Leveling with Friends: Social Networks and Indian Farmers' Demand for Agricultural Custom Hire Services

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ABSTRACT

Technology-driven gains in agricultural productivity and profitability can dramatically improve quality of life for the rural poor in developing countries. Extension efforts to disseminate agricultural technologies typically assume that farmers learn from early adopters, which catalyzes the diffusion process. In this paper we investigate how learning through social networks influences farmers' demand for laser land leveling (LLL)—a resource conserving technology—in eastern Uttar Pradesh, India. To estimate network effects we identify potential adopters using an experimental auction that elicits willingness to pay and, from among these farmers, randomly select a treatment group ("first-generation adopters") who actually employ LLL services on their land, as well as a control group. We conduct a second auction one year later to elicit updated estimates of willingness to pay from the same sample of farmers. Three unique results emerge from this field experiment that improve our understanding of network effects and technology adoption. First, exposure to LLL via networks occurs primarily through visits to adopting farmers' fields rather than through conversations or seeing the technology applied. Second, having a first-generation adopter in a farmer's network increases his valuation of LLL by 27 percent on average. Third, using differences in farmers' input usage between the two auctions, we find that this network effect is importantly conditioned on the benefits associated with LLL, which implies that learning—rather than mimicry—is driving increases in demand.

JEL Codes: O13, O14, Q16

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1 INTRODUCTION

Technological innovation in agriculture can make agriculture more productive and profitable to the rural poor in developing countries, improving their day-to-day quality of life and household food security. One particular class of technology—resource-conserving technologies—is designed not only to increase productivity and reduce production costs, but also to alleviate negative environmental externalities and use water and soil resources more sustainably. Based on growing concerns about climate change, resource constraints and vulnerability, these technologies and practices have attracted widespread attention in recent years. While understanding how farmers learn about new agricultural technologies is generally important, the diffusion process of these resource-conserving technologies with their mix of private and public benefits may introduce new complications, making it simultaneously more important and more challenging to understand the underlying learning process.

Farmers have multiple sources of agricultural information at their disposal, some more valued than others. Farmers often rely on their social networks as their most trusted and reliable source of information regarding the suitability, profitability, and use of new technologies (Anderson and Feder 2007; Birner, et al. 2009). Farmer networks are therefore fundamental to most agricultural extension strategies: where farmers are geographically or socially dispersed, and where public resources for technology promotion are scarce, farmer networks can be used to widely disseminate new technologies. Such strategies typically depend on reaching out to "progressive" or "model" farmers to demonstrate the technology and incite adoption, in the hopes that other farmers will follow (Anderson and Feder 2004). In some instances, this dissemination process can be accelerated through direct interventions such as subsidies or discounts for early adopters because the information externality generated by these adopters might increase adoption in subsequent periods, even if the technology is no longer subsidized (Kremer and Miguel 2007). Other strategies may use social mobilization—bringing farmers together in cooperatives, self-help groups, or community organizations—to similarly leverage these network effects (Vasilaky 2012). Empirical evidence of farmer-to-farmer technology spillovers and their magnitudes, however, is relatively scarce to date.

One reason that empirical studies of network effects have been historically rare is that they confront a significant identification challenge due to the reflection problem (Manski 1993). The reflection problem occurs because under most circumstances it is not possible to determine if two farmers use similar technologies because one learns from or mimics the other or because the farmers are merely similar or face similar conditions and constraints. Many observational studies on social networks have implemented creative and highly convincing strategies to identify network effects, often taking advantage of panel data (Bandiera and Rasul 2006; Conley and Udry 2010; Foster and Rosenzweig 1995; Maertens 2012; McNiven and Gilligan 2012; Munshi 2004; Munshi and Myaux 2006). Recently, a handful of studies—including, but not limited to, agriculture—have used randomized interventions to identify network effects (Babcock and Hartman 2010; Cai 2013; Duflo, Kremer and Robinson 2006; Duflo and Saez 2003; Kremer and Miguel 2007; Ngatia 2012; Oster and Thornton 2012). The fact that experimental results can contradict observational results, even when these are based on analyses of experimental data as if they were observational (Duflo, Glennerster and Kremer 2007; Duflo, Kremer and Robinson 2006; Kremer and Miguel 2007), highlights the potential importance of using experimental interventions to identify network effects.

In this paper we present findings on how network effects influence demand for an agricultural technology using data from a field experiment that randomly assigns a new technology to farmers in three districts of eastern Uttar Pradesh (EUP), India. The technology in question is laser land leveling (LLL), a resource conserving technology, which we describe below. Because LLL equipment is expensive and requires some skill to operate, most Indian farmers—and all smallholders—are likely to access LLL though rental arrangements known as custom hire services. We use a pair of experimental auctions held one year apart to measure farmer demand for custom hire LLL services. These auctions were binding: if a farmer bid enough for LLL services on their land they could expect to pay real money out of pocket and receive real LLL custom hire services. After the first auction, we held a lottery to determine who would purchase the LLL services. Using this randomization, we are able to test for the effect of having an adopting farmer in a farmer's social network on demand for the technology, conditional on the number of would-be adopters in his[1] network. Because we measure demand in terms of farmer willingness to pay (WTP) rather than observed adoption, we can

[1] We use masculine pronouns throughout for ease of composition. In our sample, over 80 percent of study farmers were male.

measure network effects on in monetary terms as opposed to increased uptake at a given price. We find that farmers with early adopters in their network exhibit WTP 27 percent higher than the sample average.

This study also aims to distinguish whether network effects arise from learning or mimicry. By using data on irrigation and other input use data for the one-year period between the two auctions, we are able to separate out the effect of having a farmer who benefited more from LLL in one's network from the effect of having a farmer who benefited less. We find that having a farmer who benefited more from LLL had a positive impact on demand, whereas having a farmer who benefited less did not. This finding suggests that farmers in our sample learned about the benefits of adoption by observing adopters in their social networks, and that this learning increased demand. When addressed together, these findings increase our understanding of network effects and technology adoption and suggest methodological approaches for future studies in a similar vein.

2 LASER LAND LEVELING IN INDIA

In the 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). Uneven fields can also lead to inefficient use of fertilizers and chemicals, increased biotic and abiotic stress, and low yields (Jat, et al. 2006). Farmers in this region, like most farmers around the world, have long recognized that level plots are easier to cultivate and are more efficient than uneven plots and have devised several cultivation practices and techniques to address this, for example, the use of contoured levees and manual leveling with planks. In this sense, laser land leveling does more precisely what farmers have tried to do using more traditional knowledge and practices. The main difference between traditional practices and LLL is precision. LLL uses a stationary emitter to project a level laser plane above a plot and an adjustable scraper with a laser receiver pulled by a tractor to level the plot using the laser plan as a guide. Whereas the best traditional leveling methods have a leveling precision of ±4 cm or more, LLL can level even large plots to a precision of ±1 cm (Jat, et al. 2006).[2]

The primary benefit of LLL is a reduction in water use. This is particularly important in the Indo-Gangetic Plains, where groundwater is being extracted at increasingly unsustainable rates, and where farmers still rely on flood irrigation, which requires them to irrigate extensively, that is, until the highest point of the field is visibly submerged. Although Indian farmers do not pay unit charges for the groundwater they use, most farmers use diesel pumps for irrigation and can therefore save substantially on fuel by using less water. LLL has also been shown to improve crop establishment and growth, thereby improving the efficiency of chemical and fertilizer use while decreasing the damage caused by biotic and abiotic stress, ultimately leading to production cost reductions and increases in output and yields (Jat, et al. 2006).

In India, LLL was initially introduced in western Uttar Pradesh in 2001. Since then, the technology has achieved widespread acceptance in some areas of the Indo-

[2] LLL is feasible for plots of nearly all sizes. The only exception is plots that are so small as to make it difficult to maneuver the tractor and scraper, which for standard dimensions occurs at plot sizes less than 0.2 acre.

Gangetic Plains (IGP)—notably in the agriculturally progressive Indian states of Haryana and Punjab. Since the introduction of LLL, the number of laser land levelers in the region has risen to 925 and the acreage under LLL grew to 200,000 hectares in 2008. Agronomic trials in rice-wheat systems in this region have found that LLL results in 10-30 percent irrigation savings, 3-6 percent increases in effective farming area, 6-7 percent increases in nitrogen use efficiency, and 3-19 percent increases in yield (Jat, et al. 2006; Jat, et al. 2009). In on-farm trials, net annual farmer revenues rose from $200-300 per hectare (Jat, et al. 2009). LLL could also have public benefits in the form of reduced groundwater depletion and lower nutrient and chemical runoff. Jat et al. (2006) estimate that extended use of LLL to 2 million hectares of rice-wheat land in the IGP could save 1.5 million hectare-meters of irrigation water and 200 million liters of diesel, increase crop production by $500 million, and reduce greenhouse gas emissions by 0.5 million metric tons over three years.

In contrast to these more agriculturally developed regions of India, LLL is new to the more heterogeneous and poorer EUP region. Farmers in this region have smaller plots, and their production practices are less input intensive. Private LLL service providers have yet to extend their service networks to this quite different region, in part because the business models they have developed in the western IGP may not be viable in the EUP.[3] We exploit the lack of familiarity with LLL in the region to study if and how network effects increase demand for the technology.

[3] In a companion paper, we use the auction data we describe below to simulate novel business models to deliver LLL in the heterogeneous EUP. See Lybbert et al. (2012).

3 Experimental Design and Data Collection

3.1 Study site and sample

The state of Uttar Pradesh (UP) covers 243,000 km^2 and is home to 200 million residents, a remarkable population density even by Indian standards. UP is highly agrarian and relatively poor—70 percent of the population lives in poverty (Alkire and Santos 2010)—and EUP is relatively poor compared to the rest of the state.

The main crops grown in the area are rice and wheat, followed by mustard, sugarcane, pulses, maize, and other crops. Farmers cultivate rice during the summer *kharif* season when the monsoon provides much of the water needed for irrigation.[4] Farmers cultivate wheat in the winter *rabi* season when the crop depends more on irrigation throughout the growing season. Unlike areas in the western IGP where canals are a significant source of irrigation water, EUP depends primarily on groundwater that is extracted by diesel, rather than electric, pumps. Because LLL is completely new to EUP and there is no market or price information for the technology, this is an appropriate study area in which to gauge demand using an experimental auction. EUP is also an ideal location to test network effects on learning because information on the technology is essentially non-existent outside of the intervention.

The study began prior to the onset of *kharif* season in 2011 (that is, in March 2011), continued through the 2011/12 rabi season (approximately October 2011 to May 2012), and concluded during the subsequent *kharif* season in 2012 (in approximately July 2012) (see Figure 1 for a timeline). We selected three districts—Maharajganj,

[4] During the *kharif* season most irrigation water is used for flooding the rice fields.

Gorakhpur, and Deoria—to represent heterogeneity across farm size and productivity in the rice-wheat cropping system of EUP.[5] In each district, we randomly selected four villages from among those with a population greater than 48 households and less than 400 households. We set the lower limit to ensure there would be at least 20 farm households to participate in the study, and upper limit to avoid incomplete village rosters and the possibility that we would not capture any network links. For each district, a population of 400 households per village is greater than the 90th percentile of all villages.

To ensure our intervention would be the only source of information about LLL we did not select villages in the proximity of any of the few LLL demonstrations being conducted in EUP. While LLL has been introduced very sparsely into EUP via small-scale demonstrations, our sampling design ensures that the farmers in our sample have little or no exposure to these demonstrations. Following consultations with individuals involved in agricultural research, extension services, and farm equipment sales and custom hiring, we were able to pinpoint locations where LLL demonstrations and related demonstrations of resource-conserving technologies in EUP had been held.[6] Villages within a 10-kilometer radius of any LLL demonstrations were excluded from the sample,

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[5] To ensure comparability across households for the study, the sample selection criteria ruled out villages and households cultivating flood-prone areas that constrained rice production during the *kharif* season. The sample selection did not, however, exclude villages and households where crops in addition to rice and wheat—for example, mustard, sugarcane, pulses, or maize—were cultivated alongside wheat and rice.

[6] Only three sources of LLL demonstrations were identified in EUP: sites selected by the Cereal Systems Initiative for South Asia (CSISA), of which this study is a part; the Krishi Vigyan Kendra (KVK) center in Kushinagar, a unit of the Indian Council for Agricultural Research that is responsible for technology promotion among farmers; and one private service provider who borrowed a CSISA LLL unit, provided custom hire services, and worked in partnership with the project.

as were any villages where related promotions of resource-conserving technologies had been conducted. In the final sample only six farmers reported ever hearing of LLL, two farmers reported ever seeing LLL machinery, and one farmer reported ever using LLL, or knowing the market price of LLL hire.[7]

For each of these 12 villages, we randomly chose a paired village that met the same population criteria, was within a five-kilometer radius, and was not within a 10-kilometer proximity to any previously selected village pair. Villages were selected in pairs to assess the spatial reach of social networks both within villages and across villages.[8] Within each village, we randomly selected approximately 20 farmers from those cultivating plots of at least 0.2 acres (the minimum sized plot for LLL) to be included in the study.[9] The resulting sample totaled 478 farmers.

3.2 Experimental Design

In each village the study unfolded as depicted in Figure 1. First, the enumeration team conducted a scripted information session to introduce the sampled farmers to LLL (1). Next, a survey was conducted that featured questions about network connections within the village and with farmers in the paired village (2-3). We then conducted an experimental auction to elicit farmers' demand for the technology (4). After conducting the auction, we used a simple lottery to determine who in the pool of would-be adopters would actually purchase LLL services (5). We hired two LLL teams to provide leveling services to the farmers who won the lottery (6). During the rice and wheat

[7] We believe that the single instance of a farmer reporting to have used LLL is an instance of misreporting or enumerator error.
[8] We find that very few sample farmers discuss agriculture with farmers in the paired village.
[9] The intended sample size for each villages was 24, with an additional 12 replacement farmers pre-selected in case of absenteeism or lack of a big enough plot among the original 24 farmers.

growing seasons we used an intra-seasonal survey conducted every three weeks to collect detailed input use data (7). At the end of these two growing seasons, we conducted an endline survey and a second LLL auction (8-9) and then hired two LLL teams again to provide leveling services (10).

3.2.1 Information session

As a first step in the field experiment, we needed to introduce farmers to LLL. To do this, we held a scripted information session in each village, and ensured the sessions were as consistent as possible across villages. The information session lasted approximately one hour, and included a talk by a lead member of the enumeration team; a video showing a laser land leveler operating on a field, an interview with the service provider, and an interview with the farmer receiving the service; and a live question-and-answer session with a progressive farmer from EUP who received LLL services as part of a demonstration. At the conclusion of the information sessions, the team gave pictorial brochures about LLL to the farmers that contained the range of possible bids they could make in the experimental auction. During the information session, the team photographed all sample farmers. These photos were compiled into a composite picture for each village to be used later as a farmer photo directory to help farmers identify their network links to other farmers.

Naturally, farmers at each information session inquired about the cost of LLL services. Because the information session was designed as precursor to an experimental auction (explained in further detail below), the enumeration team answered questions in a consistent manner and in a way designed to prevent participants from anchoring on a specific price when it came time for auction bidding. Specifically, the enumeration team explained that in recent years in different Indian states where LLL services were being provided, the price had ranged from Rs. 400 to Rs. 800 per hour of LLL service.[10]

3.2.2 Survey and social networks

Next, the team conducted baseline surveys with sample farmers to collect information on farm and household characteristics. The baseline survey included a social networks module that used the composite picture described above to help farmers identify their network contacts. For the networks module, enumerators asked farmers about their connections with all study farmers in their village and the paired village using the composite pictures. Farmers were asked to identify themselves in the picture from their own village and then answer a series of yes or no questions about their relationships with the other farmers in the picture, e.g., are any of these farmers their friends? Are any in their family? With which of these farmers do they discuss agriculture? Farmers were also asked to identify the progressive farmers in the photo. The same exercise was then conducted using a composite picture of photos of sample farmers in the paired village.

With our social networks elicitation module in mind, it is useful to provide a broader description of relevant methodological dimensions to research on network effects. Prior social network studies have used a variety of definitions of social networks. In some cases, farmers' social networks have been defined as the entire village (Besley and Case 1994; Foster and Rosenzweig 1995; Munshi 2004). While using the village as

[10] LLL custom hire, as well as most custom hire services, are priced by hour rather than by acre in India. We see no evidence of anchoring to Rs. 400 per hour in the auction results (Figure 2).

the relevant social network certainly captures many if not all of a farmer's contacts, it also captures many that are not in the farmer's network (Babcock and Hartman 2010; Maertens and Barrett 2012). Although farmers in these village settings may know everyone else in their village, the degree to which they share agricultural information, or even know what techniques other farmers use, is questionable.[11] In some cases it is possible to use observable variables from existing survey data, such as caste, gender, age, wealth, literacy, or religion to refine what farmers' social networks are likely to be (Munshi and Myaux 2006). This method relies on strong assumptions regarding social interactions, and may not be appropriate in many cases. For instance, we find that farmers in our sample have agricultural contracts in different wealth and education classes, castes, and age groups.

Many recent network studies have elicited farmer network links directly. In some cases survey respondents are asked about their social networks in an open-ended manner, i.e., allowing the respondent to list any farmers they know, trust, communicate with, or exchange information with (Bandiera and Rasul 2006; Cai 2013; Duflo, Kremer and Robinson 2006; Kremer and Miguel 2007). The advantage of this approach is that it helps define the social network in a more complete manner by allowing farmers to list contacts who might be outside the sample. A disadvantage is that the analyst may not have information about the farmers' network contacts, requiring them to either expand the sample (Duflo, Kremer, and Robinson 2006) or gather information about network

[11] Conley and Udry (2010) and Santos and Barrett (2010) find that Ghanaian farmers counted around 30 percent of their village as agricultural contacts. Bandiera and Rasul (2006) find that farmers in Northern Mozambique count less than 5 percent of sunflower adopters in their village as friends or family.

contacts from the original sample farmer (Bandiera and Rasul 2006), which may be prone to measurement error. In other cases, farmers are asked to identify their network contacts from a partial or full list of other sample farmers (Conley and Udry 2010; Maertens 2012; McNiven and Gilligan 2012).

There are many ways in which a network connection can be defined. A connection can be unidirectional (A claims B as a connection or B claims A as a connection) or bidirectional (A claims B as a friend and B claims A as a connection). Connections can be defined as one-dimensional and dichotomous (that is, A and B are connected or they are not) or multi-dimensional and continuous (for example, a social distance measure composed from different measures of social connectivity such has level of trust, duration, and geographic proximity). One-dimensional measures used in the literature include friend or family (Bandiera and Rasul 2006; Kremer and Miguel 2007), information contact or information neighbor (Cai 2013; Conley and Udry 2010; Duflo, Kremer and Robinson 2006; McNiven and Gilligan 2012), and geographic neighbor (Duflo, Kremer and Robinson 2006). Because our study centers on the adoption of an agricultural technology we use agricultural contacts to define social networks. For our analysis we use unidirectional links where A claims B as a network contact (whether or not B claims A) because information is more likely to flow from the farmer claimed as an agricultural contact to the farmer claiming him rather than in the opposite direction.

Each farmer was asked to identify any other farmer in his village, or the paired village, as a network contact, although contacts in paired villages were found to be almost non-existent. In the full sample, farmers identified one agricultural contact in their village on average, and 55 percent of the sample identified at least one agricultural contact. The maximum number of agricultural contacts was nine. In the subsample used to identify network effects, farmers identified two agricultural contacts, 1.4 of which are would-be adopters of LLL and 0.7 of which are actual adopters. We explain how and why this subsample was constructed in Section 4.

3.2.3 Experimental Auction and Lottery

Several days after the information session and baseline survey, the enumeration team gathered all of the sample farmers in a given village to conduct an experimental auction to elicit their demand for LLL. We used a modified Becker-deGroote-Marchak style auction (Becker, DeGroot and Marschak 1964), in which farmers were asked, in secrecy and plot by plot, a series of yes/no questions of the type, “would you pay Rs. X per hour to have this plot laser-leveled?” for increasing values of X. Possible values were Rs. 0, 250, 300, 350, 400, 450, 500, 550, 600, 700, and 800 per hour. When a farmer said he would not pay Rs. X, the facilitating enumerator would move to the next plot. The maximum value at which the farmer agreed he would pay for LLL services is the maximum WTP for that plot, and the maximum WTP for all of a farmer’s plots is considered his overall maximum WTP for LLL custom hire services.

Just before the final price was drawn, the lead enumerator informed all participants that because of capacity constraints, we would likely not be able to provide LLL services to all auction winners. Consequently, we would use a random public lottery immediately following the auction to determine who would actually pay for and receive

LLL custom hire services. We informed farmers that we would hold a second auction one year later without a lottery because we would have more capacity at that point. Farmers were very understanding of process and accepted the lottery without issue. To ensure that the majority of farmers would enter the lottery, in each village Rs. 250 was drawn as the purchase price.[12] Around two-thirds of all farmers won the auction and therefore entered the lottery. To increase variation among those actually receiving LLL services, we then ordered the list of all auction-winning farmers by their maximum WTP and stratified them into two groups, one of which was assigned to receive and pay for LLL and the other to serve as a control group of would-be adopters.

The auction/lottery mechanism resulted in the following trifurcation of participants: (1) auction losers, (2) auction winners/lottery losers, and (3) auction winners/lottery winners. We define auction losers as "non-adopters". We further define the set of auction winners/lottery losers and auction winners/lottery winners as "would-be adopters" and the subset of auction winners/lottery winners as "first-generation adopters" where first-generation denotes adoption resulting from the first year's auction.

Because of self-selection, we expect auction losers (non-adopters) to systematically differ from auction winners (would-be adopters), and this is indeed the case. Auction winners have 20 percent more years of schooling, 60 percent greater landholdings, and are generally wealthier (as measured by a factor analytic wealth

[12] Although the price was pre-selected by the enumeration team to be Rs.250, this price was unknown and effectively random to participants. In one village Rs. 300 was selected and in another village Rs. 350 was selected, before it became clear a lower price was needed to bring enough farmers into the lottery. Subsequently Rs. 250 was selected in all other village. This difference should not change auction results in either year.

index). Because auction winners are split into lottery winners and losers at random there should no systematic difference between the two groups, and we find this to be true (table 1).

Because farmers with similar traits may also be network contacts, the number of would-be adopters in each farmer's network is likely endogenous and correlated to characteristics that might influence demand for LLL (e.g., education, wealth, progressiveness). Because we randomize adoption among would-be adopters, the number of actual first-generation adopters in each farmer's network is exogenous, conditional on the number of would-be adopters. This exogenous allocation of adopters into farmers' networks allows us to circumvent the reflection problem and identify network effects. Among farmers with at least one would-be adopter in their network, we find no significant difference in age, education, land area, wealth, or WTP in the first auction (table 2) between farmers with and without a first-generation adopter in their network using a simple t-test. Note that here we do not control for total number of would-be adopters in each farmer's network beyond limiting the comparisons to farmers with at least one would-be adopter. In our regression analysis to follow, we explicitly control for number of would-be adopters.

3.3.4 Technology delivery, input-use surveys, and follow-up auction

The lottery winners were required to pay for and receive LLL services at the drawn price at a mutually agreed-upon date during the months that immediately followed the auction. The timing of the auction was such that the LLL custom hire services would be provided to lottery winners during the 100-day fallow season between the *kharif* (summer) rice season and the *rabi* (winter) wheat seasons, which is effectively the only time farmers have to receive such services. Service provision during this time was carefully monitored to ensure that farmers had no other access to LLL services, e.g., through side selling by the service provider or by other projects operating in EUP. After the first-generation adopters received LLL custom hire services the enumeration team conducted regular surveys at three to five week intervals throughout the *rabi* and *kharif* seasons.

We used data on irrigation rates to separate out farmers that benefited more from LLL from those who benefited less, which allows us to identify social learning about the benefits of LLL. This is for two reasons. First, irrigation savings is the primary purported benefit of LLL. Second, irrigation rates are highly visible in farmers' fields, even after pumps are operating. We find that LLL adopters had irrigation rates 20 percent lower than would-be adopters who lost the lottery ($p<0.1$).[13] These water-use savings are similar to those found in agronomic trials, which is an encouraging sign that the technology is beneficial to smallholders like the ones in our sample.

In addition to gathering data on input use, including labor, we asked farmers about their exposure to LLL through other sample farmers using the photo directory: With whom have you discussed agriculture with since the auction? With who have you discussed LLL specifically? Whose fields did you see the LLL equipment operate on? Whose fields have you visited?

[13] Regression results for water-use savings due to LLL are available from the authors upon request.

In Spring 2012 we collected demand data using a second auction identical in structure to the first, but without a lottery so that all farmers who bid high enough would receive LLL custom hire services. For the purposes of this study, using WTP data from an experimental auction as an outcome variable instead of binary adoption data has several advantages. First, it allows us to measure network effects on demand in money terms. Second, it allows us to capture changes in demand that do not push a farmer across an adoption threshold, i.e., an increase in demand for farmers who would not adopt (at some price) before *or* after one year of exposure, or for farmers who would adopt before *and* after one year of exposure (at some price). To demonstrate this point, we include regressions using a constructed binary adoption variable with our results.

A comparison between the 2011 and 2012 auctions show that overall WTP increased over the course of the study. This was expected, as many farmers initially said they would only adopt LLL once they saw it with their own eyes. Mean WTP for LLL in the baseline (2011) auction was Rs. 204 per hour and, among those with WTP>0, Rs. 322 per hour. In the follow-up (2012) auction mean WTP was Rs. 310 and Rs. 382 per hour, respectively. These differences in means are both significant at the 0.01 confidence level using a t-test. Figure 2 presents histograms of bids across the two auctions. It is worth noting that in 2012 there was no clustering around Rs. 250, the price drawn in the 2011 auction. This suggests that farmers were consistently bidding their individual WTP rather than anchoring around some price expectation based on the prior year's draw price. Importantly, this also suggests that the auction was well understood by the participants.

We cannot, however, assume that the increase in demand between the two years was because of spillovers or network effects. A number of factors could lead to changes in demand from one year to another. In the next section we discuss how we identified network effects using our experimental data.

4 Estimation of Network Effects

In our analysis of social network effects, we assume a given farmer receives an LLL social network 'treatment' if he has at least one first-generation adopter (lottery winner) in his social network. The probability of having an adopter in the farmer's network is dependent on the number of would-be adopters in his network (auction winners), which could be correlated with unobservable characteristics of the farmer himself that also influence adoption. While this implies that we face a version of the reflection problem, we have a means of controlling for this problem by including the number of would-be adopters in the farmer's network in our estimation model, which we observe in this study by design. This approach is similar to that used by Miguel and Kremer (2007) and Oster and Thornton (2012). The econometric model for estimating network effects is therefore expressed as

$$y_i = \alpha + \beta_1 \cdot adopter_i + \beta_2 \cdot wouldbe_i + \beta_3 \cdot networksize_i + \varepsilon_i \qquad (1)$$

where y_i is the outcome variable of interest, which can be method of exposure to LLL, willingness to pay and adoption at different prices, or a constructed adoption variable at a given price. The variable $adopter_i$ indicates the presence of a first-generation adopter in farmer *i*'s network. The variable $wouldbe_i$ is the number of would-be adopters in *i*'s network, and $networksize_i$ is the total number of farmers in *i*'s network, which can be added to the estimation improve precision, and ε_i is an error term. The parameter β_1 is the network effect on the outcome of interest.

The variable $adopter_i$ can be either continuous (number of in-network adopters, proportion of adopting in-network adopters) or binary (presence of at least one adopter). In our analysis we use three different specifications of $adopter_i$: having at least one in-network adopter, the number of in-network adopters (which ranges from one to three), and the proportion of qualifying in-network farmers who adopted (which is either 0, 0.33, 0.5, 0.67, or 1). In our data there is very little difference between treating $adopter_i$ as continuous or binary because only 4 percent of farmers have more than one first-generation adopter in their network. Similarly, there is little difference to treating $adopter_i$ as a ratio; most farmers also have only one would-be adopter in their network so the ratio of adopters is either 0 or 1 for 85 percent of the observations. Figure 3 shows a histogram of the number of would-be adopters and adopters in farmers' networks.

Unsurprisingly, the results are very robust across specifications. We therefore focus on the impact of having at least one adopter in-network. This is mainly to facilitate interpretation, but also because of the possibility of quickly decreasing marginal effects of additional in-network adopters. While the existence of decreasing marginal effects is ultimately an empirical question, it is one we cannot answer with our data; the continuous variable for the number of adopting network contacts and the dichotomous variable for having at least one are 92 percent correlated, so we are unable to use both as explanatory variables as others have (McNiven and Gilligan 2012). Around 10 percent of the farmers who won the adoption lottery were not able to receive LLL, mainly due to heavy and untimely rains that prevented the machinery from operating in some areas. We therefore instrument for an in-network farmer having his fields leveled with him winning the lottery, which we know to be exogenous.

4.1 Exposure to LLL

There are several ways a farmer might gain exposure to, and potentially learn about, a new technology through his network contacts. Here we estimate network effects on the probability that a farmer discusses LLL with an adopting farmer, the probability that he sees an LLL unit in operation on an adopting farmer's fields, and the probability that he visits an adopting farmer's laser-leveled field. These varying forms of exposure implicitly capture alternative approaches used by extension services to disseminate new technologies and leverage social networks for this process, for example, through farmer-to-farmer contacts, through informational interventions (posters, radio programs, and similar content-oriented methods), or through demonstration effects (demonstration plots, field days, and traveling seminars) (see Anderson and Feder 2004). For all of these outcomes, we capture interactions with all farmers in the village and paired village, not only farmers listed as agricultural contacts at the onset of the study. These interactions were common; 59 percent of farmers without an adopter in their network discussed LLL with an adopting farmer, 56 percent saw the LLL unit operate, and 44 percent visited an adopting farmer's field after leveling.

We find some weak evidence that having in-network first-generation adopters increases the probability a farmer will have a conversation with another farmer about LLL. The point estimate indicates a farmer with an in-network adopter is 17 percent more likely to have a conversation about LLL with an adopter, but this effect is not statistically significant at the 10 percent confidence interval (table 3, column 1). Having in-network adopter exhibits a much larger and more pronounced effect on the probability a farmer visits a laser land leveled field, increasing it by 27 percent (table 3, column 7). We find no evidence that having an in-network farmer increases the probability a farmer would see the leveler in operation (table 3, column 4). This is likely because the operation of the leveler was a very public event, so interested farmers were able to watch the leveler in action whether or not the adopting farmer was in their network of agricultural contacts. In general, this may suggest that the diffusion of knowledge about the technology via farmer-to-farmer contacts is conditionally dependent on direct observation by the farmer: farmers may need to hear about a technology from a reliable source before seeking out their own information from observation.

4.2 Demand for LLL

While it is encouraging that farmers gain exposure to a new technology through their network contacts, ultimately we are interested in if such exposure leads to increased demand for the technology. The majority of studies on network effects on technology demand observe demand as a dichotomous adoption variable. Cai (2013), who examines network effects on demand for agricultural insurance in China by offering farmers policies at different premiums, is a notable exception. Another exception is Oster and Thornton (2012), who use hypothetical bids to estimate peer effects on demand for menstrual cups in Nepal. To estimate the impact of having an adopter in one's social network on demand, we use WTP in the second auction, a continuous measure of demand, as our dependent variable in (1). In alternative specifications we use the change in demand between the 2011 and 2012 auctions.[14]

Because laser land leveling lasts for several years, the service has characteristics of a durable good, namely that a farmer who just had a plot leveled is unlikely to have it leveled the following year, even at a low price. Therefore, the 39 farmers who had all of their plots leveled after the first auction and had no plots to bid on in the second year they were omitted from analysis.[15] We also omit farmers without any would-be adopters in their social network, as these farmers have zero probability of having an adopter in their network. We are left with 148 farmers that fit these criteria. Of those 148, 35 were first-generation adopters that had additional plots eligible for LLL in the second auction. We should mention that whereas we can only measure network effects

[14] While we could potentially increase precision by focusing on changes in demand from when the technology was first introduced via auction, we note that WTP data from the first auction is much noisier ($\frac{\sigma}{\mu} = 0.88$) than WTP data from the second auction ($\frac{\sigma}{\mu} = 0.59$). This is not surprising, as farmers had a good deal more experience with the technology before the second auction. We therefore focus on results using WTP data from the 2012 auction. Results using the change in WTP as the dependent variable can be found in the appendix.

[15] Farmers chose the plots they wanted leveled most for the 2011 auction. If these plots were leveled after the auction and lottery, the farmer was left with plots he presumably had less desire to have leveled in 2012. This could downwardly bias estimates of WTP in 2012 for these farmers. When we include only farmers who had no plots leveled in 2011 we find the same sized network effects.

on demand for these 148 farmers, we use data on network conductivity with all 290 farmers in our sample that qualified for the lottery for our analysis.

We find that farmers with at least one adopting farmer in their network were willing to pay an additional Rs. 92 per hour for LLL custom hire services than farmers without an adopting farmer in their network ($p < 0.05$). This amounts to 27 percent of average WTP in the second auction (table 4, column 1). Results using the proportion of adopters are nearly identical (table 4, column 3). When we use the total number of in-network adopters as the explanatory variable we find the network effect to be Rs. 60 per farmer (table 4, column 2). We do not, however, interpret this as a per in-network adopter effect; only 13 of the 148 farmers in the analysis have more than one adopting in-network farmer. We find similar estimates using the increase in WTP from the 2011 to the 2012 auction as the dependent variable, although with slightly less precision (table A1). In percentage terms, these network effects on demand are nearly twice as strong as those found by Oster and Thornton (2012) and Cai (2013) for menstrual cups and agricultural insurance, respectively.

4.3 Learning or mimicry?

The fact that a farmer's demand for an agricultural technology is influenced by the technology choices of those in his network does not necessarily imply social learning: network effects could also arise because of mimicry, or herd behavior (Banerjee 1992). Mimicry can either arise out of a desire to conform, or because the follower assumes the leader has good information, and has made a good technological decision.

Distinguishing learning from mimicry is difficult. Furthermore, learning has two components: farmers can learn about the profitability of a technology, or how to use a technology. Conley and Udry (2010) identify learning how to use a technology by looking at changes Ghanaian pineapple farmers make to fertilizer use over time that result from the good and bad experiences of their network contacts. Oster and Thornton (2012) distinguish learning about how to use a technology from mimicry by separately looking at Nepali girls' attempted use of menstrual cups from their successful and sustained use of menstrual cups. The technology in this study is obtained through custom hire, so farmers can potentially learn about its profitability, but not how to better use the technology. It is conceivable, however, that farmers can learn about how to adjust input use for a laser-leveled field. Testing for learning about input use on laser-leveled fields is a potential way to expand this research.

We distinguish learning from mimicry by not only looking at the impact of having adopters in one's network, but also the benefits achieved by those adopters in terms of water-use reduction. Borrowing from the methodology of Conley and Udry (2010), we divide first-generation adopters into low and high water-use farmers. We define a low water-use farmer as one who had an irrigation rate lower than the median rate for his village and a high water-use farmer as one who had an irrigation rate higher than the median rate. This distinction is not completely analogous to distinguishing farmers who save water because of LLL from farmers who does not, which would be ideal. The absence of baseline data on water use, however, prevents us from creating such a variable. While many factors could contribute to a farmer using more or less water than the that the district median, our empirical specification isolates the effect of laser land leveling on the water use of in-network adopters by accounting for the water use of in-network would-be adopters. Specifically, we control for the number of high water-use would-be adopters and the number of low water-use would-be adopters separately, rather than controlling for the total number of would-be adopters as we do in (1). The empirical model to test for learning about benefits is

$$WTP_i = \alpha + \beta_1 \cdot adopting_i \times low\ irrig_i + \beta_2 \cdot adopting_i \times high\ irrig_i + \beta_3 \cdot wouldbe_i \times low\ irrig_i + \beta_4 \cdot wouldbe_i \times high\ irrig_i + \beta_5 \cdot networksize_i + \varepsilon_i. \quad (2)$$

If mimicry drives demand we would expect β_1 and β_2 to both be positive and equal to each other. If learning drives demand we would expect β_1 to be positive and β_2 to be zero or negative. If there are no network effects, either via mimicry or learning, we would expect β_1 and β_2 to both be zero.

We find that having a low water-use adopting farmer in one's network increases WTP by Rs. 100 (p<0.1). This amounts to 29 percent of mean WTP in the second auction. Having a high water-use adopter in one's network has no discernable effect on demand (table 5, column 1). This result is robust to using the proportion of in-network adopting farmers (table 5, column 3) and similar using the total number of in-network adopters (table 5, column 2). Estimates are slightly higher using difference in WTP from the 2011 to 2012 auction as the explanatory variable (table A2). These results indicate that information spillovers for LLL arise not only because of mimicry, but because farmers learn about the benefits of the technology through their network of agricultural contacts. Whereas others have argued that network effects are more likely to drive adoption of hard-to-use technologies where learning about use is important (Oster and Thornton 2012), here we find strong network effects on demand for a relatively easy-to-use technology with uncertain (but visible) benefits.

If network effects on technology demand are fueled by learning about benefits, it is important that early adopters of a technology do benefit, and that the benefits are made as visible as possible. Extension should therefore target farmers that stand to benefit, keeping in mind that they also may need to target farmers at different levels of wealth, education, and social status in order for technology to diffuse in a more inclusive manner. Extension can work to increase visibility of benefits by encouraging farmers to keep logs of input use and other benefits that might be less easily visible than yields, and for extension to work with farmers to publicize these benefits, for instance by charting input use on roadside placards bordering fields or by combining similar promotional efforts with large-scale demonstration trials.

4.4 Zero test for spurious network effects

While we are confident that our experimental set-up prevents us from finding network effects erroneously, we perform a test by regressing WTP from the 2011 auction, held before the technology was introduced, on the network variables in (1) and (2) above. If coefficients on network variables are positive in these specifications it would be an indication that unobservable variables correlated to both demand for the technology and the number of in-network first-generation adopters are correlated, leading us to over-estimate network effects or find network effects where there should be none. As expected, we find no impact of adoption in farmers' network on their WTP for LLL before the technology was introduced (table 6).

4.5 Adoption of LLL at different prices

There are several advantages to using WTP data from an experimental auction instead of observed adoption data (typically binary) to analyze network effects.[16] First, we can monetize network effects. Estimates of increases in demand due to network effects can help inform dynamic pricing strategies for firms that may want to bring a technology to a new and uncertain market, as is the case with LLL in EUP. Second, with auction data we can see changes in demand that may not otherwise be visible. For instance, if a farmer has WTP of Rs. 350 before his neighbor adopts a technology and Rs. 450 after his neighbor adopts the technology, the analyst would only be able to see these network effects if the price of the technology does not exceed Rs. 450.

To illustrate this point with our data we construct a set of dichotomous adoption variables for WTP ≥ Price at various prices: Rs. 250, 300, 350, 400, 500, and 600. The model in (1) is modified to have a dichotomous adoption outcome as the dependent variable:

$$Adopt_i|Price = \alpha + \beta_1 \cdot adopter_i + \beta_2 \cdot wouldbe_i + \beta_3 \cdot networksize_i + \varepsilon_i \quad (2)$$

[16] Adoption data can also be continuous, i.e. amount of land, or duration, i.e. time until adoption.

Having an adopter in a farmer's network increases his probability of adoption at from 8-28 percent depending on the threshold, but the effect is only statistically significant at the 0.1 confidence level at the Rs. 250 and Rs. 350 thresholds (table 5). For any other price, we would not be able to detect network effects that we see clearly using our more continuous WTP data from the auction (table 7). In the specification with the number of adopters as the $adopter_i$ variable, network effects are only significantly different from zero at the Rs. 250 threshold (table A3). In the specification with the proportion of adopters as the $adopter_i$ variable, network effects are only significant at the Rs. 250 and Rs. 350 threshold (table A4).

In areas of the IGP where LLL markets exist, the price in 2011-12 has been between Rs. 500 and Rs. 600 per hour. If LLL was available at these prices in 2012, and we used market outcomes rather than auction outcomes, we would find point estimates on the order of 5-10 percent, all of which are not statistically significant. In a static situation, the market price of a technology is ultimately the relevant price for analyzing network effects on adoption. However, if network effects increase demand over several seasons, or if the market price of a technology stands to decrease as costs decrease or the market thickens, then detecting network effects on demand below the market price may be important.

5 Concluding remarks and Next Steps

Improvements in agricultural technology that increase agricultural production and profitability can lead to improvements in the livelihoods and food security for the rural poor. But the dissemination of promising technologies can prove difficult in developing countries, where reaching many small, heterogeneous, and isolated farmers directly with agricultural extension is prohibitively costly, or where the scale and complexity of the technology is a constraining factor. Extension therefore operates under the assumption that technology disseminated to a small set of farmers—typically progressive farmers—will result in other farmers learning about the benefits of the technology and eventually adopting if they think the technology will benefit them. However, empirical evidence of the efficacy of farmer networks in disseminating technology is limited. In part, the paucity of evidence is because identification of network effects is so challenging. Specifically, it is difficult to tell if farmers use the same technologies as others in their network because they learn from or mimic each other, or because they share similar characteristics and circumstances. In this study we use a set of experimental auctions coupled with a randomized technology intervention to asses if having first generation adopters of a new resource-conserving technology—laser land leveling—in a farmer's network increases his exposure to, and demand for, the technology.

We find that farmers with at least one first-generation adopter in their network are willing to pay 27 percent more for laser land leveling than are comparable farmers without a first-generation adopter in their network. When we separate the effect of having a first-generation adopter that experienced relatively high benefits from LLL from the effect of having a first-generation adopter that experienced relatively low benefits, we find that only having the former in-network increased demand. This finding suggests that actual learning, as opposed to mimicry, drives network effects in our sample. These network effects appear to occur predominantly from additional visits to leveled fields by farmers with an in-network adopter, rather than by conversations with adopters or by seeing the leveling unit in action.

As a methodological contribution, this study demonstrates the benefits of using an experimental auction to measure demand rather than using dichotomous adoption data. Using willingness to pay data from an auction held one year after first-generation adopters, we can estimate increases in demand due to network effects in monetary terms. This approach has two distinct advantages over using dichotomous adoption choice data. First, our estimates can better be used to inform the design of dynamic pricing strategies for new technologies. Second, we can see network effects that otherwise would be invisible. In our data network effects are substantial, but not necessarily large enough to push farmers' demand beyond the market price for the technology.

Large network effects like the ones found in this study bode well for the current extension strategy of reaching out to progressive farmers with a technology and letting it diffuse through social networks. However, the reach of these networks may be very limited. For instance, we find that farmers have a very small probability of knowing a randomly selected farmer in a village only 5 km away. It is also unclear what types of farmers are the best conduits for the broad and inclusionary spread of a technology. For instance, poorer and less educated farmers might not think a technology suitable for a wealthier and more educated farmer is appropriate for them. As a next step in this research we will examine the heterogeneity of agricultural networks and the strength of network effects across different demographic lines.

Finally, from the perspective of public policy, the network effects evidenced here suggest much for extension strategies that target smallholder farmers such as those engaged in this study. Specifically, a farmer’s exposure or willingness to pay for a technology may be predicated on the combination and interaction between farmer-to-farmer network effects, informational interventions and observable demonstrations. This suggests that multi-faceted approaches to technology promotion that leverage peer effects to generate spillovers from both information and demonstration are more effective than approaches that are more singular. This has potentially significant implications for the design and implementation of agricultural extension services in support of resource-conserving technologies.

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Figures and Tables

Figure 1. Project timeline

2011										2012						
Mar	*Apr*	*May*	*Jun*	*Jul*	*Aug*	*Sep*	*Oct*	*Nov*	*Dec*	*Jan*	*Feb*	*Mar*	*Apr*	*May*	*Jun*	*Jul*
			***Kharif* rice season**							***Rabi* wheat season**						
1. LLL info session																
2. Baseline survey														**8. Endline survey**		
3. Network survey																
	4. LLL auction #1													**9. LLL auction #2**		
	5. Post-auction lottery															
		6. LLL services												**10. LLL services**		
				7. Intra-seasonal surveys												

Figure 2. Frequency of bids for LLL custom hire in 2011 and 2012 auctions

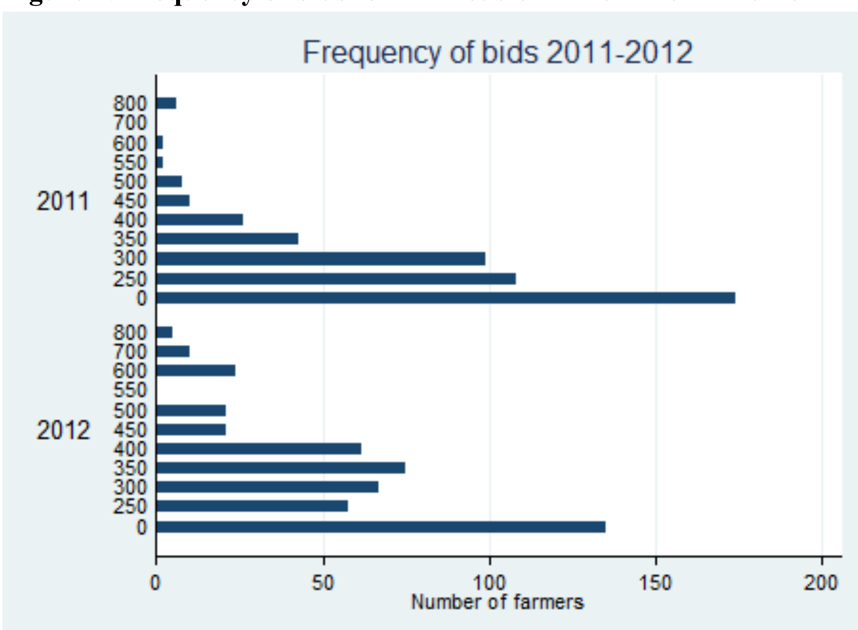

Figure 3. Number of would-be adopters (left) and adopters (right) in farmers' networks of agricultural contacts

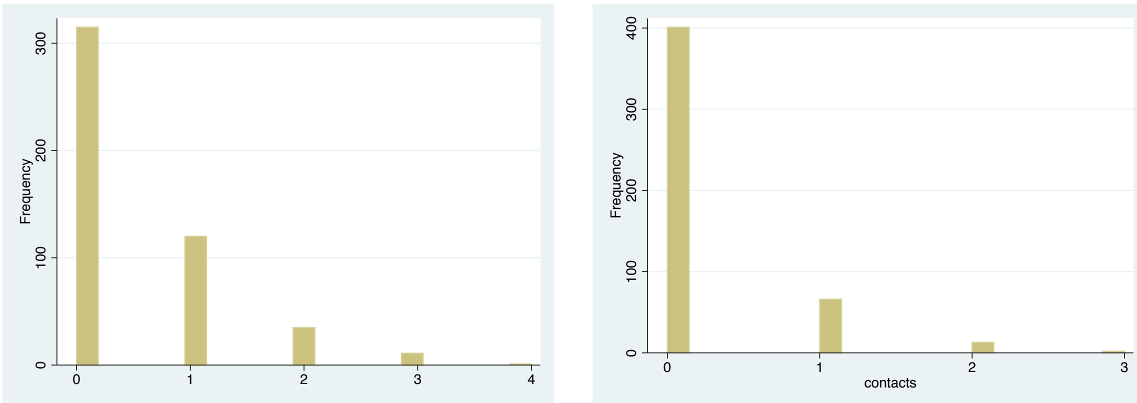

Table 1. Demographic differences between auction winners (would-be adopters) and losers (left two columns) and lottery winners and losers (right two columns)

	Auction		Lottery (would-be adopters only)	
	Losers	**Winners** (would-be adopters)	**Losers**	**Winners**
Age (years)	48.01	48.74	48.63	48.84
	(1.10)	(0.94)	(1.35)	(1.32)
Education (years)	5.69	6.93	6.87	7.00
	(0.38)	(0.33)**	(0.46)	(0.48)
Total land (acres)	1.41	2.29	2.23	2.35
	(0.27)	(0.23)**	(0.34)	(0.31)
Wealth index	-0.162	0.106	0.098	0.113
	(0.045)	(0.068)***	(0.088)	(0.105)
Observations	192	286	142	144

Notes: Standard errors in parentheses, ***, **, * denote p<0.01, p<0.05, and p<0.1 for significance of t-test for differences between auction winners and losers and between lottery winners and losers. Wealth index consists of credit access, livestock, Diwali or Eid El Khabir spending, house condition, and public works (MNREGA) participation.

Table 2. Demographic and WTP (2011 auction) differences between those with an auction winner in their network and those without (conditional on having at least one would-be adopter in their network).

	No lottery winner in network	**Lottery winner in network**	**P-value for difference**
Age (years)	48.26	49.80	0.54
	(1.94)	(1.62)	
Education (years)	7.46	6.78	0.44
	(0.65)	(0.56)	
Total land (acres)	1.93	2.78	0.20
	(0.32)	(0.51)	
Wealth index	0.23	0.14	0.67
	(0.13)	(0.14)	
WTP (2011 auction)	225	253	0.32
	(22.6)	(17.9)	
Observations	69	95	

Notes: Standard errors in parentheses. Wealth index consists of credit access, livestock, Diwali or Eid El Khabir spending, house condition, and public works (MNREGA) participation.

Table 3. Network effects on exposure to LLL

Exposure to LLL through…	…at least one conversation with adopting farmer about LLL			…seeing LLL unit operate on at least one adopting farmer's field			…visiting at least adopting farmer's field after leveling		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
At least one adopter in network	0.17 (0.10)			-0.00 (0.11)			0.27** (0.11)		
# of adopters in network		0.10 (0.08)			0.04 (0.09)			0.11 (0.08)	
Prop. of adopters in network			0.15 (0.11)			0.06 (0.12)			0.25** (0.11)
# of would-be adopters	-0.07 (0.10)	-0.08 (0.10)	-0.03 (0.09)	0.05 (0.10)	0.03 (0.11)	0.05 (0.10)	-0.10 (0.10)	-0.09 (0.10)	-0.04 (0.09)
Total network size	0.02 (0.04)	0.02 (0.05)	0.02 (0.05)	0.02 (0.05)	0.02 (0.05)	0.02 (0.05)	0.06 (0.05)	0.06 (0.05)	0.05 (0.05)
Constant	0.61*** (0.09)	0.66*** (0.09)	0.59*** (0.10)	0.47*** (0.10)	0.48*** (0.10)	0.45*** (0.10)	0.32*** (0.10)	0.38*** (0.10)	0.28*** (0.10)
Observations	148	148	148	148	148	148	148	148	148

IV linear probability models with lottery winning farmers instrumenting for farmers receiving leveling. Results are robust to IV probit specification. Standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Only farmers with at least one qualifying farmer in their networks included in analysis.

Table 4. Network effects on demand for LLL (WTP 2012)

Dependent var: WTP 2012	**(1)**	**(2)**	**(3)**
At least one adopter in network	92.45**		
	(41.47)		
# of adopters in network		59.96*	
		(32.14)	
Prop. of adopters in network			94.45**
			(43.35)
# of would-be adopters	-25.73	-31.96	-6.14
	(38.00)	(39.42)	(36.92)
Total network size	-1.03	-4.16	-3.19
	(17.82)	(17.99)	(17.89)
Constant	334.81***	358.82***	318.31***
	(37.38)	(37.29)	(39.31)
Observations	148	148	148

IV regressions with lottery winning farmers instrumenting for farmers receiving leveling. Standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Only farmers with at least one qualifying farmer in their networks included in analysis.

Table 5. Learning about benefits and demand for LLL (WTP 2012)

Dependent var: WTP 2012	**(1)**	**(2)**	**(3)**
At least one adopter in network (low irrig)	99.68* (52.70)		
At least one adopter in network (high irrig)	15.32 (60.02)		
# of adopters in network (low irrig)		93.66* (50.59)	
# of adopters in network (high irrig)		17.52 (51.98)	
Prop. of adopters in network (low irrig)			102.69* (52.96)
Prop. of adopters in network (high irrig)			7.22 (57.42)
# of would-be adopters (low irrig)	-69.22 (48.58)	-74.90* (39.64)	-54.73 (45.35)
# of would-be adopters (high irrig)	-5.94 (41.02)	-10.79 (36.80)	4.91 (38.88)
Total network size	0.46 (18.06)		-1.97 (18.05)
Constant	363.75*** (38.59)	371.01*** (38.20)	355.33*** (39.04)
Observations	148	148	148

IV regressions with lottery winning farmers instrumenting for farmers receiving leveling. Standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Only farmers with at least one qualifying farmer in their networks included in analysis.

Table 6. Zero test for spurious network effects

Dependent var: WTP 2011	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
At least one adopter in network	23.61					
	(41.37)					
# of adopters in network		-14.23				
		(32.23)				
Prop. of adopters in network			-0.97			
			(43.42)			
At least one adopter in network (low irrig)				-11.20		
				(53.19)		
At least one adopter in network (high irrig)				-40.14		
				(60.59)		
# of adopters in network (low irrig)					6.11	
					(51.14)	
# of adopters in network (high irrig)					-39.17	
					(53.47)	
Prop. of adopters in network (low irrig)						-11.41
						(53.43)
Prop. of adopters in network (high irrig)						-64.37
						(57.92)
# of adopters in network	34.07	45.28	39.12			
	(37.90)	(39.53)	(36.98)			
# of adopters in network (low irrig)				28.36	23.63	22.39
				(49.04)	(49.30)	(45.75)
# of adopters in network (high irrig)				53.33	57.85	52.18
				(41.40)	(43.76)	(39.22)
Total network size	2.26	4.11	2.88	5.46	5.79	6.13
	(17.78)	(18.04)	(17.92)	(18.23)	(18.36)	(18.21)
Constant	167.78***	168.59***	171.46***	178.28***	174.43***	185.76***
	(37.29)	(37.39)	(39.38)	(38.95)	(38.82)	(39.38)
Observations	148	148	148	148	148	148

IV regressions with lottery winning farmers instrumenting for farmers receiving leveling. Standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Only farmers with at least one qualifying farmer in their networks included in analysis.

Table 7. Network effects on constructed dichotomous adoption variables (at least one in-network adopter)

Dependent var: WTP > hypothetical price	**Rs. 250**	**Rs. 300**	**Rs. 350**	**Rs. 400**	**Rs. 500**	**Rs. 600**
At least one adopter in network	0.15*	0.09	0.28**	0.08	0.11	0.07
	(0.08)	(0.09)	(0.11)	(0.11)	(0.09)	(0.07)
# of would-be adopters in network	-0.01	-0.01	0.04	0.06	-0.08	-0.10
	(0.07)	(0.09)	(0.10)	(0.10)	(0.08)	(0.06)
Total network size	-0.02	0.00	-0.05	-0.02	0.03	0.05
	(0.03)	(0.04)	(0.05)	(0.05)	(0.04)	(0.03)
Constant	0.83***	0.75***	0.50***	0.33***	0.17**	0.12**
	(0.07)	(0.08)	(0.10)	(0.10)	(0.08)	(0.06)
Observations	148	148	148	148	148	148

IV linear probability models with lottery winning farmers instrumenting for farmers receiving leveling. Standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Results are robust to an IV probit specification. Only farmers with at least one qualifying farmer in their networks included in analysis.

Appendix: Alternate model specifications

Table A1. Network effects on demand for LLL (WTP 2012 – WTP 2011)

Dependent var: WTP 2012 –WTP 2011	**(1)**	**(2)**	**(3)**
At least one adopter in network	68.84		
	(50.10)		
# of adopters in network		74.19*	
		(38.63)	
Prop. of adopters in network			95.42*
			(52.28)
# of would-be adopters	-59.79	-77.24	-45.25
	(45.90)	(47.38)	(44.52)
Total network size	-3.30	-8.27	-6.07
	(21.53)	(21.63)	(21.58)
Constant	167.03***	190.23***	146.86***
	(45.15)	(44.82)	(47.41)
Observations	148	148	148

IV regressions with lottery winning farmers instrumenting for farmers receiving leveling. Standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Only farmers with at least one qualifying farmer in their networks included in analysis.

Table A2. Learning about benefits and demand for LLL (WTP 2012 – WTP 2011)

Dependent var: WTP 2012 – WTP 2011	**(1)**	**(2)**	**(3)**
At least one adopter in network (low irrig)	110.88*		
	(63.53)		
At least one adopter in network (high irrig)	55.46		
	(72.36)		
# of adopters in network (low irrig)		88.17	
		(60.90)	
# of adopters in network (high irrig)		54.00	
		(62.57)	
Prop. of adopters in network (low irrig)			114.10*
			(63.71)
Prop. of adopters in network (high irrig)			71.59
			(69.07)
# of would-be adopters (low irrig)	-97.57*	-108.16**	-77.12
	(58.57)	(47.72)	(54.55)
# of would-be adopters (high irrig)	-59.27	-76.11*	-47.27
	(49.45)	(44.29)	(46.77)
Total network size	-5.00		-8.10
	(21.77)		(21.71)
Constant	185.47***	197.74***	169.58***
	(46.52)	(45.98)	(46.96)
Observations	148	148	148

IV regressions with lottery winning farmers instrumenting for farmers receiving leveling. Standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Only farmers with at least one qualifying farmer in their networks included in analysis.

Table A3. Network effects on constructed dichotomous adoption variables (total number of in-network adopters)

Dependent var: WTP > hypothetical price	**Rs. 250**	**Rs. 300**	**Rs. 350**	**Rs. 400**	**Rs. 500**	**Rs. 600**
# of adopters in network	0.14**	0.07	0.14	0.02	0.04	0.02
	(0.06)	(0.07)	(0.08)	(0.09)	(0.07)	(0.05)
# of would-be adopters in network	-0.04	-0.02	0.04	0.07	-0.07	-0.10
	(0.08)	(0.09)	(0.10)	(0.11)	(0.08)	(0.07)
Total network size	-0.03	-0.00	-0.05	-0.02	0.03	0.05
	(0.03)	(0.04)	(0.05)	(0.05)	(0.04)	(0.03)
Constant	0.88***	0.77***	0.57***	0.35***	0.20**	0.14**
	(0.07)	(0.08)	(0.10)	(0.10)	(0.08)	(0.06)
Observations	148	148	148	148	148	148

IV linear probability models with lottery winning farmers instrumenting for farmers receiving leveling. Standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Results are robust to an IV probit specification. Only farmers with at least one qualifying farmer in their networks included in analysis.

Table A4. Network effects on constructed dichotomous adoption variables (proportion of in-network farmers adopting)

Dependent var: WTP > hypothetical price	**Rs. 250**	**Rs. 300**	**Rs. 350**	**Rs. 400**	**Rs. 500**	**Rs. 600**
Prop. of adopters in network	0.18**	0.10	0.25**	0.07	0.09	0.05
	(0.08)	(0.10)	(0.11)	(0.12)	(0.09)	(0.07)
# of would-be adopters in network	0.02	0.01	0.10	0.08	-0.05	-0.09
	(0.07)	(0.08)	(0.10)	(0.10)	(0.08)	(0.06)
Total network size	-0.02	-0.00	-0.05	-0.02	0.03	0.05
	(0.03)	(0.04)	(0.05)	(0.05)	(0.04)	(0.03)
Constant	0.79***	0.73***	0.46***	0.32***	0.16**	0.12*
	(0.08)	(0.09)	(0.10)	(0.10)	(0.08)	(0.07)
Observations	148	148	148	148	148	148

IV linear probability models with lottery winning farmers instrumenting for farmers receiving leveling. Standard errors in parenthesis; *** p<0.01, ** p<0.05, * p<0.1. Results are robust to an IV probit specification. Only farmers with at least one qualifying farmer in their networks included in analysis.