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Information Networks among Women and Men and the Demand for an Agricultural Technology in India

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Abstract

Although there is ample evidence of differences in how and where men and women acquire information, most research on learning household decision-making only considers access to information for a single, typically male, household head. This assumption is problematic in developing-country agriculture, where women play a fundamental role in farming. Using gender-disaggregated social network data from Uttar Pradesh, India, we analyze agricultural information networks among men and women. We test for gender-specific network effects on demand for laser land leveling—a resource-conserving technology—using data from a field experiment that combines a BDM auction with a lottery. We find that factors determining male and female links are similar, although there is little overlap between male and female networks. We also find evidence of female network effects on household technology demand, although male network effects are clearly stronger. Results indicate that extension services can better leverage female networks to promote new technologies.

Keywords: Social network analysis, peer effects, technology adoption, learning externalities, India

JEL Codes: D80, Q12, Q16

INFORMATION NETWORKS AMONG WOMEN AND MEN AND THE DEMAND FOR AN AGRICULTURAL TECHNOLOGY IN INDIA

1. Introduction

Over the last three decades, a growing body of literature on household models suggests that cooperative or non-cooperative bargaining models are improvements over the unitary household models because they account for divergent resources and preferences of household members (Alderman, et al., 1995; Fisher, et al., 2000; Jones, 1986; Manser and Brown, 1980; McElroy and Horney, 1981; Strauss and Thomas, 1995; Udry, 1996; Udry, et al., 1995). Yet in spite of the theoretical and empirical evidence that household decisions arise from bargaining processes, most of the literature on technology adoption in agriculture still assumes a unitary household where information flows into the household through a single member—typically a male household head—via his interactions with his fellow farmers, extension agents, and other sources of agricultural information. Based on the information he gathers, he then selects the technology that maximizes household utility. The assumption of the unitary model extends beyond research and into practice. Agricultural extension in developing countries is generally biased towards men, who are considered to be farm managers, especially in South Asia and especially in cereal cropping systems (Peterman, et al., 2010; Quisumbing and Pandolfelli, 2010).

An important aspect of the emerging literature on household decision-making is the recognition that asset ownership, control, and access vary among individuals in the household (Udry, 1996; Peterman, et al., 2010; Croppenstedt, et al., 2013). Social networks are a widely recognized source of social capital, and therefore an important asset. In developing countries, women’s access to agricultural information through social networks could be especially important given how deeply involved women are in agriculture. Women account for 43 percent of the agricultural labor force worldwide, and 32 percent of the agricultural labor force in India (Food and Agriculture Organization, 2011). Yet most studies on gender and access to agricultural information are limited to examining the effect of female headship on access to information, and generally conclude that female headship constrains access to information and consequently influences technology adoption and agricultural productivity (see Peterman et al., 2010). These gendered dimensions of information acquisition are clearly not restricted to female-headed households and quite likely shape agricultural decision-making and input allocation in male-headed households as well.

For some time, sociologists and psychologists have explored gender differences in access to information through social networks, such as job market information within firms and professional knowledge-sharing in small businesses (Lalanne and Seabright, 2011; Loscocco, et al., 2009). These studies have used gender-disaggregated network data to show that women's and men's networks vary along many structural dimensions. For example, in some contexts while women and men have similar network sizes, women have more ties to kin and fewer connections to non-kin individuals in their networks (Wellman and Wortley, 1990). Within a firm, women utilize their networks differently than men in accessing work-related information (Brass, 1985; Ibarra, 1992; Scott, 1996). To our knowledge, this paper is the first to look at intra-household differences in social networks and agricultural technology adoption, and one of the few to specifically examine gender-specific networks of married couples in a rural, developing country context.

We contribute to the economic literature on gendered dimensions of agriculture decision-making in three ways. First, we use gender-disaggregated data from eastern Uttar Pradesh (EUP) to analyze the distinct social networks of men and women (primarily husbands and wives). We examine the frequency of gender-specific agricultural information links, the overlap between male and female agricultural information networks, and characteristics of well-connected men and women. Second, we take a closer look at the factors that drive the formation of these gendered agricultural links. Finally, we test for network effects on demand for a new technology—laser land leveling (LLL)—using data from a field experiment. The paper proceeds as follows. In Section 2 we provide some background on social networks, gender, and learning in agriculture, and briefly introduce LLL. In Section 3 we describe the study setting and data collection process. In Section 4 we present our results and discuss some implications. In Section 5 we offer some concluding remarks.

2. Background

2.1 Gender differences in social networks

While women and men tend to interact quite differently in social settings, both use formal and informal social networks to learn about economic opportunities. These learning networks are shaped by dynamics of homophily, social identification, and various preferences and constraints (Bala and Goyal, 2000; Santos and Barrett, 2010). Networks vary in composition, size, and structure. Whereas both women and men may have network connections of similar size, men may tend to have networks with more "weak ties" while women may focus on building smaller networks with "strong ties" (Granovetter, 1973). Lalane and Seabright (2011) find that because they have a larger proportion of weak network ties, men are aware of more job opportunities, while women not only have a smaller proportion of these important weak ties, but are less inclined to opportunistically leverage their ties for information. Consequently, men in top executive jobs tend to have access to higher-return activities than women. Mobile phone usage studies reveal communication patterns that correspond to findings on weak and strong ties: women tend to make fewer calls but have longer conversations than men (Friebel and Seabright, 2011).

One reason for the predominance of strong ties in female networks is that in some cases, women have more ties to kin and fewer to non-kin. Allocation of women's time to home and childcare activities partly helps explain these differences (Marsden, 1987; Moore, 1990). Loscocco et al. (2009) find that although women's networks have more kin, they are also more diverse. Female networks also tend to differ from male networks in situations that do not involve familial connections. For instance, Ibarra (1992) and Bu and Roy (2005) also find greater diversity in female professional networks in U.S. and Chinese firms, respectively. In this paper, we use the experimental introduction of a new agricultural technology to analyze differences in male and female networks and estimate how learning by men and women through their distinct social networks affects household demand for the technology.

2.2 Social networks and agricultural information

Farmers in developing countries typically cite other farmers as their most trusted and reliable source of information, making it important to understand how links in these social networks are constructed (Feder and Slade, 1984; Rogers, 2010). Presumably, an individual forms a network link with another individual if the expected benefits of doing so exceed the costs (Jackson and Wolinsky, 1996). In the case of an agricultural information link, these benefits could include information about weather, input use, input prices, commodity prices, pest and disease management, natural resource management practices, and new technologies. Since these networks are ultimately social in nature, there are also obvious benefits beyond these purely instrumental ones, namely the enjoyment of sharing news, exchanging ideas, complaining about the weather or gossiping. Costs could include the time and effort needed to maintain the link, the opportunity cost of forgoing other social or economic activities, or the costs of acting on poor-quality or ambiguous information garnered from a network.

In this cost-benefit framework, it is clear that information links need not be reciprocal (Bala and Goyal, 2000). It is entirely possible that individual X would seek information from individual Y at some cost but Y would not seek information from X. This framework also helps explain why Man X would seek information from Man Y but not Man Z, while Man X's wife would seek information from Man Z's wife but not Man Y's wife. Furthermore, the benefit of acquiring a link to a household outside of one's spouse's network could be greater than acquiring links that are parallel to the spouse's links and bring similar information.

In addition to forming network links to receive information, access to markets, or other connections, people also tend to form links with individuals exhibiting similar traits such as gender, ethnicity, religion, wealth, family, geography, and education (McPherson, et al., 2001; Santos and Barrett, 2010). Part of this homophily can be attributed to the benefits of social identity. For example, Santos and Barrett (2010) estimate the importance of each in the formation of agricultural information links among farmers in Ghana. They find that although both identity and self-interest matter, self-interest variables—such as a potential network link having more experience or more land—matter more. Using data from the same site, Conley and Udry (2010) find that pineapple farmers not only form information links with farmers of the same gender, clan, and age groups, but also with individuals with differing levels of wealth. Relatedly, Maertens and Barrett (2013) find Indian cotton farmers' links to be correlated with both social factors such as sub-caste and agricultural factors such as soil quality. Notably, they find that non-progressive farmers tend to form information links with progressive farmers, but that these links are not reciprocated, indicating self-interest.

The vast majority of empirical studies on networks—including those cited above—use the household, and implicitly the household head, as the unit of analysis. These household heads are predominantly male. Yet, female farmers—both female household heads and women in male-headed households—are generally more dependent on social networks than men for information because social institutions and livelihood systems inhibit women's ability to access public extension agents (Katungi, et al., 2008; Peterman, et al., 2010; Subedi and Garforth, 1996). Gender norms, for example, may inhibit women's ability to interact with visiting extension agents, who are predominantly male (Kondylies and Mueller, 2013; Quisumbing and Pandolfelli, 2010). Similarly, linguistic barriers may prevent women from communicating with agents where women only speak local dialects (Fletschner and Mesbah, 2011).[1] Constraints on mobility—whether cultural or because of time burdens—may prevent women from leaving the household to join community-based groups, interact with extension agents, purchase inputs from dealers, or seek information and services outside of the village (Fletschner and Mesbah, 2011; Meinzen-Dick and Zwarteveen, 1998). Furthermore, women may not be seen as agricultural decision-makers, particularly in male-headed households, and therefore may not be targeted by extension workers. This "perception-bias" towards men may be particularly strong in South Asia, where women do not typically manage their own plots as they do in some parts of sub-Saharan Africa (Peterman, et al., 2010; Quisumbing and Pandolfelli, 2010).

[1] We found this to be the case in the study site; many women spoke Bhojpuri, but not standard Hindi.

Existing studies generally do not allow for the possibility that females and males in the same household belong to distinct social networks, and therefore receive different information. A rare exception is Subedi and Garforth (1996), who elicit husbands and wives' distinct sources of agricultural information in two Nepali villages. They find that both women and men list progressive farmers in their social networks as their most important reliable source, but also find that men benefit much more from formal information sources like extension workers than women. They also find that men have larger networks of same-sex agricultural contacts than women. In this paper we also explore differences between male and female networks, but we take a much closer look at what drives network formation. We also estimate the effect of gender-specific network links on household demand for an agricultural technology.

2.3 Laser land leveling in India

This study exploits the experimental introduction of a new water-saving technology into eastern Uttar Pradesh: laser land leveling (LLL). In flood-irrigated rice-wheat systems of the Indo-Gangetic Plains, 10-25 percent of irrigation water is lost because of poor management and uneven fields (Jat, et al., 2006). LLL is a process of precisely smoothing the land surface using a laser-guided drag scraper attached to a tractor, which reduces undulations to a height of 1 to 2 centimeters compared to traditional leveling methods that achieve reductions to only 4 to 5 centimeters (Jat, et al., 2006). Essentially, LLL is a better way to do something farmers already understand the importance of and have been doing for generations.

The primary benefit of LLL is a reduction in water used for irrigation. Jat (2006) finds that LLL reduces water use by 10-30 percent, and in our sample LLL decreased water use by 26 percent (Lybbert, et al., 2013). Indian farmers do not pay unit charges for the water they use, but they do pay for diesel used to operate shallow tubewells. Agronomic trials have also shown that LLL can decrease weed pressure, resulting in lower requirements for herbicides and manual weeding (Jat, et al., 2006). Because of reduced biotic and abiotic stress, and more efficient input use, LLL can also increase yields (Jat, et al., 2006). LLL has gotten a foothold in wealthier areas in the Western Indo-Gangetic Plains (IGP), where water resources are very strained. In the study area, however, the technology is essentially unheard of (Lybbert, et al., 2013).

3. Data

3.1 Study setting and sample selection

Data for this study were mostly collected for a larger project on LLL in EUP as part of the Cereal Systems Initiative for South Asia (CSISA), an initiative of the Consultative Group on International Agricultural Research (CGIAR). The majority of farming households in the study area cultivate rice during the summer monsoon (*kharif*) season and wheat during the dry winter (*rabi*) season. The three districts included in this study—Maharajganj, Gorakhpur, and Deoria—represent the regional spectrum of productivity in rice-wheat cropping systems. In each district, we randomly selected eight villages based on three criteria: (1) the villages were not flood-prone and thus farmers can cultivate rice during the *kharif* season and wheat during the *rabi* season; (2) the population in the village was not less than 48 households but not larger than 400 households; and (3) the village was not within a 10 km radius of any other research or extension activities operating in the area that involved LLL or other conservation agricultural practices.[2] After initially selecting four villages per district, we selected a paired village at random from all qualifying villages located along a 5 km radius from each of the four initial villages giving us eight villages per district.[3] In each village, we randomly chose 20-24 households from a village roster.

Our survey team collected data from 470 households, 385 of which are male-headed and 75 are female-headed. From these male-headed households we successfully collected complete data from 351 women that identified themselves as the primary female decision-maker in the household.[4] Typically, this

[2] Data from the baseline survey indicate that this strategy was effective: only six farmers in the sample reported ever having heard of LLL.
[3] We selected villages in pairs to investigate social network links across villages. We found male links to be extremely rare, and do not include the few we found in this study.
[4] Women's data from 24 study households could not be collected because either the household members were not present at the time of data collection or due to other emergencies of the female primary decision makers. We do not believe that there is any systematic bias in the households that did not participate in the women's survey.

woman is the wife of the male head of household.[5] We use these 351 male-headed households and 75 female-headed households as our study sample.

The study site is located in northern India, which is generally characterized as a highly patriarchal society. Women have relatively little autonomy compared to women residing in southern India (Jejeebhoy and Sathar, 2001). Lower caste households in the rice-wheat system of EUP typically depend heavily on female household labor for both production activities, whereas higher caste households usually hire female labor (Paris, et al., 2000). Indeed, this is the pattern we find in our data. In general-caste households, 39 percent of wives work on the household's farm compared to 60 percent in other households. Similarly, wives in general-caste households spend 22 percent of their time working on the farm and wives in other households spend 43 percent of their time doing so (Table 1). Women in male-headed and female-headed households also spend their time differently. While women in female-headed households spend 60 percent of their time on the farm on average, women in male-headed households only spend 27 percent of their time in farm work. 32 percent women in female-headed households work on other farms as compared to only 14 percent in male-headed households.

<<Table 1 here>>

3.2 Social networks and household characteristics

To define social networks we surveyed men and women directly about their network links with other men and women in the sample. This is in contrast to studies that define social connectivity using variables like group membership or the number of people a respondent can reach out to for information. While helpful, the former does not account for informal social connections, which can be particularly important for women (Katungi, et al., 2008; Peterman, et al., 2010; Subedi and Garforth, 1996). The latter does not capture

[5] Of these female primary decision makers, 80 percent reported being the wife, 10 percent the mother, and 10 percent a sister, sister-in-law, mother-in-law, or "other".

information about individuals on both ends of a network link, which is essential to understand network composition and formation.

To accomplish this we had farmers identify their network links using village-level photo directories. Our initial contact with sample household heads (male and female household heads) was at an information session held in March-April 2011 where we introduced LLL using a live explanation, video of the machinery in action, and a discussion session with an early adopter from the region. At the conclusion of the information session, we informed attendees that in a few days they would be offered the opportunity to bid on and potentially receive LLL services for the upcoming season. At this information session we took a photo of each household head, and these photos were compiled into village photo directories. Wives of male household heads were not generally at the information session—10 percent reported attending—and we did not photograph them at this time.

Two to three days later we conducted a household survey with a detailed social networks module in which each household head was asked to identify other heads in his or her village as a source of agricultural information. Specifically, enumerators asked respondents, "With which of these people do you discuss agriculture?" We also asked about family and friendship ties, but use agricultural information links (agricultural links, hereafter) for most of our analysis as these links are most germane to technology diffusion (Conley and Udry, 2010; Maertens, 2013; Magnan, et al., 2013; McNiven and Gilligan, 2012). We also asked household heads to identify those in the photo they deemed "progressive," and use their responses to identify progressive farmers, as determined by their peers.

We conducted social network surveys with women several months later in November 2011, near the end of the 2011 *kharif* rice season. Because the photo directories contained pictures of household heads and not their wives, we asked each woman (female household head or wife of male household head) to identify each man in the photo directory living with a woman to whom they discuss agriculture with, and also female household heads with which they discuss agriculture.[6] We did not ask about wives' interactions with others' husbands (which would likely be non-existent due to cultural norms). We also asked women to identify those farmers in the photo who live with a progressive woman, and used this information to identify progressive women in the sample. Only 35 women were identified as being progressive, and 20 of these are married to a progressive man.

Ideally we would have conducted the women's network survey at the same time as the household heads' survey in March-April 2011, but, the gendered aspect of technology adoption and social networks only emerged as a result of subsequent visits to the village during intra-seasonal input-use surveys, when we noticed how knowledgeable women in male-headed households were about LLL and how interested they were in obtaining it in the future. This observation led us to expand our investigation into female social networks as a potential conduit for agricultural information. However, it is possible that this delay in the sequence of surveys could have resulted in endogenous link formation among women, increasing the size of female networks compared to male networks. For instance, women may have sought out women in adopting households to discuss agriculture, or LLL specifically, because they were early adopters of the technology. In our to analysis follow we test for endogenous link formation, discuss its consequences for analysis, and attempt to mitigate bias that this endogeneity could cause.

As part of the initial survey with household heads, we asked a series of questions about household and plot characteristics. Using data from this survey, we created a factor-analytic wealth index.[7] The household survey also contained questions about information sharing within the household between husbands and wives. We asked women similar questions about information sharing with their husbands when surveying the wives. We collected GPS data for each household to calculate straight-line distances as an imperfect proxy for the travel time to interact face-to-face with a potential contact.

[6] Because the villages chosen in our sample are relatively small in size, the women surveyed were aware of who belonged to the households of those in the photo directory.

[7] The wealth index consists of house condition; ration card possession; landholdings, and ownership of cell phones, vehicles, TVs, satellite dish, and livestock.

3.3 Technology demand and adoption

As part of the larger LLL adoption study, we conducted a field experiment that consisted of a pair of binding technology auctions, one before the introduction of LLL (April 2011) and one after (April 2012). The auctions allowed us to measure household demand (as willingness to pay) for LLL technology. The first auction was used both to measure baseline WTP and to identify potential adopters. The second auction revealed WTP after one year of exposure to the technology through social networks. Immediately following the first auction we held a lottery to randomly allocate LLL among would be adopters to test for network effects without the bias normally inherent in studies of network effects due to the reflection problem (Manski, 1993). Essential details on the auctions and lottery as they pertain to this paper follow. More details about the auction and lottery can be found in Lybbert et al. (2013) and Magnan et al. (2013).

For both auctions we employed a discretized Becker-DeGroot-Marschak (BDM) (1964) mechanism to elicit willingness to pay. The auctions were binding, and therefore incentive compatible. In a BDM auction, participants bid against an unknown price, and not against each other. The auctions are designed so that participants have no incentive to bid anything but their true willingness to pay for LLL. In both auctions, the head of household bid alone for the technology; wives and other family members were not present and bidding was done as privately as possible between the enumerator and participant. Importantly, auctions were held two to three days after the information session so that participants could talk to their wives and others in the village about the technology and how much to bid in the auction. Household heads selected the plots they most wanted laser leveled for the auction. Plot-by-plot, the enumerator recorded whether or not the farmer was willing to pay for leveling at eight different prices between 250 and 800 Rupees per hour.[8,9]

[8] In the 2011 auction they could select up to three plots they wanted leveled and in the 2012 auction they selected as many plots as they wanted. Most households therefore had unleveled plots to bid on in 2012 even if they received LLL in 2011.

[9] During the study the conversion rate was approximately Rs. 45 to 1 USD.

Following several practice rounds, participants selected their non-hypothetical willingness to pay for LLL on each of their plots. A price was then drawn from an envelope, which varied by auction between Rs. 250, 300, and 350 per hour.[10] Before drawing the final price, the presenter explained to participants that because of capacity constraints, we would hold a public lottery immediately following the auction to see who would actually receive and pay for LLL. The presence of this lottery does not change the optimal bidding strategy, and participants were generally very understanding of the process. Anyone bidding at or above the drawn price was considered a "would-be adopter," and was immediately entered into a lottery to actually receive and pay for LLL. The lottery was stratified on demand by ordering would-be adopters by their maximum WTP and then sorting them into groups to receive a red or a white poker chip. A member of the audience then drew a chip from a bag filled with half of each color chip to determine the lottery winners. Immediately following the lottery, members of the enumeration team approached winning participants to set up a date for LLL service delivery. Sixty percent of participants won the first auction, and thirty percent won the lottery.

One year later we held a second auction, allowing households another chance to adopt LLL, or otherwise get LLL on plots not laser-leveled after the first auction and lottery. Participants had one rice season and one wheat season between auctions to learn about the technology from their own experience (if they were adopters) and the experiences of others in the village. In the second auction, participants could bid on any of their plots not laser-leveled after the first auction (there was no way to receive LLL in the region outside our study). Bid choices were the same as in the first auction, but the price drawn was Rs. 400.

[10] Following the first auctions in which a binding auction price of Rs. 350/hour and Rs. 300/hour were selected, it was decided that a lower price of Rs. 250/hour would be used to ensure a larger pool of treatments and controls to randomize.

4. RESULTS

4.1 Intra-household communication and decision-making

As a starting point, we note that women in the study area are involved in agriculture, especially women in relatively poor households. In addition to supplying labor on the family farm, women discuss agriculture with their husbands, including use of agricultural technology. Among wives of male household heads, 48 and 57 percent of rich and poor wives, respectively, reported talking about agriculture with their husband, and 36 percent of all wives and 44 percent of poor wives reported talking specifically about agricultural technology with their husband. Nearly two-thirds of men in the sample reported discussing agricultural technologies with their wives when separately asked. Furthermore, 70 percent of these men said that their wife's opinion regarding technology choice is either important or very important. It is therefore unsurprising that LLL was a topic of conversation between husbands and wives: over 60 percent of women talked to their husbands about LLL over the course of the study. LLL was also a frequent topic of conversation between women: approximately 60 percent of women reported talking to other women about LLL. Table 2 contains descriptive statistics on intra-household communication about agriculture and LLL specifically.

<<Table 2 here>>

4.2 Network size and structure

As a first step to understanding the role of female social networks in information dissemination, we examine the frequency of agricultural information links in our sample and the characteristics of well-connected individuals. We then estimate the determinants of link formation for men's and women's social networks. We do not consider links between men and women for reasons explained earlier.

Any two respondents of the same sex in the same village present two potential links: X can claim Y as a link and Y can claim X as a link. In a village with N sample households there are therefore $N \times (N-1) \times 2$ possible links. In our sample there are 5,308 potential connections between men for which we have network data of their wives, 5,308 between wives in male-headed households, and 7,720 total possible connections between all women.[11] Only 4.8 percent of all possible agricultural links between men exist. Agricultural links are even less frequent between wives: 3.4 percent of such potential links exist. Connections were slightly more frequent (3.7 percent) among women when female household heads are included. This level of connectivity is very low, even compared to other studies that have found links in sampled networks to be rare (Conley and Udry, 2010; Maertens, 2013; Santos and Barrett, 2010).

While it might seem that women would mostly interact with the wives of their husbands' links (Fischer and Oliker, 1983), resulting in considerable overlap between male and female networks, this is not the case in our sample. The probability of an information link existing between two wives whose husbands share an information link is 4.8 percent, compared to 3.4 percent if they do not. This difference is not significant using a Mann-Whitney test (p=0.23). Put another way, only 6.6 percent of wives' agricultural information contacts are in the same household as their husband's contacts. A summary of agricultural information links can be found in Table 3.

<<Table 3 here>>

To further articulate the idea of network structure, we illustrate male and female networks from two villages in our sample using a network map. Figure 1 represents the sampled network map in Baspar village, Maharajganj district. In this figure, each node represents a male or female farmer in the village sample. Male farmers (typically the head of the household) are denoted by a white circle and labeled as "m_farmer#" nodes, while female farmers (typically the spouse of the head of the household or another important female household member) are denoted by a solid black circle and labeled as "f_female#" nodes. The solid black squares indicate that the household is headed by a female. The size of each node is scaled to a measure of the node's degree centrality, or the number of ties that a node has relative to the total number of ties in the entire network.

The thin lines between male and female nodes denote male and female farmers belonging to the

[11] We limit our analysis to wives where network data was available for both sides of the pair. This is primarily to allow us to estimate network formation using dyadic standard errors (Fafchamps and Gubert, 2007).

same household. Thick lines indicate that two farmers exchange information about agriculture, with single arrowheads representing a unidirectional relationship in which farmer x claims farmer y as a member of his/her agricultural advice network, and double arrowheads representing a bidirectional relationship or a mutual claim of membership between farmers x and y. Thick dashed lines represent relationships between male farmers and thick solid lines denote relationships between female farmers.[12]

In Baspar, male farmer 15 is an important source of agricultural information. Six other men identify him as a person they talk to about agriculture, but he identifies no one in the sample that he talks to about agriculture. Note the absence of a corresponding role for male farmer 15's wife. She has no network links to other women in the sample. In contrast, female farmer 22 plays a very central role in the female network, with five women reporting talking to her about agriculture. No men in the sample claim to talk about agriculture with her husband, and he only claims to talk to one man in the sample (the aforementioned male farmer 15). Figure 1 illustrates that there is very little overlap in male and female networks. Also of note in Figure 1 is that there are two households (4 and 10) that are only connected to other households by female links.

<<Figure 1 here>>

Figure 2 represents the sampled network in Mathia Maffi village, Deoria distict. Similar to Baspar (and the entire sample) there is little overlap between male and female networks. For some households (3, 11, and 25) in this village, women are much more connected, and for others (1, 17, and 21), men are more connected. We chose to depict Mathia Maffi because it illustrates the important role that female household heads can play in female networks. Here, female farmers 13, 24, and 26 are important sources of agricultural information as many women claim to talk to them about agriculture.

<<Figure 2 here>>

[12] Note that for the purposes of this figure, farmers were numbered 1 through 26 in each village. However, where either both male and female members or males in female-headed households are missing from the sequence, this denotes farmers who could not be found at the time of the social network survey.

4.3 Characteristics of central farmers

To reach a large number of households with a new technology, extension agents typically work with—or should work with—well-connected individuals in agricultural information networks. In the previous subsection we demonstrated that well-connected men and women are not necessarily members of the same household. Knowing the characteristics of well-connected men and women can help extension agents identify these individuals and reach them first with new technologies.

To better understand the characteristics of well-connected men and women, we regress the number of agricultural information links each person has onto individual and household characteristics. We do this separately for men and women (females in male-headed households and female household heads). Furthermore, we separately analyze links *to* the individual (number of people that claim to talk to him/her about agriculture), links *from* the individual (number of people he or she claims to talk to about agriculture), and links moving in either direction. The econometric model is:

$$\begin{aligned} Links_i = \alpha + \beta_1 \cdot Age_i + \beta_2 \cdot Edu_i + \beta_3 \cdot Wealth_i + \beta_4 \cdot Land_i + \beta_5 \cdot Caste_i + \beta_6 \\ \cdot Qualify_i \\ + \beta_7 \cdot Progressive_i + \beta_8 \cdot Male\ HH\ head_i + \beta_9 \cdot Works\ on\ farm_i + \varepsilon_i \end{aligned} \quad (1)$$

In (1), Age_i and Edu_i are the age and education (in years) of the individual, man or woman. $Wealth_i$ and $Land_i$ are household-level variables, where the former is a factor analytic index and the latter is acres of land. $Caste_i$ is a binary variable for the household being general caste and $Qualify_i$ is a binary variable for the household winning the 2011 LLL auction, and therefore being a potential early adopter. $Progressive_i$ is a binary variable for either the man or woman in question being identified as progressive by at least one of their peers in the sample. $Male\ HH\ head_i$ is a binary variable for a woman living in a male-headed household (as opposed to being a female household head) and $Works\ on\ farm_i$ is a binary variable indicating that the woman in question works on the household farm (all men work on their household farm).

The most interesting result from this estimation (Table 4) is that wealth (as measured by a factor analytic index) is positively correlated with the number of men claiming man *i* as an agricultural information contact, but negatively correlated with the number of women claiming woman *i*. Wealth is uncorrelated with the number of men that *i* claims as an agricultural information link, and again negatively correlated with the number of women that woman *i* claims. These estimates indicate that poor women are better connected than their wealthy counterparts, and for poor households female information networks are especially important. We also find that progressive men are likely to be claimed by more men as an agricultural information link, but progressive women are not. However, progressive women are more likely to claim more agricultural information links than their non-progressive counterparts whereas progressive men are not.

4.4 Network formation

Now we turn to the question of how network links are formed. This can help us better understand the degree of homophily, or lack thereof, in male and female agricultural information networks. To do this, we regress a binary variable for the existence of a link between individuals *i* and *j* onto a series of variables indicating social and physical distance between *i* and *j*. We follow the regression specification described by Fafchamps (2009) and used in some form by Santos and Barrett (2010) and Maertens and Barrett (2013). For continuous variables (age, years of education, wealth index score, cultivated area) we use the absolute value of the difference between *i* and *j*, and also an interaction term between the absolute value of the difference and a binary variable for $i > j$. The parameter estimate for the standalone variable is therefore the effect of the difference on the individual with the lower value and the parameter estimate for the interacted variables is the effect of the distance on the individual with the higher value.

For binary variables (caste status, progressive status, whether the woman works on the family farm, and primary soil type) we use binary variables for *i* but not *j* exhibiting the trait, for *j* but not *i* exhibiting the trait, and for both *i* and *j* exhibiting the trait. The omitted categorical variable is for neither *i* nor *j* exhibiting the trait. To control for endogenous (to receiving LLL) link formation, we include a binary variable for *j* adopting LLL conditional on having qualified for the LLL lottery. For physical distance between homes we use kilometers between the households using GPS readings. Because village populations vary and the sample size within each village is rather consistent, we also control for the number of households in the entire village. We also include a variable for whether households *i* and *j* share family ties, as reported by the household head. We write the model as:

$$\begin{aligned} Link_{ijv} = \beta_{family} \cdot same\ family_{ijv} + \boldsymbol{\beta_{C1}} \cdot \left|\boldsymbol{X_{iv}^{C}} - \boldsymbol{X_{jv}^{C}}\right| + \boldsymbol{\beta_{C2}} \cdot \left|\boldsymbol{X_{iv}^{C}} - \boldsymbol{X_{jv}^{C}}\right| \cdot I(\boldsymbol{X_{iv}^{C}} \\ > \boldsymbol{X_{jv}^{C}}) + \boldsymbol{\beta_{D1}} I\left(\boldsymbol{X_{iv}^{D}} = 1, \boldsymbol{X_{jv}^{D}} = 0\right) + \boldsymbol{\beta_{D2}} I\left(\boldsymbol{X_{iv}^{D}} = 0, \boldsymbol{X_{jv}^{D}} = 1\right) \\ + \boldsymbol{\beta_{D3}} I\left(\boldsymbol{X_{iv}^{D}} = 0, \boldsymbol{X_{jv}^{D}} = 0\right) + \beta_{qualify} \cdot Qualify_{jv} + \beta_{adopt} \cdot Adopt_{jv} \\ + \beta_{dist} distance_{ijv} + \beta_{pop} village\ population_{v} + \mu_{ijv} \end{aligned} \quad 2)$$

where $\boldsymbol{X^C}$ denotes the vector of continuous explanatory variables and $\boldsymbol{X^D}$ denotes the vector of binary explanatory variables. To account for correlation in the error term across pairs *ij* and *ji* we employ dyadic standard errors calculated using the method of Fafchamps and Gubert (2007).[13]

We find that men were 6.8 percentage points (compared to a mean of 4.8 percentage points) more likely to talk about agriculture with men in the same family. Poorer men were more likely to report discussing agriculture with wealthier ones, whereas wealthier husbands were not significantly more likely to report talking to poorer ones (although the point estimate is negative). This asymmetry in conversations (or in reporting about conversations) could reflect strategic link formation if men in wealthier households have more or better information about agriculture than their poorer counterparts. Compared to agricultural information links between two non-progressive men, a progressive man was 3.1 percentage points more likely to discuss agriculture with a non-progressive man, a non-progressive man was 9.6 percentage points more likely to discuss agriculture with a progressive man, and a progressive man was 9.0 percentage points more likely to discuss agriculture another progressive man. These findings indicate that progressive farmers are not only information providers, but also information seekers.

[13] To generate dyadic standard errors we use the code written by Marcel Fafchamps and available on his personal webpage: http://web.stanford.edu/~fafchamp/resources.html.

We find no influence of age difference, soil type, or geographical distance in male link formation. As expected, we find that man *j* being a LLL adopter did not influence man *i*'s probability of discussing agriculture with him, as the survey on male networks was conducted before anyone in the sample could adopt LLL. Together, these findings suggest that self-interest is more important than identity in male agricultural network formation, although family plays a large role. The results lend some support to the common extension strategy of reaching out to progressive farmers with new technologies. Furthermore, they do not suggest that homophily in information networks would lead to a network-induced information trap (Barrett and Carter, 2013).

The factors influencing women's link formation are similar to those for men, with a few exceptions. Family ties increase the probability of a network link by 5.1 percentage points, compared to a mean of 3.4 percent. Unlike for men, we find no influence of wealth on female link formation. We do find that age plays a role: younger women were more likely to discuss agriculture with older women. As with men, we find that progressive women were more likely to be both seekers and providers of agricultural information than non-progressive women. We find that non-progressive women were 3.3 percentage points more likely to discuss agriculture with a progressive woman than another non-progressive woman. Compared to the probability of two non-progressive women discussing agriculture, progressive women were 2.3 percentage points more likely to discuss agriculture with a non-progressive woman and 6.4 percentage points more likely to discuss with another progressive woman.

Unsurprisingly, women that work on the household farm were 2.2 percentage points more likely to discuss agriculture with another woman who also does so than one who does not. Somewhat surprisingly, however, women who work on the household farm were equally likely to discuss agriculture with a woman who works on the farm than with one who does not. We find that female headship influences link formation. Women living in a male-headed household were 2.3 percentage points more likely to discuss agriculture with a female head of household than with another woman living in a male-headed household. Female household heads were more likely to discuss agriculture with another woman than were females living in male-headed households, but there was no statistical difference between the probability that they would discuss with another female head (2.6 percentage points) or with a woman in a male-headed household (2.2 percentage points). Clearly, female heads of households are more linked in female networks as both seekers and providers of agricultural information. This is consistent with the illustration in Figure 2.

Wealth has no significant influence on women's network formation, but landholdings do have a small influence. For every decimal (0.01 acre) of landholdings difference, the woman in the household with more land is 0.4 percentage points less likely to discuss agriculture with the woman in the household with less land. We also find that caste matters: a general caste woman is 1.4 percentage points more likely to talk to a non-general caste woman than a non-general caste woman is to talk to another non-general caste woman about agriculture. Distance does not have a significant effect on the probability of link formation, however the point estimate has an unexpected positive sign. We have no plausible explanation for why this might be, but find it interesting that household proximity does not seem to incite discussions about agriculture, all else equal.

Recall that unlike the household head's network survey, we conducted the wives' network survey several months after the introduction of LLL. This presents the possibility that female agricultural information links—as we measure them—are endogenous to technology adoption. We find some evidence of this: if household *j* adopted LLL conditional on winning the auction, then wife *j* was 1.0 percentage point more likely to be claimed by wife *i* as an information link. Although this effect is not statistically significant ($p = 0.144$), it is important to consider this effect when comparing the probability of link formation between men and women. If 30 percent of women are in adopting households and a link to an adopting woman is 1 percentage point more likely, the probability of a female link would be inflated by 0.3 percentage points compared to a mean of 3.4 percentage points. Our complete results on determinants of agricultural information link formation can be found in Table 4.

4.5 Network effects on household technology demand

The empirical literature on social learning and network effects has grown rapidly in recent years. A persistent challenge to the econometric identification of network effects is the reflection problem (Manski, 1993): under normal circumstances it is not possible to tell if two people use similar technology because one learned from or mimics the other, or because they simply share similar traits or characteristics—observed or unobserved—that lead them both to adopt the technology. To circumvent the reflection problem several recent studies have randomly allocated a new technology or practice to a subset of network members to identify network effects on subsequent adoption (Babcock and Hartman, 2010; Cai, et al., 2013; Duflo, et al., 2006; Duflo and Saez, 2003; Kremer and Miguel, 2007; Ngatia, 2012; Oster and Thornton, 2012). In a companion paper we estimate network effects among (predominantly male) household heads on demand for LLL using data from the same field experiment in EUP. We find strong network effects, particularly when network effects on *i*'s demand are conditioned on *j* benefiting from LLL, indicating social learning rather than mimicry drives the adoption process (Magnan, et al., 2013). Here we present estimates of distinct male and female network effects in the same set of agricultural households.

We estimate network effects similarly to Oster and Thornton (2012) and Miguel and Kremer (2007). In the context of our study, the base regression model is:

$$\begin{aligned} WTP_{iv} = \beta_0 + \beta_1 \cdot M\_Adopter_{iv} + \beta_2 \cdot F\_Adopter_{iv} + \beta_3 \cdot M\_Qualified_{iv} \\ + \beta_4 \cdot F\_Qualified_{iv} + \beta_5 \cdot M\_Total_{iv} + \beta_6 \cdot F\_Total_{iv} + \varepsilon_{iv} \end{aligned} \quad (3)$$

In (3), WTP_{iv} is household *i*'s (from village *v*) demand for LLL, quantified as the household head's willingness to pay in the 2012 auction, one year after LLL was introduced. $M\_Adopter_{iv}$ ($F\_Adopter_{iv}$) is a binary variable for whether or not household *i* has a male (female) link to any household *j* in the same village *v* who was an early adopter of LLL via the auction/lottery mechanism. We use binary variables for having an adopter in-network because most people have either zero or one links to an adopting household (this is especially true for men). To ensure that $M\_Adopter_{iv}$ ($F\_Adopter_{iv}$) is exogenous, we control for the number of qualifying household *j*'s in *i*'s male (female) network. These variables are $M\_Qualified_{iv}$

and $F\_Qualified_{iv}$, respectively. We also control for total male and female network sizes (M_Total_{iv} and F_Total_{iv}, respectively) to improve precision. No household that lost the lottery adopted LLL. However, some households that won the lottery did not adopt, generally due to untimely heavy rains. Due to this noncompliance, we instrument for having at least one in-network adopter with having at least one in-network lottery winner.

Even though we randomly selected early adopters of LLL from a pool of would-be adopters, we potentially have an additional endogeneity challenge for estimating female network effects. Recall that we asked husbands about their network connections prior to the auction and lottery for the technology, so network links are completely exogenous to the lottery, which we show in Table 5. However, we asked wives about their networks four to five months after some sample households received LLL. It is therefore possible that women had sought out women from adopting households to discuss agriculture during this time interval. As stated earlier, women were 1.0 percentage point more likely to form a link with a woman in an adopting household (although this effect is not statistically significant). If these same women were more interested in having their household adopt LLL, then their bid in 2012 may reflect higher demand even if they do not have a link to an adopting household. To mitigate any bias we account for baseline differences in WTP by either controlling for WTP in the auction preceding the introduction of LLL or by regressing the difference in WTP between the 2012 and 2011 auctions onto the explanatory variables.

From estimating (3) we find male network effects to be strong and significant in one specification, and large but not significant in the other (Table 6, columns 1 and 2). In the first specification (Table 6, column 1) we regress WTP in the second auction on network variables. We find that having a male link to an adopting household increases WTP by Rs. 87 compared to a mean of Rs. 310. Regressing the change in WTP on network variables yields a network effect of Rs. 66 compared to a mean change of Rs. 110, although this change is not significant to conventional levels. We find small negative point estimates for female network effects in both specifications, but neither is close to significance. These negative coefficients suggest that upward bias in female network effect estimation is not a problem.

It is likely that estimating (3) presents a muddied picture of network effects because doing so does not account for the information household *i* receives through male and female networks. If household *i* receives information from household *j* and members of household *j* are benefiting from LLL (or believe they are) we would expect this information to increase *i*'s WTP. However, if members of household *j* are not benefiting from LLL (or believe they are not) we would expect this information to either not affect or decrease *i*'s WTP. To allow network effects to be conditional on benefits we decompose household *i*'s links to water saving households and links to non-water saving households. We choose water savings because it is the primary touted benefit of LLL (Jat 2006, 2009), and we find this to be the case in our study area as well (Lybbert, et al., 2013).

To calculate whether or not household *j* saves water, we use retrospective data from the baseline survey on irrigation over the year preceding the intervention. We collected the same retrospective data on water use during the intervention year in the endline survey. To classify a household as water saving we use a binary variable for whether the household used at least 10 percent less water in 2012 than in 2011. LLL is purported to save from 10-30 percent (and this is the range we stated in the information session), so we set the threshold at the low end of this range. Water use fluctuates for both LLL adopters and non-adopters, so we include variables for network connectivity to both water saving and non-water saving households interacted with adoption status (adopter or qualified for lottery). This isolates the effect of having an adopting water saver or an adopting non-saver in-network. The regression model therefore becomes:

$$\begin{gathered} WTP_{iv} = \beta_0 + \beta_1 \cdot M\_Adopter\_nosave_{iv} + \beta_2 \cdot M\_Adopter\_save_{iv} \\ +\beta_3 \cdot F\_Adopter\_nosave_{iv} + \beta_4 \cdot F\_Adopter\_save_{iv} \\ +\beta_5 \cdot M\_Qualified\_nosave_{iv} + \beta_6 \cdot M\_Qualified\_save_{iv} \\ +\beta_7 \cdot F\_Qualified\_nosave_{iv} + \beta_8 \cdot F\_Qualified\_save_{iv} \\ +\beta_9 \cdot M\_Total_{iv} + \beta_{10} \cdot F\_Total_{iv} + \varepsilon_{iv} \end{gathered} \tag{4}$$

In (4), we would expect β_2 (β_4) to be positive in the presence of social learning from a male (female) link's good experience with LLL, and for β_1 (β_3) to be negative in the presence of social learning from a male (female) link's neutral or bad experience from LLL.

We find that male links to water saving households have a strong positive effect on WTP in both model specifications (Table 6, columns 3 and 4). Having at least one male link to a water saving household increases WTP by Rs. 129-140. Male links to a non-water saving household have a smaller and insignificant effect, with a positive point estimate in one specification and a negative point estimate in the other. Female links to a water saving household have a small and insignificant effect. Interestingly, having at least one female link to a non-water saving household has a slightly larger and negative effect, although this effect is only significant in one of the two specifications (column 4). This suggests that women who learn about negative (or at least less positive) experiences with LLL through their networks are able to translate this knowledge into decreased household demand for LLL.

5. Concluding remarks

Economists typically model household decisions from the point of view of one individual who maximizes a single optimization problem given a single set of endowments and constraints. The emerging economic literature on social networks, information, and technology adoption has for the most part adopted this unitary household framework. In this paper we used social network data from men and women—mostly husbands and wives—to estimate models of network formation. We found that the underlying factors that shape network linkages between males are generally similar yet result in networks with very little overlap.

The question of how female networks can be used to disseminate technology is an important one that certainly merits more research. Our findings suggest that female social networks can help households gather more information about a technology than they would receive through male networks alone. We find weaker evidence that these female network effects can affect household decisions on agricultural technology use or adoption. With a technology that is particularly beneficial to women—for instance, mechanical rice transplanters that were being promoted in the study area concurrent with LLLs— it is possible that female network effects would be much stronger. It is important to invest more effort in learning how social networks form and operate for both men and women in a variety of contexts. These networks may be very effective at disseminating certain agricultural technologies.

Efforts to better leverage gendered networks through rural producer organizations, cooperative societies, and self-help groups offer one possible area of intervention and investment (Markelova, et al., 2009; Vasilaky, 2013). Another area relates to the staffing and training of extension agents in a more gender-relevant manner to expand the number and role of women in extension service provision and thus improve access to female social networks (Haug, 1999; Kondylis and Mueller, 2013; Liepins and Schick, 1998). Other areas include the design of novel business models and targeted public subsidies that leverage these social networks to promote the information about and adoption of new technologies and practices among women whether or not they are considered the primary household decision-maker. More generally, these interventions and investments suggest the need for greater analytical attention to be given to institutional innovations—the novel use of networks to exchange knowledge and information—as an accompaniment to agricultural technological innovation in developing countries.

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Figures and Tables

Figure 1. Men and women's agricultural information networks, Baspar village, Maharajganj district

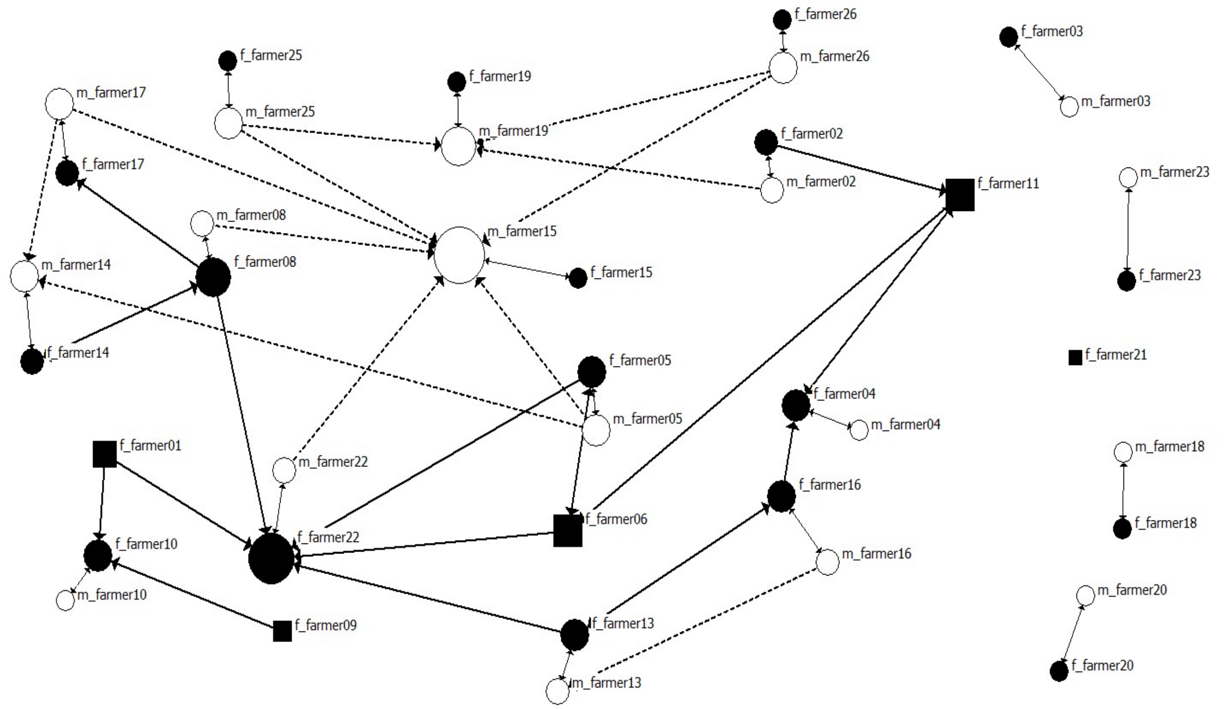

Figure 2. Men and women's agricultural information networks, Mathia Maffi Village, Deoria District

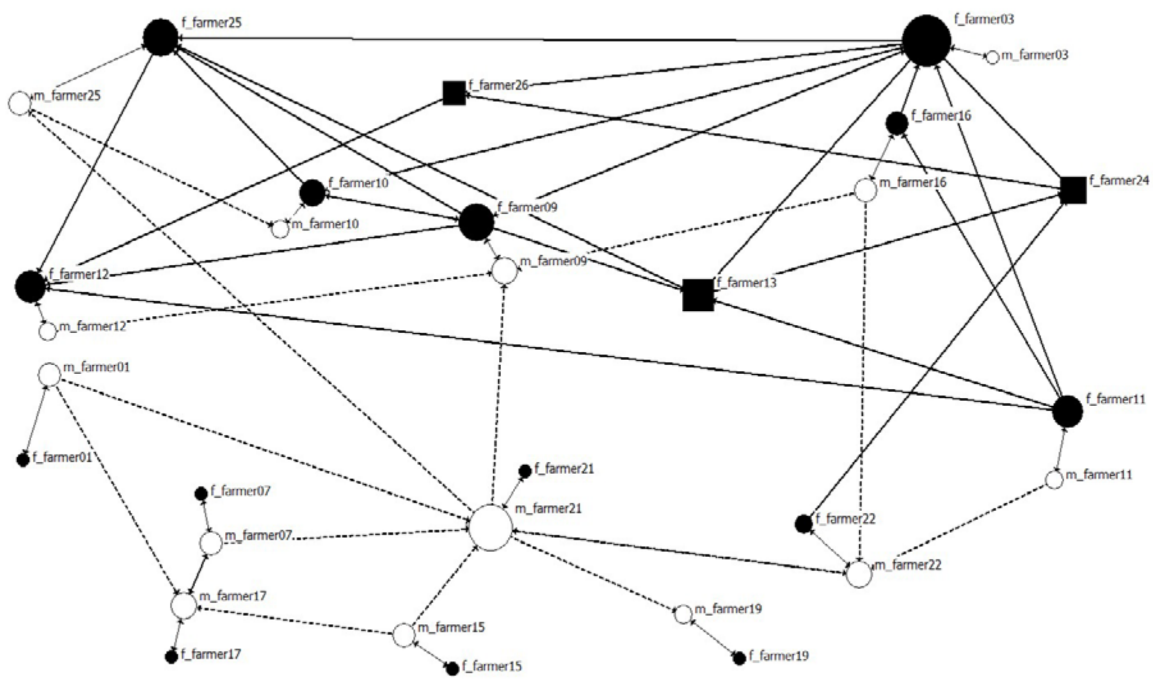

Table 1. Prevalence of female agricultural among sample households

Indicator	Overall	General caste	Other caste/ Muslim	Male headed households	Female household heads
Woman works on family farm {0,1}	0.50	0.39	0.60***	0.52	0.40*
Woman works on other farm {0,1}	0.19	0.09	0.28***	0.14	0.32***
Percent time spent working on a farm	0.33	0.22	0.43***	0.27	0.60***
N	385	211	174	351	75

Notes: ***Denotes difference between caste classification or gender of household head is significant with p<0.01 using t-test (continuous variables) or Chi-square test (binary variables)

Table 2. Intra-household discussion of agriculture and LLL by wealth class

		Overall	Poor	Wealthy
Wives say	Talk about ag with husband	0.48	0.57	0.40***
	Talk about ag technology with husband	0.36	0.44	0.30*
	Talk about ag LLL with husband	0.67	0.72	0.64*
	Talk about LLL with other women	0.49	0.56	0.45**
Husbands say	Discuss ag technology with wife	0.62	0.66	0.58
	Wife's opinion on ag tech and crop choice important or very important[b]	0.70	0.68	0.66
	Discussed LLL with wife following auction	0.61	.65	0.58
	N	346	155	191

Notes: Means reported.
[a] Options were "not at all", "small extent", "medium extent", and "large extent".
[b] Options were "not important", "important", and "very important". *,**,*** denote p<0.1, 0.05, 0.001 using t-test (continuous variables) or Chi-square test (binary variables) for difference between poor and wealthy.

Table 3. Summary of potential and actual within-village agricultural links in sample

Unidirectional link type	Possible links	Actual links	Percent
Men	5,308	252	4.8
Women (wives of male household heads)	5,308	182	3.4
Women (including female household heads)	7,720	284	3.7
Men and women (same household)	5,308	12	0.2
Women | Men	252	12	4.8
Men| Women	182	14	6.6

Note: Probability of wife-to-wife link conditional on husband-to-husband link is not statistically different from probability of wife-to-wife link conditional on no husband-to-husband link (p = 0.23).

Table 4. Characteristics of most connected men and women in social networks

Dependent variable: Number of links	**Others claiming *i* as link** Men	**Others claiming *i* as link** Women	**Number *i* claimed as link** Men	**Number *i* claimed as link** Women	**Links in either direction** Men	**Links in either direction** Women
Age	0.11	-0.12	-0.00	0.12	0.11	-0.00
	(0.15)	(0.13)	(0.10)	(0.17)	(0.21)	(0.25)
Education (years)	0.02	-0.08	0.02	0.05	0.04	-0.03
	(0.04)	(0.12)	(0.03)	(0.22)	(0.06)	(0.26)
Wealth index	0.59**	-0.43*	-0.05	-0.39**	0.54	-0.82**
	(0.26)	(0.22)	(0.20)	(0.17)	(0.39)	(0.33)
Area farmed by household	0.03	0.11	0.01	-0.07***	0.05	0.04
	(0.06)	(0.11)	(0.06)	(0.02)	(0.08)	(0.11)
HH is general caste	-0.04	0.04	0.16	1.05**	0.12	1.09
	(0.37)	(0.50)	(0.48)	(0.47)	(0.54)	(0.66)
HH qualified for 2011 auction	0.11	0.58	0.58	-0.20	0.69	0.37
	(0.29)	(0.43)	(0.43)	(0.52)	(0.58)	(0.83)
Individual claimed as progressive	2.11***	0.79	0.00	2.13**	2.12**	2.92**
	(0.47)	(0.51)	(0.40)	(0.96)	(0.76)	(1.33)
Male headed HH		-0.08		-0.52		-0.60
		(0.45)		(0.52)		(0.79)
Female works on HH farm		0.11		1.47**		1.58**
		(0.35)		(0.56)		(0.70)
Constant	-0.24	1.32*	0.98	0.27	0.75	1.60
	(0.88)	(0.75)	(0.72)	(0.81)	(1.33)	(1.25)
Observations	358	444	358	444	358	444
R-squared	0.12	0.03	0.01	0.05	0.07	0.05

Village-clustered standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 5. The influence of social distance between *i* and *j* on husbands and wives' agricultural information links

	Husbands (mean = 0.048)			Wives (mean = 0.034)		
Dependent variable: Ag info link {0.1}	**Coef.**	**Dyadic Std. Err.**	**Marg. effect**	**Coef.**	**Dyadic Std. Err.**	**Marg. effect**
Related (family or in-law)	1.619	(0.269)***	0.068	1.542	(0.364)***	0.051
$\|\Delta age\|$ (10 years)	0.024	(0.045)	0.001	-0.154	(0.086)*	-0.005
$\|\Delta age\|$ if $age_i > age_j$	-0.112	(0.077)	-0.005	0.093	(0.091)	0.003
$\|\Delta edu\|$ (years of schooling)	0.002	(0.018)	0.000	-0.138	(0.114)	-0.005
$\|\Delta edu\|$ if $edu_i > edu_j$	-0.013	(0.029)	-0.001	-0.037	(0.197)	-0.001
$\|\Delta wealth\|$ (wealth index)	0.278	(0.076)***	0.012	-0.031	(0.124)	-0.001
$\|\Delta wealth\|$ if $wealth_i > wealth_j$	-0.191	(0.120)	-0.008	-0.154	(0.170)	-0.005
$\|\Delta land\|$ (ha)	0.023	(0.019)	0.001	0.008	(0.035)	0.000
$\|\Delta land\|$ if $land_i > land_j$	0.004	(0.015)	0.000	-0.130	(0.076)*	-0.004
i general caste, *j* not	-0.220	(0.285)	-0.009	0.413	(0.230)*	0.014
j general caste, *i* not	-0.139	(0.285)	-0.006	0.156	(0.214)	0.005
Both general caste	0.308	(0.258)	0.013	-0.078	(0.283)	-0.003
i progressive, *j* not progressive	0.742	(0.401)*	0.031	0.698	(0.254)***	0.023
j progressive, *i* not progressive	2.309	(0.318)***	0.096	0.988	(0.250)***	0.033
Both progressive	2.145	(0.335)***	0.090	1.922	(0.369)***	0.064
i has heavy soil, *j* has light soil	-0.060	(0.195)	-0.003	-0.004	(0.222)	0.000
j has heavy soil, *i* has light soil	-0.334	(0.241)	-0.014	-0.148	(0.272)	-0.005
Both have heavy soil	-0.231	(0.257)	-0.010	-0.135	(0.265)	-0.004
i works on family farm, *j* does not				0.729	(0.256)**	0.024
j works on family farm, *i* does not				-0.031	(0.258)	-0.001
Both work on family farm				0.670	(0.299)**	0.022
i is household head, *j* is not				-0.670	(0.338)**	-0.022
j is not household head, *i* is				-0.699	(0.414)*	-0.023
Both are household heads				-0.777	(0.426)**	-0.026
j qualified for LLL lottery	0.128	(0.231)	0.005	0.179	(0.214)	0.006
j adopted LLL	-0.023	(0.244)	-0.001	0.293	(0.201)	0.010
Household distance (km)	-0.076	(0.180)	-0.003	0.265	(0.163)	0.009
Village population	1.199	(3.395)	0.050	-6.157	(3.062)**	-0.205
Gorakhpur district	0.122	(0.337)	0.005	-0.734	(0.331)**	-0.024
Deoria district	-0.336	(0.250)	-0.014	-0.902	(0.297)***	-0.030
Constant	-4.866	(0.567)***		-2.100	(0.702)***	
N		5308			7720	

Wealth index consists of house condition; ration card possession; landholdings; and ownership of cell phones, vehicles, TVs, satellite dish, and livestock. Omitted dummy variable for dichotomous variable is for neither *i* nor *j* exhibiting the trait. Omitted district variable is for Maharanjganj district. ***p<0.01, **p<0.05,*p<0.1.

Table 6. Gender-disaggregated network effects on willingness to pay for laser land leveling

Network effects on WTP, conditional on benefits	**(1) WTP**	**(2) ΔWTP**	**(3) WTP**	**(4) ΔWTP**
Male link to adopting HH {0,1}	87.35**	65.61		
	(37.24)	(45.54)		
Female links to adopting HH {0,1}	-11.49	-25.26		
	(25.39)	(21.79)		
Male link to adopting non-water saving HH {0,1}			17.03	-36.38
			(52.69)	(73.14)
Male links to adopting water saving HH {0,1}			128.79***	140.26**
			(46.61)	(66.14)
Female link to adopting non-water saving HH {0,1}			-45.52	-75.92**
			(38.69)	(37.47)
Female links to adopting water saving HH {0,1}			31.28	49.63
			(36.03)	(40.80)
Male links to qualifying HHs	-18.69	-45.88*		
	(20.76)	(23.91)		
Female links to qualifying HHs	25.52	28.47**		
	(18.18)	(14.19)		
Male links to non-water saving qualifying HHs			24.31	13.88
			(29.47)	(40.73)
Male links to water saving qualifying HHs			-37.44	-67.85**
			(26.35)	(27.24)
Female links to non-water saving qualifying HHs			23.65	34.75**
			(16.62)	(15.19)
Female links to water saving qualifying HHs			27.69*	23.26
			(16.02)	(17.89)
Total male links	-4.81	3.43	-9.27	-2.59
	(11.08)	(14.17)	(11.51)	(11.73)
Total female links	-14.56	-13.62	-16.78*	-16.39
	(11.59)	(10.20)	(9.98)	(10.27)
Male headed household	30.34	-5.02	26.36	-12.88
	(21.21)	(24.25)	(23.80)	(24.90)
Female network data available	109.61**	63.08	91.92**	32.56
	(43.60)	(57.50)	(41.46)	(52.11)
WTP 2011	0.26***		0.27***	
	(0.05)		(0.05)	
Constant	129.29***	64.72	139.05***	82.60
	(41.94)	(55.02)	(41.70)	(52.04)
Observations	422	422	422	422

IV regressions with winning the lottery instrumenting for adopting LLL. Village-clustered standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.