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Leveling with Friends

Social Networks and Indian Farmers' Demand for Agricultural Custom Hire Services

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Contents

Tables

Figures

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 who catalyze the diffusion process. This research was undertaken to understand how information about a new agricultural technology is transmitted through social networks, and what effect information gained through social networks has on technology demand at the household level. The technology in question is laser land leveling (LLL)—a resource-conserving technology—which we introduced in eastern Uttar Pradesh, India as part of the study. Using an experimental auction, we obtain farmers' willingness-to-pay for the technology and identify potential adopters. We then randomly select half of these farmers to actually receive LLL services on their land, creating random variation in the number of adopters in each farmer's social network. We conduct a second auction one year later with the same sample of farmers and estimate network effects on farmers' updated willingness-to-pay. Four main results emerge: First, exposure to LLL through networks occurs primarily through visits to adopting farmers' fields. Second, having a first-generation adopter in a farmer's network increases the farmer's valuation of LLL by nearly 30 percent on average. Third, the network effects on demand are importantly conditioned on benefits associated with LLL, which implies that learning—rather than mimicry—is driving increases in demand. Fourth, network effects are strongest between poor farmers.

Keywords: social learning, network effects, technology adoption, experimental auction

JEL Codes: O13, O14, Q16

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1. INTRODUCTION

Technological innovation 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 technologies—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. Understanding how farmers learn about new agricultural technologies is of general importance, but even more importantly, the diffusion process of these resource-conserving technologies with their mix of private and public benefits increases the urgency of fast and widespread dissemination from a societal perspective.

Farmers have multiple sources of agricultural information at their disposal, some of which they value more than others. Farmers often rely on their social connections 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 agricultural extension strategy: Where farmers are geographically or socially dispersed, and where public resources for technology promotion are scarce, farmer networks are needed to widely disseminate new technologies. Such strategies typically depend on reaching out to *progressive* or *model* farmers to adopt and demonstrate, in the hopes that other farmers will follow (Anderson and Feder 2004). In some instances, the 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 for the historical lack of empirical studies on network effects is that they confront the reflection problem, a major identification challenge (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; Maertens 2013; McNiven and Gilligan 2012; Munshi 2004; Munshi and Myaux 2006). Recently, a handful of studies 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).

In this paper we present findings on how network effects influence exposure to and demand for an agricultural technology using data from a field experiment. In the experiment, we randomly assign 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 that we describe in Section 2. Because LLL equipment is expensive and requires some skill to operate, most Indian farmers—and all smallholders—are likely to access LLL through rental arrangements known as *custom hire services*. To measure demand for LLL custom hire services, we held a pair of experimental auctions one year apart, in 2011 and again in 2012. These auctions were binding: Farmers who bid enough for LLL services on their land could expect to pay real money out of pocket and receive real LLL custom hire services. After the first auction, a lottery was held to determine who would purchase the LLL services. Using this randomization, we are able to measure the effect of having an in-network adopter on a farmer's demand for the technology, conditional on the number of would-be adopters in his network.[1] Because we measure demand in terms of farmers' willingness-to-pay (WTP) rather than observed adoption, we can quantify network effects in monetary terms as opposed to increased uptake at a given price.

We find that farmers with an adopter in their network are more likely to be exposed to LLL, primarily through visits to a leveled plot. More importantly, we find evidence of substantial network effects on LLL demand. Farmers with an early adopter in their network of agricultural contacts exhibited higher demand than those who did not. We attribute these network effects to learning rather than pure mimicry because only the presence of in-network farmers who benefited from LLL positively affected demand. Network effects appear to be particularly strong between relatively poor farmers, indicating that among heterogeneous farmers, network effects are complex and also heterogeneous.

The paper is organized as follows: In Section 2 we provide some background information on LLL, particularly its use and implications for agriculture in India. In Section 3 we discuss our study location and experimental design. In Section 4 we present an empirical model to estimate network effects and discuss our identification strategy in more detail. Section 5 contains our main results. In Section 6 we present a placebo test and results using alternative network definitions, and in Section 7 we conclude.

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

2. BACKGROUND: LASER LAND LEVELING IN INDIA

In the flood-irrigated rice–wheat systems of the Indo-Gangetic Plain (IGP), 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 more efficient than uneven plots. In response, cultivation practices and techniques have been devised to address this, for example, the use of contoured levees and manual leveling with planks. In this sense, LLL simply improves on farmer practices that are based on traditional knowledge and accumulated experience. 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 plane as a guide. Whereas the best traditional leveling methods have a leveling precision of ±4 cm or more, LLL can level 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 IGP, 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 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 rose to 925, and the acreage under LLL grew to 200,000 hectares, by 2008 (Jat et al. 2009). Agronomic trials in rice–wheat systems in this region have found that LLL results in 10–30 percent savings in irrigation water use, a 3–6 percent increase in effective farming area, a 6–7 percent increase in nitrogen use efficiency, and a 3–19 percent increase in yield (Jat et al. 2006, 2009). In on-farm trials, net annual farmer revenues rose by \$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 fuel, 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 (see Lybbert et al. 2013). We exploit the lack of familiarity with LLL in the region to study if and how network effects increase demand for the technology.

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

3. EXPERIMENTAL DESIGN AND DATA COLLECTION

Study Site and Sample

The state of Uttar Pradesh (UP) covers 243,000 kilometer (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 with the rest of the state.

The main crops grown in the EUP 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.[3] 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 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 for an experimental auction. EUP is also an ideal location to test network effects on learning because information on the technology is essentially nonexistent outside of the intervention.

The study began prior to the onset of *kharif* season in 2011 (that is, in March 2011), continued through the 2011/2012 *rabi* season (approximately October 2011 to May 2012), and concluded during the subsequent *kharif* season in 2012 (in approximately July 2012). We selected three districts—Maharajganj, Gorakhpur, and Deoria—to represent heterogeneity across farm size and productivity in the rice–wheat cropping system of EUP.[4] 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 the 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 that our intervention would be the only source of information about LLL, we did not select villages in the proximity of any of the few small-scale LLL demonstrations being conducted in EUP. 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.[5] We excluded villages within a 10-km radius of any LLL demonstrations from the sample, as well as 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, one farmer reported ever using LLL, and one farmer reported knowing the market price of LLL hire.[6]

For each of these 12 villages, we randomly chose a paired village that met the same population criteria, was within a 5-km radius, and was not within a 10-km 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. Within each village, we randomly selected approximately 20 farmers from

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

[4] 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.

[5] 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 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.

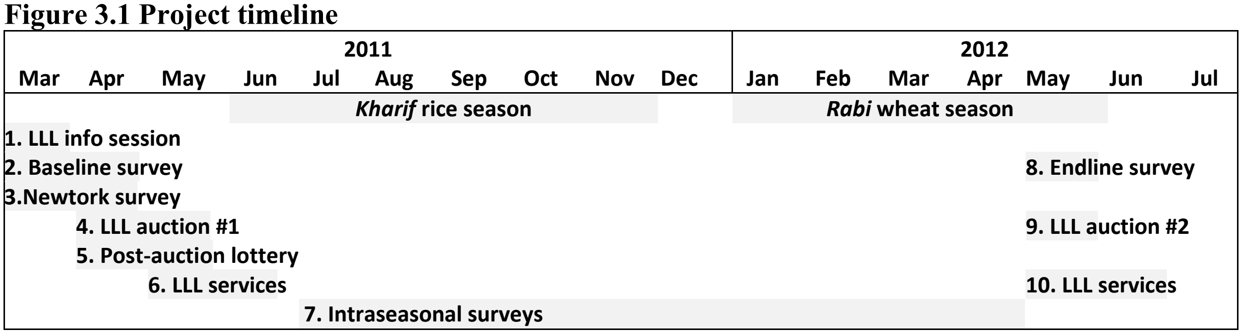
[6] We believe that the single instance of a farmer reporting to have used LLL is an instance of misreporting or enumerator error.

those cultivating plots of at least 0.2 acres (the minimum plot size for LLL) to be included in the study.[7] The resulting sample totaled 478 farmers. We found that only 39 farmers in the entire sample knew a sample farmer from the paired village, and only 4 discussed agriculture with a sample farmer from the paired village. We include intervillage links in farmers' networks, but we do not distinguish these from intravillage links due to their low frequency.

Experimental Design

In each village the study unfolded as depicted in Figure 3.1. First, the enumeration team conducted a scripted information session to introduce the sampled farmers to LLL (1), details of which are provided in Lybbert et al. (2013). Next, the team conducted a survey featuring 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 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 *kharif* (summer) rice season and the *rabi* (winter) wheat season, we conducted intraseasonal surveys at approximately three-week intervals coinciding with major activity phases of the cropping season 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 to farmers who won the second auction (10).

Figure 3.1 Project timeline



Source: Authors.
Note: LLL = laser land leveling.

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 that the sessions were as consistent as possible across villages. The information session lasted approximately one hour. It 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 (but outside the study area) who received LLL services as part of a separate demonstration. 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. At the conclusion of each information session, the team gave farmers pictorial brochures about LLL that contained the range of possible bids they could make in the experimental auction.

[7] The intended sample size for each village was 24, with an additional 12 replacement farmers preselected in case of absenteeism or lack of a large enough plot among the original 24 farmers.

Naturally, farmers at each information session inquired about the cost of LLL services. Because the information session was a 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 400 to 800 Indian rupees (Rs.) per hour of LLL service.[8]

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. 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, such as, Are any of these farmers your friends? Are any in your family? With which of these farmers do you 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 module in mind, it is useful to provide a broader description of relevant methodological approaches used by others to study 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 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.[9] 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 information contacts 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, that is, 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 to 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 her to either expand the sample (Duflo, Kremer, and Robinson 2006) or gather information about network 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 2013; McNiven and Gilligan 2012).

There are many ways in which a network connection can be defined. A connection can be unidirectional (B is in A's network if A claims B) or bidirectional (B is in A's network if A claims B or B claims A). Connections can be defined as one-dimensional and dichotomous (that is, A and B are connected or they are not) or multidimensional and continuous (for example, a social distance measure

[8] LLL custom hire, like most custom hire services in India, is priced by hour rather than by acre. We see no evidence of anchoring to Rs. 400 per hour in the auction results (Figure 2.2).

[9] 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.

composed of different measures of social connectivity such has level of trust, duration of relationship, 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 information contacts to define social networks. For our main analysis we use unidirectional links 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. In Section 6 we present results generated using friendship and family linkages and also using bidirectional linkages.

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 an auction in the style of Becker, DeGroote, and Marschak (1964), in which farmers were asked, in secrecy and plot by plot, a series of yes-or-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 on any plot is considered the farmer's maximum WTP, which is the value we use in our analysis.

Just before the final price was drawn, the lead enumerator informed all participants that because of capacity constraints, we would 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. Auction winners would have a 50 percent chance of winning the lottery. Farmers were very understanding of the process and accepted the lottery outcomes without issue. To ensure that the majority of farmers would enter the lottery, in each village Rs. 250 was drawn as the purchase price.[10] Around two-thirds of all farmers won the auction and therefore entered the lottery. To increase variation in demand among those actually receiving LLL services, we 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 but lottery losers, and (3) auction and lottery winners. We define auction losers as *nonadopters*. We define the set of both auction winners but lottery losers and auction and lottery winners as *would-be adopters* and define the subset of auction and lottery winners as *adopters*. Because of self-selection, we expect auction losers (nonadopters) 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 index).[11] Because auction winners are split into lottery winners and losers at random, there should be no systematic difference in age, education, landholdings, wealth, and WTP between the two groups, and we find this to be true (Table 3.1).

[10] Although the price was preselected 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 villages.

[11] The wealth index consists of house condition; ration card possession; landholdings; and ownership of cell phones, vehicles, TVs, satellite dish, and livestock. We tried several variations of this index and saw no differences in results.

Table 3.1 Demographic differences between auction winners (would-be adopters) and losers (left two columns) and lottery winners and losers (right two columns)

Variable	Auction		Lottery (would-be adopters only)	
	Losers	Winners (would-be adopters)	Losers	Winners
Age (years)	48.01 (1.10)	48.74 (0.94)	48.63 (1.35)	48.84 (1.32)
Education (years)	5.69 (0.38)	6.93 (0.33)**	6.87 (0.46)	7.00 (0.48)
Total land (acres)	1.41 (0.27)	2.29 (0.23)**	2.23 (0.34)	2.35 (0.31)
Wealth index	–0.175 (0.047)	0.085 (0.059)***	0.055 (0.076)	0.114 (0.091)
Willingness-to-pay, 2011 (Rs./hour)	36.72 (7.42)	317.13 (6.30)***	317.96 (9.01)	316.32 (8.83)
Observations	192	286	142	144

Source: Authors.

Notes: Rs. = Indian rupees. Standard errors in parentheses. Only farmers with at least one in-network would-be adopter are included. Wealth index consists of house condition; ration card possession; landholdings; and ownership of cell phones, vehicles, TVs, satellite dish, and livestock.

Because farmers with similar traits may also be network contacts with each other, the number of would-be adopters in each farmer's network is likely endogenous and correlated to characteristics that might influence his own demand for LLL (for example, education, wealth, progressiveness). Because we randomize adoption among would-be adopters, the number of each farmer's actual in-network adopters is exogenous, conditional on the number of in-network 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 between farmers with and without a first-generation adopter in their network using a t-test (Table 3.2). 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, which makes this a stronger test because farmers with more than one would-be adopter in their network are more likely to have at least one adopter in their network. In our regression analysis to follow, we explicitly control for the number of would-be adopters.

Table 3.2 Demographic and willingness-to-pay (2011 auction) differences between those with an auction winner in their network and those without

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

Source: Authors.

Notes: Rs = Indian rupees. Standard errors in parentheses. Only farmers with at least one in-network would-be adopter are included. Wealth index consists of house condition; ration card possession; landholdings; and ownership of cell phones, vehicles, TVs, satellite dish, and livestock.

Technology Delivery, Input-Use Surveys, and Follow-Up Auction

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 season, 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, for example, 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 intraseasonal surveys (described earlier) with both adopters and nonadopters. Using these data we find that LLL adopters had irrigation rates 23 percent lower than would-be adopters who lost the lottery ($p < 0.1$).[12] These water-use savings are in the range of those found in agronomic trials, which is an encouraging sign that the technology is beneficial to smallholders like the ones in our sample. We do not find statistically significant reductions in other inputs, although point estimates have the expected negative sign.

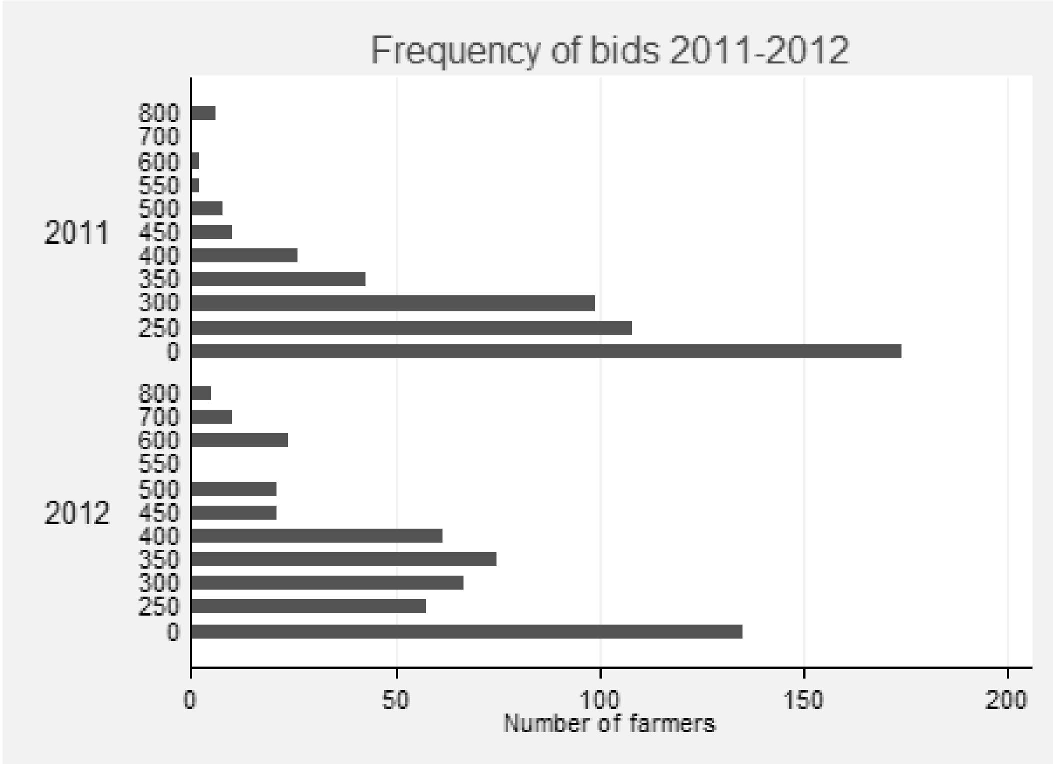
In addition to gathering data on input use, enumerators asked farmers about their exposure to LLL through other sample farmers using the photo directory: With whom have you discussed agriculture since the auction? With whom have you discussed LLL specifically? Whose fields did you see the LLL equipment operate on? Whose fields have you visited? We use these data to test for network effects on exposure to LLL.

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, such as 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 shows that overall WTP increased over the course of the study. This was expected, as many farmers initially said they would adopt LLL only after 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. Both of these differences in means are significant at the 0.01 confidence level. Figure 3.2 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. 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 identify network effects using our experimental data.

[12] Results of this analysis are available from the authors upon request.

Figure 3.2 Frequency of bids for laser land leveling custom hire in 2011 and 2012 auctions



Source: Authors.

4. ESTIMATION OF NETWORK EFFECTS

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

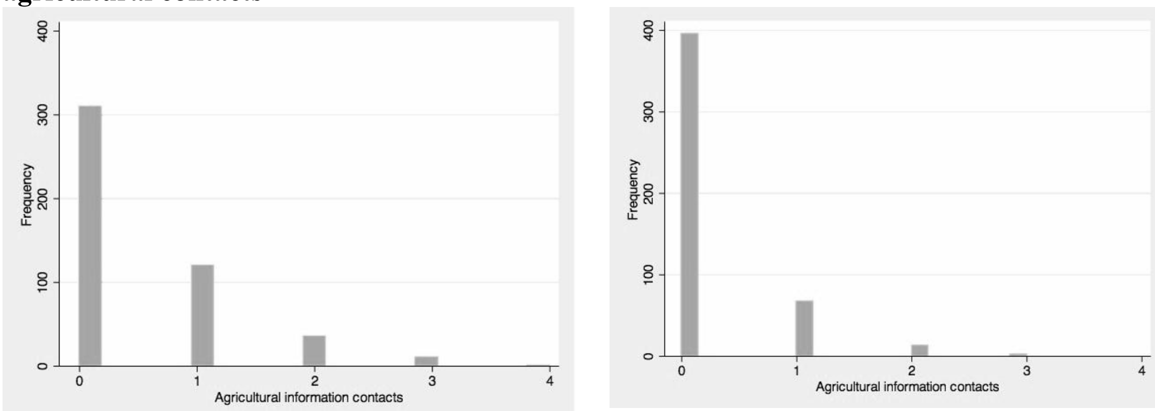
$$y_i = \alpha + \beta_1 \cdot adopter_i + \beta_2 \cdot wouldbes_i + \beta_3 \cdot networksize_i + X_i'^{\beta_4} + \varepsilon_i, \tag{1}$$

where y_i is the outcome variable of interest, which can be method of exposure to LLL, WTP, or a binary adoption variable at a given price. The variable $adopter_i$ indicates the presence of adopters in farmer i's network, $wouldbes_i$ is the number of would-be adopters in i's network, $networksize_i$ is the total number of farmers in i's network, and ε_i is an error term. X_i is a vector of control variables we can include to improve precision such as farmer age, education, and wealth index score. In some specifications we include WTP in the first auction as an additional control.[13] Generally we find that control variables do not increase precision, but we include them in some model specifications. The parameter β_1 is the network effect on the outcome of interest.

There are several ways we can formulate the $adopter$ variable. It can be a binary variable for the presence of at least one adopter, the number of in-network adopters (which ranges from 1 to 3), or the proportion of qualifying in-network farmers who adopted (which is either 0, 0.33, 0.5, 0.67, or 1). Network contacts in our sample are somewhat rare. In the full sample, farmers identified only 0.71 agricultural information contacts in their village on average, out of roughly 20 potential contacts. Friends and family linkages were more common; in the full sample, farmers claimed 1.13 friends or family members on average. Because network links are infrequent, there is very little difference between treating $adopter_i$ as a continuous or binary variable. Only 4 percent of farmers have more than one first-generation adopter in their network. Similarly, there is little difference in treating $adopter_i$ as a ratio; most farmers also have only one would-be adopter in their network, so the proportion of adopters is either 0 or 1 for 85 percent of the observations. Figure 4.1 shows a histogram of the number of in-network would-be adopters and adopters.

[13] An alternative to including WTP from the first auction as a control would be to use the difference in WTP between the two auctions as the dependent variable. 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 opt to impose less structure on the model by controlling for 2011 WTP rather than using the difference in WTP.

Figure 4.1 Number of would-be adopters (left) and adopters (right) in farmers' networks of agricultural contacts



Source: Authors.

We therefore focus on the impact of having at least one in-network adopter. 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 conduct a formal test as others have done (Bandiera and Rasul 2006; Maertens 2013; McNiven and Gilligan 2012). Results using total number of adopters and proportion of qualifying adopters can be found in the Appendix. All of our results are very robust across specifications.

Our full sample includes 478 farmers. Of these, 286 (60 percent) won the auction, 144 (30 percent) won the lottery, and 122 (26 percent) received leveling services. Because LLL 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 (just 8 percent of the full sample) who had all of their plots leveled after the first auction in 2011 and had no plots to bid on in the second auction in 2012 were omitted from analysis.[14] 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 149 farmers (31 percent of the full sample) that fit these criteria for agricultural information networks and 174 for friends and family networks (36 percent of the full sample). Of these farmers, about 20 percent received LLL after the first auction but still had plots left to bid on in the second auction.[15] While we can only measure network effects on demand for these 149 or 174 farmers (depending on network type), we use data on network connectivity with all 478 farmers in our sample. Table 4.1 contains descriptive statistics on network variables, as well as other model variables, for the subsample used for analysis.

[14] Farmers chose the plots they most wanted leveled 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 network effects of the same size.

[15] We did not count farmers as being in their own network.

Table 4.1 Descriptive statistics of complete sample and networks analysis subsamples

Variable	Full sample	Would-be agricultural information (ag info) network > 0	Would-be friends and family (FF) network > 0
Ag info contacts	0.71 (1.00)	1.66 (1.04)	
Would-be adopter ag info contacts	0.48 (0.75)	1.36 (0.63)	
Adopting ag info contacts	0.21 (0.49)	0.58 (0.69)	
At least one would-be ag info contact adopter {0,1}	0.17 (0.38)	0.48 (0.50)	
FF contacts	1.13 (1.92)		2.41 (2.59)
Would-be adopter FF contacts	0.71 (1.19)		1.76 (1.35)
Adopting FF contacts	0.33 (0.72)		0.84 (0.96)
At least one would-be FF contact adopter {0,1}	0.22 (0.42)		0.56 (0.50)
Age (years)	48.45 (184.6)	50.25 (15.93)	49.92 (15.32)
Education (years)	6.43 (5.50)	7.16 (5.61)	7.53 (5.45)
Wealth index	–0.02 (0.90)	0.23 (1.14)	0.23 (1.12)
Talked about LLL with at least one adopter {0,1}	0.62 (0.49)	0.65 (0.48)	0.63 (0.49)
Saw LLL unit operate in village {0,1}	0.58 (0.49)	0.58 (0.49)	0.56 (0.50)
Visited leveled field {0,1}	0.45 (0.50)	0.42 (0.50)	0.49 (0.50)
WTP 2011 (Rs./hour)	204.50 (173.07)	230.20 (186.98)	239.94 (180.56)
WTP 2012 (Rs./hour)	310.42 (184.55)	341.95 (184.18)	335.63 (172.52)
N	478	149	174

Source: Authors.

Notes: LLL = laser land leveling; WTP = willingness-to-pay; Rs. = Indian rupees. Standard deviations in parentheses. Average number of potential contacts in each village is 20. There are 422 observations of WTP in 2012 in the full sample.

Compliance with lottery outcomes was high. No lottery-losing farmers were able adopt LLL. However, 22 of the farmers who won the adoption lottery (15 percent) were not able to receive LLL, mainly due to heavy and untimely rains in 2011 that prevented the machinery from operating in some areas. We therefore instrument for the presence of an in-network farmer having his fields leveled with the presence of an in-network lottery winner, which we know to be exogenous conditional on the number of in-network would-be adopters.

5. RESULTS

Exposure to Laser Land Leveling

A farmer might gain exposure to and potentially learn about a new technology through his network contacts in several different ways. 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 field, and the probability that he visits an adopting farmer's laser-leveled field. These 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—not with only the farmers listed as agricultural contacts at the onset of the study. Exposure to LLL through farmers not listed as an agricultural information link 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.

Table 5.1 contains estimates of network effects on exposure outcomes, which were obtained using an instrumental variables linear probability model.[16] We find some weak evidence that having in-network first-generation adopters increases the probability that a farmer will have a conversation with another farmer about LLL by around 18 percent, but this effect is not always statistically significant at the 10 percent confidence interval (Table 5.1, columns 1 and 2). Having an in-network adopter has a larger and more pronounced effect on the probability that a farmer visits another farmer's laser-leveled field, increasing this probability by 27 percent (Table 5.1, columns 5 and 6). We find no evidence that having an in-network farmer increases the probability that a farmer would see the leveler in operation (Table 5.1, columns 3 and 4). Our results suggest that seeing results is essential; the diffusion of knowledge about the technology via farmer-to-farmer contacts is conditionally dependent on direct observation by the farmer.

Table 5.1 Network effects on exposure to laser land leveling (LLL)

	At least one conversation with adopting farmer about LLL		Seeing LLL unit operate on at least one adopting farmer's field		Visiting the field of at least on adopting farmer	
Exposure variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
At least one adopter in	0.18*	0.14	0.03	0.05	0.27**	0.27**
network	(0.10)	(0.10)	(0.11)	(0.11)	(0.10)	(0.11)
# of would-be adopters	–0.08	–0.00	0.05	0.01	–0.11	–0.10
	(0.09)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
Total network size	0.03	0.01	0.01	0.01	0.07	0.06
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)
Age (years)		0.01***		-0.00		0.00
		(0.00)		(0.00)		(0.00)
Education (years)		0.01*		0.01		0.01
		(0.01)		(0.01)		(0.01)
Constant	0.62***	0.06	0.49***	0.52**	0.31***	0.21
	(0.09)	(0.20)	(0.10)	(0.22)	(0.09)	(0.21)
Observations	149	149	149	149	149	149

Source: Authors.

Notes: IV linear probability model with lottery-winning farmers instrumenting for farmers receiving leveling. Marginal effects reported. Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. Only farmers with at least one qualifying farmer in their networks included in analysis.

[16] We employ an instrumental variables (IV) linear probability model instead of IV probit because of the potentially endogenous binary variable of having at least one in-network adopter.

Demand for LLL

It is encouraging that farmers gain exposure to a new technology through their network contacts, but ultimately we are concerned with whether such exposure leads to increased demand for the technology. The majority of studies that examine network effects on technology adoption observe demand as a dichotomous adoption variable. Cai (2013), who examines network effects on demand for agricultural insurance in China, is a notable exception. By offering farmers policies at different premiums, she is able to quantify network effects on demand in monetary terms. 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 in-network adopter on demand, we use WTP in the second auction as our dependent variable in equation (1), which is a more continuous measure of demand than a binary adoption outcome.

We find that farmers with at least one adopting farmer in their network were willing to pay an additional Rs. 91 per hour for LLL custom hire services than farmers without an adopting farmer in their network ($p < 0.05$). This is 28 percent of average WTP in the second auction. When we include control variables, point estimates are slightly lower, ranging from Rs. 74–82 (Table 5.2).[17] In percentage terms, these network effects are nearly twice as strong as increases in WTP found by Oster and Thornton (2012) and Cai (2013), respectively.

Table 5.2 Network effects on demand for laser land leveling (LLL)

Dependent variable: Willingness-to-pay 2012 (Rs./hour),	**(1)**	**(2)**	**(3)**
At least one adopter in network	90.51**	82.20**	73.68*
	(40.99)	(40.99)	(40.00)
# of would-be adopters	–26.50	–16.77	–24.16
	(37.64)	(39.92)	(38.87)
Total network size	0.17	–1.57	–1.08
	(17.57)	(17.69)	(17.19)
Age (years)		1.28	1.03
		(1.10)	(1.07)
Education (years)		–2.52	–3.90
		(3.20)	(3.23)
Wealth index		18.65	13.05
		(14.02)	(15.01)
Willingness-to-pay 2011 (Rs./hour)			0.26***
			(0.08)
Constant	333.81***	278.29***	254.34***
	(37.18)	(83.47)	(81.63)
Observations	149	149	149

Source: Authors.

Notes: Rs. = Indian rupees. IV regressions with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Only farmers with at least one qualifying farmer in their networks included in analysis. Wealth index consists of house condition; ration card possession; landholdings; and ownership of cell phones, vehicles, TVs, satellite dish, and livestock.

[17] When we use the number of in-network adopters as the explanatory variable, we find the network effect to be Rs. 50-59 per farmer (Table A2, columns 1-3), although we do not interpret this as a per in-network adopter effect; only 13 farmers had more than one adopter in their network.

Adoption of LLL at Different Prices

Several advantages are apparent in using WTP data from an experimental auction instead of observed adoption data—which is typically binary—to analyze network effects.[18] First, we can monetize network effects. These estimates 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. This is most important when most farmers' WTP is lower than the market price of a technology.

To illustrate this point with our data, we construct a set of dichotomous adoption variables for $WTP \geq Price$ at various prices: Rs. 250, 350, 500, and 600. We modify the model in equation (1) to have a dichotomous adoption outcome as the dependent variable:

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

Our estimation of equation (2) indicates that having an adopter in a farmer's network increases his probability of adoption by 7–15 percent depending on the threshold, but the effect is statistically significant only at the Rs. 250 ($p < 0.1$) and Rs. 350 ($p < 0.05$) thresholds. At higher thresholds we do not detect network effects that we see clearly using the WTP data from the auction (Table 5.3).

Table 5.3 Network effects on constructed dichotomous adoption variables

Dependent variable: Willingness-to-pay > hypothetical price	Market price range			
	Rs. 250	**Rs. 350**	**Rs. 500**	**Rs. 600**
At least one adopter in network	0.15*	0.26**	0.10	0.10
	(0.08)	(0.11)	(0.08)	(0.08)
# of would-be adopters in network	–0.02	0.04	-0.07	-0.07
	(0.07)	(0.10)	(0.08)	(0.08)
Total network size	–0.01	-0.04	0.03	0.03
	(0.03)	(0.05)	(0.04)	(0.04)
Constant	0.83***	0.50***	0.17**	0.17**
	(0.07)	(0.10)	(0.08)	(0.08)
Observations	149	149	149	149

Source: Authors.

Notes: Rs. = Indian rupees. IV linear probability models with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. Only farmers with at least one qualifying farmer in their networks included in analysis. Results are robust to including age, education, wealth, and willingness-to-pay 2011 as control variables (not shown).

In the 2012 auction we set the price—unknown to farmers at the time of the auction—at Rs. 350 per hour. If we had information only on whether or not farmers won the auction, and therefore adopted LLL, at the price of Rs. 350, we would estimate that having at least one in-network adopter increased the probability of adoption by 26 percent ($p < 0.05$). However, in areas of the IGP where LLL markets exist, the price in 2011/2012 was between Rs. 500 and Rs. 600 per hour. If farmers were required to pay those prices instead of Rs. 350 and we used adoption outcomes rather than auction bids to measure demand, we would find point estimates on the order of 7–10 percent that are not statistically significant ($p > 0.3$). 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 understanding network effects on demand below the market would be important.

[18] Adoption data can also be continuous (amount of land) or duration (time until adoption).

Learning or Mimicry?

The fact that a farmer's demand for an agricultural technology is influenced by the technology choices of farmers in his network does not necessarily imply social learning: Network effects could also arise because of mimicry or herd behavior (Banerjee 1992). Mimicry can arise either out of a desire to conform or because the follower assumes the leader has good information and has made a good technological decision. For instance, Maertens (2013) found that Indian farmers adopted transgenic *Bt* cotton following progressive farmers in their networks without observing their outcomes because these farmers were generally successful and thought to make good decisions, a behavior she terms "learning-imitation." Network effects could also occur because one person's adoption increases the benefits to subsequent adopters through noninformational channels, although we do not consider this possibility here, as it would not occur in the context of our experiment.[19]

Social learning has two components: Farmers can learn about the benefits of a technology or how to use a technology. Conley and Udry (2010) identify learning how to use a technology by looking at changes that Ghanaian pineapple farmers make to fertilizer use in reaction to the good and bad experiences of their network contacts. Oster and Thornton (2012) distinguish learning how to use a technology from mimicry by separately looking at Nepali girls' attempted use of menstrual cups from their successful and sustained use. Because LLL is obtained through custom hire, farmers can potentially learn about its profitability but not how to better use the technology.[20] In this study we test whether farmers learn about benefits by separately estimating the effects of in-network adopters that benefited from LLL and those who did not, borrowing loosely from the empirical approach of Conley and Udry (2010).

We consider a farmer to benefit from LLL if he uses at least 10 percent less water after adopting LLL than before. We chose the 10 percent threshold because it is on the lower bound of expected water savings from LLL (Jat et al. 2006). To calculate differences in irrigation before and after the introduction of LLL, we used retrospective irrigation data collected before the first auction (in 2011) on 2010/2011 irrigation hours and retrospective irrigation data collected after the second auction (in 2012) on 2011/2012 irrigation hours. We call farmers (both adopters and nonadopters) that reduced their water use by at least 10 percent from 2010/2011 to 2011/2012 "water-savers." We call all other farmers "nonsavers."

Many factors besides LLL could contribute to a given farmer's network contacts' using more or less water than in the previous year. To account for changes in water use not related to LLL that could be correlated to unobservable farmer and network characteristics, we control for the number of water-saving would-be adopters and the number of nonsaving would-be adopters in each farmer's network. The empirical model to test for learning about benefits is

$$WTP_i = \alpha + \beta_1 \cdot (adopting\ watersavers)_i + \beta_2 \cdot (adopting\ nonsavers)_i + \beta_3 \cdot (wouldbe\ watersavers)_i + \beta_4 \cdot (wouldbe\ nonsavers_i) + \beta_5 \cdot networksize_i + X_i{}'\beta_4 + \varepsilon_i. \quad (3)$$

If mimicry drives demand, we would expect both β_1 and β_2 to be positive and roughly 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 through mimicry or learning, we would expect both β_1 and β_2 to be zero.

[19] Consider the case where a farmer purchases an LLL unit to use on his own fields or calls for custom service hire. Once the leveler is in the area, the effective price of LLL custom service hire could go down. Because we control the market and the adoption price in this study, we do not consider these potential market-driven network effects.

[20] 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 line of research.

We find that having a water-saving in-network adopter increases WTP by around Rs. 150 ($p < 0.01$). This amounts to 46 percent of mean WTP in the second auction. A nonsaving in-network adopter has no significant effect on demand, and point estimates are slightly negative (Table 5.4). These results indicate that information spillovers for LLL arise 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 highly visible) benefits. This bodes well for sustained use of LLL.

Table 5.4 Learning about benefits and demand for laser land leveling

Dependent variable: Willingness-to-pay (Rs./hour) 2012	(1)	(2)	(3)
At least one adopter in network (water savers)	156.24***	142.28***	150.11***
	(51.31)	(51.45)	(49.52)
At least one adopter in network (nonsavers)	-4.59	-10.70	-24.57
	(54.72)	(54.65)	(52.72)
# of would-be adopters (water-savers)	-71.07*	-58.53	-71.34*
	(41.59)	(44.20)	(43.04)
# of would-be adopters (nonsavers)	11.11	20.21	14.40
	(42.44)	(44.21)	(42.77)
Total network size	1.12	-0.80	0.04
	(17.24)	(17.41)	(16.86)
Age (years)		1.31	1.02
		(1.09)	(1.05)
Education (years)		-1.14	-2.58
		(3.18)	(3.19)
Wealth index		15.61	11.46
		(13.69)	(14.61)
Willingness-to-pay 2011 (Rs./hour)			0.27***
			(0.08)
Constant	342.72***	275.98***	251.98***
	(36.01)	(82.32)	(80.30)
Observations	149	149	149

Source: Authors.

Notes: Rs. = Indian rupee. "Water saving" denotes using at least 10% less water in 2011/2012 than in 2010/2011. IV regressions with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Only farmers with at least one qualifying farmer in their networks included in analysis. Wealth index consists of house condition; ration card possession; landholdings; and ownership of cell phones, vehicles, TVs, satellite dish, and livestock.

Network Effects across Wealth Classes

Heterogeneity within villages and within social networks could have implications on how networks impact technology adoption. Farmers may find the experience of some adopters more influential than that of others. For instance, novice farmers might be more likely to experience network effects from more experienced farmers, as Conley and Udry (2010) found in Ghana. Conley and Udry (2010) also find that farmers are more likely to learn from farmers in the same wealth class and from farmers with larger farms. Maertens (2013) finds that farmers are more likely to be influenced by the technology choices of progressive farmers than those of other farmers.

Here we test for network effects within and across wealth class. Our motivation for doing this is to examine whether current extension practices of reaching out to relatively wealthy and more connected farmers will result in network effects that will lead to dissemination that also includes poorer farmers. We create two wealth classes of farmers of equal size in each village. Farmers at or below the village median wealth index are considered "poor" and farmers above the village median are considered "rich," although very few farmers in our sample are actually rich by most standards. These divisions are rather ad hoc, but importantly divide each village into roughly equal-sized groupings so that there are adopters and would-be adopters from both wealth classes in the farmers' social networks. The empirical model is similar to equation (3), but instead of separating water-saving from nonsaving in-network farmers, we separate poor from rich in-network farmers:

$$WTP_i = \alpha + \beta_1 \cdot (adopting\ poor)_i + \beta_2 \cdot (adopting\ rich)_i + \beta_3 \cdot (poor\ wouldbes)_i + \beta_4 \cdot (rich\ wouldbes)_i + \beta_5 \cdot networksize_i + X_i'\beta_4 + \varepsilon_i. \quad (4)$$

Rich farmers were more likely to win the first auction and thus were more likely to adopt LLL (Table 5.5). On average, farmers have a 0.16 probability of having a poor in-network adopter and a 0.37 probability chance of having a rich in-network adopter. Poor farmers have a 0.12 probability of having a poor in-network adopter and a 0.42 probability of having a rich in-network adopter. Rich farmers have a 0.19 probability of having a poor in-network adopter and a 0.33 probability of having a rich in-network adopter. The fact that rich and poor farmers have similar probabilities of having rich and poor farmers in their networks indicates that there is substantial wealth heterogeneity within social networks and even within villages.

Table 5.5 Network effects in heterogeneous farmer networks

Dependent variable: Willingness-to-pay 2012(Rs./hour)						
	All		"Poor"		"Rich"	
P(≥1 poor adopter)	0.16		0.12		0.19	
P(≥1 rich adopter)	0.37		0.42		0.33	
	(1)	**(3)**	**(4)**	**(6)**	**(7)**	**(9)**
At least one poor adopter	141.52*	120.99*	371.75**	280.03**	63.85	53.59
	(73.99)	(71.22)	(140.18)	(139.24)	(82.00)	(80.90)
At least one rich adopter	75.24	65.38	163.76*	164.87*	13.09	0.19
	(47.36)	(46.12)	(83.26)	(87.66)	(55.90)	(54.55)
# would-be poor adopters	–113.50	–105.38	–406.74***	–368.95***	1.16	35.39
	(68.67)	(68.18)	(130.62)	(128.61)	(75.76)	(78.18)
# would- be rich adopters	–0.29	3.22	–167.82**	–185.03**	42.28	63.06
	(48.37)	(49.41)	(76.45)	(88.32)	(47.61)	(49.74)
Total network size	7.07	9.27	21.12	31.44	–15.07	–20.16
	(23.23)	(22.45)	(28.83)	(30.83)	(23.83)	(23.51)
Age (years)		0.85		–1.01		2.28*
		(1.09)		(1.78)		(1.35)
Education (years)		–4.09		–7.29		–3.01
		(3.26)		(5.87)		(3.80)
Wealth index		12.79		229.24		–4.24
		(15.16)		(142.39)		(16.64)
WTP 2011 (Rs./hour)		0.27***		0.28*		0.16
		(0.08)		(0.15)		(0.10)
Constant	345.87***	272.68***	427.48***	578.95***	322.37***	182.86*
	(37.05)	(83.19)	(66.45)	(173.09)	(43.29)	(100.29)
Observations	149	149	65	65	84	84

Source: Authors.

Notes: WTP = willingness-to-pay; Rs. = Indian rupees. IV regressions with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Only farmers with at least one qualifying farmer in their network included in analysis. Wealth divisions are made at the village level.

Overall, we find the effect of poor in-network adopters (Rs. 120–142, $p < 0.1$) to be much stronger than that of rich in-network adopters (Rs. 65–75, $p > 0.1$). When we look at the effects on poor and rich farmers separately, we see two striking outcomes. First, network effects from both poor and rich in-network adopters are prevalent only on poor farmers. Second, on poor farmers there is a much greater effect of poor in-network adopters (Rs. 280–371) than of rich in-network adopters (Rs. 164–179). While our estimates are not precise enough to statistically distinguish the effects of poor and rich in-network adopters from each other at the 0.1 confidence level, the differences are striking and could have implications for inclusive technology dissemination. Extension often reaches out to well-connected farmers because they are the most likely to adopt, the most likely to be successful, and are thought to be the most influential. While this may be true, it is important to reach out to relatively poor farmers to fully take advantage of network effects.

6. PLACEBO TEST AND ALTERNATIVE NETWORKS

Placebo Test for Spurious Network Effects

While we are confident that our randomization prevents us from finding network effects erroneously, we perform a placebo test by regressing WTP from the 2011 auction, held before the technology was introduced, on the network variables in equations (1) and (2). Coefficients on network variables that are significantly positive (or negative) in these specifications would indicate the presence of unobservable variables correlated to both demand for the technology and the number of in-network first-generation adopters, conditional on would-be adopters. This correlation would lead us to overestimate network effects or find network effects where none should be found. As expected, we find no significant impact of adoption in farmers' network on their WTP for LLL before the technology was introduced in any specification (Table 6.1).

Table 6.1 Placebo test for spurious network effects

Dependent variable: Willingness-to-pay 2011	(1)	(2)	(3)	(4)
At least one adopter in network	25.05	25.05		
	(40.90)	(40.90)		
At least one adopter in network (water savers)			–24.80	–24.80
			(52.96)	(52.96)
At least one adopter in network (nonsavers)			59.29	59.29
			(56.48)	(56.48)
# of would-be adopters	36.57	36.57		
	(37.55)	(37.55)		
# of would-be adopters (water savers)			51.70	51.70
			(42.92)	(42.92)
# of would-be adopters (nonsavers)			19.27	19.27
			(43.80)	(43.80)
Total network size	0.14	0.14	–0.73	–0.73
	(17.52)	(17.52)	(17.79)	(17.79)
Age (years)		1.01		1.04
		(1.10)		(1.11)
Education (years)		4.87		4.68
		(3.18)		(3.27)
Wealth index		18.42		17.63
		(13.92)		(14.04)
Constant	168.25***	168.25***	172.96***	172.96***
	(37.10)	(37.10)	(37.17)	(37.17)
Observations	149	149	149	149

Source: Authors.

Notes: "Water-saving" denotes using at least 10% less water in 2011/2012 than in 2010/2011. IV regressions with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Only farmers with at least one qualifying farmer in their networks included in analysis. Wealth index consists of house condition; ration card possession; landholdings; and ownership of cell phones, vehicles, TVs, satellite dish, and livestock.

Friends and Family Network Links

People form different types of links for different reasons. In our analysis we focus on agricultural information links because these would logically be the most likely to transmit information about a new agricultural technology. However, it is possible that farmers learn about agricultural technologies from people with whom they do not regularly speak about agriculture. We therefore conduct the same analysis on demand and learning as in Section 5 using friends and family networks.

We find little evidence that friends and family networks impact demand for LLL. When we separate water-saving and nonsaving farmers, we find that having a nonsaving adopter in-network decreases WTP by Rs. 72 ($p < 0.1$). Having a water-saving adopter in-network has no significant effect, although the point estimate is positive (Table 6.1, column 2). While logical, these findings differ from those obtained using agricultural information links. When we define our network links in a more inclusive manner—agricultural information contacts, friends, or family—we find no significant effect of having an in-network adopter (Table 6.2).

Table 6.2 Alternate network types

Dependent variable: Willingness-to-pay 2012	Friends and family (FF)		Agricultural information contacts of FF	
	(1)	(2)	(3)	(4)
At least one adopter in network	–8.22		–4.27	
	(35.13)		(32.72)	
At least one adopter in network (water savers)		36.44		55.72
		(37.19)		(34.89)
At least one adopter in network (nonsavers)		–71.69*		–36.67
		(42.89)		(37.75)
# of would-be adopters	13.61		6.82	
	(22.49)		(17.00)	
# of would-be adopters (water savers)		–23.15		–35.62*
		(26.52)		(20.78)
# of would-be adopters (nonsavers)		61.17**		43.92**
		(27.85)		(21.02)
Total network size	–4.89	–5.22	–2.23	–2.43
	(7.33)	(7.17)	(6.36)	(6.19)
Constant	330.84***	330.26***	329.91***	325.50***
	(25.49)	(23.52)	(22.87)	(20.46)
Observations	174	174	223	223

Source: Authors.

Notes: "Water saving" denotes using at least 10% less water in 2011/2012 than in 2010/2011. IV regressions with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Only farmers with at least one qualifying farmer in their network included in analysis.

Network effects on demand are muted when we use friend and family links instead of or in addition to agricultural contact links. This indicates two things in our study area: Farmers' agricultural networks are specialized, and agricultural information is gleaned more from relationships focused on agriculture than from casual and broad discussions that might arise with family and friends. McNiven and Gilligan (2012) also find that specialized agricultural information links to early adopters have a much stronger effect on adoption than other types of links. Conley and Udry (2010), however, found that using a broader definition of a network link did not change their key results.

Bidirectional Network Links

For our main analysis we used unidirectional network links. If Farmer A said he talks to Farmer B about agriculture but Farmer B did not say he talks to Farmer A about agriculture, then Farmer B is in Farmer A's agricultural information network but Farmer A is not in Farmer B's agricultural information network. This seems logical; a farmer seems more likely to report regularly talking to someone from who he gains information than talking to someone to whom he gives information.

As a robustness check to our findings using unidirectional links, we estimate network effects using bidirectional links; Farmer B is in Farmer A's network if Farmer B reported to talking about agriculture (or being friends of family) with Farmer A *or* Farmer A reported talking about agriculture (or being friends of family) with Farmer B. For agricultural information contacts, our estimates have the same sign as they do using unidirectional links, but are muted. For friends and family networks, our results are similar using unidirectional and bidirectional links, and in both cases network effects are smaller than those through agricultural information networks. When we include bidirectional links for both agricultural information and friend and family networks, we find slightly stronger links than we do using unidirectional links (Table 6.3).

Table 6.3 Network effects using bidirectional agricultural information (ag info) links

Dependent variable: Willingness-to-pay 2012	Ag info contacts (1)	Ag info contacts (2)	Friends and family (FF) (3)	Friends and family (FF) (4)	Ag info contacts or FF (5)	Ag info contacts or FF (6)
At least one adopter in network	42.50		13.36		26.85	
	(34.43)		(28.15)		(29.41)	
At least one adopter in network (water savers)		91.34**		52.02*		83.59***
		(38.15)		(29.72)		(28.87)
At least one adopter in network (nonsavers)		–16.77		–35.14		–23.26
		(43.03)		(34.84)		(34.41)
# of would-be adopters	5.53		10.23		3.55	
	(17.43)		(13.26)		(9.80)	
# of would-be adopters (water savers)		–24.96		–16.11		–24.62*
		(21.83)		(16.76)		(12.86)
# of would-be adopters (non savers)		25.46		34.37**		26.92*
		(22.52)		(17.27)		(13.72)
Total network size	0.53	2.07	–3.09	–2.84	–0.24	–0.42
	(11.10)	(11.05)	(5.38)	(5.29)	(4.79)	(4.69)
Constant	308.02***	310.84***	307.09***	310.11***	305.96***	303.64***
	(25.72)	(23.63)	(21.46)	(19.33)	(21.60)	(18.65)
Observations	208	208	259	259	303	303

Source: Authors.

Notes: "Water saver" denotes using at least 10% less water in 2011/2012 than in 2010/2011. IV regressions with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Only farmers with at least one qualifying farmer in their aggregate networks are included in analysis.

While our results using friends and family links are weaker than those using agricultural information links, and our results using bidirectional links are weaker than those using unidirectional links, point estimates have the expected sign. When we include learning in the model, we see a positive and significant effect of an in-network water-saving adopter or a negative effect of an in-network nonsaving adopter. The results using alternative network definitions and to a lesser extent directionalities demonstrate the importance of intuition, context, and precision in defining social relations and their influence on WTP for a given technology.

7. CONCLUDING REMARKS

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 services 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 assess whether 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 28 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 benefited from LLL from the effect of having a first-generation adopter who did not benefit, we find that the effect on WTP is an increase of nearly 50 percent for the former and zero for the latter. 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 from conversations with adopters or seeing the leveling unit in action.

As a methodological contribution, this study demonstrates the benefits of using an experimental auction to measure demand. Using WTP 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 not be detectable. 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 such as 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. Our results also underscore the importance that early adopters succeed, as network effects are importantly conditioned on early success with the technology. While introducing technologies to farmers with a high likelihood of experiencing success is important, it is also important to consider reaching out to poor farmers. We find network effects from poor farmers to poor farmers to be especially strong, indicating the importance of inclusive extension to achieve inclusive dissemination. Finally, we note that while network effects are strong within a given village, their reach may be very limited. For instance, we find that farmers have only a small probability of knowing a randomly selected farmer in a village only 5 km away.

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 WTP 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 multifaceted 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.

APPENDIX: SUPPLEMENTARY TABLES

Table A.1 Network effects on exposure to laser land leveling (LLL): Alternate network variables

Dependent variable: 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 the field of at least on adopting farmer			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
# of adopters	0.10	0.08			0.06	0.08			0.10	0.10		
	(0.08)	(0.08)			–0.09	–0.09			(0.08)	(0.08)		
Proportion of adopters			0.15	0.12			0.09	0.12			0.24**	0.24**
			(0.11)	(0.11)			(0.11)	(0.11)			(0.11)	(0.11)
# of would-be adopters	–0.08	–0.01			0.03	–0.01			–0.09	–0.09		
	(0.10)	(0.10)			–0.1	–0.11			(0.10)	(0.11)		
Total network size	0.02	0.00	0.01	0.01	0.01	0.01	0.03	0.02	0.06	0.06	0.04	0.04
	(0.05)	(0.04)	(0.03)	(0.03)	–0.05	–0.05	(0.03)	(0.03)	(0.05)	(0.05)	(0.03)	(0.03)
Age (years)		0.01***		0.01***		0		–0.00		0.00		0.00
		(0.00)		(0.00)		0		(0.00)		(0.00)		(0.00)
Education (years)		0.01**		0.01*		0.01		0.01		0.01		0.01
		(0.01)		(0.01)		–0.01		(0.01)		(0.01)		(0.01)
Constant	0.66***	0.09	0.57***	0.07	0.50***	0.55**	0.50***	0.53***	0.37***	0.24	0.24***	0.12
	(0.09)	(0.20)	(0.08)	(0.18)	–0.1	–0.22	(0.08)	(0.19)	(0.10)	(0.22)	(0.08)	(0.18)
Observations	149	149	149	149	149	149	149	149	149	149	149	149

Source: Authors.

Notes: IV linear probability models with lottery-winning farmers instrumenting for farmers receiving leveling. Marginal effects reported. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Only farmers with at least one qualifying farmer in their networks included in analysis.

Table A.2 Network effects on demand for laser land leveling: Alternate network variables

Dependent variable: Willingness-to-pay 2012	(1)	(2)	(3)	(4)	(5)	(6)
# of adopters	58.75*	50.20	52.93*			
	(31.82)	(32.06)	(30.89)			
Proportion of adopters				92.14**	82.93*	80.81*
				(42.78)	(43.21)	(41.74)
# of would-be adopters	–32.58	–20.29	–32.31	–7.39	–0.66	–9.91
	(39.09)	(41.69)	(40.30)	(36.52)	(38.70)	(37.46)
Total network size	–3.01	–4.40	–4.57	–1.88	–2.46	–2.81
	(17.71)	(17.82)	(17.17)	(17.62)	(17.82)	(17.20)
Age (years)		1.32	1.00		1.22	0.95
		(1.11)	(1.07)		(1.11)	(1.08)
Education (years)		–2.12	–3.51		–2.71	–3.84
		(3.20)	(3.11)		(3.32)	(3.23)
Wealth index		17.08	12.36		19.22	12.86
		(13.96)	(13.52)		(15.37)	(14.97)
Willingness-to-pay 2011 (Rs./hour)			0.28***			0.27***
			(0.08)			(0.08)
Constant	357.61***	294.26***	271.51***	312.78***	265.99***	231.88***
	(37.01)	(84.47)	(81.70)	(30.59)	(71.60)	(69.81)
Observations	149	149	149	149	149	149

Source: Authors.

Notes: Rs. = Indian rupees. IV regressions with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. Only farmers with at least one qualifying farmer in their networks included in analysis. Wealth index consists of house condition; ration card possession; landholdings; and ownership of cell phones, vehicles, TVs, satellite dish, and livestock.

Table A.3 Network effects on constructed dichotomous adoption variables (total number of in-network adopters)

Dependent variable: Willingness-to-pay > hypothetical price	Market price range			
	Rs. 250	Rs. 350	Rs. 500	Rs. 600
# of adopters in network	0.14**	0.12	0.04	0.02
	(0.06)	(0.08)	(0.07)	(0.05)
# of would-be adopters in network	–0.05	0.04	–0.07	–0.09
	(0.08)	(0.10)	(0.08)	(0.07)
Total network size	–0.02	–0.05	0.03	0.04
	(0.03)	(0.05)	(0.04)	(0.03)
Constant	0.88***	0.56***	0.19**	0.14**
	(0.07)	(0.10)	(0.08)	(0.06)
Observations	149	149	149	149

Source: Authors.

Notes: Rs. = Indian rupees. IV linear probability models with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. Only farmers with at least one qualifying farmer in their networks included in analysis. Results are robust to including age, education, wealth, and WTP 2011 as control variables (not shown).

Table A.4 Network effects on constructed dichotomous adoption variables (proportion of in-network farmers adopting)

Dependent variable: Willingness-to-pay > hypothetical price	Market price range			
	Rs. 250	Rs. 350	Rs. 500	Rs. 600
Proportion of adopters	0.18**	0.23**	0.09	0.09
	(0.08)	(0.11)	(0.09)	(0.09)
# of would-be adopters	0.01	0.09	–0.05	–0.05
	(0.07)	(0.10)	(0.08)	(0.08)
Total network size	–0.01	–0.01	0.01	0.01
	(0.02)	(0.03)	(0.02)	(0.02)
Constant	0.80***	0.52***	0.12*	0.12*
	(0.06)	(0.08)	(0.06)	(0.06)
Observations	149	149	149	149

Source: Authors.

Notes: Rs. = Indian rupees. IV linear probability models with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. Only farmers with at least one qualifying farmer in their networks included in analysis. Results are robust to including age, education, wealth, and WTP 2011 as control variables (not shown).

Table A.5 Learning about benefits and demand for laser land leveling (alternate network variables)

Dependent variable: Willingness-to-pay (WTP) (Rs./Hour) 2012	(1)	(2)	(3)	(4)	(5)	(6)
# of adopters (water savers)	150.83***	138.21***	144.16***			
	(49.56)	(49.59)	(47.88)			
# of adopters (nonsavers)	–26.80	–30.46	–29.11			
	(43.51)	(43.58)	(42.16)			
Proportion of adopters (water savers)				165.12***	156.43***	160.72***
				(51.58)	(52.06)	(50.13)
Proportion of adopters (nonsavers)				–7.74	–13.93	–24.96
				(51.74)	(51.57)	(49.80)
# of would-be adopters (water-savers)	–71.00*	–57.17	–68.72	–56.33	–51.49	–60.68
	(41.50)	(44.10)	(43.05)	(39.79)	(42.87)	(41.37)
# of would-be adopters (nonsavers)	27.66	37.47	26.17	19.96	25.54	18.50
	(44.74)	(46.89)	(45.65)	(39.63)	(41.35)	(39.95)
Total network size	–1.05	–1.05	–2.64	–0.76	–1.15	–1.35
	(17.33)	(17.33)	(16.94)	(17.16)	(17.38)	(16.77)
Age (years)			1.11			0.95
			(1.05)			(1.05)
Education (years)			–2.54			–2.66
			(3.19)			(3.17)
Wealth index			10.69			14.13
			(14.66)			(14.59)
WTP 2011 (Rs./hour)			0.27***			0.27***
			(0.08)			(0.08)
Constant	342.90***	268.72***	246.82***	332.87***	275.64***	249.59***
	(36.62)	(83.26)	(80.69)	(36.42)	(82.06)	(79.51)
Observations	149	149	149	149	149	149

Source: Authors.

Notes: Rs. = Indian rupees. IV linear probability model with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. Only farmers with at least one qualifying farmer in their networks included in analysis. Wealth index consists of house condition; ration card possession; landholdings; and ownership of cell phones, vehicles, TVs, satellite dish, and livestock.

Table A.6 Network effects in heterogeneous farmer networks (total number of in-network adopters)

Dependent variable: Willingness-to-pay (WTP) 2012 (Rs./hour)		**All**			**"Poor"**			**"Rich"**	
P(≥1 poor adopter)		0.16			0.12			0.19	
P(≥1 rich adopter)		0.37			0.42			0.33	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
At least one L adopter	144.18*	134.70*	121.46*	377.39***	363.06**	268.46*	63.21	44.63	51.29
	(73.62)	(73.42)	(71.05)	(138.54)	(138.45)	(138.10)	(82.07)	(81.70)	(81.06)
At least one H adopter	45.04	37.53	43.52	94.66	101.36	105.19*	18.23	10.81	15.73
	(37.15)	(37.36)	(36.11)	(58.15)	(62.09)	(59.47)	(50.46)	(49.64)	(49.26)
# would-be L adopters	–109.08	–93.04	–96.68	–419.49***	–412.62***	–373.99***	3.37	48.27	41.76
	(66.56)	(68.98)	(66.63)	(129.48)	(131.46)	(127.41)	(75.52)	(78.79)	(78.19)
# would- be H adopters	–17.62	–9.39	–21.34	–153.03**	–186.47**	–167.81*	40.69	72.89	60.61
	(40.78)	(43.36)	(42.02)	(76.04)	(86.30)	(83.81)	(47.93)	(49.72)	(49.88)
Total network size	–5.40	–5.70	–5.83	9.22	22.28	15.70	–15.86	–22.61	–22.11
	(17.72)	(17.91)	(17.30)	(27.56)	(29.03)	(28.07)	(23.82)	(23.76)	(23.55)
Age (years)		1.17	0.88		–0.14	–0.87		2.34*	2.28*
		(1.11)	(1.08)		(1.81)	(1.75)		(1.36)	(1.34)
Education (years)		–2.46	–3.65		–5.00	–5.95		–2.36	–3.10
		(3.32)	(3.23)		(5.97)	(5.74)		(3.76)	(3.75)
Wealth index		17.96	11.72		237.46*	183.48		–2.36	–4.48
		(15.28)	(14.88)		(133.90)	(131.46)		(16.60)	(16.50)
WTP 2011 (Rs./hour)			0.28***			0.34**			0.16
			(0.08)			(0.14)			(0.10)
Constant	355.45***	302.23***	277.53***	455.13***	615.86***	558.18***	322.97***	201.47**	182.86*
	(36.94)	(85.21)	(82.64)	(69.07)	(172.48)	(168.49)	(43.08)	(100.39)	(100.17)
Observations	149	149	149	65	65	65	84	84	84

Source: Authors.

Notes: Rs. = Indian rupees. IV regressions with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. Only farmers with at least one qualifying farmer in their network included in analysis. Wealth and landholdings divisions are made at the village level.

Table A.7 Network effects in heterogeneous farmer networks (proportion of in-network farmers adopting)

Dependent variable: Willingness-to-pay (WTP) 2012 (Rs./hour)		**All**			**“Poor”**			**“Rich”**	
P(≥1 poor adopter)		0.16			0.12			0.19	
P(≥1 rich adopter)		0.37			0.42			0.33	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
At least one L adopter	143.57*	133.19*	121.46*	364.66**	348.59**	263.69*	64.91	45.99	53.02
	(73.47)	(73.27)	(70.91)	(140.64)	(139.91)	(139.68)	(81.92)	(81.51)	(80.90)
At least one H adopter	67.07	61.10	62.37	140.40*	150.36*	146.84*	14.17	3.73	7.55
	(47.99)	(48.65)	(47.00)	(79.83)	(84.29)	(81.73)	(60.03)	(59.35)	(58.84)
# would-be L adopters	–98.62	–84.25	–88.32	–387.22***	–381.15***	–345.31***	1.98	45.32	38.44
	(67.35)	(69.39)	(67.06)	(130.73)	(131.59)	(128.06)	(76.31)	(79.20)	(78.62)
# would- be H adopters	–5.80	–1.42	–10.44	–124.76*	–160.81**	–138.82*	44.77	74.72	63.51
	(37.89)	(40.21)	(38.93)	(66.90)	(75.02)	(74.05)	(47.54)	(49.43)	(49.52)
Total network size	–5.23	–5.23	–5.24	13.32	29.06	22.39	–15.06	–21.61	–20.88
	(17.72)	(17.91)	(17.31)	(28.07)	(29.89)	(29.19)	(23.83)	(23.70)	(23.49)
Age (years)		1.08	0.81		–0.39	–1.01		2.33*	2.27*
		(1.12)	(1.09)		(1.84)	(1.78)		(1.36)	(1.35)
Education (years)		–2.89	–4.06		–6.52	–7.34		–2.33	–3.08
		(3.34)	(3.25)		(6.07)	(5.87)		(3.79)	(3.79)
Wealth index		19.86	13.58		261.89*	206.84		–2.11	–4.05
		(15.47)	(15.08)		(138.16)	(137.75)		(16.67)	(16.57)
WTP 2011 (Rs./hour)			0.27***			0.31**			0.16
			(0.08)			(0.14)			(0.10)
Constant	337.56***	294.45***	268.43***	406.61***	597.97***	538.30***	319.74***	200.86**	181.87*
	(37.67)	(84.43)	(81.97)	(66.64)	(166.49)	(164.82)	(45.78)	(100.59)	(100.43)
Observations	149	149	149	65	65	65	84	84	84

Source: Authors.

Notes: Rs. = Indian rupees. IV regressions with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. Only farmers with at least one qualifying farmer in their network included in analysis. Wealth divisions are made at the village level.

Table A.8 Placebo test for spurious network effects (alternate network variables)

Dependent variable: Willingness-to-pay 2011 (Rs./hour)	Total number of adopters				Proportion of adopters			
	Average network effects		Learning about benefits		Average network effects		Learning about benefits	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
# of adopters	–12.68	–8.52						
	(31.93)	(32.01)						
# of adopters (water savers)			–17.44	–17.44				
			(50.84)	(50.84)				
# of adopters (nonsavers)			–6.17	–6.17				
			(44.67)	(44.67)				
Proportion of adopters					1.13	7.78		
					(42.87)	(42.94)		
Proportion of adopters (water savers)							–24.47	–15.93
							(53.51)	(53.49)
Proportion of adopters (nonsavers)							50.20	40.99
							(53.68)	(52.99)
# of would-be adopters	47.65	38.92			42.05	33.96		
	(39.22)	(41.83)			(36.59)	(38.46)		
# of would-be adopters (water savers)			34.59	34.59			50.83	34.19
			(45.62)	(45.62)			(41.28)	(44.05)
# of would-be adopters (nonsavers)			41.49	41.49			26.87	26.16
			(48.18)	(48.18)			(41.11)	(42.49)
Total network size	1.64	2.03	1.93	1.93	0.55	1.30	–0.21	0.72
	(17.77)	(17.81)	(17.95)	(17.95)	(17.66)	(17.71)	(17.80)	(17.86)
Age (years)		1.07		1.06		1.00		0.98
		(1.10)		(1.11)		(1.11)		(1.11)
Education (years)		4.17		4.25		4.15		4.01
		(3.31)		(3.36)		(3.30)		(3.36)
Wealth index		22.46		23.10		23.32		23.57
		(15.25)		(15.42)		(15.27)		(15.40)
Constant	169.84***	89.63	91.22	91.22	171.67***	92.87	170.50***	96.86
	(37.13)	(84.77)	(85.95)	(85.95)	(39.22)	(83.52)	(37.78)	(84.32)
Observations	149	149	149	149	149	149	149	149

Source: Authors.

Notes: Rs. = Indian rupees. "Water saving" denotes using at least 10% less water in 2011/2012 than in 2010/2011. IV regressions with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Only farmers with at least one qualifying farmer in their networks included in analysis. Wealth index consists of house condition; ration card possession; landholdings; and ownership of cell phones, vehicles, TVs, satellite dish, and livestock.

Table A.9 Other network types (number of in-network adopters)

Dependent variable: Willingness-to-pay 2012 (Rs./hour)	Friends and family (FF)		FF or Ag info contacts	
	(1)	(2)	(3)	(4)
# adopters in network	5.49		19.16	
	(24.95)		(23.36)	
# adopters in network (water savers)		17.98		42.76
		(33.57)		(32.01)
# adopters in network (nonsavers)		–31.66		–24.67
		(32.45)		(28.20)
# of would-be adopters	7.61		–6.28	
	(27.01)		(21.84)	
# of would-be adopters (water savers)		–18.69		–36.97
		(28.75)		(23.26)
# of would-be adopters (nonsavers)		57.31*		47.30*
		(31.82)		(25.95)
Total network size	–4.17	–6.72	–1.28	–4.33
	(7.34)	(7.31)	(6.42)	(6.40)
Constant	330.03***	327.38***	332.46***	328.67***
	(24.64)	(24.18)	(21.25)	(20.66)
Observations	174	174	223	223

Source: Authors.

Notes: Rs. = Indian rupees. "Water saving" denotes using at least 10% less water in 2011/2012 than in 2010/2011. IV regressions with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. Only farmers with at least one qualifying farmer in their network included in analysis.

Table A.10 Other network types (proportion of in-network adopters)

Dependent variable: Willingness-to-pay 2012 (Rs./hour)	Friends and family (FF)		FF or agricultural information contacts	
	(1)	(2)	(3)	(4)
Proportion of adopters in network	–8.63		15.06	
	(37.98)		(36.56)	
Proportion of adopters in network (water savers)		29.16		55.70
		(37.60)		(37.07)
Proportion of adopters in network (nonsavers)		–53.07		–22.43
		(39.12)		(34.93)
# of would-be adopters	12.29		5.30	
	(20.86)		(15.97)	
# of would-be adopters (water savers)		–20.55		–30.57
		(24.54)		(19.18)
# of would-be adopters (nonsavers)		49.80**		37.57*
		(25.17)		(19.13)
Total network size	–4.70	–5.18	–2.06	–2.35
	(7.20)	(7.20)	(6.33)	(6.24)
Constant	331.66***	332.51***	323.45***	323.65***
	(27.00)	(24.15)	(24.24)	(21.37)
Observations	174	174	223	223

Source: Authors.

Notes: Rs. = Indian rupees. "Water saving" denotes using at least 10% less water in 2011/2012 than in 2010/2011. IV regressions with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** p < 0.01, ** p < 0.05, * p < 0.1. Only farmers with at least one qualifying farmer in their network included in analysis.

Table A.11 Bidirectional agricultural information links (number of in-network adopters)

Dependent variable: Willingness-to-pay 2012	Agricultural information (ag info) contacts		Friends and family (FF)		Ag info contacts or FF	
	(1)	(2)	(3)	(4)	(5)	(6)
# adopters in network	35.61		13.08		26.09	
	(25.42)		(19.31)		(19.72)	
# adopters in network (water savers)		68.60*		32.95		41.79
		(36.68)		(25.23)		(26.23)
# adopters in network (nonsavers)		–1.09		–22.81		–6.66
		(29.75)		(26.25)		(22.39)
# of would-be adopters	–2.23		6.39		–4.57	
	(19.33)		(15.20)		(12.43)	
# of would-be adopters (water savers)		–21.32		–14.16		–20.28
		(22.61)		(17.73)		(14.66)
# of would-be adopters (nonsavers)		22.23		34.62*		22.26
		(23.72)		(19.03)		(15.34)
Total network size	–1.07	0.20	–3.33	–4.36	–0.86	–1.85
	(11.16)	(11.15)	(5.35)	(5.35)	(4.80)	(4.81)
Constant	321.80***	315.53***	312.08***	313.98***	317.92***	316.66***
	(22.88)	(23.05)	(18.89)	(18.85)	(17.88)	(17.79)
Observations	208	208	259	259	303	303

Source: Authors.

Notes: Water saving denotes using at least 10% less water in 2011/2012 than in 2010/2011. IV regressions with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Only farmers with at least one qualifying farmer in their aggregate networks are included in analysis.

Table A.12 Bidirectional agricultural information links (proportion of in-network adopters)

Dependent variable: Willingness-to-pay 2012 (Rs./hour)	Agricultural information (ag info) contacts		Friends and family (FF)		Ag info contacts or FF	
	(1)	(2)	(3)	(4)	(5)	(6)
Proportion of adopters in network	0.26		27.80		48.75	
	(11.11)		(31.68)		(34.22)	
Proportion of adopters in network (water savers)		77.05**		48.45		82.95***
		(38.01)		(30.54)		(30.58)
Proportion of adopters in network (nonsavers)		–12.71		–20.08		5.37
		(41.12)		(33.95)		(33.54)
# of would-be adopters	47.26		12.29		6.07	
	(36.48)		(12.61)		(9.27)	
# of would-be adopters (water savers)		–8.34		–9.94		–13.73
		(19.40)		(15.44)		(11.44)
# of would-be adopters (nonsavers)		27.74		28.56*		21.22*
		(20.75)		(15.33)		(11.97)
Total network size	0.26	–0.05	–3.39	–2.91	–0.44	–0.63
	(11.11)	(11.05)	(5.35)	(5.31)	(4.77)	(4.71)
Constant	302.49***	307.55***	299.87***	307.38***	297.31***	296.05***
	(27.63)	(25.19)	(23.31)	(20.88)	(22.55)	(20.17)
Observations	208	208	259	259	303	303

Source: Authors.

Notes: Rs. = Indian rupees. "Water saving" denotes using at least 10% less water in 2011/2012 than in 2010/2011. IV regressions with lottery-winning farmers instrumenting for farmers receiving leveling. Standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Only farmers with at least one qualifying farmer in their aggregate networks are included in analysis.

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