better understand the nature of institutions that are successful in the transfer of technology to females resulting in higher agricultural productivity for the country.

1.3 Low Productivity and Gender

Uganda reached its peak production of cotton in the 1960s to 1970s, producing between 200,000 and 300,000 bales⁶. Productivity has varied over the 20th century, mostly because of the political implications of Idi Amin's regime. In the post-colonial era, Uganda's second independent president, Idi Amin, initiated a campaign against Ugandans of Indian origin, the primary owners of Uganda's ginneries, driving out the cotton business. By 1978 output had fallen to 11,000 bales.

Because of this hiatus in cotton growing, cotton growing knowledge skipped generations within households. And the reintroduction of cotton during President Museveni's term has not revived production levels back to their previous levels, particularly in Eastern and Northern Uganda, the regions that have less current political clout. As a result, output remains low and female cotton growers are among the weakest producers. Currently, Uganda has 50 ginneries and produces about

⁶USDA: A bale of cotton weighs about 500 pounds.

25,000 tons of lint, or 135 thousand bales of cotton annually ⁷. This is about half of what it was producing in the 1970s, and a far cry from the 1 million bales that the CDO claims that the country has the potential to produce (Baffes, 2009).

A large portion of where Uganda's cotton production is falling short at the village level is amongst the women who are currently growing cotton. This is the result of several engendered agricultural institutions that set the stage for the current productivity differentials in cotton across gender (Baffes, 2009). The first of these is that women lack land tenure rights in male-headed households. While this is not true for female-headed households, the agricultural practices and norms that dominate females' social networks are largely determined by the females in traditionally male-headed households. There is little discussion about cash crop production issues and land maintenance, as few women within male-headed households have the need to discuss such issues. Therefore, while this research looks at the outcomes of female heads, their outcomes are very much a product of the norms that persist amongst all female growers, as they belong first and foremost to female social networks.

For the majority of females, cash crops have not been a viable production option since the time when the British first introduced cash crops to Uganda. This is because the British were the first to define an overarching land tenure system. Concurrent with the introduction of cotton as a new income source, the British redefined roles and ownership between genders. During pre-colonial times, no over-

⁷185,000 tons= 1 million bales.

arching land tenure system existed across Uganda. The British were the first to introduce property rights beyond a clan's appraisal. Women had always had only secondary rights to the land of their spouses, but because this was formalized at the time that cotton was introduced, there was little to no possibility of involvement in growing cotton, unless their husband mandated it. As a result, women rarely owned their own land, and therefore did not have the opportunity to decide to grow a cash crop. If they assisted their husbands in growing a cash crop, it was that husband that allocated the inputs and collected to the revenue from that output.

1.4 Project Overview & Data Collection

This project investigates how informal social networks affect a female's productivity, as compared to the effects of formal institutional training programs, and also investigates how information is transferred among individuals in a network. The study was instigated by a survey conducted by the World Bank in 2009, which uncovered a four-fold productivity differential between male and female cotton growers (Baffes, 2009). Other studies have pointed to inferior inputs and the fact that women do not own their land and therefore do not invest in their land as a potential cause of low productivity. However, because the females in our sample are heads of the household and own their resources, these are not potential causes.

Testing whether gender specific training might close these differences, was the first initiative taken on under the umbrella of a larger project funded by the Gender Action Plan in 2009, initiated by Laoura Maratou (University of Maryland) and John Baffes (World Bank, Economic Prospects Group). The subsequent step, developed by this research's author, was to investigate the informal institutions, female social networks, that surround cotton production. That is, beyond land tenure, inputs, and formal training programs, my objective is to test whether there is a lack of information flow, lack of a network around production, or bottlenecks within existing networks that are contributing to the stark differences in output across gender. This portion of the study was supported by Markus Goldstein, and funded by the Development Economics Group at the World Bank.

In the preliminary stages, I conducted informal focus meetings with groups of females in Northern Uganda, Lira District. From these meetings, it became clear that females knew little about each others' problems and solutions with regards to growing cotton, and even more generally in terms of food crops. It also became clear that individual and group interviews did not lend themselves to the most accurate information. Meetings very often resulted in requests for donations rather than a receptive discussion about growing issues. I realized, however, that groups did want to learn new information, and I began to devise a game that might provide real incentives for learning, and enable me to observe how females learn.

After two trial runs of the game, I conducted the information games in 20 Ugandan villages, randomly chosen from a sample of cotton producing villages in the North and East of Uganda. These were a subset of villages chosen for the overall training program, mentioned above. The information games were experimental games to test how females learned information specific to growing cotton in group settings along networks, and what types of incentives encouraged information exchange most, competitive or group incentives⁸. The information games provided intricate data on the information learned, which were then analyzed in terms of what types of incentives encouraged greater learning via networks. The games concurrently served as training sessions in and of themselves. Namely, during a session of one information game, each participant was trained in one agricultural information

⁸Training sheets are in Appendix A.

point about growing cotton. Such information was taken from traditional extension agents' training sheets that individuals would otherwise learn in standard training programs. However, each female was officially trained in only one of twelve points (on spacing, weeding, thinning, etc.⁹), and was obliged to learn all other points from other participants.

My initial plan, however, was to perturb the existing social networks to enable statistical identification of network effects, since the information games were not yet a solution to this. The possibility that emerged was to try and affect a change in networks at the village level, and then compare outcomes of individuals across villages. Specifically, I found that unless villages were immediate neighbors, information did not spread easily between individuals within different villages. Therefore, I assume that an individual's social network in this study is contained within the village in which he or she is residing. Upon a second return visit in early summer 2009, I was able to work on my initial idea of encouraging new networks amongst females. No other research within the social network literature had done this previously, and to my knowledge only one other study within development economics is carrying out a similar approach to testing the effects of social networks on repayment of loans in micro finance (Field et al., 2011).

In this second stage of the project, I randomly paired females who participated in the above games with one another, based on village location and program status.

⁹See Appendix A.

More specifically, only some of the females who participated in the games were also surveyed for this study. These are the female-headed households that were chosen for the overall training study, some of whom were randomly selected for training, and all of whom were surveyed by our team. I thus aimed to pair females chosen for the larger training study with females who only participated in my game. This incorporated more people in the SNI, even if they were not surveyed, and thus gave participants more possibilities for developing new links.

Each pair was then encouraged to develop a team, and a viable production strategy for the year, by identifying weaknesses and ways in which they could aid one another. They were also strongly encouraged to review and update the information that they had learned in the information games throughout the growing season. The combination of the games sessions and the latter local pairing is what I refer to as the Social Network Intervention (SNI), or Social Network Program here on out. I then compare the effects of the randomly assigned SNI training method to the effects of the traditional Training (TR) program that I was integral part of developing, managing, and carrying out.

1.5 Dissertation Organization

The next sections delve into each stage of the SNI. This chapter reviews the information games. The chapter reviews the experimental context on which it was

based, develops an economic model, and predicts the information that each player learned over subsequent rounds using maximum likelihood and non-linear estimation. I show, empirically, that females learn more information from their peers when subjected to competitive (tournament) incentives versus team (group or collaborative). Specifically, I show that the number of information points learned by participants under tournament incentives first order stochastically dominates¹⁰ the number of information points learned by participants under team incentives.

Chapter 3 evaluates the second stage of the research, namely, the combined effects of the information games that are analyzed in Chapter 2, and the randomized mentored pairing, with a difference and difference methodology. Within this chapter, I also investigate through which channel the SNI program affected participants: through the learning that occurred in the games, or through the pairing that occurred in the second stage. On average, the effects of the two programs are comparable, economically and statistically. Yet the SNI costs a fraction of what the standard Training program costs. However, the distributional effects suggest that the SNI intervention serves as a better poverty-alleviating tool than the Training program. I find that the impact of the SNI exhibits diminishing returns, with the greatest average effects are for low-to mid-yielding farmers. In contrast, I show that the standard agricultural training program benefits already high-yielding farmers. Much of the effects of the SNI program appear to be generated by the learning,

¹⁰First order stochastic domination (FOSD) of a random variable over another random variable implies that the CDF of the first variable lies below that of another.

and not only the pairing of individuals, though the learning would likely not have occurred without the mentored pairing. Even after controlling for attendance at the information games, the coefficient on the SNI program remains significant.

Chapter 4 concludes by evaluating this work on three fronts: overcoming the empirical challenge of identifying network efforts, using local networks to overcome constraints and current limitations of extension training, and how policy can proceed with regards to equalizing production across genders by changing males' as well as females' incentives for agricultural change.

Chapter 2

Incentives for Information Exchange: Getting Women to Share

2.1 Abstract

I use results from experimental games played amongst rural female farmers in Uganda, participating in agricultural training, to understand how and why different types of incentives encourage information exchange amongst females adopting new technologies. The information game devised for this study was meant to serve as a blueprint for networking that its female participants could then replicate as an everyday model for disseminating information. Each participant was trained in one aspect of growing cotton and encouraged to exchange and mentor other participants in order to accumulate a full set of information points. That is, participants specialized in one aspect of the cotton production process before exchanging their expertise. Several rounds of networking under different incentives schemes reveal the types of incentives, in particular, team vs. tournament, that are most effective at encouraging females to network with other females regarding cotton production,

a new technology in these areas.

I find that the distribution of total information points learned under tournament incentives first order stochastically dominates (FOSDs) the distribution of total information points learned under team incentives. However, the probability that any particular information point is learned under team incentives is greater than under tournament incentives. These results hold even after controlling for players' effort and first-order network size. They have important implications for improving the efficacy of training programs in development, which rely on "trickle-down" methods of to disseminate information. The incentive structure, which specialized each participant in one aspect of growing cotton, can also serve as an effective paradigm for distributing information in other training programs.

2.2 Introduction

Extension workers in many developing country settings are often challenged by the fact that few individuals who are trained in agriculture successfully implement new growing techniques or teach and encourage the untrained to do so as well (Evenson, 1980). Although learning through social networks can have large impacts on agricultural outcomes (Conley and Udry, 2010), social networks do not always facilitate spill-over effects from development programs (Duflo et al., 2006). These types of economic and behavioral failures put methods of extension training into question, can result in wasted resources, and can prolong a path out of poverty.

One of the main reasons for studying social networks in the development economics literature is to better understand learning and adoption processes in rural areas. Traditional markets for new technologies are often absent in such areas because of low population density or low literacy rates. Activating social ties may be a way to alleviate such constraints. Qualifying the incentives behind such learning is the objective of this study, with a focus on the less-studied networks of female producers.

Extension trainers use many types of informal incentives for motivating trainees, where the subtleties of their effects may not be considered. For instance, in this study's context of cotton farmers in Uganda, extension trainers are often employees of local ginneries who reward with seeds or appoint to village boards the farmer(s) with the highest yields in the previous seasons, regardless of the heterogeneity in agricultural or financial shocks to farmers. The latter can be seen as a tournament incentive, where there is a fixed amount of seed, and the relatively most successful producers are rewarded. The same extensionists also provide team incentives by revisiting or working with the most productive villages. What are the repercussions of such incentive schemes, and the order in which they are introduced? And how do they facilitate extension trainers' foremost objective of expanding farmers' knowledge base and improving production outcomes?

The impetus for the following game stems from evidence gathered during the baseline study for an agricultural training program in Uganda funded by the World

Bank in January to March of 2009. Data show that women are less networked amongst themselves as compared to men, where men's networks are 70% male, and females' are 50% female, even though females share more in common (in terms of production and time inputs) than with other male growers. Female growers are also less likely to be connected to reported key information leaders in their village, who are generally male. Therefore, if substantial resources are to be expended on training women to grow a relatively new cash crop, and networking and information sharing is a primary reason behind the benefits accrued from many development programs, then it is imperative that the right type of incentives are implemented to encourage the desired type of information exchange.

The following game was conducted in 20 villages in Eastern and Northern Uganda, with groups of 14 women in each village, some of whom participated in our baseline and social network surveys. The game served as a tool for the social networking intervention (SNI), in which farmers were encouraged to establish one new link and share information on growing cotton acquired from training or otherwise, but also as an experimental game whose results would reveal what type of economic incentives encourage different types of information exchange.

Two types of incentives were awarded to women for accumulating agricultural information on growing cotton through assigned game networks, which they were taught at the start of the game: a tournament incentive and minimum-team incentive. The game was designed to realistically mimic information sharing among

women. Contextually foreign games, such as mazes or board games, were avoided. I also avoided incentive schemes that would be difficult to implement in reality, such as piece rate schemes. With the help of the local agronomists conducting the training interventions, I identified the major points that these trainers would be presenting in their standard training. However, it was how I taught and disseminated the information that differed from the standard Training program.

2.3 Experimental Literature

The suitable provision of incentives is a theme that first emerged in the labor economics literature in the context of encouraging effort towards firm production. Lazear and Rosen (1981) first analyzed the rank-order payment scheme, or tournament incentive that had been prevalent in so many labor contracts until then, but not explicitly modeled. It argued that rewarding risk-averse workers based on their relative position to others is less costly than observing and rewarding workers based on their marginal products. Since then, the literature on designing incentives for workers' effort has grown well beyond labor economics, and developed into its own niche within experimental economics. Comparisons of tournament and piece rate incentives continue into the present literature (Bull et al., 1995; Marinakis and Tsoulouhas, 2006). Some of the studies took to viewing the worker as a part of a team that collectively produces a firm's output, rather than as an individual who is competing against her fellow colleagues (Carpenter et al., 2009). More variations

on the tournament scheme emerged: inter team vs. intra team competition (Fatas and Neugebauer, 2005) and means to reward the incentive scheme itself: exogenous vs. endogenous reward payments. Many other questions, though peripheral to this study, surrounded optimal incentive structures, such as behavioral perversities resulting from offering incentives at all. Benabou and Tirole (2006) find that effort is not monotonically increasing in incentives, where there are decreasing returns to the prize size awarded, while Gneezy et al. (2003) show that preference over prizes can change with the prevailing institutional incentive.

The issue of team incentives continued to grow inside the experimental literature, particularly with regards to public goods contributions (Groves, 1973), or encouraging teams to better contribute towards a common good as a team (Barton Hamilton and Owan, 2003; Orrison et al., 2004). Team incentives generally take the form of a communally-generated pie that is distributed amongst the team. Team members are awarded a fixed fraction of the teams' collective product, or a portion contingent on their effort level or contribution.

A comparison of outcomes under tournament and team incentive schemes followed, where effort varied from serving as an input into own utility or a team goal. In a team goal scenario, free riding is a natural concern: where reducing effort is beneficial to one's own utility, and compromises the team outcome. That is, even in team goal or public good scenarios, tournament structures can reveal themselves as the more effective mechanism in inducing worker effort (Irlenbusch and Rucahala,

2008; Sutter, 2006).

The strength of this finding, however, is questionable when we consider incentives schemes according to gender. Both field and lab experiments reveal that women are not only more likely to contribute in teams or groups to public goods, but that they are less successful than men under competitive incentive structures (Gneezy et al., 2003; Niederle and Vesterlund, 2007). Ivanova-Stenzel and Kubler (2005) show that women perform sub-optimally to men when playing in competitive structures on mixed gender teams.

In the context of the game proposed here, I am inclined to view participants as members of a team who are contributing to a common pool of knowledge. Che and Yoo (2001) show that whether we choose to view a group of workers as individuals who are in competition with one another, or as a team, depends on the mutual accountability between individuals and the life span of their organization. Taking this into consideration, village members share a long lasting and binding commitment that lends itself to my participants viewing themselves as a team. Furthermore, I consider individuals' exertion of effort as contribution to a common or public good, here an information pool. Both Romer (1990) and Kranton and Bramoulle (2007) are examples in which information is treated as a public good.

Ultimately, we have no prior knowledge of the type of incentive scheme that is actually optimal for females, particularly in a village setting, despite the former

observations. Predicting which incentive is likely to induce greater effort and ultimately more learning is confounded by a number of opposing forces. On the one hand, tournaments are historically more effective at encouraging effort, but when effort is directed towards an intangible public good like information, other strategic motives may make it optimal to lie or withhold information in a tournament setting. Furthermore, there is evidence that women are less motivated by competitive incentive schemes than men (Gneezy et al., 2003), potentially less likely to compete in patriarchal environments such as the ones I am studying (Gneezy et al., 2009), traditionally more inclined to contribute to public goods, especially in a rural developing country context (Greig and Bohnetb, 2009; Kilavuka, 2003; Morduch, 1999), and are inherently more pro-social than men (Skoe et al., 2002) according to social psychologists. With these findings, I am inclined to believe that women are possibly more inequity-averse than men, and might expect them to prefer a more egalitarian payment scheme (Teyssier, 2007). Can social norms amongst village women trump the effects of competitive incentives? (Fehr et al., 1998).

2.4 Model

I adapt a model from Irlenbusch and Rucahala (2008) to demonstrate my incentive scheme succinctly. The min-team incentive is characterized as follows. y_i is production, or the number information points that a participant i learns. It is determined by i 's effort, e_i , a continuous variable, and a stochastic component, ϵ_i ,

such that $y_i = e_i + \epsilon_i$, where ϵ_i is uniformly distributed within an upper and lower bound $\sim U[-\bar{\epsilon}, +\bar{\epsilon}]$. An individual's objective is to choose effort with the objective of maximizing their expected payoffs less their total cost, which is convex in effort, $C(e_i) = \frac{e_i^2}{c}$, where, c is a constant that scales the cost of effort. Each person within the team must learn at least \bar{k} information points if the team is to win a prize.

$$\text{Max}_i \Pi_{i=1}^{14} \Phi(y_i) E(P^{TE}) - \frac{e_i^2}{c} \quad (2.1)$$

where $\Phi(y_i) = \text{Prob}(y_i) \geq \bar{k}$, or $\text{Prob}(\epsilon_i) \geq \bar{k} - e_i = \frac{\bar{\epsilon} - k + e_i}{2\bar{\epsilon}}$. Optimal effort is given by:

$$e_i^* = \left(\frac{c}{4\bar{\epsilon}}\right) \left(\frac{\bar{\epsilon} - k + e_i^*}{2\bar{\epsilon}}\right)^{13} E(P^{TE}) \quad (2.2)$$

Notice that this team incentive depends on the probability that each player achieves at least a known \bar{k} , and that there is no benefit to contributing effort beyond that minimum (unlike Reichmann and Weimann (2008)).

Similarly, the objective in the tournament incentive is also to maximize effort over one's expected payoffs:

$$\text{Max}_{e_i} \phi_i(y_1 \dots y_{14}) E(P^{TO}) - \frac{e_i^2}{c} \quad (2.3)$$

where $\phi_i(e_1 \dots e_{14}) = \text{Prob} y_i \geq y_j, \forall j$, and optimal effort is given by¹ :

¹where $\frac{\delta \phi_i(y_1 \dots y_{14})}{\delta e_i} = \frac{1}{2\epsilon}$

$$e_i^* = \frac{c}{4\bar{\epsilon}} E(P^{TO}) \quad (2.4)$$

For the purpose of comparing effort levels, let us assume that $E(P^{TE}) = \frac{1}{N} E(P^{TO})$, where $N=14$, $e_i \in (0, 12)$, because an individual can learn between one and twelve points, and $\bar{\epsilon} \in (1, 11)$, because the number of points learned may randomly vary by an addition one to eleven points. Tournament incentives will induce greater learning than team incentives if $\frac{c}{4\bar{\epsilon}} E(P^{TO}) > (\frac{c}{4\bar{\epsilon}})(\frac{\bar{\epsilon}-k+e_i^*}{2\bar{\epsilon}})^{13} \frac{1}{14} E(P^{TO})$. This will clearly occur if

$$e_i^{TE*} < 0.6\bar{\epsilon} + \bar{k} \quad (2.5)$$

since team effort, without the second term, is $\frac{1}{14}$ th that of tournament effort.

However, if

$$e_i^{TE*} > 0.6\bar{\epsilon} + \bar{k} \quad (2.6)$$

then team incentives could trump tournament incentives.

In order to derive a closed form solution, I suppose $N=2$. Taking the ratio of optimal team relative to tournament effort yields:

$$\frac{e_i^{TE*}}{e_i^{TO*}} = \frac{(4\bar{\epsilon}^2 - 4\bar{\epsilon}k)^{\frac{1}{2}}}{8\bar{\epsilon}^2 - cE(P^{TO})^{\frac{1}{2}}} \quad (2.7)$$

The partial derivative of $\frac{e_i^{TE*}}{e_i^{TO*}}$ with respect to $\bar{\epsilon}$ is

$$\frac{-16\bar{\epsilon}^2k - cE(P^{TO})k - 32\bar{\epsilon}^3k}{(8\bar{\epsilon}^2 - cE(P^{TO})\frac{1}{2})^2} \quad (2.8)$$

This indicates that when players' expected level of uncertainty in learning via networks takes on larger positive values, optimal team effort is decreasing relative to optimal tournament effort, since the numerator is then negative and the denominator is positive. For negative values of $\bar{\epsilon}$, there is a range in which optimal team effort is increasing relative to tournament incentives.

2.5 Game Description

Players: Fourteen female-headed and non-female-headed household participants.

Player ID: Each individual receives a number between 1 and 14 signifying her identity (rather than by name, to disassociate people from existing ties).

Random Network Assignment: Participants' numbers are then randomly assigned some size network between 1 and 4 individuals. For example, if person 1 is randomly assigned to 3 links, then 3 unique numbers from a uniform distribution between 1 and 14 are selected.

The random assignment of a network is not binding. Once a woman talks to her assigned network, she's allowed to branch out to others. This serves two similar purposes: To help those who are less networked or less adept at networking to begin participating in the game, and to serve as a possible instrument for a person's true network size, taken from the social network survey².

Three rounds: Each round has a different incentive for learning new information from other players. Round 1 offers no prize. It serves as a round from which I can derive a measure of effort (and learning speed) for each individual, to be discussed in Section 2.7. Round 2 gives out one prize for the most collected information. Round 3 gives out a group prize if all individuals acquire a minimum specified number of information points about cotton growing that was decimated during the game. In each round I see how the different incentives encourage individuals to pass out information. I quantify the speed of interaction by tracking one unique point of information given out in each round.

Treatments: The following treatments are introduced to participants in the order of treatment one, followed by treatment two or three, where the latter two treatments are introduced in a random order to account for order effects, when evaluating outcomes after round one. Each round is timed to last 12 minutes.

²About half of the women in each experiment are those who are surveyed the day before this game is played.

Treatment one (No Prize): The unique pieces of information are concerned with cotton growing. Players are told to learn the information known in their assigned networks, and to teach their information point in return. By gathering how much of the information they correctly learned from their assigned network, controlling for network size, I can estimate a measure of learning effort.

Treatment two (One Grand Prize): Now individuals play for one grand prize that only one individual can claim. The woman acquiring the most information points is rewarded at the end of all rounds.

Round three (Group Prize): Now individuals play for a group prize. If every individual of the 14 women acquires at least 5 points, then the entire group receives a prize.³

(Prizes): Because I am not interested in the the effects of the stakes on behavior, and because both the structure and level of prizes affect behavior (Ehrenberg and Bognanno, 1990), prizes and winners are left unknown across treatments. The 2010 survey did survey participants, ex post, on what they believed the prizes to be worth. The results are summarized in 2.1. For most game participants, their expectations of the prize value corresponded to the actual cost of the prize, which was in the range of 2.50-5.00 US dollars. Expectations for the group prize had a

³Note that the game was conducted in the above order as well as with the order of round two and three reversed, to enable us to ensure that the incentive itself, and not the order in which the incentives are presented, is what drives learning.

greater variance, with the highest frequency of expectations on 10 and 100 USD, where the group prize was worth 10 USD. A piece rate incentive was not considered, because measuring output of all training participants by extension trainers would be realistically unfeasible on a national scale.

2.5.1 Game Instructions

Every individual is taught one piece of information in confidentiality from thirteen information points concerning cotton growing, which were identified as knowledge that most farmers (in the East and North of Uganda) lack.

An individual is required to first speak with the individuals randomly assigned to them, and then, only after speaking with these two individuals can they continue to seek to develop new links (this is to ensure that there is at least some random element to the size of one's network that is not a function of person specific characteristics). The participants return at the end of each round to privately recount what they learned.

2.6 Results

Result 1) Women learn more under tournament incentives than under team incentives. The distribution of total information points learned under tournament

incentives first order stochastically dominates (FOSDs) the distribution of total information points learned under team incentives. FOSD indicates that the learning distribution under tournament incentives is uniformly below the learning distribution under team incentives, i.e. higher values are realized with greater probability under tournament incentives. Thus, while FOSD implies that the mean number of points must be higher under tournament, it also means that there is a higher probability of learning more points across the entire distribution of total points learned.

A non-parametric Wilcoxin matched-pairs signed-ranks comparing the median number of points learned between treatments, pooling over the order in which treatments were received, confirms that the median frequency in learning significantly differs between the two treatments ($p=0.0001$). Although there may be differential learning effects, dependent on the order in which incentives were introduced (particularly in terms of learning how to play the game optimally), these incentives should cancel each other in the pooled data-set. Figure 2.1 plots the total number of points learned in a game, pooling the results across different treatment orders. I find that the distribution of total information learned under tournament incentives FOSDs the total information learned under team incentives.

Result 2) The probability that a unique information point is learned under team incentives is higher than under tournament incentives.

A non-parametric Wilcoxin matched-pairs signed-ranks confirms that the higher

percentage of participants learning the unique point under team incentives, 68%, vs. the percentage of participants learning the unique point under tournament incentives, 50%, are significantly different, with a p-value close to zero.

Result 3) Playing the game under tournament incentives before team incentives results in better “learning how to learn” the unique information point. That is, all else equal, we should not expect a statistically significant difference in the cumulative number of points learned across treatments depending on the order in which those treatments were introduced.

Table 2.2 shows that there is no statistical difference between the amount of information learned depending on the order of the incentives, but that there is a significant difference in whether an individual learned the unique information point in round 3, depending on the order of incentives, namely 75% chance of learning the unique point in round 3 if the individual received the tournament incentive first.

However, when I test for whether the total number of points learned by round 3 is statistically different depending on the order in which the incentives were received in a regression framework that controls for first round effort, order is significant. Table 2.3 shows that the coefficient on order is negative, where order=1 if team was received before tournament. This confirms that the tournament-team incentive ordering increases the total information learned by round 3.

These results suggest that the order in which incentives are introduced does not have a significant impact on overall learning, but does have a significant impact

on learning a particular information point. This may be because in the tournament game, players can observe who are the outstanding performers, and, as a result, when I repeated the game with team incentives the outstanding players are singled out as good transmitters of the unique information point, thus affecting the outcome based on what was observed in the previous round with tournament incentives.

2.7 Estimation of Game Incentives' Effects

In order to investigate the effects of team versus tournament incentives, while controlling for effort and ability, I estimate a generalized Poisson model⁴. I assume that the stochastic shocks to production, or learning, ϵ , take on only positive values from the support of the Uniform distribution on which it is defined: $\epsilon \in (0, \epsilon+)$. That is, I assume that the stochastic shocks only take on positive values for individuals, given that the prize should have a positive incentive on effort, and I do not assume any loss aversion by the i th player in the tournament game should the j th player win. Therefore, I expect tournament incentives to have relatively stronger effects on total learning than team incentives, given my models' predictions. I estimate:

$$Pts_{i2} = \alpha + \beta * order_{i2} + \delta * e_{i1} + \eta * size_i + e_{i2} \quad (2.9)$$

where “Pts” is the number of points learned by the end of round 2, “order” equals one if a group received the team (round2) followed by the tournament

⁴This enables us to account for over-or under-dispersion in the learning outcome variable.

(round3) incentive, “e” is individual i’s effort and ability to acquired information, measured as the total number of points the individual learned from her assigned partners in round 1, and “size” is the number of individuals the player was instructed to talk to in round 1. Here I look at the number of points learned by the end of round 2, since it captures the pure effects of tournament vs. team incentives, whereas round 3 totals represent a cumulative effect of incentives.

The effort variable is an approximate measure for an individual’s effort to learn within the confines of the game rules, where players were only instructed to learn from their assigned network in round 1. I also control for the number of individuals a player is assigned to, as the size of network varied between 1 and 4 links. After round 1, they were encouraged to talk to others outside their assigned network, once they had completed speaking to the former.

My results in Table 2.3 from estimating a generalized Poisson model in column(1) indicate that tournament incentives are significantly more effective at encouraging overall learning, even after controlling for effort and network size. “Total 2” is the total number of points learned by the end of round 2, and “order” is equal to 1 if the individual received a team incentive in round 2, and “0” if she received a tournament incentive in round 2.

The estimation results from a Probit with “Learn 2” as the dependent variable are inconclusive at determining which incentive results in a greater number of indi-

viduals learning the unique point.

Round 3 estimations conform to my plots showing that tournament followed by team incentives results in players learning how to learn in the game (where Order=0 if tournament (round 2) is followed by team (round 3) incentives) after controlling for effort and network size.

Finally, because team incentives were introduced with a minimum number of points to be learned in order for the group to receive a prize, there may be no individual incentive to exceed that minimum. Therefore, to make a more fair comparison across tournament and team incentives, I estimate the effects of the treatments on the learning outcome less the minimum required under team incentives (3 point minimum). These results are presented in column (5) above. It indicates that tournament incentives remain more effective in explaining the variance in the number of points learned beyond three.

2.8 Discussion

These results inform us that tournament incentives—despite behavioral evidence that females are more pro-social and public good oriented than men, as well as the complication that a competitive incentive structure might lead to strategic disincentives for sharing—still induce the greatest information dispersion among

women in female networks, even after controlling for their initial effort and ability. Therefore, it is unlikely that mechanisms like inequity aversion are at play. However, there is some evidence that team incentives are more effective at disseminating any one particular information point as the probability of Learn2 is higher under team than tournament incentives. This is a useful finding in that extension trainers may want farmers to amass and retain as much information as possible, but, should also encourage them to learn specific points from one another that trainers and most growers might be unaware of.

Finally, the order in which incentives are introduced matters for how well a participant learns to play the game. All else equal, I should expect the same amount of total information to be learned regardless of the order in which incentives are introduced. On the contrary, introducing tournament incentives prior to team incentives leads to more information learning, suggesting that that this ordering of incentives leads to more efficient playing strategies. This ordering of incentives runs counter to the order in which extension agents seem to naturally introduce incentives⁵, which may create barriers to adopting a new technology if the same villages are given an advantage in training from year to year.

⁵Namely, they choose a village to work in first (team incentive), and reward the best workers with seeds (tournament incentive) in subsequent years.

2.8.1 Further Work

I would first like to expand my empirical estimation to test for whether the initial network structure⁶ that I imposed on participants can help explain why tournament incentives are stronger at impacting overall learning, yet team incentives encourage dissemination of learning particular information. Preliminary results show that network structure has an impact on learning, though the size of one's network does not. For instance, predicting whether a unique point is learned, with and without pooling over treatments, on size of network yields insignificant size effects. However, the structure of one's network, i.e. the distance to an information point from which a player is situated from within her assigned network, has a significantly negative effect, on whether the point was learned.

For a subset of the participants in my information games, I have detailed information on participants' actual networks as well as baseline data on their production and demographics. I would like to look at how participants' actual networks, both in size and quality⁷ relate to outcomes in the information games, as well as how participants' performance in the game relates to their production outcomes.

Finally, I also would like to learn more about the type of information being disseminated. Because I recorded exactly what information points were learned by participants, I can look at whether a wider variety of information points are learned

⁶Recall, that each individual received a network between 1 and 4 individuals at random.

⁷Quality of the network is measured as the number of well-connected individuals in a farmer's network, where "well-connected" individuals are all those farmers deemed knowledgeable by surveyees.

under team incentives relative to tournament, as well as when there are more errors in reporting information learned, data which were also recorded.

2.9 Figures and Tables

Figure 2.1: Total Agricultural Information Learned, Pooled over Treatment Order

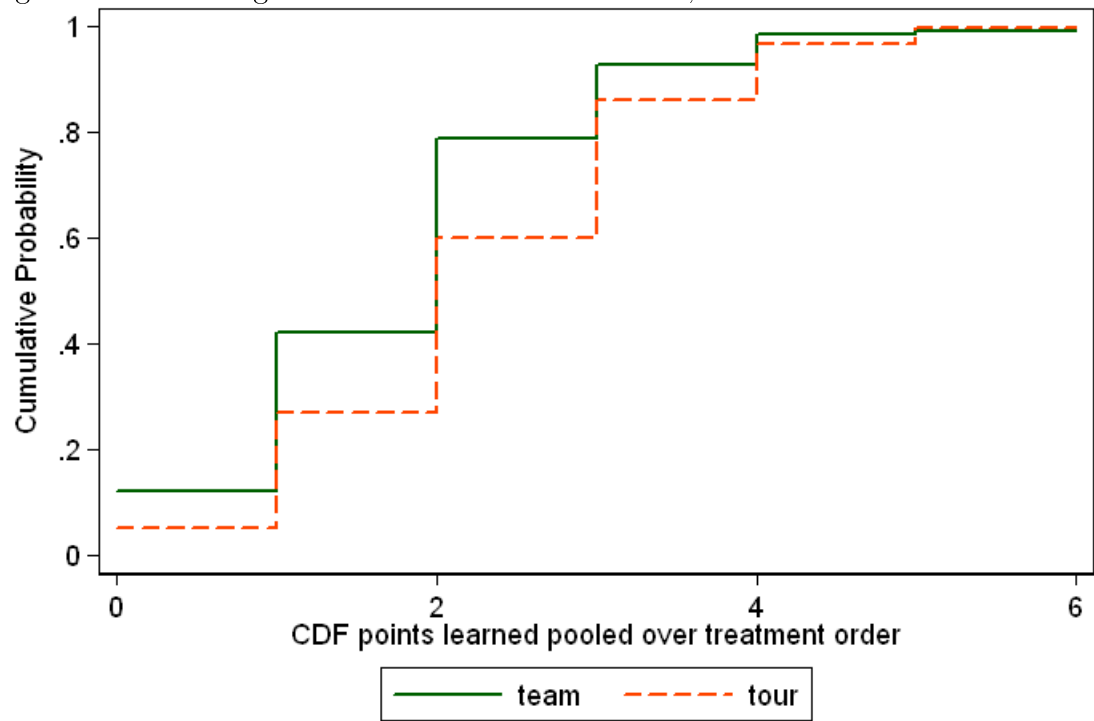


Table 2.1: Expectations for Tournament versus Team Prize Values (UG Shs)

	Mean	Std Dev	Min	Max
Tournament	156,718	173,886	1,000	100,000
Team	35,170	68,563	1	500,000

Table 2.2: Differences in Information Learned Over Rounds

	Mean(Tour-Team)	Mean(Team-Tour)	Wilcoxon(p-value)	Ksmirnov(p-value)
Total3 Rnd 3	6.65	6.41	0.21	0.94
Learn3	0.75	0.45	0	0

Table 2.3: The Effects of Effort and Incentives on Learning

Estimation	Total2	Learn2	Total3	Learn3	Total2Less5
	Rnd 2	Rnd 2	Rnd 3	Rnd 3	Rnd 2(Less Min Pts)
	GPoisson	Probit	GPoisson	Probit	ZTP
Order (Rnd2:Team=1) (Rnd3:Tour:Team=1)			-0.0568* (-1.675)	-0.867** (-2.574)	
Effort (Rnd 1 Pts)	.078*** (2.46)	0.0007 (0.01)	0.0711*** (2.615)	0.195* (1.741)	0.131** (2.12)
Size Network	-0.015 (-0.71)	0.058 (0.93)	-0.0154 (-1.025)	-0.0446 (-0.527)	-0.039 (-0.67)
Constant	1.50*** (29.03)	-0.06 (-0.31)	1.870*** (34.42)	0.635* (1.840)	0.71*** (5.60)
Observations	263	263	263	263	229
Dispersion	0.630	.	0.591	.	

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

Chapter 3

As Good as the Networks We Keep?

Expanding Social Networks via Randomized Information

Exchange

3.1 Abstract

This research isolates the impact of female social networks for subsistence farmers in rural Uganda for a re-emerging cash crop. I devised a social networking intervention (SNI), randomized at the village level, to tease out the pure effects of females' social networking on both females' and males' agricultural outcomes. The objective was to exogenously engineer social links by strategically placing new agricultural information (and provide training on this information “point”) with individuals embedded in pre-existing female social networks. Participants were encouraged to share, teach, and verify information over time with a randomly assigned partner. This would instigate their achieving a full knowledge set via newly created “weak links”.

Difference in difference estimates of the treatment effects show that the expansion of females' social networks significantly increases productivity for farmers producing at the average yield of production, up to four times the average household's annual yield for cotton. The impact of the SNI exhibits diminishing returns for the highest yielding quantile of producers, suggesting that learning between farmers is most productive for low- and mid-yielding producers. In contrast, the standard agricultural training program benefits already high-yielding farmers. The SNI intervention has its strongest impact on females' production, but also spills over to males' yields, increasing overall welfare of the village. I find that the average effects of the two programs are comparable, but they lead to different marginal effects along the distribution of producers. The SNI benefits the lowest-yielding producers most, while the Training program benefits the highest-yielding producers most.

From a policy perspective, these findings are substantial. In many developing countries, women supply the majority of agricultural labor, exhibit substantially lower yields compared to their male counterparts; however, due to cultural norms, women are rarely the recipients of training programs, particularly those that generate their own cash flow. A simple expansion of females' networks to promote new technologies is a not-yet utilized, but clearly effective tool for helping the poorest farmers.

3.2 Introduction to Social Networks

In the last few decades, the focus of economic growth in developing countries has shifted from country-wide prescriptions to testable micro-development programs at the local level. Agricultural growth, in particular, is seen as the building block for alleviating hunger and poverty, as agriculture is the primary source of livelihood in the rural developing world. Programs aimed at increasing agricultural productivity are regarded as the most powerful means to reducing poverty as compared to nonagricultural programs (Asfaw et al., 2011; Thirtle et al., 2001). An essential stage in any program intended to increase productivity is the dissemination of new techniques and technologies by agricultural extension agents and trainers. This stage is frequently one of the weakest links in the process. One of the reasons for the lack of clear success in this effort is that trainers' success in reaching and affecting all individuals in a particular location relies on the effectiveness of social networks, which are often unknown to an outsider and difficult to identify. While extension agents may bring new technologies with each program, what works best in practice in a remote village can widely differ from what is taught or what outside trainers perceive as being important for local production. It is through individuals' personal ties that external information is disseminated within a remote area, tested and localized, ultimately creating usable and believable knowledge. Thus, many welfare-improving technologies are never adopted because individuals are not connected to effective social networks.

Understanding the impact of social networks on individuals' outcomes is, thus, central to development at the microeconomic level. Identifying these impacts, however, suffers from serious problems and it is difficult to prove that such impacts even exist and to what degree they impede or assist progress. There is no shortage of evidence that individuals with strong links to social networks, large social networks or almost any measure of social connectedness are more likely to adopt and experience better outcomes. However, social connectedness is endogenous and therefore I cannot isolate the impact of social networks on decision making for the reason that dynamic individuals belong to social networks. Unobservable characteristics of an individual, such as networking ability and sociability, which affect an individual's productive outcomes, are correlated with the type of network that an individual forms, confounding the impact of network effects, and biasing the estimated impact of social network measures.

This paper examines a research project that measured the impact of social networks for subsistence farmers in rural Uganda. To deal directly with the identification problem I implemented a social networking intervention (SNI), randomized at the village level, to tease out the pure effects of females' social networking on both females' and males' agricultural outcomes. The SNI exogenously increased the size of the average woman's social network in treatment villages and left existing networks intact in control villages. I show that the treatment increases productivity for farmers producing at the average yield of production, and up to four times the average household's annual yield for cotton. The intervention has its strongest im-

pact on females' production, but also spills over to males' yields, increasing overall yields in the village.

By using an intervention to exogenously increase the size of networks, I am avoiding many of the problems faced in the literature on social networks and am able to measure the value, on the margin, of adding to network size for the average female farmer. Thus, I avoid the type of network endogeneity that occurs when measures of the social network are defined using descriptive statistics of the networks' outcomes: the size of the network, the average age and work experience of the network, and the education level of the network. All of these characteristics of an individual's network reflect her ability to connect with such individuals, which would likely be correlated with her productive outcomes. Another common way to measure an individual's network is by summarizing the average outcomes of the individuals in the network: e.g. the number of individuals who decide to adopt a new technology, or the percentage of contacts who choose one input amount over another. These measures suffer from endogeneity issues known as the reflection problem. The reflection problem refers to the idea that an individual's outcome may seem to be affected by his or her network only because her network faces the same unobservable shocks or influences that simultaneously influence the individual, and not because the individual is in fact mimicking her network's actions (Manski, 1993). More complex graph-based measures of networks-including cohesion¹ or reach of the network²-lead

¹Cohesion refers to the minimum number of nodes that would need to be removed to disconnect a group.

²Reach refers to the number of nodes within X number of steps from an individual.

to better understandings of social networks, but do not deal with the endogeneity problem.

This is one of two research studies, to my knowledge, on social networks in the development literature that uses a randomized encouragement design aimed at exogenously changing the social networks of women. Field et al. (2011) 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. Other research, such as Leonard (2007) and Marmaros and Sacerdote (2002) use natural exogenous variation to identify network effects. Leonard (2007) uses the sudden and exogenous replacement of clinicians in local health facilities to identify health care quality's effect on patient's learning about health care via their social network. Marmaros and Sacerdote (2002) uses the exogenous placement of college freshman's to identify the effects of social networks on future labor outcomes. I am interested in determining whether social networks are a means to improve female's production of a relatively new crop, and to estimate social network (SN) effects without statistical bias. Randomization of a social network intervention (SNI) at the village level allows us to test both these hypotheses. By comparing outcomes of farmers assigned to the SNI to farmers in a control group, over time, I can estimate the impact of expanding a female's network. The estimated network effects will not be diluted by potential spillovers of the SNI, because individuals in the treated and control groups are in separate villages. Furthermore, the SNI was implemented in the presence of a randomly assigned cotton-training

program, denoted as TR, which enables us to distinguish between the pure effect of social networks on productive outcomes, and the additive effect of social networks when coupled with a training program.

The decision to structure the SNI around females was inspired by an earlier study in rural Uganda on cotton producers that revealed male-heads' of households yields to be 3-4 times that of female-heads' of households yields (Baffes, 2008). This is a tremendous welfare loss and reflects the general phenomena in developing countries of females operating far below their full potential, while males continue to receive training (Chambers, 1993). As females supply 70-80% of agricultural labor in rural Uganda and are responsible for 80% of food crop production (Tanzarn, 2005), this is also a tremendous loss to national welfare. Other studies have looked at possible reasons for these productivity differentials (Quisumbing, 2003; Udry, 1996). 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 productivity³. No study has yet looked at whether under-utilization of females' social networks could be behind this production schism.

Cotton production is particularly interesting to these purposes because it is being re-introduced in Uganda for the first time since the 1970's. Due to civil war

³Women are unable to allow their land to lie fallow for fear of losing control of their plot (Udry and Goldstein, 2006).

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 of the cash producing crops. Udry’s seminal work shows that it is precisely in these circumstances, where new technologies are nascent, that social networks should have their greatest impacts (Conley and Udry, 2010).

3.3 Social Networks and Technology Adoption

In development economics, there are two groups of studies on social networks that focus on estimating the impact of social networks on technology adoption and “learning”, in terms of correct input use and resource allocation. The first group studies the effect of individuals’ existing social capital (ego network) on the decision to adopt new technologies (Bandiera and Rasul, 2006; Isham, 2002; Maertens, 2010; Matuschke and Qaim, 2009; Young, 2009). The second group looks at the effect of individuals’ social capital on input use, testing whether learning occurs inside the network (Conley and Udry, 2010; Darr and Pretzsch, 2008; Goldstein and Udry, 1999; Kremer et al., 2009; Munshi, 2004).

The above literature employs different methodologies to deal with the endogeneity of social networks. The adoption-network literature attempts to identify network effects by controlling for a gamut of individual level characteristics that

may confound individuals' network effects, in the hope that these variables will control for all unobservable characteristics of the individual. Matuschke and Qaim (2009) find that the endogenous group network measures, such as the average number of adopters in an individual's network, impact an individual's decision to adopt a new crop. Bandiera and Rasul (2006) also use endogenous network measures, i.e. the number of sunflower plant adopters in an individual's network, to predict an individual's decision to adopt. They too find that endogenous network measures significantly influence an individual's outcomes. Specifically, they find that the relationship between the probability that an individual adopts sunflower production and the number of adopters in that individual's network is inverse-U shaped. In other words, the probability of an individual's adopting sunflower production increases with the number of adopters in their networks at a decreasing rate, and eventually declines with the number of adopters. Unlike the former two studies, Isham (2002) identifies the effects of networks using the exogenous variation in an individual's networks caused by ethnic fractionalization and land inequality. He finds that social capital, when instrumented for, using tribal affiliations, has significant impacts on adoption decisions. However, there are many other aspects of an individual's production network that are not captured by ethnic affiliation, which a researcher would want to identify.

The learning-network literature relies on dynamic decision making to capture network effects. Namely, the individual only makes decisions after observing the actions of his network's members. If all actions and decisions are captured sequen-

tially, and we believe that the actions of one individual are caused by observing the outcomes of others', then information x at time t for person j , should identify the decision or outcomes of individual i at time $t + 1$. With detailed data on the outcomes and order of outcomes for all individuals in a network, this literature argues that the reflection problem is bypassed. Conley and Udry (2010) and Goldstein and Udry (1999) rely on the dynamic decision making assumption to identify learning from one's network, as well as detailed information on geography, soil, credit and family relationships that should control for confounding productivity factors. They find strong evidence of social learning, where farmers' decisions on inputs are affected by the successful outcomes of their neighbors in previous periods. Munshi (2004) adds to this result by showing that more learning occurs in more homogenous populations. Maertens (2010) also uses a similar dynamic decision making methodology as Conley and Udry (2010), but for predicting adoption decisions rather than inputs or outputs. Her research goes further and looks at distinguishing the channels by which individuals decide to adopt: social learning, imitation or social pressures, which are similarly outlined in Young (2009). Leonard (2007) looks at the decision to visit a health care facility with new clinicians as similar to the decision to adopt a new technology and uses a methodology similar to that of Conley and Udry (2010) by assuming individuals can only learn from the experience of people who visited the facility before they became sick. These methodologies rely on meticulous data collection and the belief that the available observable control variables, such as soil characteristics, are sufficient for dealing with confounding unobservable variables, such as weather and other productivity shocks, which concurrently affect the indi-

vidual and their network.

Duflo et al. (2006) is one study that uses an experimental design to identify social networks' effects. In Duflo et al. (2006), farmers are randomly selected from among the parents of children on school lists to participate in fertilizer-use trials. They compare the average outcomes of those individuals who were reported speaking to selected farmers with the average outcomes of individuals who were reported speaking to the control group. Essentially, they are exogenously altering the information present in some randomly selected social networks. According to their randomization, their identification strategy relies on the fact that there are no significant spill-over effects of the information from the networks of trained individuals to the networks of untrained individuals. Namely, they state, "farmers participating in each pilot were randomly selected from the parents of a school list, and that participating in the trials is randomly assigned within a school. Parents from the same schools that were not selected form a control group"(Duflo et al., 2006). However, when interventions are likely to have significant externalities, randomization across individuals will not capture the full effect of a program. That is, if the networks of trained and untrained are in close enough proximity to each other, it is very likely that individuals who spoke to trained farmers could have then shared the information with individuals in the network of untrained farmers. As a result, the differences in average outcomes of untrained and trained networks will not be detectable, which is what the authors find, when in fact differences may exist.

My research does not rely on controlling for unobservable household variables or the dynamic learning assumption. And unlike Duflo et al. (2006), my experimental design tests for the actual impact of social networks, whereas the Duflo et al. (2006) experimental design attempts to estimate the effect of a training program at diffusing information across already-existing networks, but not the impact of social networks themselves. Similar to Field et al. (2011), I directly perturb the networks of our sample population by randomly pairing individuals within selected villages. New pairs are encouraged to discuss their problems and solutions in growing cotton, create a mutual long term goal for increasing cotton output, and re-exchange information about growing cotton that they received in focus meetings. The SNI is meant to encourage information flow across new links. In this way, I would like to measure the actual impact of adding a new link to a grower's network.

The next four sections motivate the sample population selected for this study. Section 3.6 explains the randomization. Section 3.7 outlines a simple model to motivate my empirical estimation in Section 3.8. Section 3.9 tests the potential channels by which the SNI is affecting outcomes. Section 3.10 concludes.

3.4 Women and Cotton in Uganda

I follow Baffes (2008) and use female heads of households as our sample population. This avoids revisiting the issue of land ownership as a potential cause for

gender specific productivity differentials. I expect that the expansion of social networks for production, particularly for a new cash crop, has a high potential for improving females' outcomes. The reason behind these expected gains is due to females' networks traditionally being less oriented toward production alone than males' (Edmeades et al., 2008; Katungi et al., 2006). This may be because females face a starker tradeoff between economic and non-economic social networks. 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 (Granovetter, 2005). Responsibilities close to the home also restrict females from participating in geographically dispersed social networks and community projects, and force their relations 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). Female-headed households are also more likely to be poorer or more marginalized in their community, particularly those who have been widowed or divorced⁴. Hoang et al. (2006) emphasizes that "development workers' inadequate understanding of local social networks, norms, and power relations may further the interests of better-off farmers and marginalize the poor," who are disproportionately female. Large "structural holes" in females' production networks, therefore, likely exist, and establishing new links with a like grower should create a more complete production network for

⁴However, divorced, separated or widowed females who are not subsumed back into male-headed households, but retain some own property rights, are not necessarily the most resource constrained individuals in rural society.

every farmer in a village by closing some of these gaps. Nascent and weaker links are also more likely to propagate new and novel information along their paths, and their introduction can potentially have the greatest impact (Granovetter, 1974; Santos and Barrett, 2005).

3.5 Data

Our full sample population is comprised of male- and female-headed households that grew cotton in 2008 in rural Uganda. The SNI was directed at female-headed households⁵, while cotton training was administered to both groups. In the first stage, we randomly selected cotton growing villages from a complete list of all cotton growing villages in one Eastern district (Bukedea District) and one Northern district (Oyam District) of Uganda. We then stratified our sampling by female- and male-headed household status. The SNI consisted of an in-depth survey of the grower's social networks, participation in information games⁶, in which participants learned some of the information that would later be taught to them if randomly selected for the training treatment, and being paired with a "buddy" in their village area with whom they were encouraged to develop an agricultural link⁷.

The pairing occurred by first stratifying the cotton growing participants into

⁵The head of household was defined as the individual who made land, resources and income allocation decisions in the household.

⁶The information games are detailed in the previous chapter.

⁷See end extension training sheets in the appendix, from which 10-12 points were taught via the games.

2 to 3 geographic areas of the village⁸, and then randomly pairing individuals. We used a random number generator to print out lists of numbers randomly drawn from a uniform distribution, $U[0, x]$, where x represents the number of individuals in the group. For example, if the group was comprised of 14 women, then $x = 14$. 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. The pairing occurred among all the female-headed households in our sample as well as the additional female cotton growers in the village who participated in the information games. A random re-pairing occurred if the individuals were already neighbors, or if both were to receive training⁹ to maximize the effects of networking.

3.6 Randomization

In order to capture the effect of a social network intervention, randomization occurred at the village level as we would expect externalities from both programs, SNI and TR, between the treated and untreated within a village. By randomizing the SNI and TR programs across villages, I am able to measure the effect of the SNI treatment, the TR treatment, and the complimentary effect of both treatments.

⁸This to ensure that females were not separated by large geographic constraints.

⁹This only occurred in villages that were selected for the TR.

Figure 3.1 shows my three treatment groups: SNI, TR, and SNI+TR, that I will compare to the control groups who received no treatments. Figure 3.2 shows the breakdown of the SNI treatment, which will be exposted more fully in Section 3.9. This figure indicates that most individuals participated in the games and pairing, but a small group only participated in the pairings. Treatments Table 3.1 represents the combinations of effects between the two treatments.

The first round of a large-scale household survey was administered to 36 villages in 4 regions of Uganda: North (13 villages), Northeast (13 villages), West (5 villages) and West-Nile (5 villages)¹⁰ from February through May 2009. Figure 3.3 shows the sample size breakdown by treatment group. The household survey consisted of questions on household demographics, input use and outputs for cotton and other crops grown, household control of financial assets including sales from cotton, and a separate survey instrument on farmers' social networks regarding adoption, cultivation and marketing of cotton. While only some villages were selected to receive one of two agricultural technology programs, every village in our sample was visited by our team. Therefore, the effects from my results cannot be attributed purely to a behavioral response to our visits.

To facilitate farmers learning proper cotton growing techniques, and to estimate the impact of a low-budget agricultural training program, villages were ran-

¹⁰This results in a survey of 500 households. Approximately 175 households in each Northern region and 75 households in each Western region were randomly selected for the survey.

domly selected for participation in the TR. As Figure 3.3 shows, a total of 13 villages received SNI, and 18 villages received TR. In each village, approximately 14 heads of households were randomly selected to be visited by a local agronomist three times a week to undergo five training stages in 2009¹¹: 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. Half of the participant sample is female heads of households. Among the 18 villages randomly selected for agricultural training, another subset of villages was chosen to participate in the SNI. Among the 8 villages not selected for agricultural training, 4 received the SNI and 4 did not.

In the SNI group, each pair received a Polaroid photo of themselves and their team member, chose a team name, identified cultivation issues and chose a collaborative goal, as well as potential times when they would meet to exchange information. They then presented this to their peers at a group meeting. In this way they were strongly encouraged to build a relationship around what they would learn in the coming year about growing cotton via their new link, and have the group recognize this.

¹¹This was part of the larger RCT which 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).

3.7 Model

I use a conceptual model that is limited to the household's decision of choosing inputs to produce cotton, given their access to new links and training, which are exogenous in the model and in our data due to the design of SNI. I measure the household's maximization of yields. It would be ideal to measure profits of the individual farmer, which would incorporate the selling price of cotton and the cost of labor and inputs¹². An increase in profits, as opposed to yields, would ensure that growing cotton improves a farmer's welfare and is in fact lucrative. However, assigning shadow wages to family labor on cotton plots, and quantifying the hours worked by family and hired labor is a daunting exercise that we did not feel would produce accurate measures of profits. Rather, I assume that an increase in cotton yields does translate into a increase in household welfare. I do have qualitative evidence from the household surveys that the income produced from cotton is generally used on such things as purchasing school supplies and covering medical costs that otherwise would be foregone. Therefore, while I cannot show that cotton is the ideal choice of cash crop, I do know that it does alleviate short term liquidity constraints for subsistence farmers. In this way I believe that an improvement in yields is welfare enhancing.

Household i chooses a vector of inputs, \bar{x} , to maximize a production function

¹²It should be noted that the price of cotton is not determined by perfectly competitive market forces. Cotton prices are set by the government's announcement of an indicative price. Although the price is not fixed, it is highly suggestive of what price ginner will pay for cotton at harvest time (Baffes, 2008).

at time period t :

$$F_{it}(\bar{x}_{it}|SN_{it}, KN_{it}) = b * \bar{x}_{it}^{\eta} SN_{it}^{\gamma} KN_{it}^{\delta} \quad (3.1)$$

subject to a budget constraint $\bar{p}'\bar{x}_{it} \leq I_{it}$ where $t = 0 \dots T$, SN is a continuous variable representing one aspect of the i 's social network and is affected by the exogenous variation from SNI: $SN = f(SNI)$, and KN, knowledge, is affected by the exogenous variation from the TR program $KN = g(TR)$. The b , η , γ , and δ are unknown parameters (for ease of notation I suppress the i subscript unless necessary). I choose to model the problem statically, as the decision to grow cotton is not a dynamic one in terms of inputs, i.e. cottonseed cannot be carried over from one season to the next. Social networks would generally be modeled to evolve over time, and could be endogenized in the model; however, their evolution, particularly for females, is likely determined outside the realm of cotton production networks. These difficulties explain, in part, why I chose to introduce exogenous variation in social network size and model networks as otherwise fixed.

The sign and magnitude of η , γ , and δ is representative of the returns to output from any one of these inputs, which is an empirical question to be answered with the data. SN can be thought of as the sum of weighted links: $SN_{it} = \sum_{i \neq j} \delta^{n_{ij}t} sn_{ijt}$, as in Jackson and Wolinsky (1996), where n_{ij} is the number of links for the shortest path between i and j ($n_{ij} = \infty$ if there is no path between i and j), sn_{ij} is the value of one link between i and j , and $0 < \delta < 1$ indicates that the value of a link

is proportional to the distance between i and j .

The optimal, non-corner solution, will yield the function $x_t^*(SN_t, KN_t, I_t, \bar{p})$, and the optimized production function¹³,

$$F^*(\bar{x}_t^*(SN_t, KN_t, I_t, \bar{p})|SN_{it}, KN_{it}) = b\bar{x}_t^*(SN_t, KN_t)^\eta SN_t^\gamma TR_t^\delta \quad (3.2)$$

If $F(\cdot) = -e^{-(\cdot)}$ ¹⁴, and substituting in SNI and TR for SN and KN respectively, then taking logs gives us an estimatable function¹⁵:

$$\log y_t^*(SN_t, TR_t) = \beta + \eta x_t^*(SN_t, TR_t) + \gamma SN_t + \delta TR_t \quad (3.3)$$

I am interested in the difference in outcomes between the control group versus the treated groups as a result of a change in SNI, where SNI and TR equal one if an individual received a new link or training, and zero otherwise. This is captured by Equation 3.3 in first differences for those who did and did not receive the SNI, controlling for the TR treatment:

$$\log y_t - \log y_{t-1} = \gamma(SN_t - SN_{t-1}) + \eta(X_t - X_{t-1}) + \delta(TR_t - TR_{t-1}) \quad (3.4)$$

¹³For now I exclude income, I , and prices \bar{p} , from my optimal solution, since my focus is on the effects of SNI, and SNI relative to TR, on individuals' outcomes. Including them as controls would reduce some of the variance in the error term, but estimates will remain unbiased based given my identification strategy.

¹⁴This does not impose any strict assumptions on the utility function when $F(\cdot)$ is exponential, and leads to a linear prediction of log yields. For instance the measure of Absolute Risk Aversion with respect to x is not constant as it would be with only one input, is $\frac{\delta U^2 / \delta X}{\delta U / \delta X} = \eta\gamma * SN\delta * KN$. Similarly, the relative risk aversion is $\eta X\gamma * SN\delta * KN$.

¹⁵Taking the log of yields will also be useful empirically, as a number yields are close to zero, and a log transformation re-weights the distribution towards the lower tail.

This can also be written using a dummy variable for time¹⁶:

$$\log y_t = \alpha + \beta t + \rho SNI_t + \mu TR_t + \nu SNIxTR_t + \eta SNxTRxt + \gamma SNIxt + \delta TRxt \quad (3.5)$$

As the model cannot capture all determinants of yields, we observe y with some error u , such that Equation 3.5 becomes:

$$\log y_t = \alpha + \beta t + \rho SNI_t + \mu TR_t + \nu SNIxTR + \eta SNxTRxt + \gamma SNIxt + \delta TRxt + u_t \quad (3.6)$$

Using the data on outcomes and treatments I can estimate Equation 3.6. Assuming that the u_{it} are iid distributed disturbances with some known distribution that are uncorrelated with the regressors, or $E[SNI_t u_t | Z_t] = 0$ where $Z_t = [SNI_t, TR_t, SNIxTR_t, SNxTRxt, TRxt]$, the estimated effect of the SNI, $\hat{\gamma}$, will be unbiased.

The estimation of η in 3.6 is equivalent to a triple difference across both treatments and time, and γ captures the double difference across time and SNI. The estimated $\hat{\gamma}$ captures the average treatment effect (ATE) of the SNI that is:

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

—

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

¹⁶Where holding TR constant at zero, we can see that the two specifications yield equivalent results: $[(y|SNI = 1, t = 1, TR = 0) - (y|SNI = 1, t = 0, TR = 0)] - [(y|SNI = 0, t = 1, TR = 0) - (y|SNI = 0, t = 0, TR = 0)] = [(\alpha + \rho) - (\alpha + \rho + \beta + \gamma)] - [\alpha - (\alpha + \beta)] = \gamma$, just as it would in the first difference equation if TR is held constant at 0.

$\hat{\delta}$ captures the simultaneous average effect of SNI and TR¹⁷, on yields. The ATE is equivalent to $E[y|SNI = 1, t = 1, TR = 0] - E[y|SNI = 0, t = 1, TR = 0]$, or the average treatment effect on the treated, where $t = 1$, and TR is held constant at zero, if we believe that there would have been no difference in yields between my treatment and control groups in the absence of the SNI and TR, i.e. $[E(y|SNI = 0, t = 1, TR = 0) = E(y|SNI = 0, t = 0, TR = 0)]$. This is a fair assumption to make, given that my program was randomly assigned. However, because we were fortunate enough to follow my control and treatment groups over time, I can control for such trends, where β in Equation 3.6 captures:

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

or the differential trend in yields over time in the absence of the interventions.

Because the SNI is an encouragement design, my estimates reveal the intent to treat (ITT), or the intent to change individuals' networks. That is, everyone who participates in the SNI meeting is regarded as having participated in the SNI, even if she did not follow any of my suggestions over the course of the year.

The above outline frames a number of testable hypotheses:

- (1) $\frac{\delta y_t}{\delta SN_t} = \frac{\gamma}{SN_t} F^*(\cdot) > 0$, or the marginal impact of social networks is positive.

¹⁷ $\delta = [E(y|SNI = 1, t = 1, TR = 0) - E(y|SNI = 1, t = 0, TR = 0)] - [E(y|SNI = 0, t = 1, TR = 0) - E(y|SNI = 0, t = 0, TR = 0)] - [E(y|SNI = 1, t = 1, TR = 1) - E(y|SNI = 1, t = 0, TR = 1)] - [E(y|SNI = 0, t = 1, TR = 1) - E(y|SNI = 0, t = 0, TR = 1)]$

$$(2) \frac{\delta^2 y_t}{\delta^2 SNI_t} = \gamma(\gamma - 1) \frac{\delta^2 F^*(\cdot)}{\delta^2 SNI} \leq 0, \text{ or decreasing returns to scale in SNI.}$$

(3) $\frac{\delta y_t}{\delta s_{nj}} = \gamma \delta^{n_{ij}}$ implies that the effect of an additional link to person j is decreasing with the distance from j .

3.8 Empirical Estimation of Program Effects

A summary of the data is shown in Table 3.2. The data indicate that the interventions were evenly allocated across control and treatment groups, with slightly under half the total number of villages receiving the SNI, and slightly over half receiving TR. The average Ugandan cotton farmer in our sample produces between 100 and 200 kilograms per year. This concurs with previous studies on cotton production in Uganda, which find that the average subsistence farmer produces about 100 kilograms of cotton lint per annum, while an average US cotton farm yields about 500 kilograms per acre (Baffes, 2008). To situate this in tangible terms, one kilogram of seed cotton¹⁸ 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. 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 3.4. The average farmer produces less than

¹⁸Seed 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 cotton produces.

500 kilograms per season, which is well below the maximum farmer's production in 2009 of 2,000 kilograms, resulting in a high variance in yields.

The number of acres used to grow cotton ranges between one-half to one acre on average. Land is generally not a scarce resource¹⁹, though having sufficient labor to clear and prepare the land is. Therefore measures of yield will reveal this constraint, while the total kilograms of cotton harvested will not. I also summarize yield per seed, denoted as “ypseed”, since yield per unit land alone may not reflect accurate planting technique and input use. For example, farmers with more seed are able to replant in areas where no germination takes place, while another succeeds with the first round of seeds because of good technique. Both farmers may yield the same, but the second farmer yielded more per seed. Yield per seed was 52 kilograms in 2009 and fell down to 37 kilograms in 2010. It should be noted, however, that seed is freely or nearly freely provided by cotton ginners, so that yield alone may be the most appropriate outcome measure. The drop in yields, acreage used for cotton and yield per seed, is the result of delayed rains in Northern and Eastern Uganda during the course of the intervention. My interest remains in measuring the impact of the SNI in two ways. First, I measure the impact that the SNI had on increasing the probability that a household maintained cotton as a cash crop despite the drought. Second, I estimate the impact that the SNI had on output, and intermediate input decisions for farmers, while controlling for the impact of the TR intervention.

¹⁹Many households own land that is not cleared for production.

3.8.1 Choice to Grow Cotton

I first look at the impact of the SNI on farmers' decisions to grow cotton in the presence of the training intervention, clustering all standard errors at the village level to account for within village correlations between households' error terms on outcomes. Table 3.3 estimates the effect of the SNI and TR on remaining a cotton grower between 2009 and 2010, despite the adverse weather shocks mentioned earlier. I 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 zero if the individual ceased to grow cotton in 2010, and equals one if they planted cotton. The marginal effect of expanding a farmer's network by one link increases the probability of remaining a cotton grower by 18%. On the other hand, introducing training to a farmer increases the probability of remaining a cotton grower by only 11% and is insignificant.

Table 3.3, Column 2, estimates an Ordered Probit model, where the decision to not plant is 0, the decision to plant but then realize no yields is assigned a 1, and the decision to plant and realize positive yields is assigned a 2. My estimates reveal the significance of the SNI and TR in effecting the outcome variable. Though from a welfare perspective, I cannot state that growing cotton is necessarily an optimal component to a household's production basket.

A hurdle model might also be appropriate, where the decision to plant is modeled as a Logit or Probit, and conditional on a non-zero yield the distribution is modeled as a Poisson. However, this model would not capture the difference between a zero yield due to no attempt to plant cotton versus a zero yield where the farmer made an attempt but yielded zero, which are two substantially different decisions and outcomes. Table 3.3, Columns 3 and 4 estimate a hurdle Logit Poisson model. Column 3 shows that the SNI had both a significant impact on individuals' decisions to continue growing cotton between 2009 and 2010 and a significant impact on the potential output that they realized. Even more surprising, the SNI had a stronger and more significant positive impact on growing behavior than the TR.

3.8.2 Cotton Output

Table 3.4 estimates Equation 3.6, the triple difference in difference (η coefficient), and difference in difference across the TR and SNI variables (γ and δ coefficients respectively), on log of yields in Columns 3 and 4. I also run my estimations with yields in levels as I am interested in the interpretation of the programs' effects on yields, not log yields, in Columns 1 and 2. I am interested in the coefficients on $SNIxt$, γ , and $SNIxTRxt$, η , that is, the pure impact of the SNI intervention over time on outcomes, and the additive impact of the SNI relative to the TR treatment over time. At the same time, I also check that the estimated coefficients on SNI , and TR are insignificant. SNI , and TR are dummies for having been selected for

the *SNI* and *TR* treatments. They capture whether selected households are significantly different in their yields from households who were not. Similarly, the t variable measures whether there is a significant time trend in yields, which I expect to be negative given the drop in yields between 2009 and 2010. The first four columns of Table 3.3 show my initial estimates in yields and log of yields. Selection into the programs was random as indicated by the insignificant effect of *TR* and *SNI*. The negative and significant coefficient with respect to t reveals the downward trend in yields that is exhibited in the summary statistics of Table 3.2. The estimated impacts of *SNIxt*, $\hat{\gamma}$, and of *SNIxTRxt*, $\hat{\eta}$ are insignificant. However, both estimates are significant under the log yields specification in Columns 3 and 4. The additive effect of SNI on TR program is insignificant everywhere.

As Table 3.2 indicates, yields are overdispersed, where the variance in yields exceeds its mean. As Figure 3.4 shows, the average producer, before and after the treatments, is clustered below a 500 kilogram yield per year, so that the deviation from the mean yield is quite high for those few producers in the right tail of the distribution. Hence, the above result that the SNI treatment had an insignificant impact is not surprising if the upper portion of the yield distribution could gain little from the program. I would not expect a significant impact from social networks for the highest producers, who are already far above the mean yield, given that their knowledge base is likely saturated for this type of information. It is farmers with production yields in the low- to mid-quantiles that I would expect to benefit the most from new networks and basic growing information. I did not exclude top

producing farmers from the study, however, because they may play a critical role in information dissemination.

I now look at the average impact of the program for those producers located around the mass of the yield distribution in Figure 3.4. These are individuals who yielded 500 kilograms per acre or less in 2009. Those who yielded greater than 500 kilograms per acre in 2009 are removed from the sample, which constitutes 15% of my original sample²⁰. Columns 5 and 7 of Table 3.4 estimate Equation 3.6, conditional on having grown 500 kilograms of cotton per acre or less in 2009:

$$E(\log y_t | y_t < 500) = E(\alpha + \beta t + \rho SNI_t + \mu TR_t + \nu SNIxTR \quad (3.7)$$

$$+ \eta SNxTRxt + \gamma SNIxt + \delta TRxt + u_t | y_t < 500) \quad (3.8)$$

They show that the SNI treatment has a positive and significant impact on yields and log yields respectively. Dropping down to households who harvested less than 400 kilograms of cotton in 2009, reveals an even greater impact of SNI, as shown in Columns 6 and 8. This result is also of economic significance, as the average cotton yield in rural Uganda is 100-200 kgs per year, and the significance of these effects extend to households who began with yields of up to 400-500 kilograms. That is, even households who are well above the mean yield, benefit from the SNI.

²⁰ A household is dropped from the sample in both years if its yield in 2009 was less than 500 to maintain a balanced panel.

In fact, the impact of the SNI program for these producers ranges from 66 to 74 additional kilograms of cotton per acre, which is 50 % increase from the average farmer’s cotton yield between 2009 and 2010²¹.

3.8.3 GLM Estimation

The above estimation assumes that $E[\ln(y)|X] = Xb$, which shifts the distribution of yields below zero when a small constant, c , is added to zero-valued yields. It may be more appropriate to assume: $\ln(E[y|X]) = Xb$, which can be estimated by a generalized linear model with a log link. That is, the mean of the datum is linked to its predictors by a logarithmic function. The benefit of this specification is that the conditional mean should be positive, but the realized outcome can be zero (Nichols, 2010), something that occurs frequently in the labor literature with income and wage data, and with developing country data where yields and income exhibit a mass near zero. We need only to specify a distribution for $(y_i|Z_i)$, so that the $E[y|X]$ is defined. My results are robust to several distributional specifications (Gamma, Poisson, Gaussian), but modeling the conditional yields as a Poisson distribution fit the data best. If $(yield_i|Z_i) \sim P(\mu_i)$, then the mean of the distribution is defined as $\mu_i = \exp(\alpha + \beta t + \rho SNI_t + \mu TR_t + \nu SNI_x TR_t + \eta SN_x Trxt + \gamma SN_t xt + \delta TR_t xt)$. Table 3.5 estimates Equation 3.6 using a GLM log link and Poisson distribution. The significance of SNI’s effect still holds for producers producing 400 kilograms or

²¹The average yield across both years is 140 kilograms/acre. A 70 kilogram increase in output would result in 50 % increase in yields for the average farmer.

less, as seen in Column 2. The estimated marginal effects (not listed) of the SNI from the GLM estimation are a 30% increase in yields for the average farmer, a 36% increase for women, and a 19% increase for men.

3.8.4 Inputs for Cotton

There are two channels through which the SNI could impact yields: it could change the input decisions for cotton production, and/or it may change the techniques used by farmers (timing, weeding, thinning, and harvesting) to produce cotton. The differential impact of the SNI on outcomes between males and females may be a result of a change, or lack thereof, in either intermediate step. I check whether the SNI impacted the use of inputs in producing cotton.

In Tables 3.7 and 3.8 I look at the impact of the SNI on input use across the entire sample, and for males and females separately, using yields and log yields in a triple difference. These estimations suggest that there is a shift in the number of acres used for cultivating cotton, and a less consistent shift in the amount of seed used as a result of the SNI. The seed results are strongest for the log-transformed data, and remain significant for the female sample, but not male.

That said, another channel through which the SNI may have impacted output is through the improvement in planting techniques themselves. If input use has not

changed substantially in our data, where seed use is controlled by the ginneries' allocation of seeds to each household, and land use is constrained by available labor, then the effects of the program can be largely attributed to changes in growing techniques. In Section 3.9 I investigate further whether the improvements generated by the SNI were caused by the information training conducted during the information games or the generation of randomized pairings.

3.8.5 SNI and Training as Substitutes

I have found that the complementary impact of SNI on TR is insignificant, that is, the estimate of η is insignificant in all of my specifications. This may be because the TR program induces its own social networking effect such that SNI does not bring any additional gain to individuals who received TR. Therefore, each intervention seems to affect individuals' outcomes independently. I therefore, look at how the impact of the SNI (with and without TR) compares to the impact of TR (with and without SNI).

Table 3.6, Column 1 and 2 allow us to compare the effect of the SNI for those who received training compared to those who did not receive training in Columns 1 and 2. Column 2 compared to Column 1 shows that the SNI had its greatest economic and statistical impact for individuals who did not receive TR, where SNI increased yields by 74 kilograms per acre for those without TR²², versus 26 kilograms per acre for those who did receive TR, which was insignificant. In Column

²²We can also see this in Table 3.4 Column 6.

4, I estimate the converse of Column 2; namely, the impact of TR for individuals who did and did not receive the SNI. The results show that the effect of the TR where there was no SNI administered increased yields by 82 kilograms per acre and was significant, but increased yields by 34 kilograms per acre where SNI did occur and was insignificant. If I compare the effects of SNI versus TR, I see that the two programs are of comparable efficacy for increasing cotton yields. Therefore, the two programs appear to be feasible substitutes at increasing productivity in villages. The results hold true for the GLM specification as well, as shown in Columns 4-6.

Whether social capital behaves as a substitute or complement to standard training programs may depend on the program type itself. Jonathan Isham and Ramawamy (2002) suggest that when programs are delivering private goods with large information spillovers, then the influence of social capital on information sharing is high. The highest returns to investments in social capital, however, are when “the economic good that a development project is designed to deliver is characterized by high levels of nonexclusiveness or non-rivalry.” Of course, most training programs aim to deliver new knowledge, where knowledge is the quintessential public good. In that sense, I believe that the marginal investment in a social assessment will be relatively small compared to the potential benefits of the investment, regardless of whether the agricultural training itself is meant to deliver a private good.

What is significant about this finding is that, whereas a training program re-

quires the coordination of several agricultural extension agents²³: repeated travel to remote villages along unpaved roads, as well as coordination with the recipients of the training, the SNI is a one-time pairing of individuals and dissemination of information. A training program such as TR would cost between 300-600 dollars per village per year. Uganda has over 95 districts, each with around 10 sub-counties, and 5-10 villages per sub-county. For a conservative estimate, for over five thousand villages, the cost of a training program could range from one to three million US dollars (USD), depending on the number of trainers and their expertise. The SNI would amount to a one-time travel cost and the time of one individual to organize the SNI. At the national level the SNI would cost on the order of one hundred to five-hundred thousand USD.

3.8.6 Cumulative Impact

To gain a more complete picture of the SNI's impact on output for every quantile of producers by output, I plot the marginal impact of SNI on yields, conditional on households' yields being less than X kilograms per acre in 2009, where $X \in (0, 2000)$, and the estimates' corresponding t-statistics. Figures 3.5 and 3.6 plot the estimates of γ , the impact of SNI, from Equation 3.6 for yields $< X$ for the total sample of households, and for female-headed households alone. These graphs confirm hypothesis (2), namely, that the marginal effect of SNI is decreasing for

²³Agricultural education, extension and training programs ensure that information on new technologies, plant varieties and cultural practices reaches farmers and those who need them most.

higher yielding farmers. This also shows that the impact of the SNI is greatest for female-headed households producing up to 400 kilograms per year. Females producing between 0 and 400 kilograms per year experience an increase in yields of up to 70 kilograms per acre for the additional link that is added to their social network, as seen by the peak in the distribution in Figure 3.6.

The effect of the SNI also spills over to male-headed households in the lowest quantile of producers, i.e. those yielding up to 200 kilograms per year, as seen in Figure 3.7. The effects for males do not reach statistical significance at the 10 % level, but are nevertheless non-negligible. This confirms hypothesis (3), namely that the value to a male farmer i of an additional link to person j is decreasing with the distance to j . Granted, I do not directly test for this relationship by mapping the networks within villages, and then estimating the average effect of the SNI program along specific network paths. However, villages are quite small, and the individuals in our sample are very likely connected to one another within a few degrees of separation. Therefore, males in the sample who did not participate in the SNI are in some way connected to the females who did. Given that the females did expand their networks, the males likely did so as well, and this appears to have a muted effect on males' yields.

3.8.7 Impact against Mean Yield

To avoid the bias generated by dropping individuals producing above a certain yield, as I did for the previous Figures, I instead capture the local effect of SNI for a rolling band-width, controlling for the TR programming. For a band-width of ± 100 kgs/acre in 2009, the main regression is estimated repeatedly, and the SNI effect is plotted against the mean yield for this sliding band-width using a non-parametric polynomial regression with Epanechnikov kernel²⁴. I plot the effects of the SNI and TR to compare the distribution of the effects, with bootstrapped confidence intervals²⁵, Figures 3.10 and 3.11.

Figure 3.10 and 3.11 show that social network intervention aided growers who started with very low production levels, whereas the training program aided farmers across a greater spectrum. The total gains are comparable, but the distribution of the effects is clearly different. These graphs show that SNI and Training may appear to be substitutes on average, but along the distribution of producers, they are effectively different tools for yield improvement. The SNI is best at assisting the lowest producers, while it has no significant effect beyond those producing 400 kgs/acre or more in 2009. Thus, it does not add additional value to the highest-end producers, and appears to serve as an excellent poverty tool because it targets the weakest producers. The training program in comparison has a more even effect, in-

²⁴The Epanechnikov kernel down-weights observations farther from the mean where $K(u) = (3/4)(1 - u^2)$, where $u = \frac{(x - x_i)}{h}$, for $-1 < u < 1$, and $u = 0$, for $-1 > u > 1$.

²⁵Confidence Intervals are wider at the upper tails because there are fewer producers in that portion of the distribution.

creasing output for those who produced 400 kgs/acre, all the way up to 800 kgs/acre in 2009. The training program, therefore, appears to be a much better tool for increasing overall output, especially for higher producers. This would be relevant for policies that would like to increase the growth of Uganda's cotton industry at the global level²⁶.

One further graph confirms the reported distribution of the SNI program effects. Figures 3.12 and 3.13 plot the marginal impact of the SNI and TR programs, estimated within five yield quantiles in 2009²⁷. For these estimates, I do not overlap the band-widths for each estimation, hence the fewer estimates are plotted than in the Figures 3.10 and 3.11. The graphs still confirm the overall trends in the conditional effects of SNI and TR.

3.9 New Links or Information?

There are a two ways that I will test whether the effects that I pick up from the SNI program are caused by learning or new networks. The first method will look at the impact of SNI and TR on individuals' true social networks over time, and on the amount of information that they learned through the training programs.

If SNI affected networks and not learning, then I can deduce that it was through

²⁶Estimates for the higher level producers, however, are not efficient, given that there are few individuals in our sample producing above 600 kgs/acre.

²⁷The first quantile has an average yield of 52 kilograms per acre; the second quantile has an average yield of 87 kilograms per acre; The third quantile has an average yield of 140 kilograms per acre; the first quantile has an average yield of 290 kilograms per acre; and the last quantile has an average yield of 463 kilograms per acre.

networks, primarily, that the SNI program had its greatest impact.

To do this, I will first check the impact of the SNI and TR programs on perceived and stated size of social networks between 2009 and 2010. Secondly, I will test the impact of the SNI and TR programs on the information learned on yields. I can devise a measure of information correctly learned and stated using surveyees' results from a quiz that we included in the 2010 follow-up household survey, administered to all participants in the treatment and control groups. I calculate the percentage of correctly answered questions out of 12 questions. I also have computer scores of information learned during the games in 2009, but unfortunately, non-SNI treatment groups did not participate in these games, so I cannot conduct a panel analysis of the effects of SNI on information learned.

As a check to my cross sectional results, I compare them with my previous panel estimates. Namely, I repeat the first regression of yields on the SNI and TR programs using the 2009-2010 panel, and then compare this SNI effect to the SNI effect when using only the 2010 cross section. Given that the assignment of programs is random, the impact of SNI and TR should not be statistically different whether I use panel or cross-sectional data. The slope estimates on SNI are statistically significant in predicting yields at the 10% level and in predicting information learned at the 5% level.

Table 3.9 shows that the impact of SNI is statistically significant in explaining their grade on the survey quiz of the twelve information points in year two of the

study. The impact of SNI is not significant in explaining an individual's potential change in network size from 2009 to 2010. This may suggest that receiving the information via social networks versus increasing network size is the channel by which the SNI program affected outcomes most. Of course, we should keep in mind that the program only encouraged a change in network size by one link.

The second way in which I can check whether information or new links is driving the effect of SNI on yields is by focusing on the subset of females who participated in the pairings meetings and the social network survey, but who were unable to attend the initial information games. I create another treatment variable, "Information", denoting whether an individual attended the meetings and networked (=1), or simply was paired with an individual in round 2 (=0). If SNIxt remains significant after having controlled for "Information", then I might conclude that the program's effect is operating via the first meeting and information games, and not through the second meeting of pairings. "Might", because having received the information is conditional on the choice to attend the information game meetings, which we cannot observe, biasing my estimate of "Information's" effect.

Table 3.10 includes the estimates of the "Information" variable in the panel model, including a spline for individuals producing about 400 kilograms per acre. The spline helps us to avoid dropping observations for yields above 400 in 2009. The estimated model shows that Information is not quite significant in explaining the change in yields. TR remains significant, but the SNI becomes insignificant. Thus, these results also support that it is the first game meeting that seemed to

have the most impact on yields from conducting the SNI. However, these results are not conclusive given the endogeneity of “Information”, and because I only have cross-sectional data from 2010 to estimate the impact of the SNI on learning and networks. Therefore, neither individual random effects in the error term nor individual fixed effect variables as regressors can be used to control for unobservable variation that may be correlated with Information.

3.10 Discussion

This is the first experimental design in the development literature to identify the causal impacts of social networks on productive agricultural outcomes. Previous research has not been able to claim a causal effect of social networks, while other literature estimated the effect of a training program at propagating new information across existing networks. To circumvent these shortcomings, I exogenously perturbed networks, focusing only on females, whose output lags behind men’s and whose potential to improve yields via social networks appeared to be large. My estimates are robust to several specifications, including a generalized linear model that approximates a linearized production function for yields of cotton.

I estimated the SNI’s own impact, and additive impact on the TR program using linear regression, log linear, and generalized linear model with a log link for mean yields. All of my results indicate that the SNI had a significant impact on

yields for individuals who produced less than 500 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 shows that an additional link in conjunction with encouraged learning increases yields by about 70 kilograms per acre, and this effect declines for the highest yielding farmers. Much of this impact is driven by an increase in females' yields in villages where there was no TR, and seems to be driven by the learning that occurred across new links, rather than through instigating a substantial change in network size.

The additive impact of SNI on TR is insignificant. Essentially, the two programs provide different methods of training individuals, at widely dispersed costs, with distinctly different effects along the distribution of producers. In comparison to the training intervention, the SNI has its greatest impact for the lowest-yielding farmers making it a low cost tool for reducing poverty. This is a substantial finding, given that females comprise 80% of the agricultural labor force in Uganda, yet rarely receive direct agricultural training. Furthermore, female-headed households can serve as an example for others of how low yielding producers more generally can increase their production.

3.11 Figures and Tables

Table 3.1: Treatments, Sample Size

	TR	No TR	Totals
SNI	96	59	155
No SNI	120	50	170
Totals	216	109	325

Table 3.2: Means in 2009 & 2010

	2009	2010	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)
Sex	0.48	0.48	0.48
(Female=1)	(0.50)	(0.50)	(0.50)
Kgs 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 (Kgs/Acre)	182.0	139.5	160.6
	(208.7)	(234.9)	(223.1)
Kgs 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 3.3: Probit, OProbit, HPlogit

	(1)	(2)	(3)	(4)
	0=Dropped logit & Poisson	0=Dropped 1=Attempted 1=Attempted&0 2=>0	Hurdle (Logit)	Hurdle (Poisson)
SNI	0.565** (2.272)	0.699*** (3.115)	0.922** (2.208)	0.335** (2.022)
TRAINING	0.334 (1.579)	0.428** (2.286)	0.578 (1.614)	0.241 (1.536)
TrxSNI	0.0657 (0.207)	0.0159 (0.0558)	0.212 (0.409)	-0.184 (-1.078)
Observations	325	325	325	325

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

Table 3.4: Triple and Double Differences

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Triple D: Yield	DD	Triple D:Ln Yield	DD	DD	DD	LnYield	LnYield
					Yield<500	Yield<400	Yield<500	Yield<400
t	-97.84*** (-4.275)	-103.9*** (-4.951)	-3.127*** (-8.404)	-2.965*** (-7.631)	-87.63*** (-3.506)	-76.74*** (-3.685)	-3.061*** (-7.751)	-3.176*** (-7.013)
SNI	58.85 (1.569)	48.78 (1.480)	-0.0983 (-0.251)	0.123 (0.577)	-11.32 (-0.460)	-8.464 (-0.359)	-0.428 (-1.164)	-0.419 (-1.034)
TR	26.98 (0.745)	19.30 (0.651)	0.124 (0.368)	0.292 (1.228)	-3.574 (-0.147)	8.357 (0.432)	0.0257 (0.0809)	0.0950 (0.311)
TrxSNI	-15.22 (-0.256)		0.334 (0.725)		42.23 (1.282)	31.53 (1.050)	0.681 (1.621)	0.638 (1.420)
SNIxt	1.332 (0.0457)	12.70 (0.461)	1.593** (2.699)	1.291** (2.502)	66.68* (1.828)	74.69*** (2.899)	1.795** (2.592)	2.118*** (3.428)
TRxt	75.83* (1.791)	84.51*** (3.483)	1.160 (1.645)	0.929* (1.979)	100.6** (2.163)	82.73* (1.881)	1.165 (1.659)	1.234 (1.667)
TRxSNIxt	17.20 (0.352)		-0.457 (-0.491)		-38.33 (-0.632)	-48.27 (-0.909)	-0.725 (-0.723)	-0.989 (-1.025)
Constant	140.2*** (7.076)	145.6*** (6.206)	4.534*** (17.07)	4.415*** (19.39)	130.8*** (6.921)	113.2*** (8.307)	4.496*** (16.98)	4.398*** (17.41)
Observations	646	646	646	646	596	574	596	574
R-squared	0.047	0.047	0.238	0.237	0.047	0.045	0.232	0.245

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

Table 3.5: Double Difference, GLM

	(1)	(2)	(3)	(4)
		DD	DD	DD
		yield1<400	yield1<400	yield1<400
	DD	GLM	GLM	GLM
t	-0.944*** (-3.714)	-1.109*** (-2.989)	-1.482*** (-2.760)	-1.012*** (-2.706)
SNI	0.268 (1.484)	-0.155 (-0.767)	-0.497* (-1.916)	0.0489 (0.226)
TR	0.107 (0.659)	-0.0277 (-0.149)	-0.0124 (-0.0680)	-0.0213 (-0.102)
TrxSNI		0.348 (1.389)	0.592* (1.774)	0.226 (0.846)
SNIxt	0.173 (0.682)	1.001** (2.351)	1.468** (2.126)	0.862* (1.910)
TRxt	0.774*** (3.502)	1.206*** (2.621)	1.020* (1.669)	1.554*** (3.279)
TRxSNIxt		-0.830 (-1.585)	-0.694 (-0.884)	-1.168** (-2.096)
Constant	4.993*** (34.63)	4.874*** (33.93)	4.847*** (49.53)	4.884*** (28.92)
Observations	646	592	288	304

Robust z-statistics in parentheses

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

Table 3.6: Double Difference For Trained and Untrained, GLM

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Linear yield1<400 Trained	Linear yield1<400 Untrained	Linear yield1<400 SNI	Linear yield1<400 No SNI	GLM yield1<400 Trained	GLM yield1<400 Untrained	GLM yield1<400 SNI	GLM yield1<400 No SNI
Linear								
t	5.996 (0.153)	-76.74*** (-3.556)	-2.049 (-0.132)	-76.74*** (-3.623)				
SNI	23.06 (1.227)	-8.464 (-0.347)						
SNIxt	26.42 (0.564)	74.69** (2.797)						
TRAINING								
TRxt			39.89 (1.702)	8.357 (0.424)				
			34.47 (1.135)	82.73* (1.850)				
Constant	(8.764)	(8.016)	(5.341)	(8.168)				
t	121.6***	113.2***	104.8***	113.2***	0.0481 (0.159)	-1.132** (-2.478)	-0.0198 (-0.129)	-1.132** (-2.517)
GLM								
SNI					0.174 (1.212)	-0.0777 (-0.344)		
SNIxt					0.154 (0.466)	1.112** (2.305)		
TRAINING								
TRxt							0.323 (1.566)	0.0712 (0.426)
Constant					4.801*** (42.24)	4.729*** (38.22)	4.652*** (24.99)	4.729*** (38.82)
Observations	386	188	265	309	386	188	265	309
R-squared	0.014	0.073	0.041	0.033				

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

Table 3.7: Triple Difference of Seeds Acreage

	(1)	(2)	(3)	(4)	(5)	(6)
	Seed (kgs)	Acreage	Seed:Females	Acreage:Females	Seed:Males	Acreage:Males
t	-2.577*** (-5.890)	-0.691*** (-6.707)	-2.717*** (-5.434)	-0.425*** (-3.665)	-2.571*** (-3.955)	-0.800*** (-5.198)
SNI	0.385 (0.392)	-0.308 (-1.473)	0.676 (0.771)	0.124 (1.049)	0.409 (0.296)	-0.498* (-1.819)
TR	0.198 (0.280)	-0.155 (-0.827)	1.128 (1.393)	0.269** (2.762)	-0.397 (-0.471)	-0.383 (-1.515)
TRxSNI	-1.556 (-1.296)	0.190 (0.772)	-1.873 (-1.701)	-0.292* (-1.779)	-1.447 (-0.870)	0.459 (1.370)
SNIxt	0.492 (0.385)	0.382** (2.143)	1.823 (1.332)	0.108 (0.523)	-0.378 (-0.212)	0.497** (2.267)
TRxt	0.494 (0.680)	0.313** (2.149)	0.109 (0.129)	-0.0143 (-0.0841)	1.241 (1.143)	0.514** (2.741)
TRxSNIxt	0.894 (0.590)	-0.281 (-1.222)	0.126 (0.0770)	0.0348 (0.142)	0.957 (0.451)	-0.466 (-1.557)
sex	-1.402*** (-5.570)	-0.329*** (-5.619)				
Constant	7.205*** (13.72)	1.651*** (8.294)	3.679*** (5.877)	0.627*** (9.675)	6.083*** (12.94)	1.465*** (6.439)
Observations	645	650	312	315	333	335
R-squared	0.114	0.150	0.154	0.146	0.066	0.099

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

Table 3.8: Triple Difference of Ln(Seeds) and Acreage

	(1)	(2)	(3)	(4)	(5)	(6)
	LnSeed (kgs)	LnSeed (kgs)	LnSeed:Fem	LnAcreage:Fem	LnSeed:M	LnAcreage:M
t	-2.867*** (-12.21)	-2.181*** (-17.88)	-3.715*** (-10.66)	-2.469*** (-7.414)	-2.580*** (-6.615)	-2.099*** (-9.859)
SNI	0.0184 (0.101)	-0.277 (-1.275)	0.171 (0.971)	0.0832 (0.316)	-0.113 (-0.585)	-0.457* (-2.052)
TR	0.107 (0.801)	-0.0287 (-0.161)	0.217 (1.358)	0.393** (2.130)	-0.141 (-1.046)	-0.391* (-2.008)
TrxSNI	-0.405 (-1.574)	0.00593 (0.0199)	-0.672** (-2.135)	-0.415 (-1.141)	-0.0670 (-0.250)	0.336 (1.012)
SNIxt	1.260* (1.744)	1.139** (2.274)	2.077* (1.996)	1.413* (1.900)	0.990 (1.329)	1.067** (2.158)
TRxt	0.751 (1.165)	0.717 (1.593)	1.110 (1.454)	0.688 (1.140)	1.166 (1.546)	1.093** (2.318)
TRxSNIxt	0.124 (0.125)	-0.312 (-0.436)	-0.203 (-0.155)	-0.475 (-0.502)	-0.312 (-0.294)	-0.488 (-0.654)
Sex	-0.582*** (-4.169)	-0.603*** (-4.985)				
Constant	2.290*** (12.65)	0.725*** (3.571)	1.198*** (10.73)	-0.725*** (-5.355)	1.680*** (26.58)	0.216 (1.568)
Observations	645	650	312	315	333	335
R-squared	0.211	0.203	0.256	0.226	0.167	0.158

Robust t-statistics in parentheses

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

Table 3.9: Cross Sectional Impact: SNI on Yields

	(1) Yield	(2) SNI on Information Learned	(3) SNI on Network Size
SNI	60.18* (1.710)	0.0483** (2.307)	0.273 (0.621)
TRAINING	102.8* (1.848)	0.0406* (1.701)	0.677 (1.512)
TrxSNI	1.976 (0.0262)	-0.0375 (-1.052)	-0.780 (-1.430)
Constant	42.33*** (2.854)	0.378*** (25.95)	3.708*** (10.96)
Observations	325	324	263
R-squared	0.057	0.021	0.012

Robust t-statistics in parentheses

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

Table 3.10: Another “Treatment Group”
Learning or Networks?

VARIABLES	(1) TRIPLE D: Yield	(2) Yield	(3) Networks	(4) Yield Control for Info
t	-97.84*** (-4.258)	-98.97*** (-4.203)	-1.947 (-1.654)	-65.90** (-2.573)
SNI	58.85 (1.608)	526.1*** (11.83)	-1.258 (-1.006)	535.9*** (10.52)
TRAINING	26.98 (0.744)	39.21 (1.029)	-0.498 (-0.395)	56.53** (2.486)
TrxSNI	-15.22 (-0.258)	29.36 (0.673)	2.034 (0.870)	
SNIxt	1.332 (0.0453)	101.3*** (3.494)	0.559 (0.397)	3.998 (0.143)
TRxt	75.83* (1.751)	76.06* (1.758)	1.488 (0.964)	24.18 (0.864)
TRxSNIxt	17.20 (0.346)	-114.9** (-2.337)	-2.857 (-1.125)	
dummy400xSNI		-570.4*** (-13.09)	1.108 (1.163)	-564.6*** (-12.61)
sex		-37.61* (-1.701)	-0.992 (-1.167)	-46.14** (-2.150)
Info				11.92 (0.451)
Infoxt				59.18** (2.226)
Constant	140.2*** (7.126)	188.3*** (5.402)	6.916*** (4.535)	188.4*** (5.013)
Observations	646	646	529	646
R-squared	0.047	0.368	0.015	0.371

Robust t-statistics in parentheses

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

Figure 3.1: Experimental Design: Overall Program

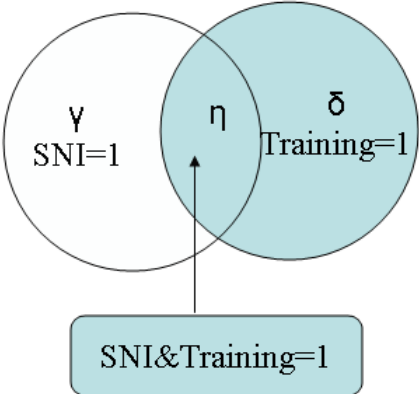


Figure 3.2: Experimental Design: Social Networking Program

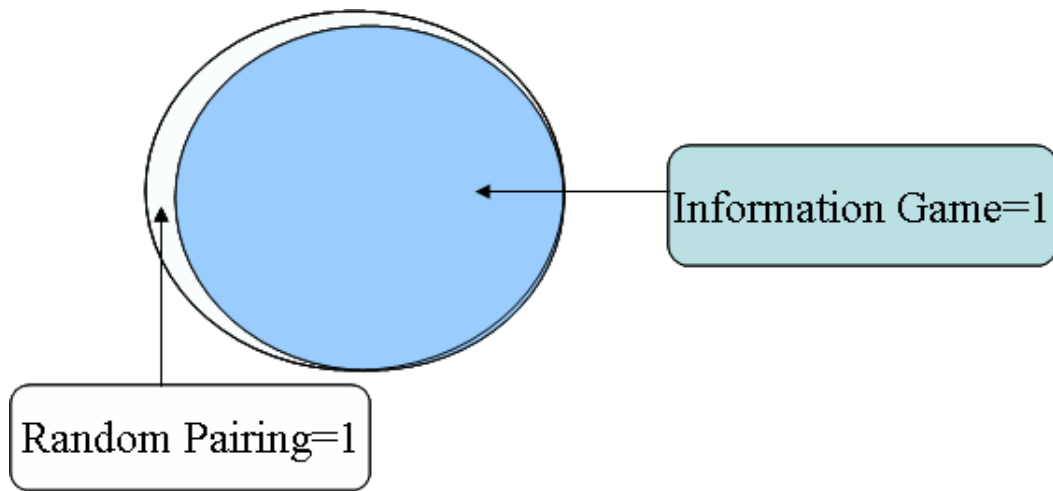


Figure 3.3: Sampling Villages

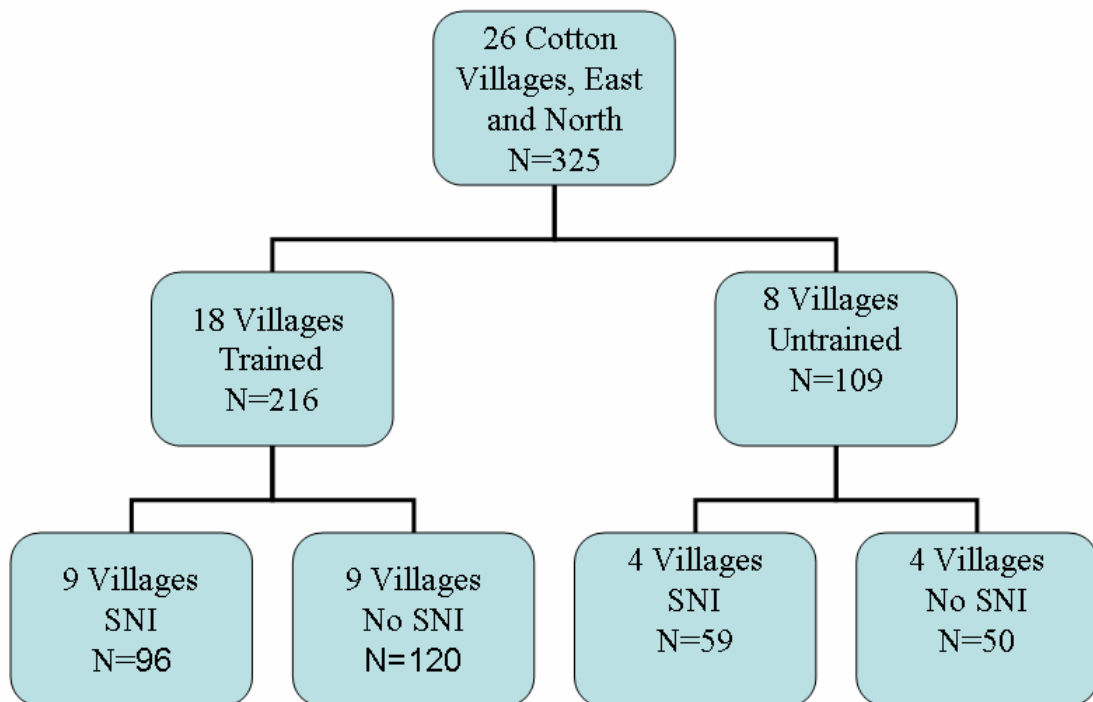


Figure 3.4: Non-Parametric Frequency of Yields

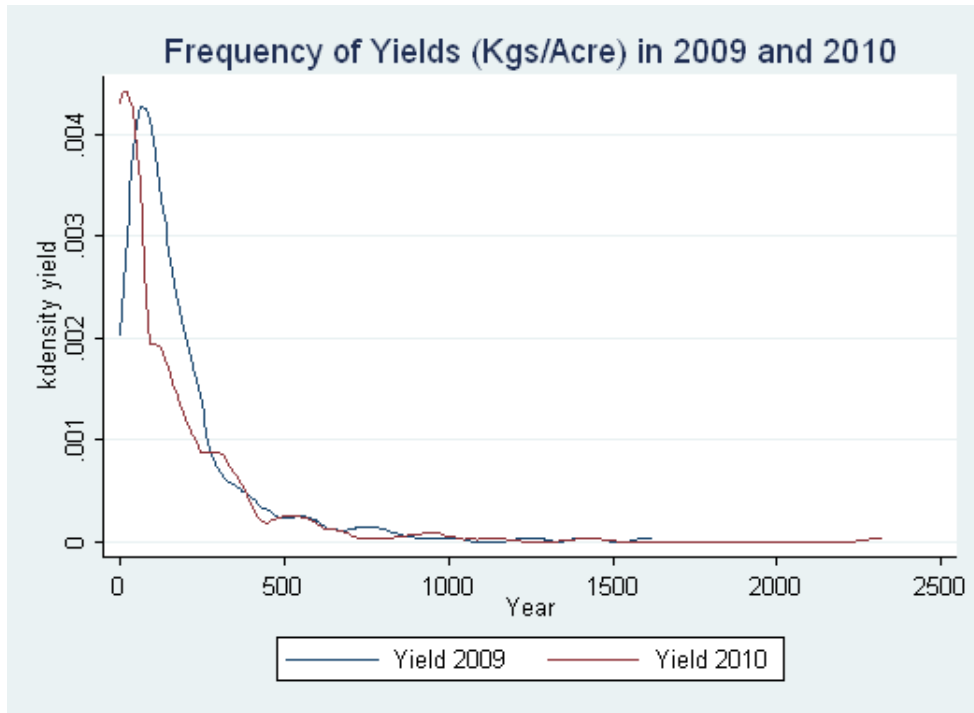


Figure 3.5: Cumulative Effect of SNI on Yields

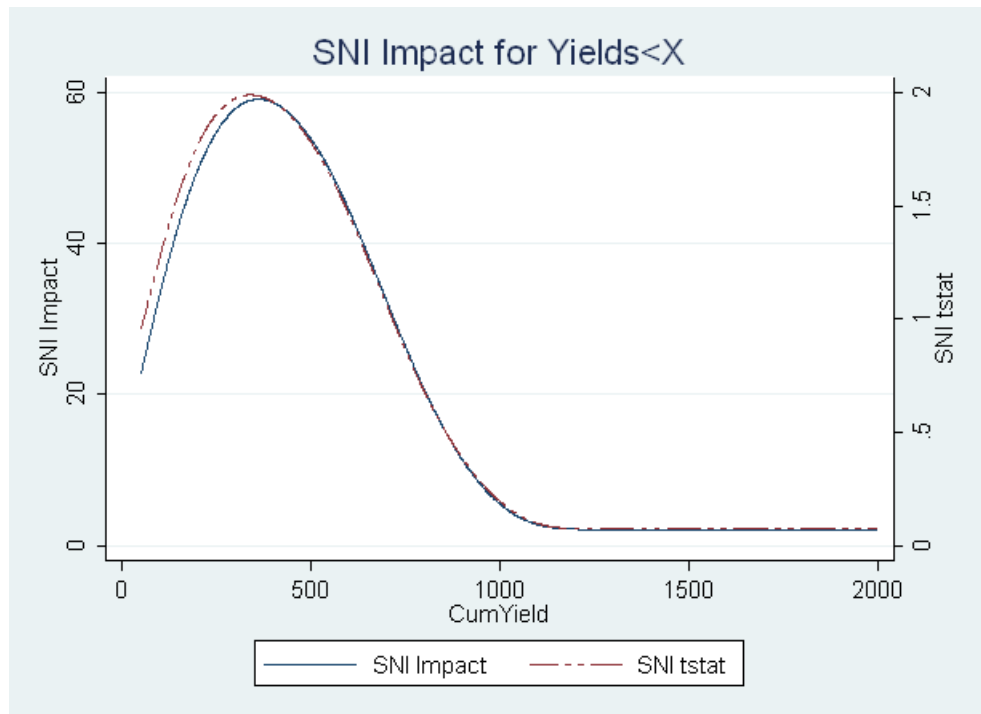


Figure 3.6: Cumulative Effect of SNI on Yields for Females

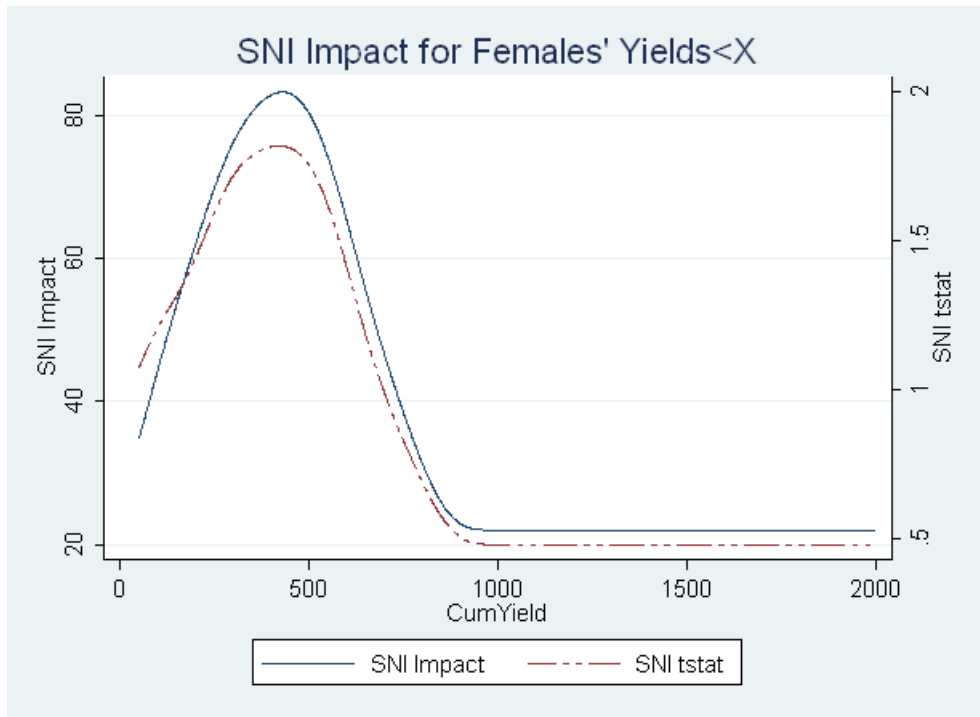


Figure 3.7: Cumulative Effect of SNI on Yields for Males

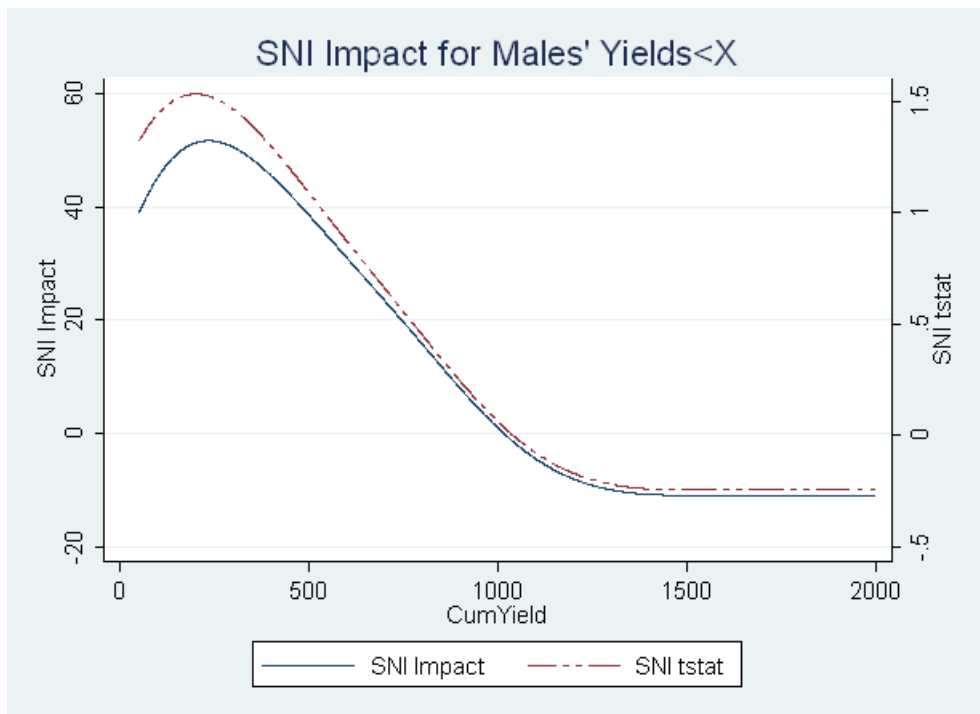


Figure 3.8: Cumulative Effect of SNI on Yields, Estimated by GLM

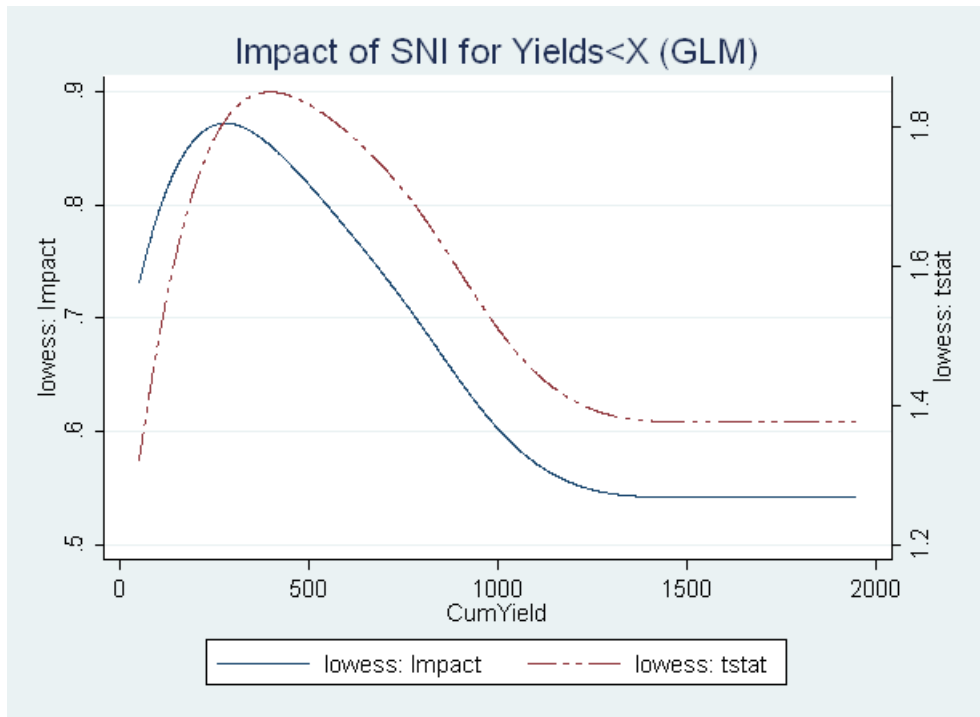


Figure 3.9: Cumulative Effect of SNI on Yields for Females, Estimated by GLM

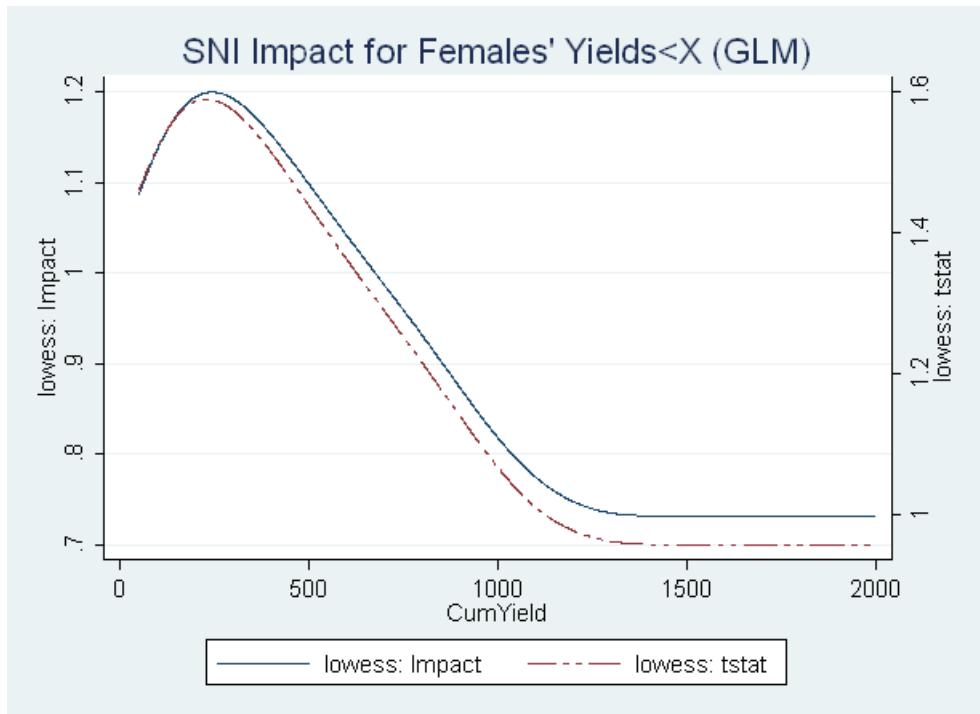


Figure 3.10: Effect of SNI by Mean Yield

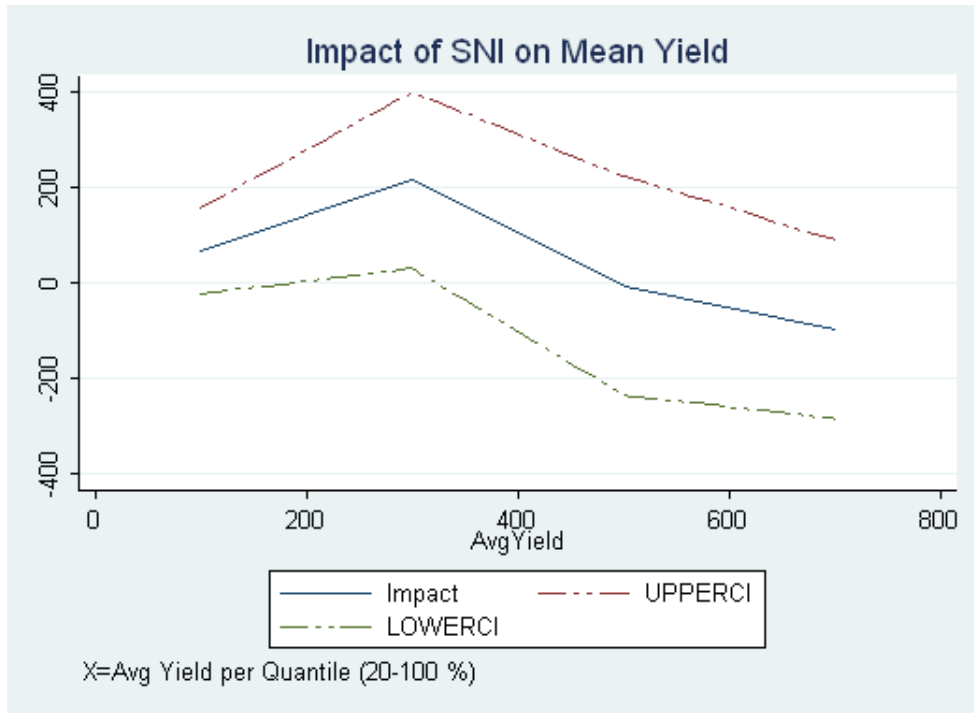


Figure 3.11: Effect of TR by Mean Yield

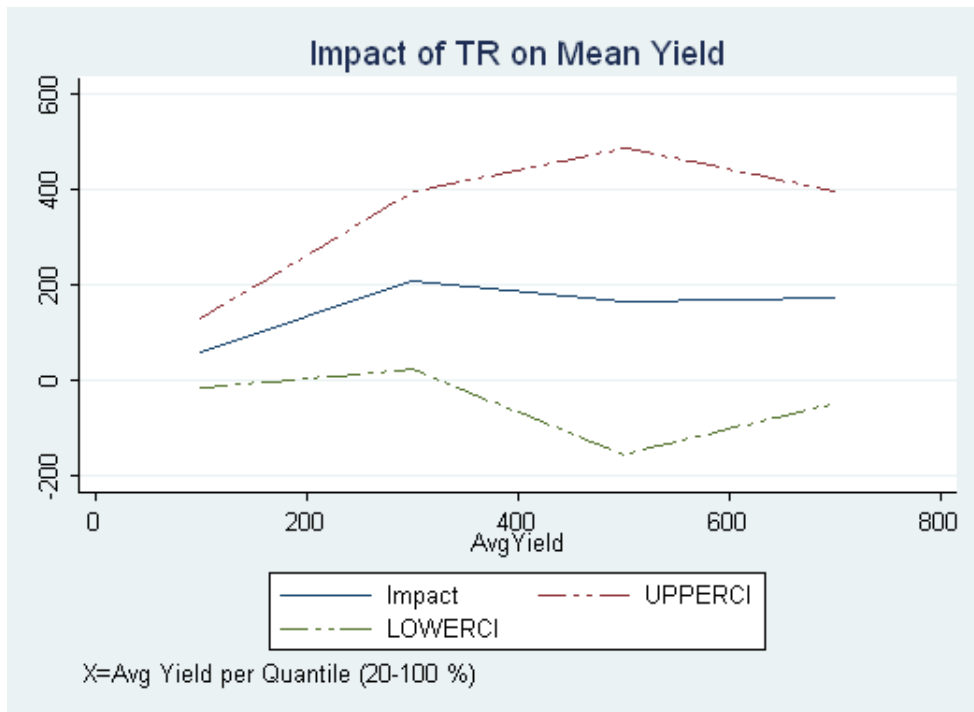


Figure 3.12: Effect of SNI by Quantile

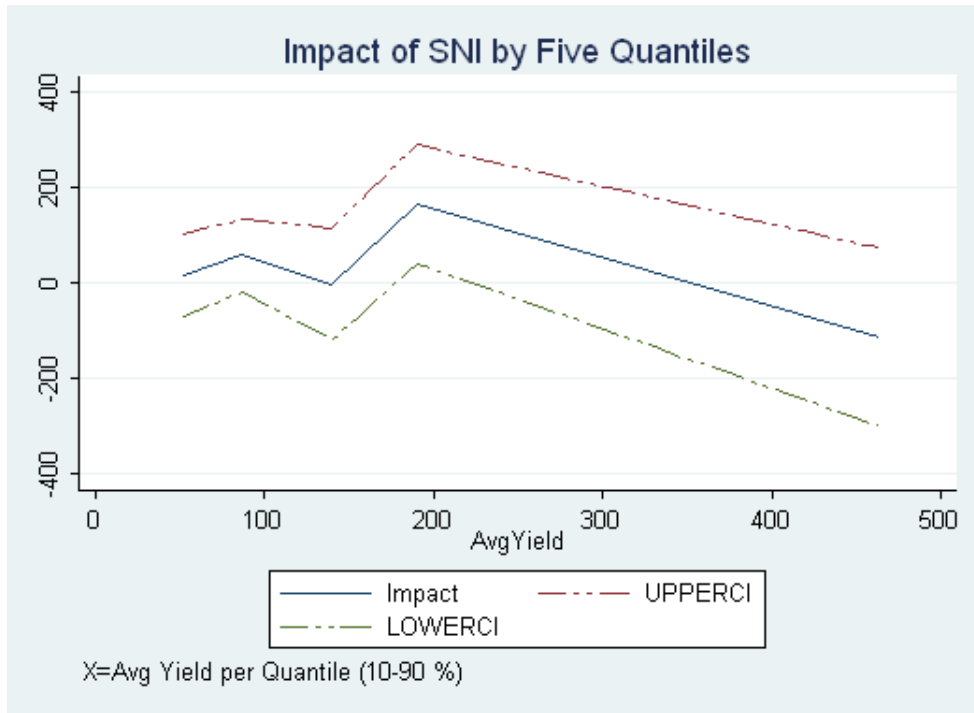
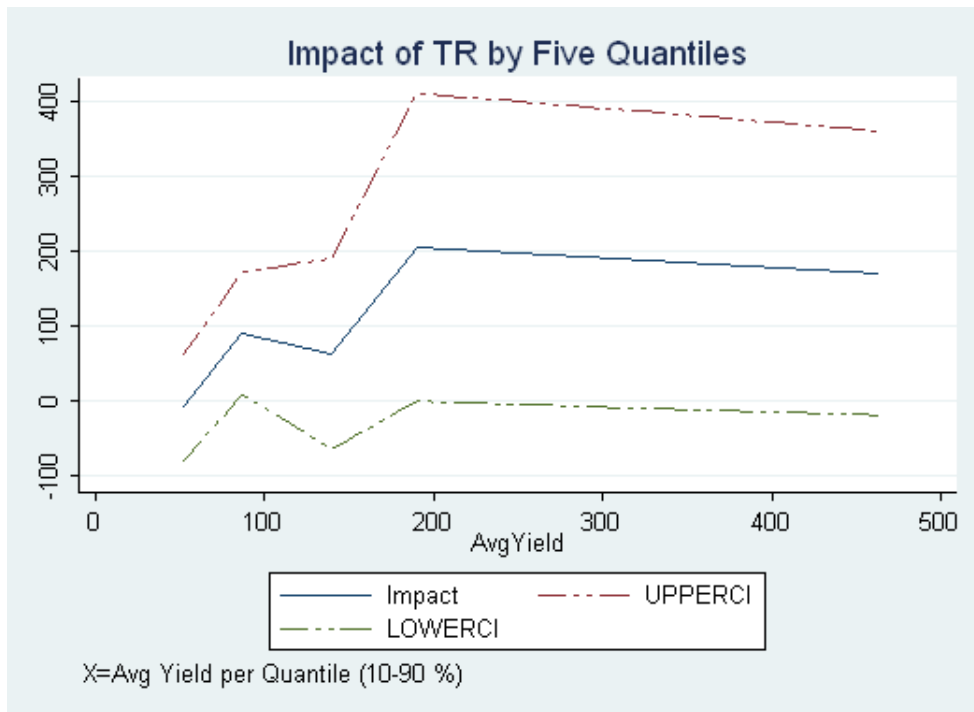


Figure 3.13: Effect of TR by Quantile



Chapter 4

What Have We Learned?

The focus in development on testing local programs has become a favored tool for identifying the variables that affect progress most. Randomizing the treatment of those programs allows researchers to separate a variable's effect from the many other confounding channels that simultaneously affect individuals' outcomes. By randomizing the encouragement of new links and new information across this study's sample, I am able to parse out the causal impact of social capital (new links and their information) on individuals' yields. This is a contribution to the academic literature on social networks, but also a stepping stone for development programs overall. An essential component to any training program is its ability to have sustainable effects. I find that the latter depends on how well a program can leverage existing networks, and germinate newer networks as well.

Agricultural development is a foundational step to progressing past rural poverty, yet one of the most difficult to implement. Agricultural programs require time, inputs, and transmission of new knowledge. The SNI is a program that in-

creased farmers' output without the continual intervention of outside agents, which the TR required. In addition to potentially serving as a poverty-reducing tool, the SNI also circumvents the potential biases towards male-focused training that exist in developing countries , and the barriers in networking between males and females. As such, my findings are relevant to the developing country context where males disproportionately receive more training programs as compared to females, and where there is limited information exchange across genders. Utilizing local informal institutions can be more impactful than traditional training programs in terms of benefiting the most vulnerable producers in a community, and at a fraction of the cost. This is because a program that draws its strength of communication from existing ties is much more likely to influence the peripheral and small yielding producers than a training program, which benefits the already highest yielding producers.

As Jonathan Isham and Ramawamy (2002) stress, it is important that such findings on social capital be given a context for policy practitioners. "A pinch of trust with a dash of social cohesion; then let simmer for six or seven centuries" is not a strategy for development. As a practical implementation of my findings, I advocate that for optimal effects, programs similar to the actual social network intervention outlined here be used, rather than the more traditional idea of advocating groups, such as farmers' groups or female groups. I find, from the experimental extension of this work, and through my qualitative studies, that promoting groups strengthens already existing social structures in a village, while developing new and random links helps to propagate new information from peripheral individuals, whose voices

might otherwise be subsumed by a well regulated social structure. Furthermore, I find that competitive incentives, rather than group incentives, are better at propagating information exchange amongst females.

While this research shows that social network-based training can bootstrap the worst-off females, we cannot forget that the same program may not produce similar results for males, and that female-targeted programs may not improve overall welfare of a society if we do not also work with men. As Jemimah Njuki, a Kenyan sociologist and gender specialist at the International Livestock Research Institute (ILRI) aptly stated at the Institute for Food and Policy Research in January 2011, “If we do not put money in pockets of men, we will not manage to put money in the pockets of women” (Njuki, 2011). What is useful about this evaluation of the SNI, is that the general equilibrium impacts of the SNI are measured. Namely, I calculate the average impact of the SNI by village estimating the impact on the yields of both female and male respondents, and also separately for both males and females. The effects of the program do not seem to have negative spill over effects on males. Quite the opposite, males of the lowest-producing quantile, in fact, improve indirectly from the females’ SNI program. Even incorporating a handful or less of high-yielding male farmers into female-targeted programs, could be enough to quell a village’s concerns that the program is unfairly targeting females. In most villages, I found that once males understood that females were being educated in agricultural information that were bringing them up to par, their beliefs that the program would threaten their own social standing and agricultural output dissolved.

In all cases, males were allowed to observe the information games, but were asked not to participate.

There are several outcomes that I take from this research, which can also be extended to development research and programs in other parts of SSA, Africa at large, and developing countries, where individuals live without the tools that allow for constant and accessible communication. No doubt, applying this research could not be uniform even across a country, but the purpose behind the training methodology outlined here is founded on the idea that individuals know what is useful for them. In identifying network effects, I find that female farmers naturally absorb information when the proper incentives provide open channels for communication.

Figure 4.1: Author with Female Growers



Chapter 5

Appendix A

5.1 12 Game Points

1. Ladybirds are good insects (show picture)
2. Spacing between rows is 75 cm (3 sheets long)
3. Spacing between plants is 30 cm long (1 sheet)
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 clothe with applying pesticides. It's harmful to your health.

10. Check germination after 5 days-replants seeds at gaps to get even crop cover
11. Prepare land several weeks in advance for cotton planting
12. Cotton is good for mixed and rotational crop
13. At most, breastfeed children no more than 2 years

5.2 Extension Training Sheets

FRIENDLY INSECTS IN COTTON



Baby Ladybird



Adult Ladybird



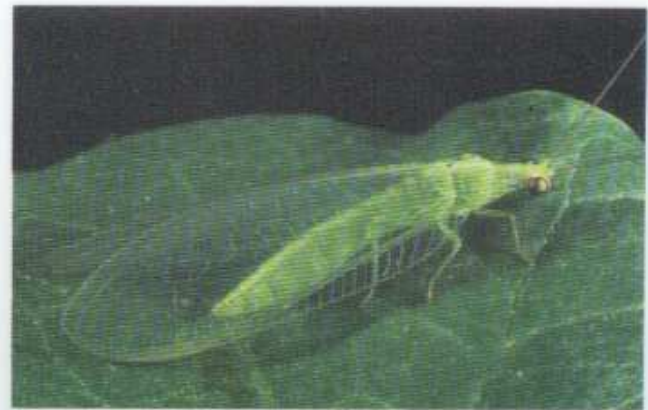
Aphid Eater



Aphid Eater



Aphid, Bollworm Eater



Bollworm Eater



Ngingingini



Spider (pest eater)



COTTON PESTS AND THEIR DAMAGE



Seedling Disease



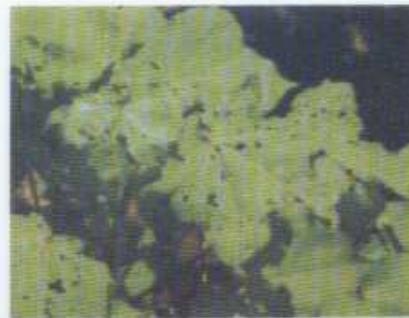
Aphids



Aphid Damage



Lygus



Lygus Damage



Bollworm Egg



American Bollworm



Spiny Bollworm



Damaged Shoot



Stainer



**Agricultural
Productivity Enhancement Programme (APEP)**

58 Lumumba Avenue, Nakasero
P.O. Box 7856 Kampala, Uganda.
Tel: 031 - 350 700, Fax: 031-350 701
E-mail: info@apepuganda.org
www.apepuganda.org



Stained Cotton

Cotton Pest

- Aphids which suck off plant sap and drop honey dew
- Lygus bug which tatters young cotton leaves
- Mites which lead to crinkling of leaves
- Bollworms which burrow into young squares, flowers and bolls causing them to fall off after their feeding
- Cotton stainers which stain the lint to brown colour



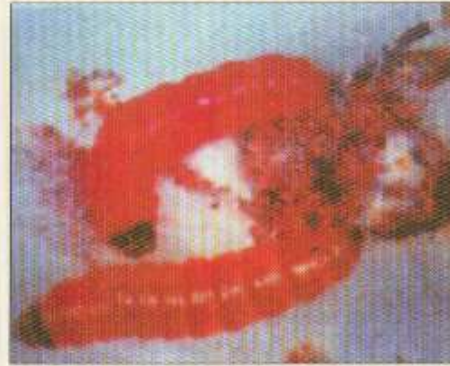
Jassids



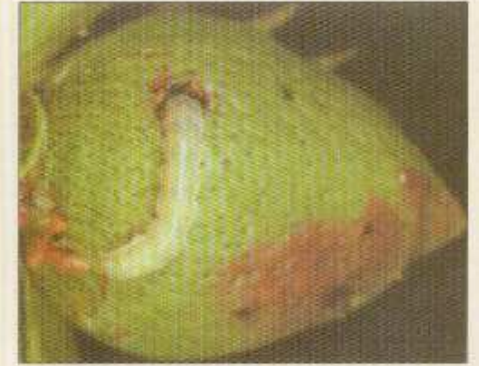
Lygus Bug



Aphids



Pink Bollworm



American Bollworm

Spraying

- Use appropriate spraying equipment
- Use recommended insecticides
- At mixing half fill the tank of sprayer with clean water
- Add recommended amount of chemical to tank
- Fill tank with water to 15 or 20 litres
- Use clean nozzle for spraying – smaller the better
- Spray one row per pass
- Cover whole plant with spray



SOROTI Cotton Ginnery



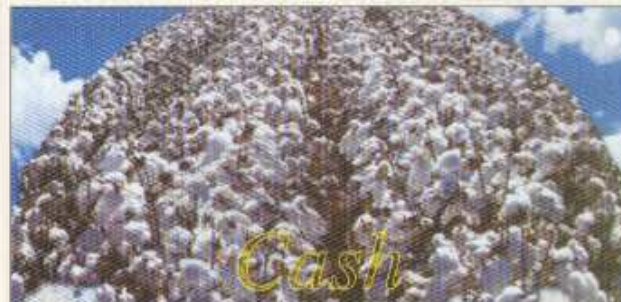
A correct way of spraying one row of cotton moving in the same direction as the wind with Knapsack sprayer

When to Spray

- Avoid spraying between mid day and 3.00 p.m.
- Avoid spraying when it is about to rain
- For Lygus bug - 5th to 7th week after planting
- For bollworm larvae - 8th to 9th week after planting

Why to Grow Cotton ?

- Cotton brings cash to the farmer
- Cotton opens land for the next crop
- Cotton is good rotation crop
- Cotton is good mixed crop
- High profits can be made from cotton production
- Cotton gives foreign exchange to our country
- Cotton is in demand by ginners



Cotton can pay school fees

Planting of Cotton

- Prepare land weeks in advance
- Plant from May to July
- Spacing between plants = 30 cm
- Spacing between rows = 75 cm
- Seed rate = 7 kg per acre (17.5 kg/hectare)
- Plant 3–5 seeds per hole



Spacing between plants = 30 cm



Spacing between rows = 75 cm

Gap Filling

- Check germination 5 days after planting
- Replant seeds at gaps to provide uniform crop cover

Thinning

- 3 weeks after planting, cotton seedlings should be thinned
- Always thin cotton and retain 2 healthy seedlings at one spot
- More than 2 seedlings at one place will reduce cotton yield

Weeding

- Weeds are major cause of low yields of cotton
- More weeds = less cotton
- First weeding should be done between 2nd and 3rd week after planting
- Second weeding should be carried out between 6th and 10th week after planting



Weeds

5.3 Survey Instruments

5.3.1 Social Network Survey

8 March 2010

HHID: _____

Village: _____

Enumerator: _____

Date: _____

Section A-Identifying key individuals in networks for adopting cotton.

FO: Please reference photocopied 2008 SN list for this household. Maintain same Name spellings, but order of peoples may change.

NAME of respondent	Person ID	Name, in order of importance, all the villagers whom you believe are most knowledgeable on growing COTTON in your village, even if you do not directly talk to them.	Name, in order of importance, all the villagers whom you believe are most knowledgeable on issues regarding your everyday VILLAGE affairs, even if you do not directly talk to them.
Name	ID	AN1	AN2
		1	1
		2	2
		3	3
		4	4
		5	5
		6	6
		7	7
		8	8
		9	9
		10	10
		11	11
		12	12
		13	13
		14	14
		15	15
		16	16
		17	17
		18	18
		19	19
		20	20

8 March 2010

HHID: _____

Section B-Identifying links in cotton growing. FO: Please reference photocopied 2008 SN list for this household. Maintain same Name spellings, but order of peoples may change.

NAME of respondent	Name CG (cotton grower)	C G I D	CG cotton growing status codes below	Has the CG marketed their own cotton in the past? codes below	Approximately, how many people does the CG talk to about issues regarding cotton? (answer BN4 before BN5)	Starting with the CG you talk to the most, name the villagers the CG talk(ed) to most about growing cotton. (Do not change BN4 if the total # in BN5 does not match BN4. Do not refer to AN1 or AN2.	If BN5 lists less than or equal to 3 people Why? codes below	Did this person grow cotton in the last 2 seasons?(1=Y, 2=NO)	Gender (1=M/ 2=F)	Age (or age range)	Years of education..See School Codes.	Farm equipment owned codes below. Multiple answers possible.	What is the size of this person's plot?	Units (miles, meters, km)
Name	Name CG		BN 1	BN2	BN4	BN5	BN6	BN7	BN 8	BN 9	BN 10	BN11	BN12	BN12 Units
						1								
						2								
						3								
						4								
						5								
						6								
						7								
						8								
						9								
						10								
						11								
						12								
						13								
						14								
						15								
						16								
						17								
						18								
						19								
						20								

8 March 2010

HHID: _____

NAM E of respon dent	Name CG (cotton grower)	C G I D	Relist individuals named in BN5 here. (initials are sufficient)	Is this person's cotton plot allocated next to yours (can you see their cotton plot from your cotton plot)? (1=yes/2=no) (If yes, skip to B17)	Approxi mately how far is this person's cotton plot from your cotton plot?	Units (miles, meters, km)	Is their soil quality 1=worse , 2=the same 3=or better than your soil for growing cotton?	Were they trained in cotton growing techniques by extension agents? (1=Yes/2=N o/3=DK)	If no, did they know somebody who was trained by extension agents? (1=Yes/2= No/3=DK)	How did you 1 st meet this person? codes below Multiple answers possible	Do you exchange more than agricultural information with this person? codes below Multiple answers possible	How often do you speak to this person? (number of times per month)
Name	CG Name	I D	BN14	BN15	BN16	BN16 Units	BN17	BN18	BN19	BN20	BN21	CN2
			1									
			2									
			3									
			4									
			5									
			6									
			7									
			8									
			9									
			10									
			11									
			12									
			13									
			14									
			15									
			16									
			17									
			18									
			19									
			20									

Section CN-Information Exchange

8 March 2010

HHID: _____

NAME of respondent	CG	CD	Please relist the individuals you named in BN5/BN14 here. (initials are sufficient)	What was the most significant advice that YOU GAVE this person in your network growing and marketing cotton? Codes possible Codes below in main questionnaire.	What was the most significant advice that YOU RECEIVED this person in your network growing and marketing cotton? Codes possible Codes below in main questionnaire.	Did you implement it? 1=Yes, 2=No 3=I plan to	If CN4=2,3 (did not implement) "3", why? Codes below	How soon after you received this information did you implement it? (In weeks)	Units (meters, miles, km)	Who benefits most from this relationship? 1=me 2=them 3=both	How much did you expect the INDIVIDUAL prize to be worth in the women's meeting last year (UG shillings) -99 did not participate in women's meeting	How much did you expect the GROUP prize to be worth in the women's meeting last year (UG shillings) -99 did not participate in women's meeting
Name	ID		CN1	CN3	CN4	CN5	CN6	CN7		BN22	CN8	CN9
			1									
			2									
			3									
			4									
			5									
			6									
			7									
			8									
			9									
			10									
			11									
			12									
			13									
			14									
			15									
			16									
			17									
			18									
			19									
			20									

Codes for Social Network Survey

<p>Code for BN1: 1=I currently grow cotton on my own. 2=I currently grow cotton with other family members 3= I currently grow cotton with hired labor (and family members) 4=I grew cotton in the past, but no longer grow cotton 5=I am considering growing cotton this season 6=No, I have not grown, do not currently grow, and am not considering growing cotton</p>	<p>Code for BN2: 1=I have sold seed-cotton that I grew 2=I have sold seed-cotton that I helped to cultivate 3=I have watched a friend or relative sell seed-cotton 4=No, I have not sold nor observed someone selling seed-cotton</p>	<p>Code for BN6: 0=Does not apply 1=Sick 2=Old 3=Has well connected close family member to consult 4=Cotton is not their primary concern/crop 5=Does not know how to meet more cotton growers 6= other (write in cell)</p>	<p>Code for BN11: 1=hand hoe 2=tractor 3=plough 4=slusher 5=ponga 6=draft animals (write number of draft animals) Example if 3 oxen write: 6(3) 7= other (write in cell) 9=spray pump</p>	<p>Code for BN20: 0=growing agent 1=family 2= friends within the village 3=friends in other village 4= religious group/affiliation 5= neighbor 6=group farming (rotation) 6= Other (write in cell)</p>
---	--	--	---	--

<p>Code for BN21: 0=Only Agricultural info. 1=borrowing/lending and informal credit 2=non agricultural labor, 3=religion 4=non-financial community support, 5=school 6= child care/family 7=other(write in cell)</p>	<p>Code for CN3 and CN4: Growing: 0=no information given/received 1=land type necessary to grow cotton 2=size of cotton plot 3=machines necessary to grow cotton 4=draft animals (borrowing etc.)</p>	<p>5=contacts necessary to grow cotton 6=seed spacing 7=inputs necessary for growing cotton (seeds, fertilizer, pesticides) 8= application of pesticide/fertilizer 9=laborers (including number of laborers to hire and who to hire) 10=how to harvest</p>	<p>Marketing: 11=when to sell my cotton (exact day and time of day) 12=when to sell my cotton (what week) 13=when to sell my cotton (general annual advice) 14=whom to sell my cotton to 15=with whom I should go sell my cotton 16=how to sell my cotton (what to say) 17=how to receive cotton prices (via cell phone, radio, ginnery, etc.) 18=storage of cotton 19=other (write in space provided below)</p>
<p>Code for CN6: 1=too costly 2=no perceived benefit 3=implemented in the past 4=land not available or not ready 5= other (write in cell)</p>	<p>Code for CN11: 1=family, 2=friend 3=fellow church member 4=neighbor 5=other (write in cell)</p>		

5.3.2 Household Survey (Relevant Portions)

These are the relevant portions with regards to my research of the household survey. It does not include the full household survey.

**Gender Dimension of Cotton Productivity in Uganda (WB-GAP)
Household-Level Survey in Uganda (February-April 2010)**

World Bank, University of Maryland and Makerere University

Did the household grow cotton in 2009? (1= Yes, 2=No;)

Date of interview Date: ____ Month: ____ Year: _____

Interviewed by _____

Date checked: Date: ____ Month: ____ Year: _____

Checked by: _____

Date entered: Date: ____ Month: ____ Year: _____

Data entered by: _____

Household ID: _____

District: _____ Code: _____

County: _____ Code: _____

Sub-County: _____ Code: _____

Parish: _____ Code: _____

LC1: _____ Code: _____

Village: _____ Code: _____

GPS Reading for Homestead

Latitude Reading - North: Longitude Reading – East

[N] - [____].[_____] [E] - [____].[_____]

Person ID _____

PID Cotton Plot : _____

Season cotton cultivated on this plot (circle season AND year) :

1st or 2nd Season : 2009 or 2010

Area : _____ Square Meters

Area of Cotton Plot

Household Head Name _____	Ethnicity of HH Head _____ Code: _____
Main Respondent _____ ID: _____	Religion of HH Head _____ Code: _____

Please read the following consent statement to the respondent before starting the interview:

My name is [your name]. I am part of a team of Researchers from Makerere University. We are collecting information here in [district] on cotton production, marketing, and expenditures.

Your household has been selected to participate in the information gathering exercise, through a one-to-one interview. The discussion will take about some time. Please answer all the questions truthfully. You will not be judged on your responses and we ask you to be sincere in your responses.

There is no direct benefit, money or compensation to you in participating in this study. Your participation is voluntary. However, the information you provide during this interview will help Makerere University to understand the needs of cotton farmers in [district], and to plan on how best to assist them to move forward. The researchers will keep your responses confidential.

HHID: _____

Section 2. Map of Parcels: Please draw a map of all parcels that this household has access to (exclude communal grazing lands) . FO: *Do not copy 2008 Map.*

When drawing this map, face East and draw directions. Make sure to include homestead, fallowed land, abandoned land, leased out land, etc. And give each parcel a short name (PNAME) and number, which becomes Parcel ID (PID). This map should be clear enough so that enumerators who visit this household in one year should be able to identify each field for the last 2 cropping seasons. Indicate the homestead and entrances, names of parcels, sizes of parcels, and walking distances in minutes between the homestead and each parcel. FO: *Please do not use crop names for parcel names.*

HHID: _____

Section 3-a. Land Tenure during last 2 cropping seasons. FO: Please keep PName and PID same as in 2008 Section 3A. See copy of 2008 of Section 3A.

Parcel Name	Parcel ID	Is this parcel still in use?	If no why? See codes	Size of this parcel in acres ?	Soil type of land of the parcel 1=sandy, 2=clay, 3=loam	Slope of land of the parcel 1=steep, 2=moderate, 3=flat, 4=other (specify)	Quality of land of the parcel 1=good, 2=medium, 3=poor	Tenancy? See code below	Tenure system See Code below	In which year did you first acquire this parcel? e.g., 1987 (first part)	How did you acquire this parcel? See Code below (Largest share)	If inherited did you acquire this land through somebody's formal written document will? (refer to L8) 1=Yes, 2=No	As a HH Do you have a right to Give out this parcel? See Code below.r refer to L5.	As a HH Do you have a right to Sell this parcel? See Code below	Main water source? 1=Irrigated, 2=Rain-fed, 3=Swamp	If irrigated, what % of the parcel is irrigated?	Walking time in minutes on foot from homestead? (most used route. Check with Map.)	If you were to buy/rent-in this parcel (without the buildings value), How much would you be willing to pay to buy?	How much would you be willing to pay to rent in per season?
PName	PID	L31	L32	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12	L13	L14	L15	L16
	1																		
	2																		
	3																		
	4																		
	5																		
	6																		
	7																		
	8																		
	9																		
	10																		
	11																		
	12																		

Code for L5:
1= Owner
2= Occupant
3= Tenant (who actually pays rents in cash or in-kind)

Code for L6:
1= Freehold
2= Leasehold
3= Mailo
4= Customary
5= Other (specify)

Code for L8:
1= Purchased
2= Received as gift or inheritance
3= Rented-in for fixed payments
4= Borrowed-in

5= Just walked in
6= Other (specify)

Code for L10 and L11:
1= No right to sell/give
2= With approval from extended family

3= With approval from local authority
4= Can sell/give land without approvals
5= Other (specify)
Parcel Codes:
1=not fertile

2=lost land
3=sold land
4=owner of parcel left village
5=other

HHID: _____

Section 3-b. Land Use and Conservation Practices

Ask the following questions on every single parcel identified in Section 5-a in the same order. Make sure that the tables are matched across sections.

Parcel name	Parcel ID	Person id of primary worker on the parcel	Primary Use of this parcel?				Soil and Water Conservation Practices								
			First season 2010 See code below. (actual or intended us)	Second season 2009 See code below	Is this parcel still in use? 1=YES 2=NO	If No=2 in L31, why? See codes	Mulching 1=YES 2=NO	Slush or Burn, or both 1=YES 2=NO	Intercropping with leguminous crops 1=YES 2=NO	Use of crop residues/ household refuse 1=YES 2=NO	Crop rotation 1=YES 2=NO	fallow 1=YES 2=NO	trees/cover planted on parcel 1=YES 2=NO	terracing 1=YES 2=NO	bunding 1=YES 2=NO
PName	PID	L17	L18	L19	L31	L32	L22	L23	L24	L25	L26	L27	L28	L29	L30
	1														
	2														
	3														
	4														
	5														
	6														
	7														
	8														
	9														
	10														
	11														
	12														

Code for L18-21:

- 1= Cultivated cotton
- 2=Cultivated (annual crops) non-cotton
- 3=Cultivated (perennial crops)
- 4=Rented-out for fixed payments
- 5=Sharecropped-out

6=Borrowed-out

- 7= Improved/bush fallow
- 8=Grazing/ Pasture land
- 9=Any trees
- 10=Abandoned
- 11=Virgin land

12=Other (specify)

- 13=Settlement
- Codes for L32:
- 1=land/soil deterioration
- 2=parcel sold
- 3=parcel gifted away

4=owner of parcel departed HHD

- 5=other(explain)

HHID: _____

Section 3-c. Additional source of income from Renting and Borrowing LAND in the last 12 months (last 2 cropping seasons: 1st season 2009 and 2nd season 2009).FO>List ALL parcels as on pg 3, Section 3a.

* Transaction ID: Number starts from one in each parcel.

Parcel name	Parcel ID	Transaction ID*	Is all or a part of this parcel under the following transaction? 1=Rented-in 2=Rented-out 3=Borrowed-in 4=Borrowed-out 5= sharecropped 6=None of the above (Go to next Parcel)	Transaction code	If LR1=1-4,				
					Size of the area under the trans-Action (LR1) in acres	For how many months has this area (LR2) been under this transaction?	How did you decide the payment for this land? See code below.	If LR4=1 or 3, how much did you pay/receive? (per season) (Shs)	If LR4=2 or 4, what proportion (out of 10) of the harvest did you pay/ receive? (per season)
Pname	PID	T ID	LR1	TCode	LR2	LR3	LR4	LR5	LR6

Code for LR4	share proportion of the harvest	proportion of the harvest	output payment
1= Before the production, a fixed cash payment	3= After the harvest, a fixed cash payment	5= Other (specify)	8= After the harvest, a fixed output payment
2= Before the production, a fixed	4= After the harvest, a fixed	6=No payment	
		7= Before the production, a fixed	

HHID: _____

Section 3-d. Land Holdings at the Start of the Household
Only for head and spouse

How much did you pay for bride price and in which year for each wife?

Person	Person ID**	Year of marriage	Land*** in acres	Other in-kind assets in Shs (value)		Cash in Shs
	ID		BP1	BP2	BP3	
Spouse 1						
Spouse 2						
Spouse 3						
Spouse						

*The year of starting the household is the year when the head/spouse joined the household.

**If the spouse was deceased before the survey and his/her person ID is not available, write 99.

*** Exclude the land which the head/spouse temporary rented in at the start of the household.

Possible answers for BP 2: Livestock, bicycle, other assets, radio, furniture, ox plough

HHID: _____

Section 5-a - Labour Use on Crop Production – Second Crop Season 2009 (September Dec2009 Harvest)

Ask about both family & hired labour use on a representative cotton plot, and one most important crop of the household such as maize, beans, and sunflower.

Parcel ID	Plot ID	Crop Name	Crop Code	Activity Code See Code below	Date of the activity (mm/year: Early, Mid, Late month)	Family Labour Use in the Second Crop Season 2009													Hired Labour in the 2nd Season		Hired Draft animals in 2nd Season excl. human labour			Hired machinery /tractors in 2nd season		
						Men			Women			Children (under 15 years)			Draft Animals			Total Cash expenditure in Shs	Total in-kind expenditure (evaluated) in Shs	Total Cash expenditure in Shs	Total in-kind expenditure (evaluated) in Shs	Includes labor? 1=HL 2=AN 3=HL & AN	Total Cash expenditure in Shs	Total in-kind expenditure (evaluated) in Shs		
						Men	Days	Hrs a day	Women	Days	Hrs a day	Children	Days	Hrs a day	Oxen	Days	Hrs a day									
PID	S0	CName	CID	LS1		LS2	LS3	LS4	LS5	LS6	LS7	LS8	LS9	LS10	LS11	LS12	LS13	LS14	LS15	LS16	LS17		LS18	LS19		

Activity Code (LS1) 1= clearing land 3=1 st ploughing	4= 2 nd ploughing 5= planting 6=1 st weeding 7=2 nd weeding	8= 3 rd weeding 9=thinning 10=1 st spraying 11=2 nd spraying 12=3 rd spraying	13=4 th spraying 14=5 th spraying 15= Harvesting 16= Watering crops	17= Transporting the produce 18= Post harvest activities 19= Other (specify)
---	---	---	--	--

HHID: _____

Section 5-a – Continued

Parcel ID	Plot ID	Crop Name	Crop Code	Activity Code See Code below	Date of the activity (mm/year: Early, Mid, Late month)	Family Labour Use in the Second Crop Season 2009											Hired Labour in the 2nd Season		Hired Draft animals in 2nd Season excl. human labour			Hired machinery /tractors in 2 nd season				
						Men			Women			Children (under 15 years)			Draft Animals		Total Cash expenditure in Shs	Total in-kind expenditure (evaluated) in Shs	Total Cash expenditure in Shs	Total in-kind expenditure (evaluated in Shs)	Includes labor? 1=HI 2=AN 3=HL & AN	Total Cash expenditure in Shs	Total in-kind expenditure (evaluated) in Shs			
						Men	Days	Hrs a day	Women	Days	Hrs a day	Children	Days	Hrs a day	Oxen	Days								Hrs a day		
PID	S0	CName	CID	LS1		LS 2	LS 3	LS 4	LS 5	LS 6	LS 7	LS 8	LS 9	LS 10	LS 11	LS 12	LS 13	LS14	LS15	LS16	LS17		LS18	LS19		

Activity Code (LS1) 1= clearing land 3=1 st ploughing	4= 2 nd ploughing 5= planting 6=1 st weeding 7=2 nd weeding	8= 3 rd weeding 9=thinning 10=1 st spraying 11=2 nd spraying 12=3 rd spraying	13=4 th spraying 14=5 th spraying 15= Harvesting 16= Watering crops	17= Transporting the produce 18= Post harvest activities 19= Other (specify)
---	---	---	--	--

HHID: _____

Section 7-a - Labour Use on Crop Production – First Crop Season 2009 (March – July 2009 Harvest)

Ask about both family & hired labour use on 1 most important crop of the household such as maize, beans, and sunflower.

Parcel ID	Plot ID	Crop Name	Crop Code	Activity Code See Code below	Date of the activity (mm/year: Early,Mid,Late month)	Family Labour Use in the First Crop Season 2009											Hired Labour in the 2nd Season		Hired Draft animals in 2nd Season excl. human labour			Hired machinery /tractors in 2 nd season				
						Men			Women			Children (under 15 years)			Draft Animals		Total Cash expenditure in Shs	Total in-kind expenditure (evaluated) in Shs	Total Cash expenditure in Shs	Total in-kind expenditure (evaluated) in Shs)	Includes labor? 1=HI 2=AN 3=HL & AN	Total Cash expenditure in Shs	Total in-kind expenditure (evaluated) in Shs			
						Men	Days	Hrs a day	Women	Days	Hrs a day	Children	Days	Hrs a day	Oxen	Days								Hrs a day		
PID	S0	CName	CID	LF1		LF2	LF3	LF4	LF5	LF6	LF7	LF8	LF9	LF10	LF11	LF12	LF13	LF14	LF15	LF16	LF17		LF18	LF19		

Activity Code (LS1) 1= clearing land 3=1 st ploughing	4= 2 nd ploughing 5= planting 6=1 st weeding 7=2 nd weeding	8= 3 rd weeding 9=thinning 10=1 st spraying 11=2 nd spraying 12=3 rd spraying	13=4 th spraying 14=5 th spraying 15= Harvesting 16= Watering crops	17= Transporting the produce 18= Post harvest activities 19= Other (specify)
---	---	---	--	--

HHID: _____

Section 12-c. KNOWLEDGE OF COTTON CULTIVATION DETAILS (SMALL QUIZZ)

Please ask the following questions to the respondent and circle the answer they give you

<p>QU1 Are Ladybird insects (show picture) harmful to cotton? 1=Yes 2=No</p>	<p>QU 7 How many weeks after planting cotton, should SECOND weeding occur? _____</p>
<p>QU 2 Spacing between rows of cotton is how many jerrycans? _____ (FO: Show the respondent the length of a 20 ltr jerrycan.)</p>	<p>QU 8 How many weeks after planting cotton does the bollworm appear (FO:show picture of bollworm)? _____</p>
<p>QU 3 Spacing between cotton plants is how many jerrycans?: _____ (FO: Show the respondent the length of a 20 ltr jerrycan.)</p>	<p>QU9 How many days after planting should you check for seed germination? _____</p>
<p>QU 4 How many seeds of cotton should you plant in a hole? _____</p>	<p>QU 10 If seeds did not germinate, you should replant new seeds, where? 1=same hole as where you planted the ungerminated seeds 2=in the gaps between the holes</p>
<p>QU 5 How many seedlings of cotton should be left in one hole at thinning? _____</p>	<p>QU 11 Is the bollworm eater (FO:show picture) is harmful to cotton? 1=Yes 2=No</p>
<p>QU 6 How many weeks after planting cotton, should FIRST weeding occur? _____</p>	<p>QU 12 The Lygus Bug (show picture) , which tatters young cotton leaves is bad for cotton. When should it be sprayed? _____</p>

HHID: _____

Correct answers (only for researchers, not to be given to enumerators or respondents)

- 1 Ladybirds are not harmful insects (show picture).(2)
- 2 Spacing between rows is 2-3 jerrycans
- 3 spacing between plats is 1 jerrycan
- 4 3-5 seeds per hole
- 5 Leave 2 seedlings per hole
- 6 1st weeding occurs between the 2nd -3rd week after planting
- 7 2nd weeding occurs between the 6th-10th week after planting
- 8 Bollworm (show picture) larvae appears between the 8th -9th week after planting
- 9 Check germination after 5 days
- 10 replant seeds at gaps (2)
- 11 The bollworm eater eats the bollworm and is NOT harmful to cotton (2)
- 12 The Lygus Bug (show picture) tatters young cotton leaves and should be sprayed between the 5th -7th week after planting

Bibliography

- Appleton, S., J. Hoddinott, and P. Krishnan (1999). Economic development and cultural change. *International Food Policy Research Institute* 47(2), 289–3123.
- 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*.
- Baffes, J. (2009). The cotton sector of uganda. *Africa Region Working Paper Series No. 123* (123).
- Bandiera, O. and I. Rasul (2006). Social networks and technology adoption in northern mozambique. *The Economic Journal* 116(514), 869–902.
- Barton Hamilton, J. N. and H. Owan (2003). Team incentives and worker heterogeneity. *The Journal of Political Economy* 111(2), 465–497.
- Benabou, R. and J. Tirole (2006). Incentives and prosocial behavior. *American Economic Review* 95(5), 1652–1678.
- Bull, C., A. Schotter, and K. Weigelt (1995). Tournaments and piece rates an experimental study. *Journal of Political Economy* 81, 1–33.
- Carpenter, J., S. Boweles, H. Gintis, and S. Hwang (2009). Strong reciprocity and team production. *Journal of Economic Behavior and Organization* 71, 221–232.
- Chambers, R. (1993). *Challenging the Professions: Frontiers for Rural Development*. London: Intermediate Technology Publications.
- Che, Y. K. and S. W. Yoo (2001). Optimal incentives for teams. *The American Economic Review* 91, 525–541.
- Conley, T. and C. Udry (2010). Learning about a new technology: Pineapple in ghana. *American Economics Review* 100(1), 35–69.

- Darr, D. and J. Pretzsch (2008). The spread of innovations within formal and informal farmers groups evidence from rural communities of semi arid eastern africa. *Institute of International Forestry and Forest Products, Germany, Working Paper*.
- Duflo, E. (2010). Gender equality in development. *Massachusetts Institute of Technology, Working Paper*.
- Duflo, E., M. Kremer, and J. Robinson (2006). Understanding technology adoption: Fertilizer in western kenya, evidence from field experiments. *Manuscript*.
- 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.
- Ehrenberg, R. and M. Bognanno (1990). Do tournaments have incentive effects? *The Journal of Political Economy* 98(6), 1307–1324.
- Evenson, R. (1980). The effects of agricultural extension on farm yeilds in kenya. *Yale Economic Growth Center Discussion Paper 798*.
- Fatas, E. and T. Neugebauer (2005). Between teams competition versus within team competition in a team incentive experiment. *working paper* (514).
- Fehr, E., E. Kirchler, A. Wechbold, and S. Gächter (1998). When social norms overpower competition gift exchange in experimental labor markets. *Journal of Labor Economics* 16(2), 324–351.
- Field, E., B. Feigenberg, and R. Pande (2011). Building social capital through microfinance. *University of Maryland Seminar, November 9, 2010*, <http://econweb.umd.edu/davis/eventpapers/FieldBuilding.pdf>.
- Freeman, L. (2007). Centrality in social networks. *Social Networks* 1, 215–239.
- Gneezy, U., K. Leonard, and J. List (2009). Gender differences in competition. evidence from a matrilineal and patriarchal society. *Econometrica* 77, 1637–1664.
- Gneezy, U., M. Niederle, and A. Rustichini (2003). Performance in competitive environments gender differences. *The Quarterly Journal of Economics*.
- Goldstein, M. and C. Udry (1999). Agricultural innovation and resource management in ghana. *Final Report to IFPRI under MP17*.
- 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.

- Greig, F. and I. Bohnetb (2009). Exploring gendered behavior in the field with experiments: Why public goods are provided by women in a nairobi slum. *Journal of Economic Behavior and Organization* 70(1-2), 1–9.
- Groves, T. (1973). Incentives in teams. *Econometrica* 41(4), 617–631.
- 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.
- Irlenbusch, B. and G. Rucahala (2008). Relative rewards within team based compensation. *Labour Economics* 15, 141–167.
- Isham, J. (2002). The effects of social capital on technology adoption: Evidence from rural tanzania. *Journal of African Economies* 11(1), 39–60.
- Ivanova-Stenzel, R. and D. Kubler (2005). Courtesy and idleness. gender differences in team work and team competition. *Discussion Paper No. 91, Governance and the Efficiency of Economic Systems* 91.
- Jackson, M. and A. Wolinsky (1996). A strategic model of social and economic networks. *Journal of Economic Theory* 71(1), 44–74.
- Jonathan Isham, T. K. and S. Ramawamy (2002). *Social Capital and Economic Development: Well-being in Developing Countries*. Seattle, WA: Edward Elgar Publications.
- J.R.Bibangambah (1996). *Agricultural Extension in Uganda*. Kampala, UG: Fountain Publishers.
- 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*.
- Kilavuka, J. (2003). A comparative study of the socioeconomic implication of rural women, men and mixed self help groups. *Gender Issues Research Report Series at the Organization for Social Science Research In Eastern and Southern Africa* 20(5).
- Kranton, R. and Y. Bramoulle (2007). Public goods in networks. *Journal of Economic Theory* 135, 478–494.
- Kremer, M., E. Miguel, and R. Thornton (2009). Incentives to learn. *The Review of Economics and Statistics* 91(3).
- Lazear, S. and E. Rosen (1981). Rank order tournaments as optimum labor contracts. *Journal of Political Economy* 89.
- Leonard, K. (2007). Learning in health care: Evidence of learning about clinician quality in tanzania. *Economic Development and Cultural Change* 55, 531–555.

- Maertens, A. (2010). Who cares what others think (or do)? social learning, social pressures and imitation in cotton farming in india. *University of Pittsburgh, Working Paper*.
- Maluccio, J., L. H. L, 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.
- Mangheni, M. N. (2007). *Marketing of Smallholder Crops in Uganda*. Kampala: Fountain Publishers Ltd.
- Manski, C. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies* 60(1), 531–542.
- Marinakis, K. and T. Tsoulouhas (2006). Are tournaments optimal over piece rates under limited liability for the principal? *unplished, North Carolina State University* (123).
- 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.
- Matuschke, I. and M. Qaim (2009). The impact of social networks on hybrid seed adoption in india. *Agricultural Economics* 40, 493–505.
- Morduch, J. (1999). The microfinance promise. *Journal of Economic Literature* 37, 1569–1614.
- Munshi, K. (2004). Social learning in a heterogenous population: Technology diffusion in the indian green revolution,. *Journal of Development Economics* 73, 185–213.
- Nichols, A. (2010). Regression for nonnegative skewed dependent variables. Technical Report 2, BOS10 Stata Conference.
- Niederle, M. and L. Vesterlund (2007). Do men compete too much? *Quarterly Journal of Economics*, forthcoming.
- Njuki, J. (2011). Igniting change. the gender match conference. Washington DC: International Food Policy Research Institute.
- Orrison, A., A. Schotter, and K. Weigelt (2004). Multiperson tournaments. an experimental examination. *Management Science* 50(2), 268–279.
- Prell, C., K. Hubacek, and M. Reed (2009). Stakeholder analysis and social network analysis in natural resource management. *Society and Natural Resources* 22, 501–518.

- Quisumbing, A. (1999). Male-female differences in agricultural productivity: Methodological issues and empirical evidence. *International Food Policy Research Institute*.
- 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.
- Reichmann, T. and J. Weimann (2008). Competition as a coordination device. experimental evidence from a minimum effort coordination game. *The Journal of Political Economy* 24(6), 437–454.
- Romer, P. (1990). Endogenous technological change,. *Journal of Political Economy* 98, S71–S101.
- Santos, P. and C. Barrett (2005). Interest and identity in network formation: who do smallholders seek out for information in rural ghana? *Unplished, Cornell University*.
- Skoe, E., A. Cumberland, N. Eisenberg, K. Hansen, and J. Perry (2002). The influences of sex and gender role identity on moral cognition and prosocial personality traits. *Journal of Economic Literature* 46(9).
- Sutter, M. (2006). Endogenous versus exogenous allocation of prizes in teams. *Labour Economics* 13, 519–549.
- 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.
- Teyssier, S. (2007). Optimal group incentives with social preferences and self selection. *Group d'Analyse et de Theorie Economique*.
- Thirtle, C., X. Irz, L. L. 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. *World Bank, Development Outreach*.
- Young, P. (2009). Innovation diffusion in heterogeneous populations-contagion, social influence, and social learning. *American Economic Review* 99, 1899–1924.