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Adoption of Laser Levelers and Water-Saving in Agriculture: Report on a Follow-up Pilot Study*

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February, 2013

Abstract

Water saving agricultural technologies are a potentially important but underutilized lever to conserve groundwater in India. Technologies like laser levelers have high private returns and lead to water savings, yet the adoption rates are not very high. It is often thought that social influence is an important factor in adopting new technologies. This report presents results from a pilot study in which farmers in the Indian state of Punjab were surveyed about their beliefs about, and use of, laser leveling, and about their social networks. This survey is a follow-up to an earlier pilot study exploring similar issues; the earlier study provided valuable information about laser levelers but not about social networks. In the current survey, a revised elicitation procedure is used for social network information, with much greater success.

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1 Introduction

The rapidly declining stock of groundwater for irrigation poses a significant threat to agriculture in India. As a result, there has been great interest in policies that could be used to encourage farmers to adopt various water-saving technologies. This report discusses the results of a pilot study on the adoption of one particular water-saving technology, laser leveling. This pilot represents a follow up to an earlier IGC-funded survey in which over 800 farmers in the state of Punjab were asked about their perceived benefits and obstacles to adopting laser leveling. One of the objectives of that earlier study was to map out the farmers' social networks in order to shed light on the degree to which friends, family, and other contacts influence a farmer's attitudes and adoption decision. However, the network mapping component of this first survey was unsuccessful, and the main objective of the new study reported here was to correct this shortcoming by using a revised methodology to elicit these networks. While this report will largely focus on this new network data, farmers were also asked about their attitudes to and use of laser leveling, their irrigation practices, and their agricultural practices more generally, and headline results on these topics will be reported at the end.

The next two sections provide an abbreviated overview of the background context of the study: we sketch the current situation with agricultural water policy in Punjab, explain the role that laser leveling technology can play, and describe the key elements of our earlier pilot study. (Readers who wish to delve deeper into these topics are encouraged to refer to our earlier report.) After this preamble, we present the new results on social networks from the current study, followed by a summary of other key findings. The report concludes with discussion of options for a large-scale randomized controlled trial testing how social networks can be enlisted to encourage adoption.

2 Background: Water Use and Laser Leveling

While India is the largest user of groundwater in the world (with heavy demand from both agriculture and households), current patterns of groundwater use are not sustainable in the long run. Water tables are falling rapidly, in large part due to the fact that individuals do not bear the cost of the water they use: free water extraction is a property right attached to land ownership, and the electricity needed to pump water to the surface is highly subsidized. If current trends continue, some estimates suggest that national food production could fall by around 25 percent by 2025 (Seckler et al, 1998).

In principle, the best policy to curtail over-extraction would be to price water at its social marginal cost, or barring this, to end the electricity subsidy that makes pumping water effectively free. However neither of these is practical in the short run; the first would require metering and monitoring millions of private wells nationwide, while the latter is politically problematic. Given these limitations, there is a strong argument that policy intervention to encourage the use of water-saving technologies is a logical second-best measure.

Laser leveling is one such technology: in brief, it is a method of smoothing agricultural fields to high precision by using laser guidance. Laser leveling is an "add-on" technology, in the sense that it supplements rather than replaces the traditional method of leveling a field. In traditional leveling, a grading implement with a blade is towed behind a tractor over the surface of a field; the height of the blade is adjusted manually by the operator so as to achieve a surface that appears smooth and level to the human eye. The innovation in laser leveling is to use a laser guidance system to raise and lower the blade of the grading implement automatically. The result is a significantly flatter field than an unaided human operator could achieve. Evidence suggests that the benefits of leveling can be substantial. In controlled experiments on agricultural plots, researchers at Punjab Agriculture University found that laser leveling increases crop yields by around 11 percent and results in water saving of around 25 percent, holding constant other inputs like fertilizers and seed quality. These experiments have also demonstrated that leveling reduces weeds by up to 40 percent and labor time spent weeding by up to 75 percent (Bhatt and Sharma). However, because these results were achieved by academic researchers implementing best practices, it remains to be seen whether real farmers operating in uncontrolled conditions will achieve similar benefits. Assessing this question was one purpose of our study.

2.1 Laser Leveling in Punjab

In Punjab, where both of our studies were conducted, village agricultural cooperative societies play a central role in providing access to laser leveling for farmers. These co-operatives, largely established in the last decade, offer a variety of services to farmers, including equipment rental, seed and fertilizer sales, and short term loans. In the last six years, the state of Punjab has encouraged them, by means of a 30% subsidy on the purchase price, to acquire laser levelers that are then made available for rental by farmers. At present, there are over 2000 laser leveler units in service in Punjab, most owned by cooperatives.[1] While the up-front rental cost to farmers is significant (500 rupees/hr, or roughly 750 rupees/acre), past evidence suggests that the private returns (in higher yield and lower labor costs) are high enough to recoup that investment within one to two years (Jat et al., 2009), and that the benefits of leveling persist for five years or more. Thus, leveling could be a compelling investment for farmers even if they do not internalize the positive externality of reduced water use. Despite its benefits and wide availability, adoption of this technology remains relatively low – in Punjab prior estimates indicate that only one-seventh of all cultivable land has been laser leveled.

2.2 Rental Arrangement

Cooperatives charge 500 rupees per hour for the rental service, or approximately $9 at current exchange rates. Renting a leveler is an all-inclusive service: the cooperative provides all the necessary equipment (the leveler, the grading implement, and the tractor) and the driver; no effort from the farmer is required besides paying the fee. The farmer

[1] There are a relatively small number of private owners, most of whom have large landholdings. For a smaller farmer, purchasing a laser leveler would not be cost effective.

pays only for time spent in-field, not transportation time to and from the field; a typical estimate for the time required to level a field is 1.5 hours per acre. Most cooperatives will own a single laser leveler, so in principle scheduling limitations could prevent some farmers who would like to schedule a rental from doing so; we will discuss evidence on this point below. The purchase cost of a leveler is high enough to make owning one impractical for all but the very largest landowners. While in principle there is nothing to prevent a private market in laser leveler rentals, in practice most rentals appear to take place through the village cooperative.

3 The Earlier Study

The earlier study was based on a survey designed to illuminate farmers' adoption decisions, including the channels through which they learn about laser leveling, the beliefs they hold about the benefits and costs to adoption, and the obstacles to adoption that they face. Going into the survey, we anticipated that two types of obstacle, financial constraints and lack of knowledge about the technology, might be particularly important. Financial constraints would come into play if, for example, small farmers found themselves particularly cash constrained at times just before sowing a new crop, as this happens to be the appropriate time to level one's fields. In other settings, cash constraints around the time of sowing are known to be a problem (Duflo et al., 2010). Alternatively, if farmers are unaware of, or misinformed about the benefits of laser leveling, adoption might be low. Other studies of technology adoption provide some evidence of breakdowns in information flow in this region: farmers complain that they are underserved by official information channels, such as visits from agricultural extension officers and technology demonstrations, and they list neighbors and family as an important source of information about agricultural practices (Jafry, 2007). In particular, small and female farmers were more reliant on socially transmitted information than large farmers were. One focus of our study was to collect information about both official channels and informal social network channels by which farmers learn about new technologies.

4 Study Design

We carried out the first survey in the state of Punjab in India, in the districts of Amritsar and Jalandhar. In addition to the reasons described earlier, Punjab is of interest because it produces a large fraction of the rice grown in India. (The crop yield and water saving benefits of laser leveling are considered to be greater for rice cultivation than for other crops because the typical method of irrigation is to flood the field to a depth of 2.5 to 3 inches.) The study consisted of a survey administered to households in eight villages; the objective was to reach every farming household in each of those villages. The procedure for choosing these villages and the content of the survey are described briefly below.

4.1 Village and Respondent Selection

One objective of the earlier study was to understand why some farmers have adopted laser leveling while others have not. For this reason, one criterion in selecting villages for the survey was to include villages with a range of different adoption rates. A second goal was to study both early-stage (right after the technology has been introduced) and later-stage adoption. Thus, we looked for villages in which the first laser leveler was acquired at different dates.

To make the selection, we obtained a list of all the cooperatives in two districts, Amritsar and Jallandhar, that currently offer laser leveler rental. This list included the date at which each cooperative acquired the leveler, and an estimate of the fraction of land leveled in the village. Using this list, we chose eight villages spanning a range of acquisition dates (from early 2007 through late 2010) and estimated adoption rates. In each village, the goal was to survey all land-owning farmers. In total, we surveyed 856 individual land-owning farmers across the eight villages.

4.2 Results

The results of this first pilot indicated that both financial constraints and poor information act as barriers to the use of laser levelers by farmers in Punjab. Both of these barriers tend to create a divide between farmers with larger landholdings and smaller (and presumably poorer) farmers. It is not surprising that financial constraints hit small farmers harder, but it turns out that larger farmers, particularly those with connections to local government, are also better informed about the benefits of laser leveling. This suggests that a policy intended to promote laser leveler use across farmers of all sizes may need to tailor its approach differently to different socioeconomic groups. Our original plan was to map out social networks in the surveyed villages in order to study how patterns of social relationships relate to patterns of adoption. However, the network mapping was largely unsuccessful; correcting the problems with this mapping was the main purpose of the new study we report on here.

5 Design of the New Study

Our current study was designed to correct problems that arose with mapping social networks during the first pilot. Using a revised network elicitation method, an updated survey was administered to farmers in a different set of villages than those visited previously. The process for selecting villages was similar to the first pilot except that this time villages in three districts, Amritsar, Jallandhar, and Ludhiana, were considered. As before, we chose villages spanning a range of laser leveler acquisition dates and estimated adoption rates, and also as before, the full survey was administered to each land-owning household in a village. In total, the new study comprises five villages with a total of 479 land-owning households.

Except for the changes to the social network module, the content of the survey was largely the same as in the first study, but some questions were streamlined or eliminated to avoid redundancy. One exception is on irrigation practices where a suite of questions were added. One concern behind these questions is that while laser leveling may make it *possible* for a farmer to use less water, these savings will not occur unless he adjusts his irrigation practices. To understand whether this adjustment is likely to happen, it is important to understand the incentives that govern current practices.

5.1 Network Elicitation Methodology

In the earlier pilot, survey enumerators were instructed to ask each respondent to list people within the village with whom he (the farmers are almost universally male) communicated about agricultural matters. There were several difficulties with this approach, which we have sought to respond to in the latest pilot: (1) compliance was poor, in the sense that many respondents did not volunteer any names; (2) while all farming households in a village were surveyed, matching the identities of a respondent's listed contacts to their household surveys proved to be problematic; (3) anecdotal reports suggest that some farmers were reluctant to go "on the record" about seeking farming advice out of a sense of pride; and (4) respondents tended to name people in formal positions, such as the cooperative secretary or shopkeeper, even when the natural answer to the question would be friends or family. On the last point, farmers were asked about their networks after a long series of questions on agricultural practices, so it is possible that they were inadvertently primed to think of more official sources of agricultural information.

In the updated pilot, while the tenor of the questions about social networks was generally similar, the methodology for eliciting responses was rather different. Most importantly, social network information was collected in two stages. In the first stage, prior to the main survey, our enumerators canvassed each village to form a roster of all households, including the names of the head of household and of any other co-resident farmer, with each household assigned a unique numerical identifier. Then, some time later, enumerators returned to carry out the main survey including the questions about social contacts. The roster was brought along, and when network questions were asked, the respondent was encouraged to pick out his contacts from the roster. These contacts were recorded by ID code, ensuring that they could be matched to their own survey responses. This methodology appears to have drastically improved both matching and compliance: farmers volunteer more names and those names appear less likely to be mismatched to the question. Furthermore, we suspected that both issues (3) and (4) above stemmed in part from the long series of agricultural questions at the beginning of the survey which may have induced farmers to filter their social contact responses based on a sense of what the "correct" answers should be. In the updated survey, social contact questions were asked at the beginning of the survey so that respondents would not form preconceptions about how to answer. In addition, language about "relying on others' opinions" was softened to avoid any insinuation about whether the respondent was self-reliant or not.

6 Results

6.1 Summary Statistics About Farmers' Social Network Contacts

This section provides an in-depth look at the social networks in the five villages in which we collected this data. These villages comprise 1227 households in total, approximately 381 of which own land; our social network questions were addressed to these landowning households.

Table 1 provides summary statistics about the average number of contacts reported by each farmer for five types of relationship: relatives, friends, people he spoke to at least five times in the last month ("5X," or "spoken," for brevity), farmers with neighboring plots, people with a reputation (according to the respondent) as knowledgeable and successful farmers. The first four categories involve what we will refer to as two-way relationships, in the sense that one would expect the contact to cite the same relationship with the respondent. For example, if A claims B as a relative, then B's list of relatives should include A. We refer to the last category as a one-way relationship because the fact that A regards B as prominent and respected does not necessarily imply the converse is also true. These five categories are intentionally broad and neutral; except in the last case there is no suggestion that respondents should frame their answers in terms of preconceptions about how agricultural information *should* spread.

The next two questions in Table 1 focus more sharply on how much farmers know about the laser leveling decisions of other in their village. These questions were intentionally asked at the end of the social network module to avoid coloring the responses to earlier questions. Specifically, a farmer was asked who, to his knowledge, had adopted laser leveling before he did (or at all, if the respondent had never adopted), and who had adopted laser leveling after he did. These questions will not prove whether adoption spreads by social influence, but they may be helpful in determining whether this is plausible or implausible. For example, it is harder to argue that farmer B was influenced by farmer A's adoption decision if he does not report knowing about it.

The median number of contacts reported for each category is usually one or two. The median number of people talked to is zero, but this may be because we asked the farmers to identify farmers talked to 5 times in last month which may have been mis-construed. Interestingly, there is relatively little overlap in the contacts a farmer reports for the different types of two-way relationship: the median total number of distinct relatives, friends, 5X contacts, and plot neighbors is seven. This lack of overlap may be genuine, but we cannot be sure – some respondents may have assumed that they were meant to list a contact in only one category, even though they were not told to do this.

The analysis in the next section will take up the question of whether a farmer's decision to adopt laser leveling is influenced by any prior experience that his social contacts have with the technology. Before plunging into this question, it is helpful to have a sense of the general pattern of adoption by a farmer's social contacts. For our purposes here, let us normalize Year 1 for a village to be the earliest year that any farmer in the village reports adopting laser leveling. Figure 1 reports the probability in Year t (where $t = 1, 2, ..., 6$) that a farmer has at least one social network contact who has adopted laser leveling by Year t or earlier. (This trend is labeled as "Any.") On the same figure, we report the same probability broken down by relationship type: that is, the chance that a farmer has at least one relative who has adopted by Year t, or at least one friend, and so forth.

In the first year, only 25% of farmers have any social contact who has adopted, but this percentage rises steadily over time and in the most recent crop season, almost every farmer has such a contact. We see a similar gradual rise in the probabilities of knowing an adopter in each of the relationship categories, but there is a clear difference between social contacts who are prominent, knowledgeable farmers and those in the other categories. At every point in time, contacts who are viewed as prominent and knowledgeable are substantially more likely to have adopted than contacts in the other categories. Furthermore, this gap widens substantially between Year 2 and Year 3 with the other categories catching up gradually, if at all, in later years. Altogether, this would appear to suggest that prominent, knowledgeable farmers may be a particularly critical source of information for others in the early years of the adoption process.

6.2 Peer Effects in the Adoption of Laser Leveling

Our principal motivation for collecting data on farmers' social networks is to study the role that these networks play in spreading word of mouth about laser leveling and convincing farmers to try it. In order to address this question, we will focus on lagged peer effects models in which a farmer's likelihood of adopting laser leveling for the first time may depend on the past adoption decisions of some subgroup of farmers in his village – which we call his reference group – as well as other factors. The premise of such models is that adopters pass on information about laser leveling to those who have not yet adopted and that this additional information can be instrumental in convincing non-adopters to try the technology. For our purposes here, we will be agnostic about the form that this information takes. For example, it may be that adopters talk about their outcomes, such as successful crop yields, water savings, and so forth. Alternatively, it could be that the very fact that they adopted, which reveals their confidence that laser leveling will be worthwhile, is the final straw that convinces others to follow suit.

To illustrate the approach, a very common specification for studying peer effects in technology adoption is the following

$$\Pr\left(i \text{ adopts at time } t \mid \text{has not adopted so far}\right) = f\left(\beta A_{vt-1} + \gamma X_i\right)$$

where A_{vt-1} represents the cumulative fraction of farmers in individual i's village v who had adopted at time $t-1$ or earlier, and X_i is a vector of characteristics of individual i. In order to interpret this as a model of word of mouth, we make the assumption that a farmer interacts more or less uniformly with all of the other farmers in his village. Then we can think of A_{vt-1} as the chance that farmer i interacts with another farmer who has already adopted laser leveling and passes on information that helps to persuade i to adopt. Notice that in this model, a farmer's reference group includes everyone in his village; with this in mind, let us call it the Village Peer Effect model. A second point to note is that we must be cautious in interpreting results from this model – a positive coefficient β could be evidence for the story above, but there are other interpretations that cannot be excluded. For example, it could be that farmers face pressure to conform with typical practices in the village, and so they tend to adopt when A_{vt-1} is large simply to fit in, not because they have learned from past adopters.

Under the model above, social networks do not play any special role in the spread of adoption; in effect, everyone in a village who has already adopted influences farmer i's adoption decision equally. A natural alternative is to suppose that a farmer is influenced only by his social network contacts. Write this schematically as

$$\Pr\left(i \text{ adopts at time } t \mid \text{has not adopted so far}\right) = f\left(\beta \ PeerAdoption_{it-1} + \gamma X_i\right)$$

where $PeerAdoption_{it-1}$ is some summary measure reflecting adoption at time $t-1$ or earlier by farmer i's network contacts. To distinguish this case, we call it the Network Peer Effect model. Recall that in our data, farmers classify their social contacts into five types of relationship: relatives, friends, those spoken to at least five times in the last month, plot neighbors, and farmers regarded as knowledgeable. For our purposes here, we consolidate those categories into a single class: individual j is regarded as a peer of i, written $j \in \{Peers_i\}$, if i lists j as a contact under any of these five relationships.

While there are any number of ways that a farmer could be influenced by his peers' past adoption, we will focus on three plausible specifications of the $PeerAdoption_{it-1}$ summary variable. The first is $PeerAdoptionShare_{it-1}$, which is defined as the fraction of farmer i's peers who adopted laser leveling at time $t-1$ or earlier. The second, $PeerAdoptionNumber_{it-1}$, is simply the total number of peers who adopted at $t-1$ or earlier. Finally, $PeerAdoptionAny_{it-1}$ is an indicator variable equal to 1 if farmer i has at least one peer who adopted by time $t-1$. These variables represent different conceptions of how much evidence a farmer might require to be persuaded that laser leveling is a good idea. The first two, the share and the total number, would be appropriate if farmers require an accumulation of evidence, or information, from different people in order to be convinced to adopt. If all farmers had the same number of contacts, these two variables would be essentially equivalent; to see the difference between them, consider a scenario in which farmer A has 5 peers while farmer B has 10, and the farmers are identical on other dimensions. If each has one peer who has adopted laser leveling, the total number specification stipulates that A and B will be equally likely to adopt, while the share specification stipulates that A will be more likely to adopt since one peer is a larger fraction of his contact list.

In contrast with the other two, the third variable, $PeerAdoptionAny_{it-1}$, would be appropriate if knowing at least one contact who has adopted is the critical element in tipping a farmer's decision, and if additional examples of adoption do not add much additional information. This might make sense if many farmers are already close to adopting and just need an additional nudge; for example, it may be that farmers have heard, and accepted in theory, the claims made about benefits from laser leveling, but they would like to see at least one piece of hard evidence before adopting.

To estimate these peer effects models, we use the Cox proportional hazards specification for the link function f:

$$\Pr\left(i \text{ adopts at time } t \mid \text{has not adopted so far}\right) = h\left(t\right) e^{\beta A_{vt-1} + \gamma X_i + \mu_v}$$

for the Village Peer Effect model, or

$$\Pr\left(i \text{ adopts at time } t \mid \text{has not adopted so far}\right) = h\left(t\right) e^{\beta PeerAdoption_{it-1} + \gamma X_i + \mu_v}$$

for Network Peer Effects. Under this specification, the hazard rate for adoption is the product of a common baseline hazard rate $h\left(t\right)$, which is allowed to have a flexible form and is not estimated, and a shifter term that expresses farmer i's likelihood of adoption relative to the baseline. We also allow for village fixed effects μ_v to capture unobserved factors – for example, a particularly industrious cooperative secretary – that affect all farmers within a village. The survey records date of first adoption by month and year; for our initial specifications, we aggregate so that time t is measured in years. However, because the rice crop season extends over the summer months, there is a qualitative difference between an adoption in April 2010, which occurs in time to have an effect on the 2010 crop, and an adoption in October 2010 whose effects will not be seen until the 2011 crop.

With this in mind, we break each year between July and August: adoptions prior to the break point are attributed to the current year, while later adoptions are attributed to the next year. The vector of farmer characteristics X_i includes total landholdings (in acres), self-reported land quality, indicators for belonging to a scheduled caste and for membership in the cooperative society, age, years of education, and an indicator variable for "government connections." (The latter is equal to one if the farmer reports ties to officials such as the cooperative secretary, local council members, or district and state level officials.)

Regression results are presented first without village fixed effects (Table 4) and then including them (Table 5).[2] In the absence of fixed effects, lagged adoption appears to have a positive and significant effect whether one considers the Village Peer Effect model or the Network Peer Effect models based on the share of prior adopters among one's peers or knowing any prior adopter. (The effect of the number of prior adopters among one's peers is insignificant.) However, we must be cautious in interpreting these results, as the effect that we attribute to peer influence could actually be due to unobserved differences across villages. To illustrate, suppose that Village A has a cooperative secretary who, unbeknownst to us, is unusually enthusiastic about promoting new technology. This fact will tend to make new adoption higher in every time period than we would otherwise expect, based on the observed characteristics of farmers in Village A. Then because high adoption will tend to follow high adoption in Village A, while lower adoption will tend to follow lower adoption elsewhere, the statistical estimation may tend to reconcile this pattern by imputing an inflated, or even spurious, positive effect of lagged adoption on current adoption. By including fixed effects in Table 5, we hope to control for such spurious effects. However, before moving on, let us note some of the other factors that appear to influence adoption. A farmer is significantly more likely to try laser leveling if he owns more land, has government connections, or does not belong to a scheduled caste. Moreover, being younger or being a member of the cooperative society has a significant positive effect on adoption in at least some of the specifications.

We turn next to the specification with village fixed effects in Table 5. One will imme-

[2] All standard errors are clustered at the village level.

diately notice an important change in the Village Peer Effect model: the sign on lagged adoption flips from positive to negative and insignificant. While this is a curious result, it would probably be unwise to make too much of it. Because lagged village adoption A_{vt-1} and the village fixed effect μ_v are both constant across all farmers within a village at time t, the only way to identify an effect of A_{vt-1} separately from μ_v comes from variation within a village over time. However, the time series is not long enough to separate the effects of A_{vt-1} and μ_v with much precision.

The coefficients in the Network Peer Effect models are better identified because farmers within a village have different sets of social contacts, creating within-village variation in the $PeerAdoption_{it-1}$ variables. While the effect of the number of prior adopters among one's peers is small and no longer significant, the effects of the other two variables, $PeerAdoptionShare_{it-1}$ and $PeerAdoptionAny_{it-1}$, remain positive and significant. The most natural way to interpret the coefficients on these variables is through the hazard ratio e^{β}. For example, for the "Peer Any" specification, if there are two otherwise identical farmers, one of whom has has at least one peer who has adopted laser leveling and another who has not, the first farmer will be $e^{\beta} \approx 1.51$ times as likely to adopt as the second one. Most of the other factors that were significant predictors of adoption in Table 4 remain so, and with similar magnitudes, in Table 5; the exceptions are age, which is no longer significant, and cooperative membership, which emerges as a positive and consistently significant factor. While we do not have direct measurements of wealth and social class, the pattern of results strongly suggest that richer, upper class, and better connected farmers are relatively more likely to adopt laser leveling. For example, the coefficient on landholdings, which is consistently in the neighborhood of 0.03, indicates that raising a farmer from the 25$^{\text{th}}$ percentile of landholdings to the 75$^{\text{th}}$ percentile (from 2 acres to 8.5 acres), will raise his likelihood of adopting by a factor of $e^{0.03(8.5-2)} \approx 1.22$.

The results in Tables 4 and 5 suggest that social network structure materially affects the way that knowledge and use of a new technology spread. That is, average behavior in the whole village is not enough to explain who adopts and who does not; one must also look at the individualized information conveyed by each farmer's friends and family. To provide more convincing evidence that this is the case, we estimate hybrid models that include both lagged adoption in the entire village and lagged peer adoption at the same time. We focus on the two peer variables that were consistently significant earlier, Share and Any, and omit village fixed effects to give A_{it-1} its best chance to knock the peer variables out of significance; these estimates are presented in Table 6. In both cases (columns 1 and 2), the effect of one's social network peers remains significant and changes little in magnitude when village-level adoption is included as an explanatory factor, indicating that peers are influential over and beyond the overall trend of adoption in one's village. In column 3 of the table, the two peer effect variables are allowed to compete with each other. In this case, $PeerAdoptionShare_{it-1}$ appears to be a stronger predictor of behavior than $PeerAdoptionAny_{it-1}$: the effect of the latter shrinks and becomes insignificant, while the share of one's peers who have adopted remains positive and significant.

Month by month adoption

One limitation of studying adoption on a year by year basis is that we treat some adoptions as contemporaneous when they really occur in sequence. For example, if two farmers adopt in March and April of the same year, it is reasonable to think that the first farmer's decision might have influenced the second farmer; however, our analysis thus far does not allow for this possibility since the farmers are treated as adopting at the same time. Next, in order to examine how this issue affects our results, we re-estimate some of our earlier specifications treating a month as the unit of time rather than a year; the results are in Table 7. Column 1 includes $PeerAdoptionShare_{it-1}$, column 2 uses $PeerAdoptionAny_{it-1}$, and column 3 includes both. In this month-by-month specification, the relative importance of the two peer effect variables appears to flip: having at least one prior adopter among one's peers is a positive and significant predictor of one's own adoption, both on its own and in concert with $PeerAdoptionShare_{it-1}$. In contrast, the share of prior adopters has the wrong sign and is weakly significant to insignificant. We do not have a compelling explanation for this difference in the results at annual and monthly frequencies; it is probably safest to say that while a farmer's social network contacts have a robust effect on his decision to try laser leveling, the exact functional form of that effect is not conclusively revealed in the data.

Because of the difference in the unit of time, the coefficients in Table 7 cannot be compared directly with their counterparts in the earlier tables. For example, if we use the coefficient on $PeerAdoptionAny_{it-1}$ in column 2 to compute a hazard ratio, we have $e^{\beta} \approx 1.39$. As before, this has the interpretation that having at least one social contact who has used laser leveling boosts a farmer's likelihood of adopting by a factor of 1.39. However, one must remember that this is now the additional likelihood of adopting within the current month; the likelihood of adopting anytime within the next year (that is, the next 12 months beginning with the current one), will presumably rise by an even greater factor. In this sense, the strength of peer effects appears to be greater when measured at a monthly frequency than at an annual frequency. It would be imprudent to draw firm conclusions about why this is true, but we can cautiously speculate. One possibility, as suggested above, is that by overlooking those peers of a farmer who adopted earlier than him, but in the same year, the annual data tends to underestimate peer effects by overlooking one source of influence. If so, the fact that the "annualized" effect of a peer adopter appears to grow so substantially when switching to monthly data may suggest that within-year peer effects are particularly strong. To put this point more plainly, it may be that farmers tend to adopt right after their friends do – perhaps because the idea is fresh in their minds – but that if they do not strike while the iron is hot (so to speak), the potency of the friend's example begins to fade. To examine this hypothesis more carefully would be stretching our existing data rather finely, but it is not inconceivable; for the time being we will leave it as a conjecture.

Which types of relationships matter for adoption?

Thus far, our analysis has proceeded on the implicit assumption that all of a farmer's social network contacts influence him in more or less the same way. However, it may be that certain types of contacts – prominent, knowledgeable farmers, for example – are particularly influential sources of information about laser leveling, while other types of contact matter relatively less. Because our data include the nature of the relationship between farmer and contact, we can examine this hypothesis. Our results here expand on the "any peer" specification in the monthly data just discussed. For each of the five relationship categories, relative, friend, spoken to at least five times in the last month, plot neighbor, or prominent, or knowledgeable farmer, we create a dummy variable equal to one if a farmer has a contact in that category who has already adopted. For example, $FriendAny_{it-1}$ will be equal to one if farmer i has at least one friend who adopted at time $t-1$ or earlier. Table 8 presents peer effects specifications including $PeerAdoptionAny_{it-1}$ with each of these relationship dummies individually (columns 1-5) and all together (column 6). If prior adoption by a certain type of social contact carries relatively more weight, this should show up in a positive and significant coefficient on the appropriate dummy. As the table demonstrates, the significant positive effect of having at least one prior adopter among one's peers is robust, and its size hardly changes across the specifications. However, we find no evidence that the nature of one's relationship with a prior adopter matters: all of the relationship coefficients in columns 1-5 are small and (with one exception) insignificant. The story is essentially the same when we compare all five relationship types at once. In both cases, the single exception is the significant negative coefficient on $SpokenAny_{it-1}$, suggesting that word of mouth from farmers spoken to frequently in the last month may be somewhat less influential than other sources.

Does the influence of social networks vary with farmer size?

The fact that larger farmers (those with more land) adopt laser leveling at higher rates is a very consistent thread running through the results reported so far. As discussed elsewhere, a farmer's landholding size is likely to be correlated with a number of other characteristics of interest that we do not observe (or observe imperfectly), such as his wealth, entrepreneurial spirit and openness to new technology, and access to official information channels and credit markets. Since large and small farmers are likely to differ on all of these dimensions, it is natural to ask whether they also differ in the extent to which they rely on peer networks for guidance about adopting laser leveling. We classify farmers with less than five acres, five to ten acres, or more than ten acres as small, medium, or large, respectively. Since the effect of other factors in adoption may also vary with farmer size, we split the data based on whether a farmer is small, medium, or large and run three separate regressions of the "any peer" specification from Table 7; the results are in Table 9. The most striking fact is how consistent the size of the peer effect is: the coefficient on $PeerAdoptionAny_{it-1}$ is 0.419, 0.423, or 0.349 for small, medium, or large farmers, respectively. This effect remains statistically significant for large and small farmers (but not for those of medium size).

This evidence suggests that, for practical purposes, the mechanism by which small and large farmers learn about laser leveling from their social network peers may not be that different.

Not too surprisingly, the effect of landholdings drops out of significance in two out of the three regressions, suggesting that shifting within the small, medium, and large categories is not as important for adoption as shifting between them. Many of the other variables that showed consistent effects in earlier regressions become more scattered and insignificant here – for example, scheduled caste and cooperative society membership, and to a lesser extent, government connections. We take this as an indication that many of these variables are fairly strongly correlated with land and social status; among farmers who are already stratified, they lose some of their predictive power.

6.3 The Shape of Social Networks: Stylized Facts

This section uses the example of one village, Taka Pur, to illustrate the overlapping layers of connections that link farmers together in different types of relationship. Diagrams representing these networks are presented in Figures 2, 3, and 4.

Figure 2 illustrates the network of prominent farmers; an arrow leads from A to B if farmer A listed B as someone with a reputation for being knowledgeable and successful. The most striking feature of the diagram is the extent to which respondents agree on who is prominent: the overwhelming majority of links point to just four individuals, and roughly 60% of the citations go to just two people. This data cannot tell us whether this handful of prominent farmers exerts a strong influence on the behavior of others in the village, but it alerts to the fact that this is possible. This is a feature to take into account in designing policy interventions. On the positive side, convincing a few influential individuals to adopt laser leveling may be an efficient way to persuade many others to consider it as well. On the other hand, the fact that many different farmers in a village are all influenced by the same opinion-makers can be a confounding factor for statistical analysis.

Figure 3 illustrates the network of friends. Several features are worth noting. First, the network is fragmented into six disconnected components. One of these is quite large, comprising around 60% of the respondents, while the others are small (2-5 people each). We do not wish to overemphasize the importance of fine details of this structure, in part because if respondents forgot to report some friendships, the network could be more connected than it appears. However, it appears safe to say that some individuals are more tightly knit into a dense web of contacts, while others tend to be more peripheral. It would be a natural conjecture that the former are likely to be more exposed, and the latter less exposed, to information about new technologies like laser leveling – this is a question we plan to examine in the data.

A third point is illustrated by the circled individual, Kashmir Singh. Not coincidentally, Mr. Singh is also the most frequently cited prominent farmer in Figure 2. In the friendship network, he functions as something like a linchpin: if he were to be removed from the network, the large connected component would dissolve into three separate pieces. (He is not the only such individual; for example, Malkeet Singh and Rajwant Singh play similar roles.) Notice that this role does not depend on him having a particularly large number of friendship links; in fact he has only three incoming links. Instead, the key is that he connected to a number of different social circles. One conjecture, which we hope to test, is that individuals like Mr. Singh can be particularly efficient at spreading information precisely because they can reach a broad swathe of the population with relatively few links.

A more troubling point in Figure 3 is that most of the links are reported by only one party. That is, A reports B as a friend, denoted by an arrow from A to B, but B does not mention A. There are a few potential explanations for this puzzle, all of which require further investigation. One possibility is that B reports A as a contact in a different category. Another possibility is that the elicited friendship lists are incomplete because respondents forgot or declined to mention some friends. A third possibility is that friendship should not be regarded as automatically reciprocal: A and B may take different views of how close they are. A common simplification in network modeling, partly motivated by the latter two explanations above, is to assume that both reciprocated and unreciprocated friends are valid contacts, but that they represent stronger and weaker relationships respectively.

Figure 4 presents the network of people talked to at least five times in the last month. Just as in Figure 3, there are six separate components, but their sizes are more balanced. Interestingly, the individuals who appeared to be linchpins in the friendship network do not play a particularly central role here.

With the use of specialized software for social network analysis, we begin to explore if there are regularities in the structure of the networks. We illustrate this by way of an example using the network information for most prominent farmers in the three villages we surveyed after our interim report was submitted. The three villages are -Khalra, Giddar Pindi and Sarhal Mandi. Figures 5, 6, and 7 show four pieces of information for these three villages separately. First, we show an overall map of the network in which we include the adoption and non-adoption status of the node. The green triangles indicate that the node (farmer) has not adopted laser leveling yet whereas the blue rectangle indicates that the node has adopted laser leveling already. The size of the symbol indicates the in-centrality of the node. In centrality refers to how many nodes are pointing to the node. In other words, how many farmers report that this farmer is a prominent farmer/person in the village. Second, we show the distribution of the in-degree centrality. This index for every node is calculated as a fraction of total nodes that point to the node in the network. Third, we show summary statistics for the in-degree and out-degree centrality (fraction of nodes that point out of the node). The summary measures shown are mean, standard deviation, minimum, and maximum. Finally, we also zoom into the center of the map so as to show the relationships more clearly.

Consistent with the findings in Taka pur, we find that there are a few prominent farmers identified in each village as shown in the maps in Figures 5, 6 and 7. This prominence is indicated by the size of the symbol for the node. The larger the symbol, more prominent the node. The histogram further helps us to see that in each of these three villages, about nine nodes have a centrality measure greater than 0.02. Majority of the nodes have a very small centrality measure. We also observe from the summary statistics that the average centrality measure is roughly the same. These networks statistics are very similar across the villages. We can use this to our advantage and design an intervention in which these prominent farmers are identified and then put in the center stage of information sharing. If locally delivered information from people who are considered prominent is more salient tot he farmers, this can induce multiplier effects in adoption. One additional point that stands out is that the prominent farmers are more likely to be adopters. From the center view of Figure 5, we see that there are some non-adopters as well, but majority have adopted. This is suggestive that these farmers are more entrepreneurial with their farming practises. We hope to explore the characteristics of such farmers to develop a treatment arm where we can leverage the adoption of such farmers by providing them incentives to spread information.

6.4 Other Notable Results

This section summarizes some of the other notable results from the new study.

6.5 Irrigation Practices

Besides the change in social network methodology, the second major innovation of the updated survey involved a more detailed suite of questions about how the respondents use water in irrigation. The objective of these questions was to understand with greater specificity the incentives that farmers face to conserve water. These incentives are interesting in their own right, and they cast light on the question of whether adoption of laser leveling will translate into water savings.

6.5.1 Time Trends

First, in order to understand trends over time, respondents were asked about their past and current irrigation practices. Because of changes in rural electricity policy over the last 15 years, which we sketch briefly below, farmers arguably face a lower marginal cost for water than they used to, and as we shall see, this is reflected in how they irrigate. Beginning in 1997, there have been three important policy changes regarding electricity. First, in 1997, the government announced that electric power would be made free for the agricultural sector, with an undertaking to supply roughly 6-8 hours of power per day.

(Previously farmers had paid a flat rate for power.) In practice, the supply of power turned out to be somewhat irregular from day to day. Another policy initiative in 2006 stipulated that transplantation of rice plants should begin no earlier than June 10. This measure was aimed, at least in part, at water conservation, as complying farmers would presumably begin irrigation somewhat later in the year than they had previously done. As a carrot to encourage compliance, guarantees were made that farmers would receive more reliable power supply from June 10 on. Finally, the third policy change, in 2008, was the passage of this second measure into law with enforcement provisions: farmers caught transplanting their plants before June 10 could now be fined.

With these changes in mind, our retrospective questions asked farmers about their irrigation practices in 1996, 2005, 2008, and the most recent paddy season, 2012 – in other words, before and after each policy change. The main effect of the first change would appear to be a clear reduction in the marginal cost of pumping irrigation water. The effects of the second and third changes are less straightforward, as compressing the irrigation period could induce farmers to use less water, if their irrigation practices stayed the same, or more water, if they began to use water more intensively during the shorter window of electricity availability.

Table 2 presents trends in irrigation practices, grouped into three categories, among the survey respondents who were actively farming in each year. The third category includes farmers who reported actively managing their pumps, turning them on and off as needed and in response to electricity availability, in order to reach a target level of water flow each day. The first two categories reflect progressively more hands-off management. Farmers in category 2 reported leaving pumps turned on all night, so as to get the benefit of any night-time power, while occasionally shutting them off during the day if a plot had gotten enough water. Farmers in category 1 report a completely hands-off policy of leaving pumps on all the time, day and night, so as to use electricity whenever available. Roughly speaking, these categories represent a continuum of water usage ranging from using no more than necessary to using whatever is available.

The pattern in Table 2 is clear and striking. Before the first policy change, in 1996, 65% of farmers were careful targeters and only 12% were "on all the time" types. By the most recent paddy season, the fraction of "on all the time" irrigators had almost quadrupled to 45%, while the share of careful targeters dropped to 52%. Given the change in incentives, this trend is not altogether surprising, as when electricity is free, there is little reason to economize on its use.

There are two main points to take away from this trend. The first is that a sizable minority of farmers may have become accustomed to not monitoring their water usage very carefully. For this minority, adopting laser leveling may not lead to water savings unless these farmers reassess their irrigation practices after adopting.

The second point is that, despite free electricity, the majority of farmers appear to be monitoring, and self-limiting, their water usage. For this majority, we can be more confident that laser leveler adoption should lead to water savings. In the next section we present evidence about some of incentives that induce farmers to self-limit.

6.5.2 Incentives to Conserve Water

As discussed above, subsidized electricity shields farmers from a major component of the true marginal cost of irrigation. However, farmers face other irrigation costs that create incentives to conserve water.

First, it is not generally true that rice crop yields always improve with additional irrigation; instead, there is some optimal target range of irrigation. If laser leveling reduces this target range, then adopters should prefer to use less water even in the absence of other marginal irrigation costs. For rice cultivation, the natural way to think about an irrigation target is the depth to which a plot should be flooded, in inches. Our surveyed farmers are in general agreement about what this depth should be: 85% of them suggest 3-4 inches.

This consensus appears at odds with the evidence above that some farmers seem content to use as much water as possible. One possible explanation is that farmers believe that over-watering is less harmful than under-watering. With this in mind, we asked respondents about how much harm over- and under-watering cause for one's crop yield. On a four point scale, ranging from "not at all" to "severe," farmers rated over-watering roughly one-third of a point less harmful than under-watering (2.95 vs. 3.28), a small but statistically significant difference. To frame this a bit differently, farmers are almost twice as likely to believe that under-watering is more harmful than over-watering than to believe the reverse (168 responses, vs. 89). (The remaining 76 respondents, out of 333 in total, believe that they are equally harmful.) The fact that many farmers are *relatively* less concerned about over-watering may partially explain why some use "always on" irrigation policies. However, the overall average of 2.95 out of 4 indicates that many farmers do treat over-watering seriously, suggesting that laser leveling may induce some water savings for this reason alone.

A second irrigation cost for some farmers is diesel fuel. While farmers will run their pumps using free electricity as long as it is available, depending on the frequency of power outages and on the farmer's irrigation needs, this free electricity may not suffice. When this is the case, farmers will typically switch their pumps over to diesel power. (This involves hooking the pumps up to generator/alternator equipment which is either owned, or in some cases, rented.) Because farmers who use diesel fuel must pay for it out of pocket, this raises their effective marginal cost of irrigation. Consequently, one might expect these farmers to be more responsive to opportunities to conserve water. In our survey, just over half of the farmers (52%) used diesel fuel at least once during the 2012 rice season. Table 4 breaks down the patterns in diesel usage for farmers with small (up to 5 acres), medium (5-10 acres) and large (more than 10 acres) landholdings. Farmers with more land are more likely to resort to diesel, with the usage rate rising to two-thirds for large farmers. This may reflect the fact that, holding the pump flow rate constant, more pumping time is needed to irrigate larger plots, implying that large farmers may be less likely to be satisfied with pumping only when electricity is available. Alternatively, it may be that some smaller farmers would like to supplement with diesel power but are deterred by the cost.

Among those farmers who used diesel at least once, the average consumption for the season was 177 liters. The final two rows of the table carry out a thought experiment. First, suppose that a farmer spreads his diesel pumping uniformly across all of his plots; if this were true, the 177 liters of total usage would correspond to 30 liters per acre. Next, we estimate the cost of that fuel at the current diesel price in Jalandhar, the district capital, which is approximately 75 Rs/liter. This implies an average expenditure of 2,228

Rs/acre among farmers who use diesel. For comparison, this is quite close to the average amount spent on seed and fertilizer per acre. Recall also that laser leveler rental costs around 750 Rs/acre. Thus, we estimate that a typical farmer using diesel could recover the cost of laser leveling in one year alone, based on fuel savings alone, if adopting enabled him to reduce diesel pumping by at least 34% (750/2,228). If the cost of leveling were amortized across two years (which is still conservative, as re-leveling is only needed every 2-3 years), then diesel savings of at least 17% would suffice to recover that cost.

Such savings are not unreasonable to expect. If we impute a 34% (or 17%) reduction in total hours of diesel pumping (101 hours, on average), the necessary reduction would be 34 hours (17 hours, respectively). Farmers report total pumping (electric and diesel) of approximately 420 hours per season (30 hours per week, for approximately 14 weeks). Clearly, any potential water savings would be applied toward reducing diesel pumping first, rather than electric. For a diesel user, if laser leveling could supply potential water savings of at least 8% (34/240), this would suffice to pay off its costs in just one year, disregarding other benefits including increased crop yield. Similarly, water savings of at least 4% would pay back the investment in two years. Since laser leveling has produced water savings of around 25% on experimental test plots, savings of 4-8% in the field are not *prima facie* unrealistic.

These considerations suggest that for the majority of farmers who use diesel fuel, the prospect of saving on fuel costs should provide a relatively strong incentive to adopt laser leveling and exploit its potential water savings.

6.6 Laser Leveling: Beliefs and Outcomes

Our earlier study indicated that farmers who have not tried laser leveling have systematically different beliefs about its merits than farmers who have used it. Our current survey provides much more limited evidence that this is the case. Table 10 summarizes adopters' and non-adopters' beliefs about whether laser leveling has benefits along five outcome dimensions. The differences in beliefs are smallest along dimensions that one might expect to be widely known: 100% of adopters and 96% of non-adopters believe that laser leveling reduces irrigation time and saves water, while non-adopters are only slightly less likely to believe that laser leveling increases crop yields (86% vs. 95%). Fewer in each group believe there are benefits for weeding time (34% among adopters vs. 31% among non-adopters). The largest difference in beliefs has to do with savings in labor time which adopters are substantially more likely to believe in (49%) than non-adopters (35%). Of course, agreement about the existence of a benefit does not necessarily imply agreement about how large that benefit is, so to some extent these binary responses may overstate the similarity between adopters and non-adopters.

Furthermore, as hinted at by the fraction of "Don't know" responses, non-adopters may be relatively uncertain (compared to adopters) about the magnitude of potential benefits. We have some evidence on these magnitudes because adopters were asked to quantify a number of key farming inputs and outputs before and after laser leveling. Table 11 reports the average percentage change in these variables after adopting. Adopters report crop yield improvements of 12.3% for rice and 12.1% for wheat, both of which are highly significant in t-tests. Furthermore, this average gain comes with little downside risk: farmers at the 10$^{\text{th}}$ percentile of the yield change distribution still made gains of 3.8% for rice and held even (0%) for wheat. Furthermore, adopters benefited from lower input costs. Conditional on using diesel fuel, a farmer needed 25.4% fewer liters after laser leveling, while irrigation labor costs declined by 27.4%.

We can make a conservative estimate of the monetary return to an adopter from the increase in the rice crop alone. Prior to laser leveling, an average plot produces approximately 2300 kilograms per acre, so the average gain after laser leveling is roughly 283 kg. Evaluated at the median sale price of 12 rupees/kg, this amounts to a one year gross return of 3400 rupees, or more than four times the cost of laser leveling one acre of land.

7 Concluding Remarks

An ultimate goal of the pilot study reported here, and of our earlier pilot, is to provide insight about whether, and how, pre-existing social networks can be effectively used to promote the adoption of water-saving technologies like laser leveling. With this in mind, we will close by summarizing the key findings reported here and discussing the implications of those findings for the design of a larger scale intervention.

Our analysis of adoption decisions in these villages reveals the following:

1. Lagged adoption by peers does appear to influence a farmer's own decision to adopt laser leveling. Although causality cannot be established definitively, we consider this persuasive evidence that information flow along social networks plays some role in spreading this technology.

2. However, knowing adopters does not guarantee that a farmer will try laser leveling himself. By the time of the most recent year in our data, virtually every farmer (98%) has at least one social contact who has adopted, but around 40% of farmers remain non-adopters. One would like a more detailed understanding of why they hold out: for example, are they credit constrained, do they have land that genuinely is not suitable for laser leveling, or is there some reason that they require more convincing evidence than others do? In particular, do some farmers require hands-on evidence of benefits on their own land before investing in laser leveling?

3. Two-thirds of farmers report borrowing to finance inputs, and the amounts borrowed are often more than comparable with the cost of laser leveling. (For example, the median amount borrowed for fertilizer, 10,000 Rs, would fund laser leveling of over 13 acres.) This suggests that while credit constraints may bind for some farmers, they are unlikely to provide a full explanation for incomplete adoption of laser leveling. Thus it makes sense to take a closer look at limited information flow as a complementary explanation.

4. Influence by peers is a black box in our data. If one grants that the effect we measure represents learning from prior adopters, we still cannot say which elements of that learning process are critical to triggering new adoptions. It may be that the evidence that convinces a farmer to adopt is as slight as simply knowing the fact that others have adopted, or as substantial as observing their crop yield and irrigation results with his own eyes. One of the goals of an intervention should be

to monitor the information flow among peers in more detail in order to clarify the channel of persuasion more precisely.

5. We do not find evidence that a farmer's adoption decision is influenced by the type of relationship he has – such as relative or plot neighbor – with a social contact who has adopted earlier. It may still be the case that prominent, knowledgeable farmers create larger spillover effects on others when they adopt, but if so, this is because they tend to adopt earlier and are more widely observed, not necessarily because their example is more convincing than that of other farmers.

Based in large part on these observations, we recommend that any large scale intervention incorporate the following features and objectives:

1. Test the relative importance of 'Learning from Others' versus 'Learning from Own Experience' in persuading farmers to adopt laser leveling. One way to test for the importance of own experience would be to subsidize adoption on part of a farmer's land and then monitor whether this exogenous intervention makes him more likely to invest in laser leveling on the rest of his land than a farmer who did not receive the subsidy.

2. Test which specific information about laser leveling is critical to convincing farmers to adopt. For example, while water savings are important to the community's long run well-being, reliable and significant increases in crop yield offer an immediate and tangible benefit to individual farmers. We conjecture that interventions that emphasize and quantify this crop yield benefit may be particularly effective at encouraging adoption.

3. Test how concrete evidence must be to be convincing. In order to do this, an intervention would need to monitor subtle distinctions in the information that flows between peers; for example, an intervention should be able to distinguish between a farmer who is told about peers' positive results and one who sees peers' positive results firsthand.

4. Test whether simple interventions that work in concert with pre-existing social networks can improve their success rate in disseminating information. Such interventions might include collecting information about the experience of network contacts to post in a central, public forum, reminding farmers about their peers' experience more frequently, or creating small incentives to talk to one's peers about laser leveling.

5. Carefully quantify the size of benefits from adoption of laser leveling, particular any improvement in crop yields and water savings in irrigation. While our pilot studies have provided estimates of crop yield improvements, these are based on farmers' memories of outcomes in past years, and so they may be subject to some recall error. Measuring crop yields year by year in a panel study would alleviate this concern. Our survey evidence on irrigation practices suggests that some farmers who adopt laser leveling (the "hands on" irrigators) will probably save water as a direct result, while others may not save water at all unless they change their habits about leaving pumps running. Since externalities to do with water use are the main justification for any policy intervention to promote laser levelers, measuring water savings will be a critical element of any such intervention.

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Tables and Figures

Table 1: Number of contacts per respondent

Type of contact	Mean	Median	90th %
Relative	1.2	1	3
Friend	1.62	2	3
Talked to 5+ times in last month	0.73	0	2
Plot neighbor	0.96	1	3
Total unique contacts	6.2	7	12
Viewed as knowledgeable	1.6	2	3
Adopted LL *before* respondent	0.75	0	3
Adopted LL *after* respondent	0.33	0	2

Table 2: Trends in Irrigation Practices

Irrigation Practice	1996	2005	2007	Most Recent
Pumps always on to use elec. whenever available	11.7%	28.7%	40.2%	45.0%
Pumps on all night; sometimes turn off during day	23.4%	11.5%	3.9%	3.5%
Pumps on or off to hit target water level each day	65.0%	59.8%	55.9%	51.5%

Table 3: Diesel usage, by landholding size, for 2012 season

Column1	Small	Medium	Large	Overall
Fraction using diesel	42.9%	57.6%	66.2%	52.4%
Among those using diesel:				
Mean total hours of pumping	68.1	83.1	168.3	101.2
Mean liters of diesel used	120.3	142.1	294.3	177.2
Liters per acre of landholdings	45.5	19.9	16.8	29.7
Estimated cost/acre (at 75 Rs/liter)	3,412	1,494	1,258	2,228

Table 4: Hazard rate of laser leveler adoption (village and network peer effects)

	(1) Village	(2) Peer Share	(3) Peer Number	(4) Peer Any
Village_AdoptionShare_t-1	2.402***			
	(2.61)			
Peer_AdoptionShare_t-1		1.607***		
		(3.30)		
PeerAdoptionNumber_t-1			0.053	
			(0.78)	
PeerAdoptionAny_t-1				0.488*
				(1.90)
Landholding (acres)	0.029***	0.034***	0.032***	0.033***
	(6.19)	(4.29)	(4.46)	(3.85)
Land Quality	-0.091	-0.085	-0.14	-0.125
	(-1.37)	(-1.01)	(-1.17)	(-1.10)
SC Caste	-0.714***	-0.721**	-0.623**	-0.668**
	(-2.66)	(-2.41)	(-2.08)	(-2.28)
Cooperative Member	0.264**	0.191	0.206	0.209
	(2.57)	(1.46)	(1.33)	(1.45)
Age	-0.009	-0.011*	-0.012**	-0.013**
	(-1.51)	(-1.79)	(-2.11)	(-2.00)
Education (yrs)	0.006	-0.011	-0.01	-0.013
	(0.66)	(-0.90)	(-0.76)	(-0.80)
Govt. Connections	0.512***	0.581***	0.630***	0.647***
	(4.92)	(3.36)	(3.16)	(2.88)
N	2329	2044	2044	2044

t statistics in parentheses; errors clustered by village; * p<0.10, ** p<0.05, *** p<0.01

Table 5: Hazard rate of laser leveler adoption (with village fixed effects)

	(1) Village	(2) Peer Share	(3) Peer Number	(4) Peer Any
Village_AdoptionShare_t-1	-3.133			
	(-1.36)			
Peer_AdoptionShare_t-1		1.100***		
		(3.40)		
PeerAdoptionNumber_t-1			-0.032	
			(-0.54)	
PeerAdoptionAny_t-1				0.413**
				(2.07)
Landholding (acres)	0.028***	0.029***	0.028***	0.027***
	(8.36)	(7.34)	(7.66)	(6.41)
Land Quality	-0.056***	-0.009	-0.040***	-0.038***
	(-6.66)	(-0.36)	(-8.07)	(-3.53)
SC Caste	-0.743***	-0.800***	-0.749***	-0.771***
	(-2.65)	(-2.71)	(-2.60)	(-2.68)
Cooperative Member	0.317***	0.243***	0.316***	0.278***
	(8.12)	(5.54)	(15.74)	(10.26)
Age	-0.006	-0.006	-0.006	-0.006
	(-0.75)	(-0.70)	(-0.67)	(-0.66)
Education (yrs)	0.02	0.014	0.02	0.018
	(1.25)	(0.94)	(1.12)	(1.09)
Govt. Connections	0.375***	0.404***	0.404***	0.391***
	(5.46)	(7.62)	(7.25)	(5.49)
Village 2	1.660***	1.048***	1.194***	1.192***
	(3.85)	(14.16)	(69.62)	(20.54)
Village 3	-0.201	0.367***	0.211***	0.384***
	(-1.40)	(10.13)	(4.08)	(4.13)
Village 4	-0.521**	0.215**	-0.027	0.16
	(-2.31)	(2.38)	(-0.17)	(1.21)
Village 5	-2.122***	-0.738***	-1.098***	-0.892***
	(-2.78)	(-4.79)	(-4.56)	(-5.36)
N	2329	2044	2044	2044

t statistics in parentheses; errors clustered by village; * p<0.10, ** p<0.05, *** p<0.01

Table 6: Adoption with both village and network effects

	(1) Village + Peer Share	(2) Village + Peer Any	(3) Peer Share + Any
Village_AdoptionShare_t-1	1.09	2.098**	
	(1.40)	(2.38)	
Peer_AdoptionShare_t-1	1.367***		0.980***
	(4.57)		(3.18)
PeerAdoptionAny_t-1		0.381*	0.179
		(1.83)	(0.91)
Landholding (acres)	0.033***	0.031***	0.029***
	(4.99)	(4.85)	(7.13)
Land Quality	-0.072	-0.09	-0.012
	(-1.11)	(-1.27)	(-0.51)
SC Caste	-0.737**	-0.714**	-0.807***
	(-2.54)	(-2.57)	(-2.73)
Cooperative Member	0.227**	0.269***	0.239***
	(2.05)	(3.02)	(6.05)
Age	-0.01	-0.01	-0.006
	(-1.64)	(-1.58)	(-0.68)
Education (yrs)	-0.005	-0.001	0.014
	(-0.52)	(-0.05)	(0.93)
Govt. Connections	0.541***	0.543***	0.399***
	(4.20)	(4.13)	(6.64)
Village 2			1.067***
			(11.85)
Village 3			0.416***
			(4.54)
Village 4			0.253*
			(1.95)
Village 5			-0.715***
			(-4.14)
N	2044	2044	2044

t statistics in parentheses; errors clustered by village; * p<0.10, ** p<0.05, *** p<0.01

Table 7: Hazard rate of adoption with monthly data

	(1) Peer Share	(2) Peer Any	(3) Share + Any
Peer_AdoptionShare_t-1	-0.105		-0.486*
	(-0.36)		(-1.73)
PeerAdoptionAny_t-1		0.327***	0.489***
		(3.28)	(6.30)
Landholding (acres)	0.026***	0.028***	0.026***
	(7.33)	(6.45)	(5.97)
Land Quality	-0.011	-0.025***	-0.021
	(-0.29)	(-2.64)	(-0.61)
SC Caste	-0.792***	-0.816***	-0.823***
	(-2.97)	(-2.63)	(-2.87)
Cooperative Member	0.278***	0.319***	0.265***
	(4.37)	(8.15)	(4.25)
Age	-0.007	-0.006	-0.007
	(-0.85)	(-0.69)	(-0.80)
Education (yrs)	0.023	0.024	0.024
	(1.28)	(1.22)	(1.26)
Govt. Connections	0.505***	0.382***	0.497***
	(10.35)	(5.11)	(8.75)
Village 2	1.541***	1.278***	1.580***
	(16.65)	(18.77)	(17.38)
Village 3	-0.484***	-0.646***	-0.243***
	(-5.59)	(-8.59)	(-2.94)
Village 4	-0.711***	-0.920***	-0.501***
	(-4.62)	(-7.09)	(-3.38)
Village 5	-1.827***	-1.953***	-1.659***
	(-7.87)	(-9.50)	(-6.84)
N	21675	22055	21675

t statistics in parentheses; errors clustered by village; * p<0.10, ** p<0.05, *** p<0.01

Table 8: Peer effects by type of relationship

	(1) Relative	(2) Friend	(3) Spoken to	(4) Neighbor	(5) Knowledgable	(6) All
PeerAdoptionAny_t-1	0.320***	0.372***	0.341***	0.327***	0.424*	0.553*
	(2.69)	(4.61)	(3.51)	(3.19)	(1.90)	(1.86)
RelativeAny_t-1	0.03					0
	(0.15)					0.00
FriendAny_t-1		-0.131				-0.188
		(-0.82)				(-1.09)
SpokenAny_t-1			-0.110***			-0.152***
			(-4.12)			(-3.88)
NeighborAny_t-1				0.001		-0.028
				(0.01)		(-0.18)
KnowledgableAny_t-1					-0.173	-0.244
					(-0.60)	(-0.75)
Landholding (acres)	0.028***	0.027***	0.028***	0.028***	0.028***	0.028***
	(6.64)	(5.84)	(6.57)	(6.35)	(6.70)	(6.56)
Land Quality	-0.026***	-0.029***	-0.032***	-0.025*	-0.007	-0.013
	(-3.81)	(-4.30)	(-3.92)	(-1.78)	(-0.21)	(-0.28)
SC Caste	-0.818***	-0.820***	-0.837***	-0.815***	-0.782***	-0.813***
	(-2.84)	(-2.75)	(-2.76)	(-2.72)	(-3.00)	(-4.00)
Cooperative Member	0.317***	0.322***	0.325***	0.319***	0.312***	0.320***
	(9.72)	(8.85)	(6.99)	(8.42)	(7.44)	(9.15)
Age	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006
	(-0.67)	(-0.68)	(-0.69)	(-0.71)	(-0.71)	(-0.68)
Education (yrs)	0.024	0.026	0.025	0.024	0.022	0.026
	(1.08)	(1.43)	(1.28)	(1.18)	(1.25)	(1.27)
Govt. Connections	0.384***	0.380***	0.375***	0.382***	0.382***	0.373***
	(4.77)	(5.14)	(5.13)	(4.77)	(5.08)	(4.87)
Village 2	1.266***	1.260***	1.279***	1.278***	1.274***	1.246***
	(9.44)	(16.23)	(18.61)	(18.37)	(20.68)	(7.85)
Village 3	-0.653***	-0.650***	-0.638***	-0.645***	-0.666***	-0.675***
	(-11.19)	(-8.42)	(-8.55)	(-9.55)	(-6.99)	(-7.97)
Village 4	-0.922***	-0.931***	-0.910***	-0.920***	-0.941***	-0.956***
	(-8.11)	(-7.42)	(-7.07)	(-7.86)	(-5.84)	(-6.66)
Village 5	-1.949***	-1.993***	-1.954***	-1.953***	-1.985***	-2.065***
	(-8.48)	(-9.74)	(-9.56)	(-11.14)	(-7.96)	(-7.15)
N	22055	22055	22055	22055	22055	22055

t statistics in parentheses; errors clustered by village; * p<0.10, ** p<0.05, *** p<0.01

Table 9: Hazard rate of adoption, by landholding size

	(1) Small	(2) Medium	(3) Large
PeerAdoptionAny_t-1	0.419***	0.423	0.349**
	(3.36)	(1.38)	(2.02)
Landholding (acres)	0.156	0.097***	0.006
	(1.21)	(4.03)	(1.21)
Land Quality	-0.165	-0.186	0.085
	(-0.67)	(-1.34)	(0.67)
SC Caste	-1.039**	-0.132	
	(-2.17)	(-1.53)	
Cooperative Member	0.172	-0.033	-0.052
	(0.81)	(-0.12)	(-0.21)
Age	-0.003	-0.001	-0.013
	(-0.20)	(-0.14)	(-0.84)
Education (yrs)	-0.006	0.036***	0.025
	(-0.17)	(5.36)	(0.42)
Govt. Connections	0.397	0.714***	-0.029
	(1.43)	(3.30)	(-0.11)
Village 2	1.061***	22.035	1.007***
	(6.83)	.	(3.48)
Village 3	-2.041***	20.614***	-1.209***
	(-5.22)	(46.66)	(-10.91)
Village 4	-2.370***	20.106***	-1.216***
	(-14.63)	(48.66)	(-4.47)
Village 5	-3.709***	19.487***	-1.121***
	(-31.35)	(45.44)	(-3.14)
N	11162	7121	3772

t statistics in parentheses; errors clustered by village; * p<0.10, ** p<0.05, *** p<0.01

Table 10: Beliefs about benefits of laser leveling

Believe benefit for:		Crop yield	Irrigation time	Water savings	Weeding time	Labor savings
Adopters	Yes	95%	100%	100%	34%	49%
	No	5%	0%	0%	66%	51%
	Don't know	0%	0%	0%	0%	0%
Non-adopters	Yes	86%	96%	96%	31%	35%
	No	8%	1%	1%	61%	57%
	Don't know	6%	4%	3%	8%	8%

(Note: numbers may not add to 100% due to rounding.)

Table 11: Reported changes in inputs and outputs after laser leveling

	Rice Yield	Wheat Yield	Diesel (ltrs)	Labor (hrs)
Average % change	12.30%	12.10%	-25.40%	-27.40%
Change at 10th percentile	3.80%	0%	-18.80%	-12.50%
Change at 90th percentile	22.20%	22.20%	-33.30%	-40.00%

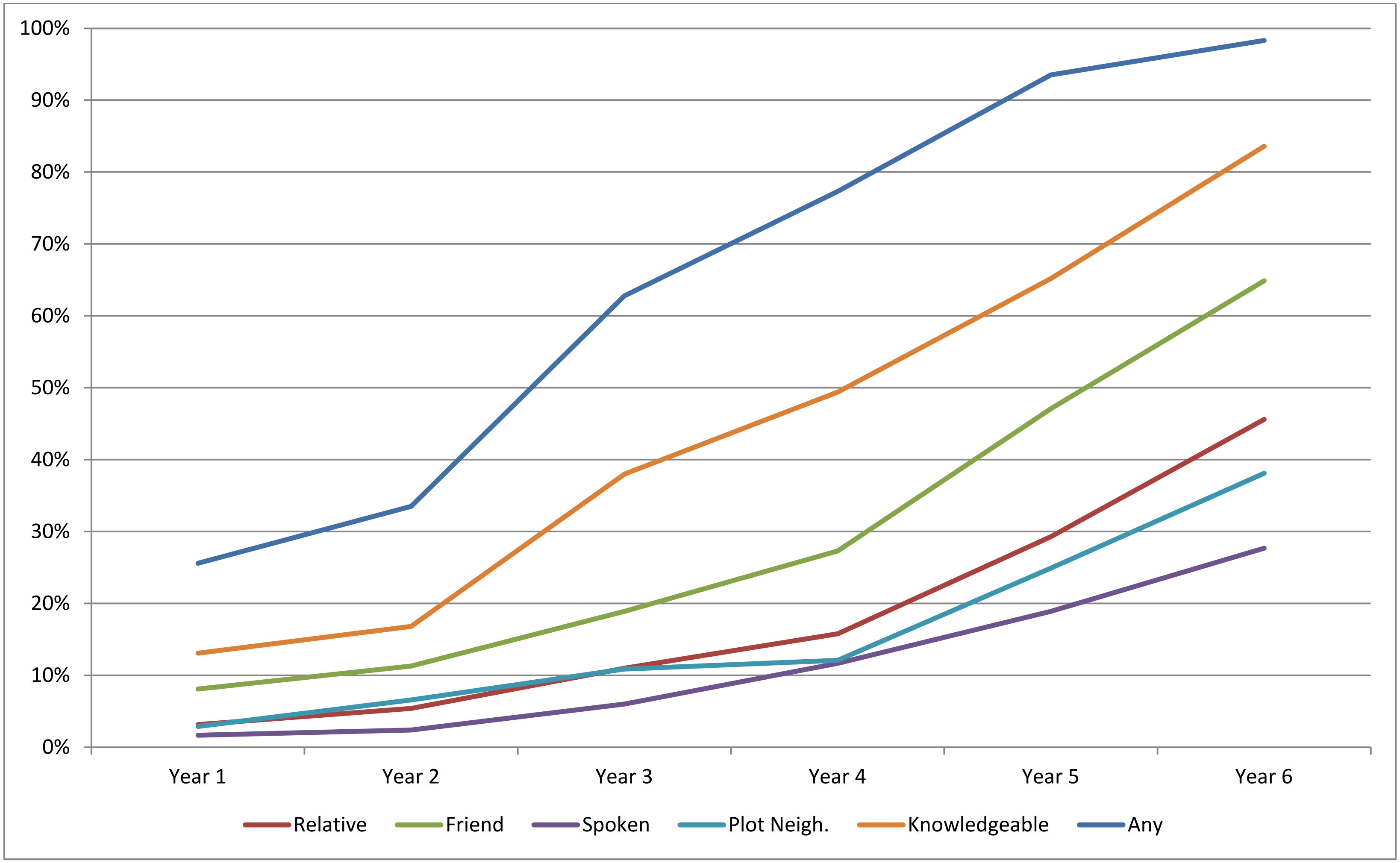


Figure 1: Probability that a farmer has at least one social network contact who has adopted by year *t*, by type of relationship

(Notes: Year 1 is the first year with any adoption in the farmer's village.)

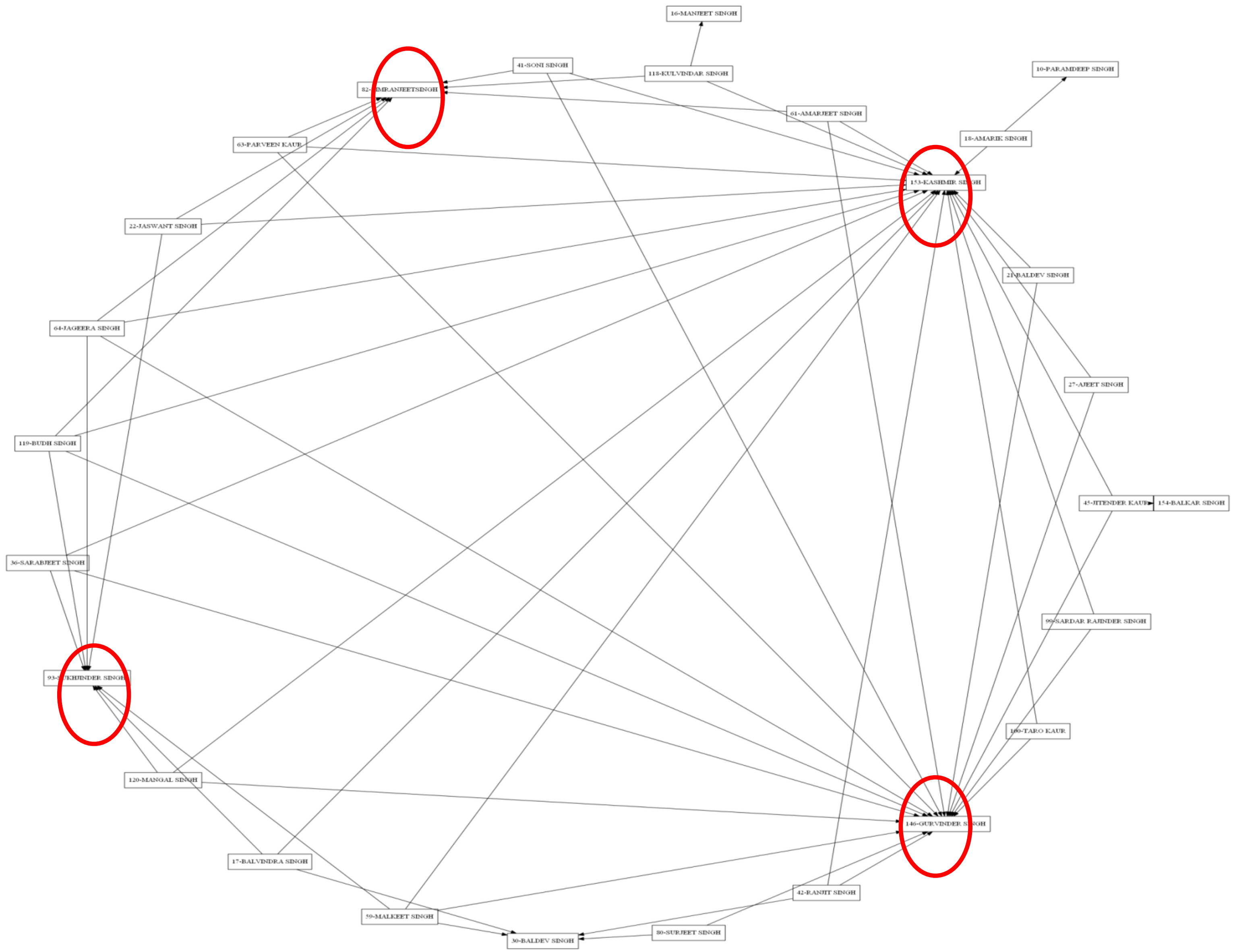


Figure 2: Detecting Influential People in the Village

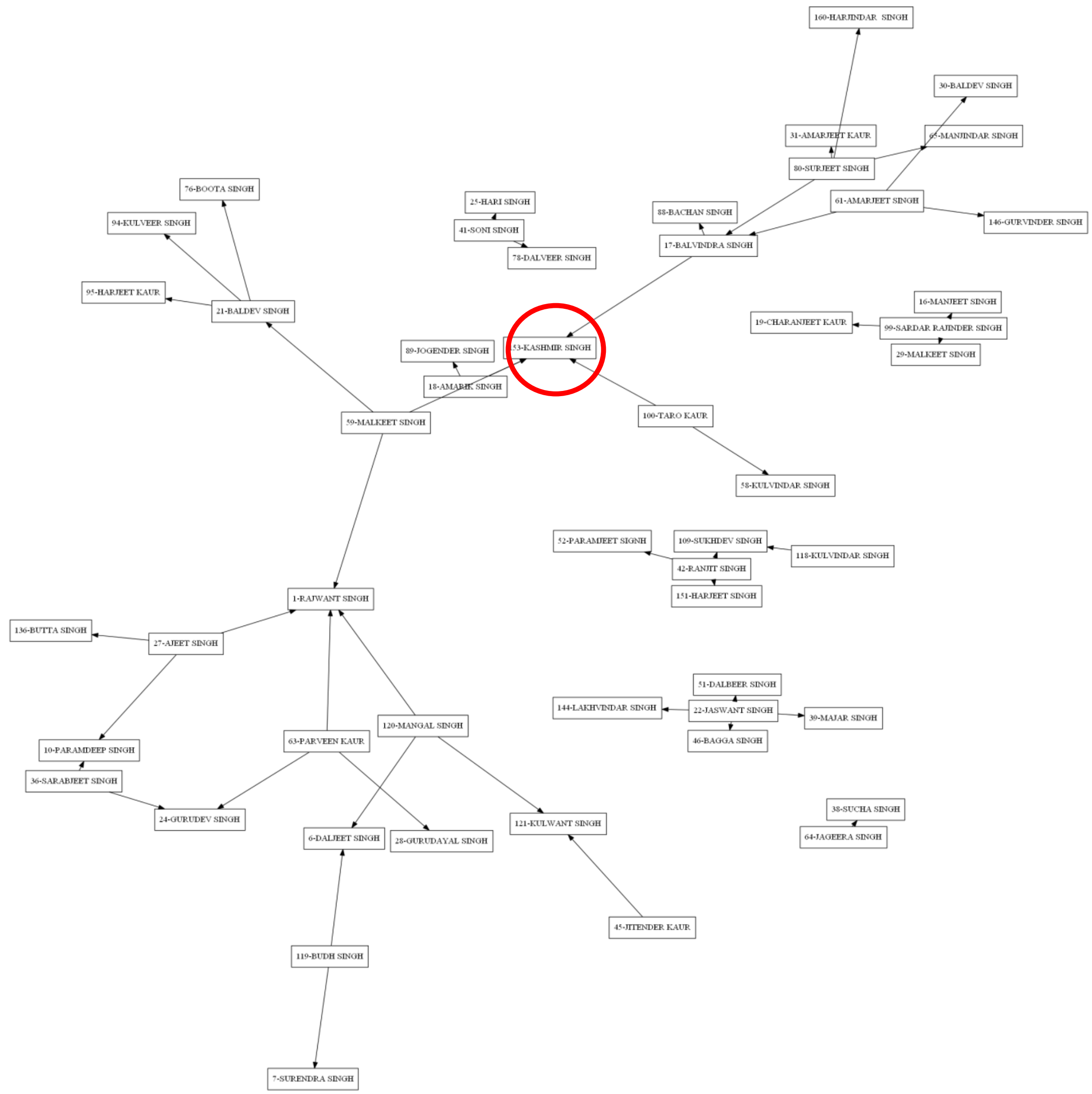


Figure 3: Friends: Several Components are observed. Critical Nodes that link the widest network are identified.

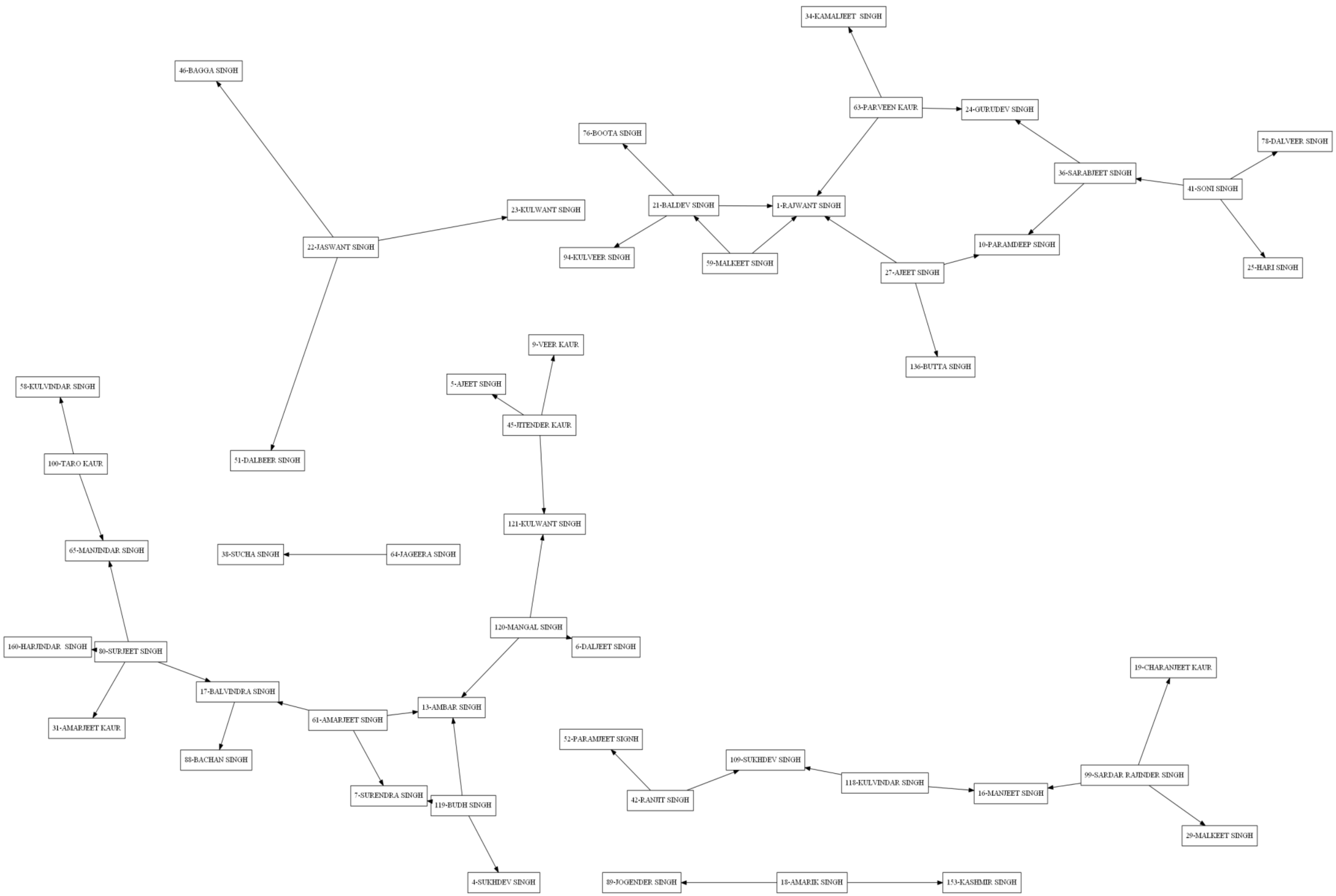


Figure 4: Contacts: People Whom the Respondents talk with more than others

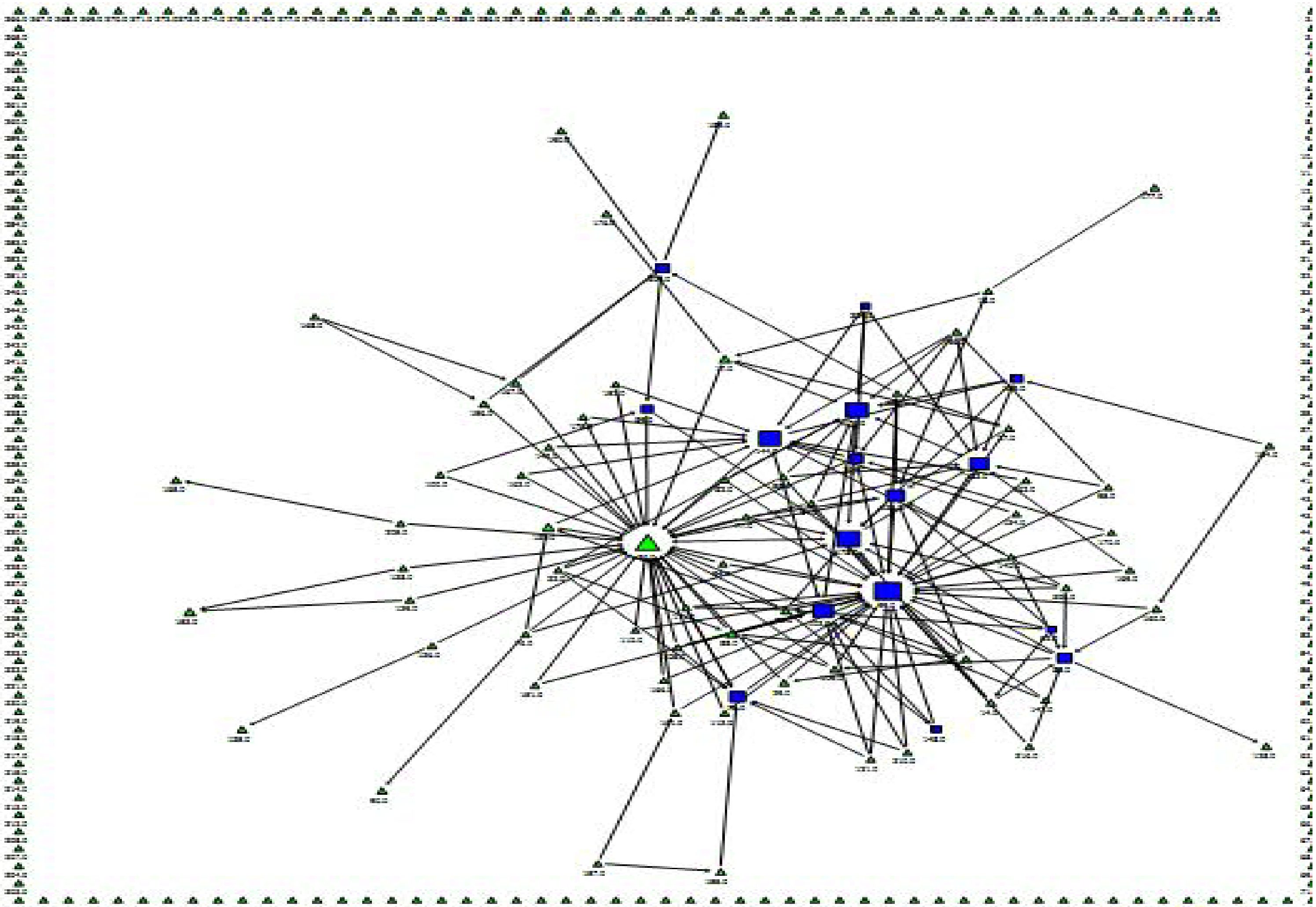


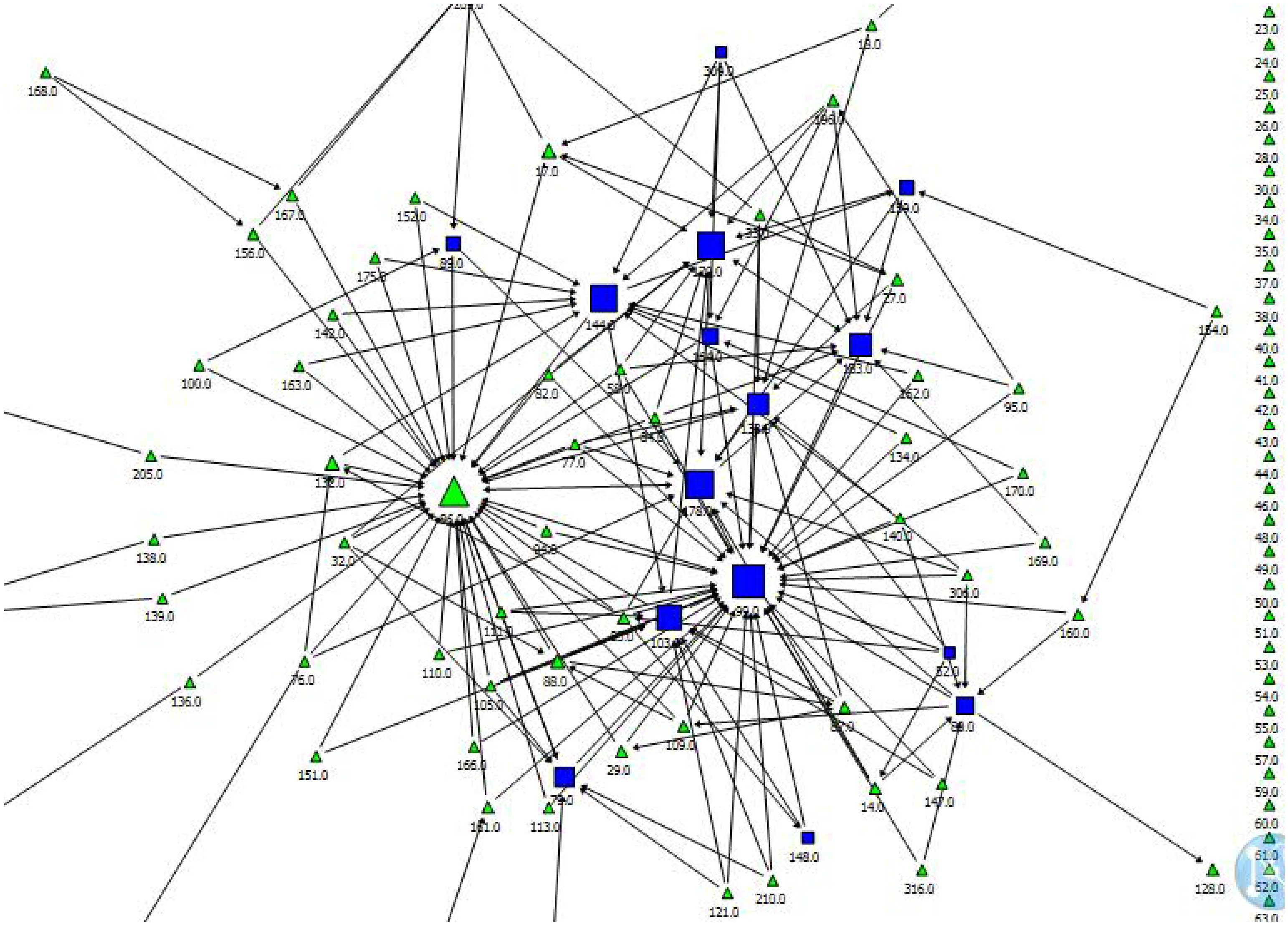
Figure 5: Network – Most prominent Farmers Sarhal Mandi

Degree Centrality Histogram

Range	Node Count In-Degree
.000 - .002	245
.002 - .004	21
.004 - .006	0
.006 - .008	6
.008 - .010	0
.010 - .012	2
.012 - .014	0
.014 - .016	0
.016 - .018	1
.018 - .020	0
> 0.020	9

DISTRIBUTION OF DEGREE CENTRALITY SCORES

MEASURES	VALUE	
	In-Degree Centrality	Out-Degree Centrality
MEAN	0.002	0.002
STD.DEV.	0.013	0.004
MIN.	0	0
MAX.	0.141	0.018


168.0
167.0
156.0
152.0
175.0
89.0
17.0
18.0
142.0
144.0
100.0
163.0
82.0
27.0
159.0
164.0
95.0
162.0
134.0
205.0
77.0
170.0
138.0
140.0
169.0
139.0
32.0
160.0
110.0
136.0
76.0
88.0
105.0
151.0
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109.0
29.0
14.0
147.0
161.0
113.0
148.0
316.0
128.0
121.0
210.0
23.0
24.0
25.0
26.0
28.0
30.0
34.0
35.0
37.0
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Center View

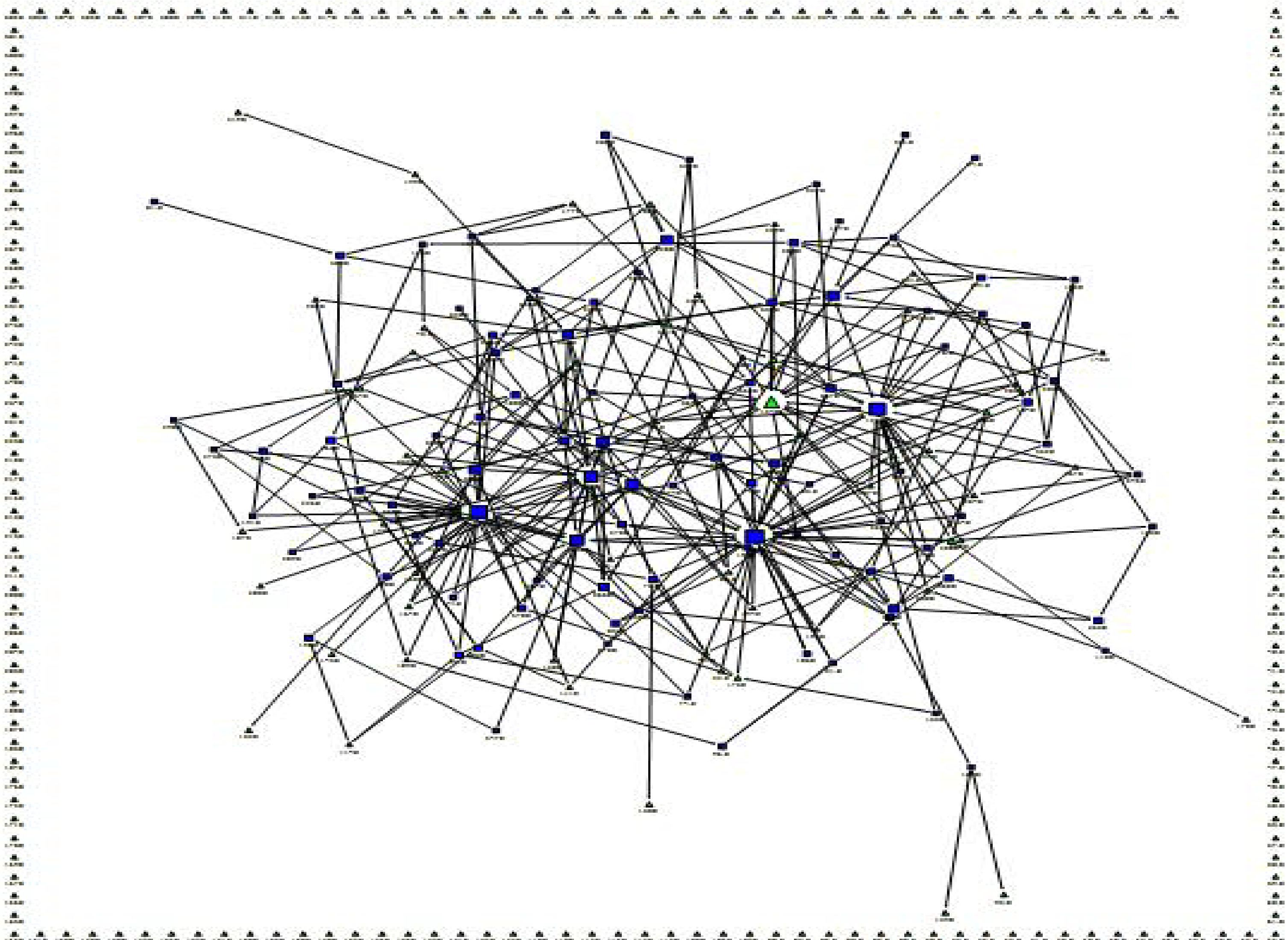


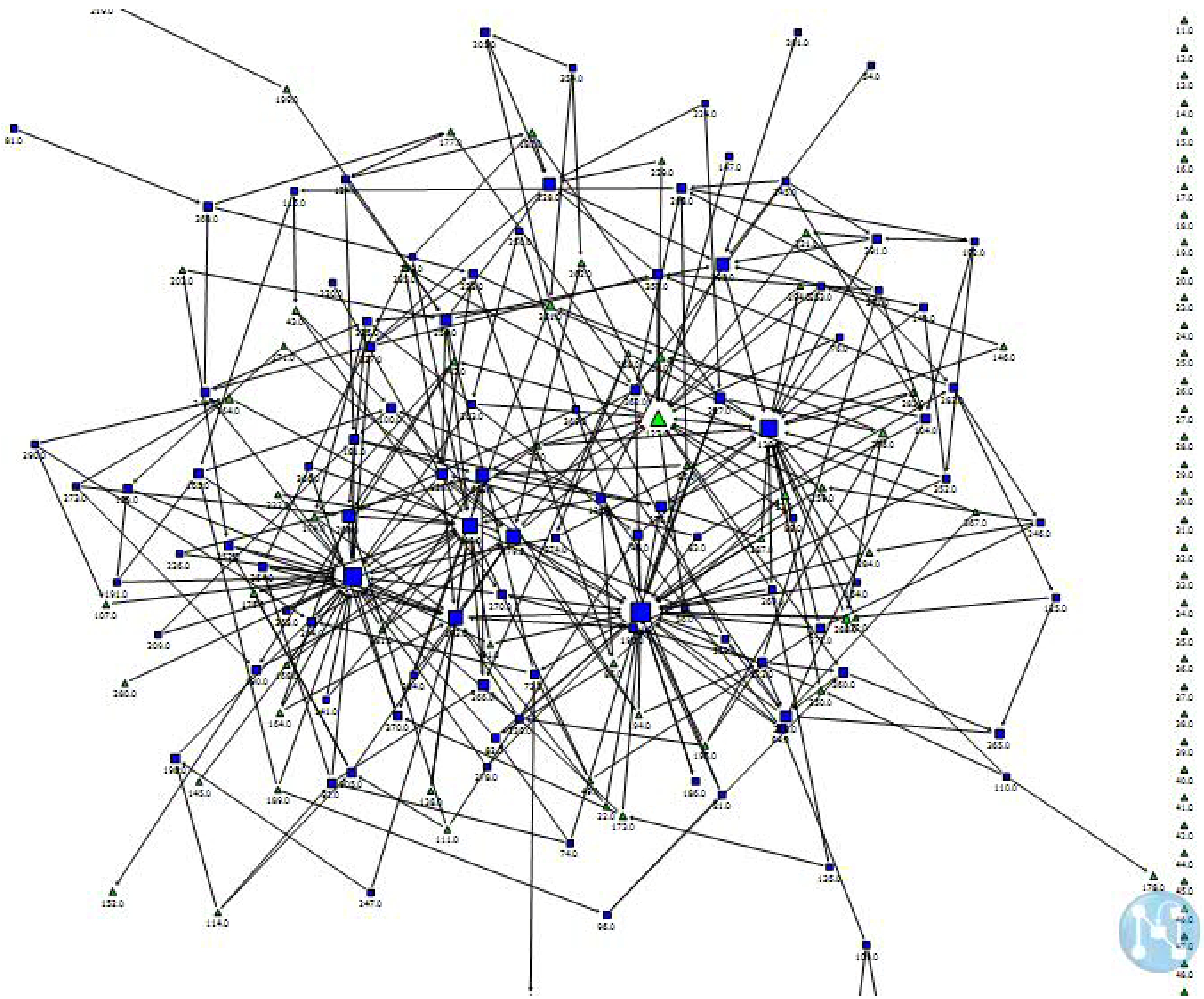
Figure 6: Network – Most prominent Farmers Giddar Pindi

Degree Centrality Histogram

Range	Node Count In-Degree
.000 - .002	245
.002 - .004	39
.004 - .006	31
.006 - .008	0
.008 - .010	12
.010 - .012	4
.012 - .014	0
.014 - .016	2
.016 - .018	2
.018 - .020	0
> 0.020	9

DISTRIBUTION OF DEGREE CENTRALITY SCORES

MEASURES	VALUE	
	In-Degree Centrality	Out-Degree Centrality
MEAN	0.003	0.003
STD.DEV.	0.01	0.004
MIN.	0	0
MAX.	0.105	0.012



Center View

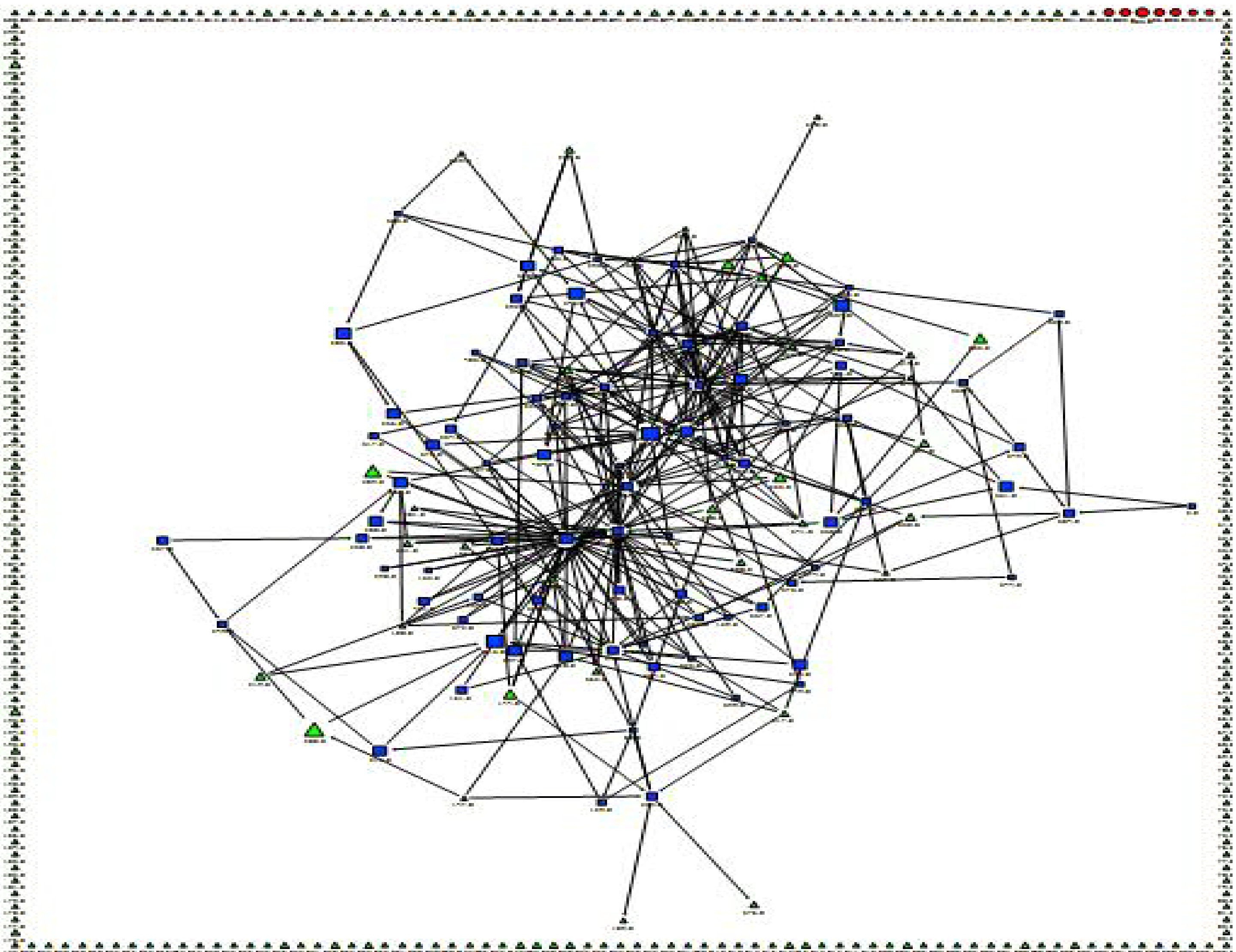


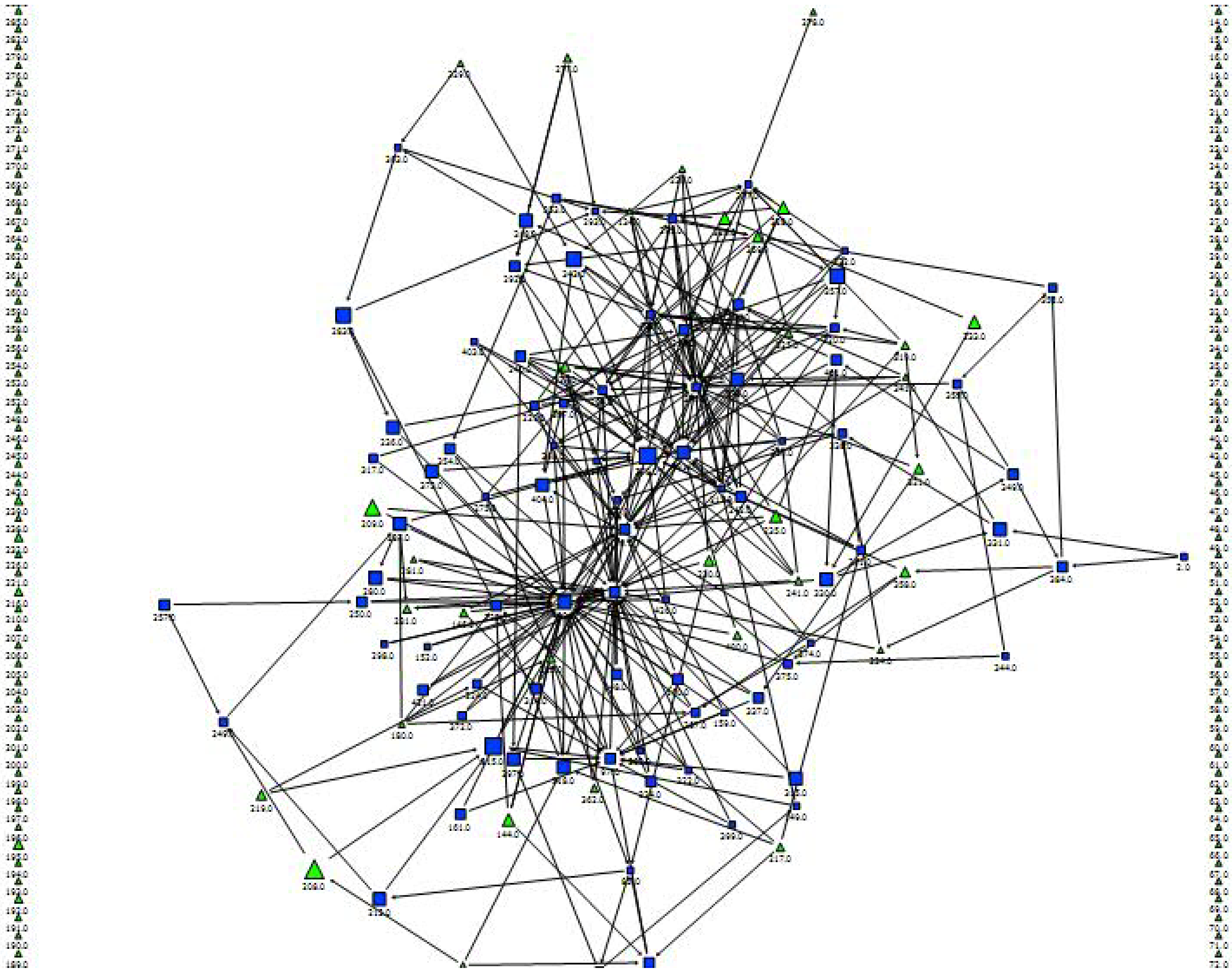
Figure 7: Network – Most prominent Farmers Khalra

Degree Centrality Histogram

Range	Node Count In-Degree
.000 - .002	332
.002 - .004	30
.004 - .006	16
.006 - .008	5
.008 - .010	7
.010 - .012	0
.012 - .014	3
.014 - .016	0
.016 - .018	1
.018 - .020	4
> .020	9

DISTRIBUTION OF DEGREE CENTRALITY SCORES

MEASURES	VALUE	
	In-Degree Centrality	Out-Degree Centrality
MEAN	0.002	0.002
STD.DEV.	0.009	0.004
MIN.	0	0
MAX.	0.116	0.017



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