Information exchange links, knowledge exposure, and adoption of agricultural technologies in Northern Uganda

K.M. Shikuku;

Wageningen University, Development Economics, Netherlands

Corresponding author email: kelvin.shikuku@wur.nl

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Abstract

Recent evidence has shown that direct provision of agricultural training to selected individuals as knowledge injection points (IPs) can help to implement a farmer to farmer extension approach. This study systematically assesses the determinants of information exchange links between trained IPs and their neighbors and the subsequent effect on awareness, knowledge, and adoption of improved varieties of maize and groundnuts and conservation farming. Using a panel dataset from northern Uganda, results of econometric analysis showed that 'proximity' in terms of sex, education, assets, and cultivated land, influenced information exchange links. Information exchange links increased awareness and knowledge for all the technologies, and adoption of maize varieties. Selection criterion for IPs, therefore, matters and considering 'proximity' between IPs and other farmers is important in designing farmer to farmer extension programs.

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1. INTRODUCTION

Agricultural productivity growth is important for economic development in sub-Saharan Africa (SSA), but is hindered by low adoption rates for yield-enhancing technologies. Informational constraints impede diffusion of agricultural technologies (Bandiera and Rasul, 2006). Identifying and promoting approaches that can address informational constraints to adoption is, therefore, a formidable challenge for policy in SSA. One such approach is the direct provision of agricultural training to selected individuals – often referred to as knowledge injection points (IPs) – and leveraging social networks for knowledge diffusion (Kondylis et al., 2016).

This study seeks to systematically assess the determinants of information exchange links between trained IPs and their neighbors and the subsequent effect on awareness, knowledge, and adoption of agricultural technologies. There has been much interest recently to understand the effect of IPs on adoption behavior of their neighbors (e.g., Kondylis et al., 2016; 2017). Most of this previous work has benefited from insights about selection of IPs (Banerjee et al., 2014; Kim et al., 2015; Beaman et al., 2016, Chami et al., 2017) and incentives for knowledge diffusion (BenYishay and Mobarak, 2014). Empirical evidence on the factors that shape information exchange links is, however, inadequate. A few notable studies have indicated that social distance plays an important role (Feder and Savastano, 2006; Santos and Barrett, 2010). Others have argued that heterogeneity among farmers in terms of biophysical characteristics – such as soil properties – might generate varied benefits of a technology implying that a farmer's experiences may not be relevant for his or her neighbor's agricultural decision making (Munshi, 2004; Magnan et al., 2015). This study systematically assesses the effect of both social distance and differences in soil characteristics on information exchange links.

Broadly speaking, the role of social distance and differences in soil characteristics is akin to homophily – a term coined by Lazarsfeld and Merton (1954) and referring to the tendency of individuals to associate disproportionately with others who are similar to themselves. Golub and Jackson (2011) showed that the probability of a link between two agents depends on their types and affects the speed of convergence of beliefs. In addition to 'homophilic neighbors', however, farmers may follow or trust the opinion of those whom they perceive to be successful in their farming even though they might share different traits (Genius et al., 2013). Several studies that assess neighborhood effects on behavior of economic agents, therefore, consider average characteristics of an individual's reference group (Bandiera and Rasul, 2006; Krishnan and Patnam, 2012). This study focuses on differences in both socio-economic and soil characteristics between a trained IP in a sub-village and his or her neighbors. Such neighbors may be 'homophilous' or 'heterophilous' to the IP in terms of social distance and soil characteristics.

In 2016, we partnered with the National Agricultural Research Organization (NARO) and Tillers International – an NGO promoting conservation farming in northern Uganda to train 126 randomly selected IPs about climate smart agricultural (CSA) technologies. The CSA technologies included drought-tolerant varieties of maize, disease-resistant varieties of groundnuts, row planting, intercropping, and conservation farming (CF) basins. Each of the selected IPs represented a sub-village. The training, which lasted for three days, included both classroom sessions and practical demonstration in the field. At the end of the training, IPs were asked to share the knowledge learnt with their fellow sub-villagers (whom we refer to as neighbors).

Our summarized findings are as follows. Proximity between IPs and their neighbors in terms of sex, education, cultivated land, and assets ownership influenced information exchange links. In addition to social distance, results showed that differences in soil characteristics specifically, soil pH and silt content influenced link formation. Information exchange links increased awareness and knowledge about the improved varieties and CF basins. Such links further increased adoption of improved maize varieties.

The paper is organized as follows. Section 2 describes the context. Section 3 discusses the theoretical framework underlying the study. Section 4 discusses the empirical approach and estimation procedure. Section 5 presents the results while section 6 concludes.

2. CONTEXT AND SELECTION OF KNOWLEDGE INJECTION POINTS

(a) *Context*

In Northern Uganda, farming – the main source of livelihoods – is facing pressure to feed a population that is growing at a much faster rate (9%) compared with the country's average population growth rate (3%) and to help reduce poverty levels which are the highest in the country (about 44% of the population lives below 1 US dollar a day) (Government of Uganda, 2016). Farmers grow a large number of crops, but report high incidences of diseases and frequent occurrence of prolonged intra-seasonal drought as bottlenecks to increased productivity (Mwongera et al., 2014). Maize and groundnuts crops are, respectively, ranked the most important cereal and legume in the region. Efforts to sustain agricultural production in the region increasingly recognize the importance of growing disease-resistant and drought-tolerant varieties of crops as well as promoting technologies that could help to conserve soil moisture (Mwongera et al., 2014). Most of these technologies being new, however, a large majority of farmers in the region are not aware of their existence and the very few who have heard about them lack exposure to knowledge on proper implementation (Shikuku et al., 2015). Current reforms by the national government to revamp the extension system recognize the role of farmer-to-farmer knowledge and technology transfer. It is, therefore, important to understand the factors that will determine whether farmers will obtain information from their peers and ultimately the effect of such information exchange links on knowledge diffusion and technology adoption.

(b) *Selection of knowledge injection points*

The procedure for selecting IPs was as follows. We generated a list of 310 sub-villages in Nwoya district and randomly selected 132 sub-villages for the study. A complete list of all households and their household heads was compiled for each of the selected sub-villages. Next, we randomly sampled 10 households from each sub-village, and randomly picked one potential IP from the sub-sample. In a meeting with co-villagers we discussed whether the selected candidate was 'representative' (specifically; not too wealthy) and interested to try out new technologies. If a candidate was rejected, we randomly picked another name from the list and repeated the process. The highest number of draws that we needed to make before selecting an IP who was endorsed by co-villagers was three and in more than 75% of sub-villages the first name was endorsed.

Selected IPs were provided a three-day training session. The trainings were organized in central locations, and IPs were invited to travel to these sites. The cost of transport to the training venue and back was refunded (USD 4, on average) and tea and lunch were provided during the training. Of the 132 IPs that we invited, 126 attended the full training. Sub-villages for which selected IPs did not attend the training were excluded from the analysis.

3. CONCEPTUAL APPROACH

The fundamental issue that training of IPs seeks to address is the notion that use of CSA technologies that could potentially increase productivity and enhance resilience to weather shocks is very low because of inadequate exposure of farmers to knowledge about the technologies. Inadequate knowledge exposure implies that farmers may not know the suitability of these technologies to their agricultural activities. Suppose, therefore, that farmers currently operate using a traditional not-CSA technology whose payoffs $\underline{y}$ are well known, but with which their vulnerability to weather shocks is high. For example, a farmer using a local variety of maize that is intolerant to drought might be well aware of its yielding potential due to many years of experimentation with the variety but might experience a major crop failure in the event that drought occurs.

Empirical predictions for this study are guided by a framework combining insights from the standard target input model as applied by Bandiera and Rasul (2006) and a model of communication proposed by Ben Yishay and Mobarak (2014). The target input model presupposes the existence of a new technology whose required target inputs for implementation are not known to farmers. Farmer j chooses the level of inputs according to his or her prior beliefs about the new technology. Without additional information, however, expected payoffs from the new technology are low, due to the gap between the farmer's inputs and the target inputs. The farmer will, therefore, seek to learn in order to maximize payoffs from the new technology.

Suppose further that there is an informed farmer k who has been trained about the new technology and knows the target. Leveraging social networks could help with diffusion of knowledge from this informed farmer to neighbors (Bandiera and Rasul, 2006; Conley and Udry, 2010). Communicating the information to other farmers requires that the informed farmer sends a signal, incurring a cost that is increasing in the precision of the message (Ben Yishay and Mobarak, 2014). Proximity between farmers j and k in terms of similarity in agricultural practices is important to ensure that the message received from the communicator is relevant to agricultural decisions of the receiver (Bandiera and Rasul, 2006). Upon receiving the signal, farmer j updates his or her beliefs about the required inputs for the new technology. As shown by Ben Yishay and Mobarak (2014), expected payoffs from learning decrease with the distance between the communicator and the receiver of the message.

IPs in this study were selected not to be very wealthy – as perceived by neighbors. As such, it can be expected that IPs will be closer to some neighbors and far from others. Furthermore, the selection criterion was not restrictive in terms of other socioeconomic factors such as age, education, membership to farmer associations, or cultivated land. The selection criteria notwithstanding, therefore, our study allows us to explore the role of social distance and soil characteristics on information exchange links. Specifically, the following hypotheses are tested in this study:

H1: Proximity in terms of social distance and soil characteristics between IPs and their neighbors increases the formation of information exchange links.

H2: Information exchange links between trained IPs and their neighbors have no effect on awareness, knowledge, and adoption of DT maize and disease-resistant groundnut varieties and conservation farming basins.

4. DATA AND DESCRIPTION OF VARIABLES

(a) *Data*

Our analysis is performed on a panel dataset that was collected through two waves of household surveys. A multi-stage sampling procedure was used to select a random sample of 1,320 farming households from 132 sub-villages in Nwoya district, northern Uganda. Ten households were randomly selected from each sampled sub-village: one IP and nine other households. In each selected household, personal interviews with the household head or spouse (in case the household head was not available) were conducted. A baseline survey was implemented in 2015 and collected data on household demographics, crop and livestock production, off-farm income, assets ownership, exposure to weather shocks, sources of agricultural information, social networks, knowledge about farming practices, and food security. A follow-up survey was conducted in 2017. During the follow up survey, 126 sub-villages whose selected IPs had actually attended the training about CSA technologies were revisited. Effort was made to interview the same respondents that had been interviewed at the baseline. In total, 1,036 respondents (122 IPs and 914 other farmers) were interviewed in the follow-up survey. The attrition rate was, therefore, about 18%. Appendix Table A1, however, shows that summary sample statistics for the original sample and that used for our analysis are very similar. Attrition is therefore not a major concern in this study. Interviews were conducted by trained enumerators in the local language using a pre-designed and pre-tested questionnaire.

(b) *Definition of dependent variables*

During the follow-up survey, sample respondents were asked: 1) whether they had been contacted by another farmer in the sub-village about new farming methods and 2) whether they had heard about or attended an activity organized by another farmer in their sub-village to train co-villagers about farming. If they answered 'yes', follow up questions asked for the name of the contact or trainer and the content of the training. We define existence of an information exchange link as a dummy variable equal to one if a farmer had contact with the IP designated to share knowledge with co-villagers in the respective sub-village and zero otherwise.

Next, we distinguish between awareness and knowledge. For each of the varieties considered (Longe 10H DT maize, DT maize generally, any improved variety of maize, Serenut 5R or Serenut 14R groundnut varieties, any Serenut groundnut variety) and CF basins, awareness is defined as equal to one if the respondent has heard about the technology and zero if otherwise. Knowledge is defined as a continuous variable measured using an exam about improved varieties. Such exams are an effective approach of assessing knowledge exposure by subjects (Kondylis et al., 2015). Questions asked in the knowledge exam are presented in the Appendix. Because questions differ in difficulty and farmers differ in their ability to respond (Lagerkvist et al., 2017), we generate the probability of answering correctly to a question, that is, $p = (q/Q)$ where q captures the number of people responding correctly to the question and Q is the total number of people. We then use the inverse of the probability, that is, $1/p$ as weight for a correct answer to that question. The final score is thus a summation of the weighted responses to all questions. This procedure ensures that difficult questions (those to which only a few farmers answer correctly) carry more weight in the final outcome.

For each of the varieties considered (Longe 10H DT maize, DT maize generally, any improved variety of maize, Serenut 5R or Serenut 14R groundnut varieties) and CF basins, adoption is defined as a dummy variable equal to one if a farmer implemented the technology on at least one household plot and zero if otherwise.

(c) *Definition of explanatory variables*

Although evidence on determinants of information exchange links in agricultural settings is scanty, Santos and Barrett (2010) provide some guidance. Define two indicator variables:

$$I_{(x_i - x_j < 0)} = \begin{cases} 1, \text{if } (x_i - x_j) < 0 \\ 0, \text{otherwise} \end{cases} \quad \text{and}$$

$$I_{(x_i - x_j \geq 0)} = \begin{cases} 1, \text{if } (x_i - x_j) \geq 0 \\ 0, \text{otherwise} \end{cases} \tag{1}$$

where for a continuous variable, $(x_i - x_j)$ measures the difference between the IP's value x_i and the neighbor's value x_j. Using Equation (1) and following Santos and Barrett (2010), social distance and difference in soil characteristics between IP i and neighbor j is measured for continuous variables (in our case, age, education, and area under maize) as: $(I_{(x_i - x_j < 0)} * |x_i - x_j|) + (I_{(x_i - x_j \geq 0)} * |x_i - x_j|)$.

For categorical variables, social distance is defined by a set of dummy variables that consider the several possible characterizations of the match (Santos and Barrett, 2010). We consider age, sex, education, size of land under maize, agricultural assets index, nonagricultural assets index, and membership to farmers' organizations. The effect of education, for example, would be expressed by the interaction between the absolute value of the difference in education with two indicator variables, higher and lower, of which, for each dyad, at least one has to be zero (Santos and Barrett, 2010). The analysis of the effect of membership to a farmers' group, for example, requires the definition of a dummy variable for each of the four possible combinations (member–member, member–nonmember, nonmember–member, and nonmember–nonmember). Table 1 presents a description of all the variables used to measure social distance including their summary statistics.

<< Please insert Table 1 about here >>

Our choice of control variables to include in the analysis of knowledge exchange links' impact on awareness, knowledge, and adoption was informed by literature (e.g., Feder and Savastano, 2006; Diagne and Demont, 2007; Kassie et al., 2011; Kabunga et al., 2012; Asfaw et al., 2012; Lambrecht et al., 2014). Specifically, we include age (years), formal education (years), and sex of the household head (1=male; 0=otherwise); and workers (number of household members aged 16 – 30 years). In a context where labor is a binding constraint, a higher number of household members aged 16 – 30 years) might mean availability of labor and can thus be expected to positively affect adoption decision. It is also expected that education has a positive effect on the adoption decision. The effect of age is, however, an empirical question. Whereas younger farmers may be more innovative and have a lower risk aversion, they also have less experience especially in a post-war context where farming was disrupted for a considerable length of time.

We further control for housing characteristics, whether household received or not credit, whether household received or not weather-related information, and size of kinship and friendship networks. We expect a positive correlation between these variables and the likelihood to adopt. Finally, we include sub-county dummies.

5. EMPIRICAL APPROACH

In order to simultaneously assess the effect of social distance and differences in soil characteristics on link formation and subsequent impacts of information exchange link on awareness, knowledge, and adoption, we employ a two-step procedure that combines difference-in-differences (DID) approach with inverse probability weighting (IPW) technique.

In the first step, we estimate the probability for farmer j to have formed an information exchange link with IP k, using the following model.

$$l_j^* = z_j'\beta 1 + x_j'\beta 2 + \varepsilon_j$$

$$l_j = \begin{cases} 1, \text{if } l_j^* > 0 \\ 0, \text{otherwise} \end{cases}$$

$$\Pr(l_j = 1 | \boldsymbol{z_j}, \boldsymbol{x_j}) = \Phi(\boldsymbol{z_j'\beta 1} + \boldsymbol{x_j'\beta 2}) \quad (2)$$

where l_j^* is a latent unobserved variable whose counterpart, l_j, is observed in dichotomous form only; where $l_j = 1$ if an information exchange link between farmer j and the IP in his or her sub-village was formed, as measured during endline survey and $l_j = 0$ if otherwise; $\boldsymbol{z_j}$ is a vector of explanatory variables measuring baseline social distance and difference in soil characteristics between farmer j and the IP; and $\boldsymbol{x_j}$ is a vector of additional baseline covariates (housing characteristics, whether household received credit, whether household received weather-related information, and size of kinship and friendship networks). $\Phi(\cdot)$ is the standard normal cumulative distribution function (CDF); $\boldsymbol{\beta 1}$ and $\boldsymbol{\beta 2}$ are vectors of parameters to be estimated; and ε_j is an error term. Estimation of Equation (2), by probit, allows us to analyze the role of social distance and differences in soil characteristics in information exchange between IPs and their neighbors. Furthermore, it generates propensity scores and matched treatment and control observations, which are used to estimate the effect of information exchange on awareness, knowledge and adoption of new technologies.

Whereas the direct beneficiaries of the training on CSA technologies are the IPs, the ultimate impact of interest here comes from the effect of diffusion of IPs' knowledge on other farmers' knowledge and use of the technologies. In the second step, we therefore use a DID estimation to assess the effect of treatment on these outcomes, where treatment of farmer j is defined as the formation of a knowledge exchange link between farmer *j* and the IP.

Within a regression framework, the underlying estimating equation is specified as:

$$y_{jt} = \alpha + \lambda t + \theta l_{jk} D_t + \mu_{jt} \qquad (3)$$

where y_{jt} is the outcome variable of interest for farmer *j* at time *t* (baseline or endline) – in our case awareness, knowledge, and adoption; l_{kj} is the treatment dummy variable for formation of an information exchange link; D_t is an indicator variable equal to one at endline and zero at baseline. Because it is possible that neighbors not directly trained by an IP can learn about the technologies from fellow farmers directly trained by an IP, we also run equation (3) with treatment defined as equal to one if at least one farmer in a sub-village reports to have been in contact with an IP about the technologies and zero otherwise.

In equation (3), the coefficient θ on the interaction between link formation l_{kj} and endline dummy D_t gives the average difference-in-differences (DID) effect of the information exchange link. Clearly, farmers who form a link with the IP in their sub-village may be systematically different from those who did not: they may, for example, be more motivated to learn about new technologies or have better ability to learn and implement new technologies. As such, the treatment variable is likely to be endogenous, and we cannot simply compare outcomes between treated and untreated neighbors, even after adjusting for differences in observed covariates (Imbens and Wooldridge, 2009).

By combining IPW with DID, our empirical estimation allows possibility of time-invariant selection bias due to initial observables (Imbens and Wooldridge, 2009; Benin et al., 2015; Mendola and Simtowe, 2015). Henceforth, we refer to our approach as IPW-DID. In the second step, therefore, the estimated propensity scores from equation (2) are used as weights in the DID equation (3). In other words, equation (3) is estimated using a DID method based on the matched observations and using the estimated propensity scores as weights according to:

$$ATT = \sum_j \varphi_j \left(\Delta y_{1j} - \Delta \hat{y}_{0j}\right) \tag{4}$$

where $\Delta y = y^{t1} - y^{t0}$ and $\Delta \hat{y} = \hat{y}^{t1} - \hat{y}^{t0}$. By extension, y_{1j}^{t1} and y_{1j}^{t0} are the baseline and endline outcomes of a farmer j who received training from an IP, respectively, and $\hat{y}_{1j}^{t1}$ and $\hat{y}_{1j}^{t0}$

are outcomes of the matched control farmer in the latter and initial period, respectively. φ_j are the weights using the propensity scores associated with the treated farmer j. For farmers in the treatment group, $\varphi = \frac{1}{p}$ whereas for those in the control group $\varphi = \frac{1}{1-p}$ where p represents estimated propensity scores.

Our estimation relies on an important condition known as unconfoundedness. More specifically, under this assumption, treatment is independent of outcomes once the vector of covariates $\boldsymbol{x}$ is controlled for. The conditional independence assumption does not require the variables in conditioning vector of covariates $\boldsymbol{x}$ to be exogenous for the identification of the causal effect of interest (Heckman and Vytlacil, 2005; Diagne and Demont (2007). The restriction imposed, however, is that values of the variables included in $\boldsymbol{x}$ should not change for any farmer when his or her treatment status changes from not-treated to treated (Diagne and Demont, 2007). It is recommended, therefore, that $\boldsymbol{x}$ includes pretreatment covariates (Heckman and Navarro-Lozano, 2004; Wooldridge, 2005; Diagne and Demomt, 2007). In this study, the conditioning set of covariates $\boldsymbol{x}$ came from baseline data that were collected before IPs received training and that are unlikely to change after ‘treatment’.

The procedure of selecting matched control observations for the treatment observations using the estimated propensity scores improves overlap in the covariate distributions between the treatment and control observations, consistent with the conditional independence assumption (Crump et al., 2006). In line with previous studies, common support was imposed in order to trim observations with propensity scores close to zero or one. Although dropping observations may lead to biased estimates, using the sub-sample can yield higher precision of the estimates than for the overall sample, resulting to greater internal validity at the expense of some of the external validity (Crump et al., 2006).

Finally, because it is possible that neighbors not directly trained by an IP can learn about the technologies from fellow farmers directly trained by an IP, we also run equation (3) with treatment defined as equal to one if at least one farmer in a sub-village reports to have been in contact with an IP about the technologies and zero otherwise.

In addition to the IPW-DID approach, we estimate an instrumental variable two-stage least squares (2SLS) regression. Whereas IPW builds selection weights using observed confounders, with 2SLS the need to identify confounders is circumvented if an appropriate instrumental variable exists. Specifically, IPW uses observed confounders to estimate treatment selection probabilities, the inverses of which are used as observation weights. In implementing IPW, it is assumed that there are no unobserved confounders, and hence the approach cannot be used directly to handle unmeasured confounding (Hogan and Lancaster, 2004). Our IPW-DID approach helps to address this problem. The method of 2SLS exploits the existence of one or more instruments, variables that are associated with receipt of treatment but otherwise uncorrelated with the potential outcomes. 2SLS can be used to adjust for unmeasured confounding, but as with the assumption of no unmeasured confounders required for IPW, the validity of an instrumental variable cannot be empirically verified and must be defended on subject-matter grounds (Hogan and Lancaster, 2004). Valid instruments are difficult to find and use of weak instruments makes the estimates highly susceptible to biases.

6. RESULTS

(a) *Descriptive statistics*

Summary statistics of the sample households, with and without weighting, are presented in Table 2. For the pooled sample (column 1), most households are male-headed with an average age of 44 years. About 42% of the household heads have completed primary level of formal education. The dependency ratio is about 56.7%. The average index for housing condition – constructed using principal component analysis and based on roofing, floor, and wall material; whether or not a household owns a toilet; and main type of cooking fuel – was negative and the average herd size is less than one tropical livestock unit, suggesting poor housing conditions and very low livestock keeping activities. More than three-fifths of the households (68%) reported to have applied for and actually received credit. About one-third of the sample households had not received weather-related information. On average, households are about 42 minutes walking from the nearest main market and about 12 minutes from the nearest main road. Sample respondents have friendship and kinship networks comprising two contacts each, on average. These statistics are close to those reported by previous studies conducted in Uganda (see for example, Kassie et al., 2011).

<< Please insert Table 2 about here >>

Comparing these statistics for 'treated' respondents versus 'control' respondents, before weighting, shows that the treatment group has a greater proportion of household heads who completed primary education; had more people who received credit and weather-related information; traveled a shorter distance to the nearest main road; and had a bigger size of friendship network. Columns 5 – 7 in Table 2, however, show that weighting observations according to the propensity score actually eliminates difference in average group characteristics.

Turning to the outcome variables, descriptive statistics in Table 3 show that at baseline (2015), very few farmers were aware of the drought-tolerant (DT) Longe 10H maize (5.2%) and disease-resistant Serenut 5R/14R groundnut (0.5%) varieties and none had heard about the conservation farming basins (Table 3, panel A). Awareness, however, increased at endline; 10.6% farmers knew about Longe 10H maize, 2.7% knew about Serenut 5R/14R groundnut varieties, and 13% had heard about the conservation farming basins in 2017. In both years (2015 and 2017) the proportion of farmers who had heard about these technologies was higher when an information exchange link existed compared to when such links did not exist.

Adoption rates for the technologies were similarly very low at baseline (Table 3, panel B). Specifically, 1.3% of the households grew Longe 10H DT maize variety in 2015. This figure increased to 3.9% in 2017. Similarly, the proportion of those who grew DT maize in general increased from 5.8% in 2015 to 14.3% in 2017. Adoption of Serenut 5R/14R groundnut varieties and conservation farming basins remained low both at baseline and endline. In both years, more farmers who had contact with IPs knew about and grew the DT varieties of maize as well as the disease-resistant groundnut varieties than their counterparts who lacked such links. The former also had more knowledge about cultivation and benefits of improved varieties of maize and groundnuts than the latter. Furthermore, more farmers with information links than those without such links knew about and grew improved varieties of maize in general and used conservation farming basins..

>> Please insert Table 3 about here >>

(b) *Determinants of information exchange links between injection points and their neighbors*

Table 4 presents results of probit regression to assess the effect of social distance and soil characteristics on information exchange link formation[1]. Average marginal effects (henceforth,

[1] Results are very similar if we use logit or linear probability model estimation.

AMEs) are reported. Each model was estimated with bootstrapped standard errors to account for heteroscedasticity.

>> Please insert Table 4 about here >>

Gender composition of the IP-neighbor pair affects the formation of information exchange links.. The reference group here is the male IP–female neighbor pair. The AME's indicate that link formation is more likely if the IP is female compared to when the IP is male, regardless of the sex of the neighbor. Link formation is 8.9% more likely when both the IP and the neighbor are female. The magnitude is the same when the IP is female and neighbor is male compared to the male IP-female neighbor pair.. Although previous studies have shown that male farmers are generally less likely than female farmers to seek advice of others (Ben Yishay et al., 2015; Santos and Barrett, 2010), our findings suggest greater willingness to learn *from* female IPs. Because formation of links depends not only on the neighbor but also the IP's effort, our results perhaps suggest that female IPs expended more effort to reach out to their neighbors than their male counterparts. Training of female IPs might enhance trust by other farmers in their competence while involvement of the community in the process of selecting IPs might increase acceptance of their messages. Ma and Shi (2015) argued that trust in competence plays an important role to influence willingness by farmers to learn. Our findings, therefore, suggest that including women in otherwise male-dominated extension services may help other women to overcome barriers to adoption posed by limited access to extension advice (Kondylis et al., 2016).

The higher likelihood of a link between female IP and female neighbor compared to when IP is male and neighbor is female is consistent with Kondylis et al. (2016) who also argued that including women among selected IPs may remove frictions in the diffusion process by empowering female farmers to seek agricultural advice. Furthermore, similarity in crop portfolios among women might render the message of the female IP more relevant (Quisumbing and Pandolfelli, 2010).

Proximity in terms of level of education influences information exchange links. Results show that neighbors form links with IPs with lower education than themselves. That is, the probability of link formation increases with social distance in terms of education, but only if the IP is less educated than the neighbor. This result is consistent with the selection criterion for IPs as applied in this study which targeted those perceived by the community as average farmers, not necessarily literate, and much interested to try out new farming technologies.

Differences between IPs and their neighbors in the amount of land cultivated with maize influence information exchange links. Specifically, the probability of link formation increases with social distance in terms of size of land under maize, independent of whether the IP cultivates more or less land than the neighbor. More specifically, the probability for link formation increases by 7.4% when the IP cultivates more land and 2.4% when the IP cultivates less land than the neighbor. Santos and Barrett (2010) also found that differences in amount of land cultivated influenced information exchange links. Kondylis et al. (2017) found that IPs with greater endowments of land were more likely to convince other farmers to adopt sustainable land management practices. They explain their finding as stemming from credibility in the source of information; farmers with larger farms may command more trust and respect within the community. In our case, however, we also find a positive effect on link formation when IP cultivate less land suggesting that both types of IPs are important in disseminating agricultural information.

We further found that ownership and types of assets determine whether farmers will establish a link with trained IPs. On the one hand, information exchange links are 6.7% more likely when both IP and the neighbor have less agricultural assets than when they both have more agricultural assets. On the other hand, information exchange links are 9.1% less likely when both IP and the neighbor have less non-agricultural assets than when they both have more non-agricultural assets. Farmers with a less endowment of agricultural assets than the IP might think of him or her as having an upper advantage than themselves in terms of implementing the technology. In other words, the IP's message might be viewed as not relevant for the decision making of the neighbor (Bandiera and Rasul, 2006; Ben Yishay and Mobarak, 2014). This finding might explain why previous approaches that only targeted wealthy and non-representative farmers were often not successful to disseminate agricultural technologies (Anderson and Feder, 2007).

Differences in terms of age did not influence information exchange links. The estimated marginal effects were very small and not statistically significant at 10% level. The direction of influence was, however, negative for younger IPs and positive for older IPs. Similarly, differences in terms of participation in farmers' organizations did not significantly influence link formation at 10% level.

Beyond social distance, differences in soil characteristics between IPs and their neighbors influence link formation. Information exchange links were 47% more likely when the soil on an IP's farm had a lower pH than that of the soil on the neighbor's farm. Such links were, however, 6.3% less likely when the IP's farm had less silt content compared to that of the neighbor.

(c) *Effect of information exchange links on neighbors' awareness, knowledge, and adoption*

Before turning to the causal effects of information exchange links, we discuss the quality of the matching process as applied in the first step of our empirical analysis. Table 5 presents results of the covariates balancing test for the matched sample. There were no significant differences in pretreatment covariates between 'link' and 'no-link' groups after matching. Furthermore, bias was substantially reduced after matching. The left panel of Figure 1 shows the distribution of the estimated propensity scores by link status. As expected, there is a larger tail of households in the control (no-link) group whose estimated propensity score is close to zero, meaning they are very different (in terms of observable characteristics) from households that had a link with trained IPs. As shown in the right panel of Figure 1, the weighting procedure discounted these observations and attached greater importance to observations of both groups that are found in the middle range of the distribution.

<< Please insert Table 5 and Figure 1 about here >>

As shown in Table 6, the standardized mean difference for overall covariates used in the propensity score (around 17.5% before matching) is reduced to about 2.8 – 3% after matching. This substantially reduces total bias by 80 – 84% through matching. The *p*-values of the likelihood ratio tests indicate that the joint significance of covariates was always rejected after matching. The pseudo-R^2 also dropped significantly from 11 – 15% before matching to 0.7 – 0.8% after matching. Therefore, the low pseudo-R^2, low mean standardized bias, high total bias reduction, and the insignificant *p*-values of the likelihood ratio test after matching suggest that the proposed specification of the propensity score was fairly successful in terms of balancing the distribution of covariates between the two groups.

>> Please insert Table 6 about here >>

Table 7 presents results of IPW-DID estimates (columns 1 and 2) of the mean impact of information exchange links between IPs and their neighbors on awareness, knowledge, and adoption of DT maize varieties (Longe 10H and Longe 5), improved maize varieties in general, disease-resistant groundnut varieties (Serenut 5R and Serenut 14R), and CF basins. The analysis estimates mean impacts comparing matched treated and matched untreated households' outcomes in the baseline and follow up. Panel A presents results with treatment defined as equal to one if an information exchange link exists between sampled respondents in a sub-village and the selected IP for that sub-village, and zero if otherwise whereas Panel B presents results with treatment defined as equal to one if a sub-village has at least one neighbor with an information exchange link with the selected IP for that sub-village, and zero if otherwise. Column 1 presents results with Radius matching whereas column 2 presents results with Kernel-based matching. Results of IPW-DID with both matching algorithms are very similar indicating robustness to the different matching methods.

In addition to IPW-DID estimates, we present results of two-stage least square regression (column 3) that used social distance variables as instruments for link formation. Results in column (3) are similar to those in (1) and (2) in terms of direction of influence, but the estimated causal effects are larger in magnitude for most of the outcomes. Furthermore, our tests for suitability of the instruments showed mixed results and did always hold for all the outcomes that we considered.

Columns (1) and (2) of Panel A in Table 8 show that information exchange links increased awareness about improved varieties and conservation farming basins. Between baseline and two cropping seasons after baseline, the probability of knowing about Longe 10H maize increased by only around 1% (not statistically significant at 10% level) more among farmers having information exchange links with a trained IP compared to those in the control group. The proportion of farmers who had heard about DT maize varieties overall (Longe 10H plus Longe 5) rose by 35%; about the same proportion, 36 – 39%, of farmers knew an improved variety of maize. Information exchange links did not significantly increase awareness about groundnut varieties. Relative to the control group, the likelihood to hear about conservation farming basins rose by 28 – 29% with information exchange links.

>> Please insert Table 8 about here >>

In addition to having heard about a technology, knowledge about how the technology works including its benefits is important. Results show that knowledge increased by 0.81 – 0.85 standard deviations above the mean for farmers who had an information exchange link with trained IPs. This means that information exchange links with trained IPs allowed farmers to learn about the benefits and agronomic practices associated with cultivation of improved varieties.

The findings that information exchange links increased awareness and knowledge are consistent with expected short-term effects of providing training to a few individuals in the population and leveraging social networks to enhance diffusion of agricultural knowledge. Together, these findings support evidence that social learning increases diffusion of agricultural knowledge (Bandiera and Rasul, 2006; Conley and Udry, 2010; Ben Yishay and Mobarak, 2014; Kondylis et al., 2016; 2017).

Information exchange links did not only increase awareness and knowledge, but also adoption. Specifically, about 11% more farmers who had information exchange links with trained IPs compared to those in the control group grew Longe 10H DT variety of maize; the corresponding figures for DT maize as a whole and improved varieties of maize generally were 25% and 26 – 28%. These findings perhaps suggest that farmers who learnt from trained IPs found the information useful and subsequently used it to improve their farming methods. The increase in adoption of improved groundnut varieties and conservation farming was however very low and statistically not significant at 10% level. For these technologies, therefore, it seems that the increase in awareness among farmers did not translate into adoption.

Results of 2SLS (column 3, Table 7) show that awareness (about maize varieties, groundnut varieties, and conservation farming basins) and knowledge increased substantially with information exchange links two cropping seasons after the training of IPs. The results further show a substantial increase in adoption of maize varieties, but no significant increase in adoption of groundnut varieties and conservation farming basins.

At the sub-village level, Panel B in Table 7 shows that awareness about Longe 10H increased between 5 – 6%; the corresponding estimates for DT maize as a whole, Serenut 4R and 14R groundnuts, Serenut groundnuts in general, and conservation farming basins are 6 – 8%, 4.5%, 2.3 – 2.6%, and 4.4 – 4.7%. Similarly, adoption increased by about 2% for Longe 10H maize, 8 – 9% for DT maize as a whole, and about 10% for improved varieties of maize generally. Estimated impacts are larger with 2SLS compared with the IPW-DID approach. For both awareness and adoption, however, the estimated impacts are mostly lower in magnitudes compared to those obtained at individual farmer level.

7. CONCLUSION

Informational constraints contribute to the adoption puzzle in sub-Saharan Africa (SSA) where implementation of yield-enhancing technologies that have been shown to play an important role in improving people's welfare remains very low. Within an extension system framework, one approach to address this problem is direct provision of training to a few carefully selected individuals – commonly referred to as knowledge injection points (IPs) – in the target population and leveraging social networks for technology diffusion. Central to the success of this approach, however, is understanding how information exchange links form between trained IPs and their neighbors. Using a panel dataset collected in northern Uganda during 2015–2017, the objectives of this study were twofold. First, we assess determinants of information exchange links between IPs selected to be representative of the target population and their neighbors, focusing on the role of social distance. Second, we assess the effect of such information exchange links on awareness, knowledge, and adoption of drought-tolerant (DT) varieties of maize, disease-resistant varieties of groundnuts, and conservation farming basins.

The first part of our analysis estimates a probit regression model to assess the determinants of information exchange links. Similarities and differences in terms of sex, education, amount of land cultivated with maize, and ownership of agricultural and non-agricultural assets influenced willingness of farmers to seek the advice of IPs in their sub-villages. We further found that differences in socioeconomic characteristics between IPs and their neighbor are important for knowledge diffusion, but effectiveness of IPs diminish when such differences are excessive.

The second part of our analysis combined propensity score matching with difference-in-differences approaches to estimate causal effect of information exchange links on awareness, knowledge, and adoption. At individual farmer-level, results showed that information exchange links increased awareness and knowledge of neighbors about the DT and improved varieties of maize as a whole, disease-resistant groundnut varieties, and conservation farming basins. Information exchange links also influenced adoption of the maize varieties, but neither groundnut varieties nor conservation farming basins. At the sub-village level, information exchange links increased awareness about maize and groundnut varieties.

We acknowledge, however, that our results cannot be generalized at the national level since the sample was not representative of the entire country. Our estimates of the causal impact of information exchange links are, nevertheless, close to those of the few previous studies that assess effect of farmer-to-farmer extension on knowledge diffusion and technology adoption (see for example, Kondylis et al. 2017). The findings of this study thus contribute to the limited body of knowledge on identification of IPs, factors that influence information exchange links, and impacts on adoption of agricultural innovations. Together the findings of this study suggest that with careful selection of IPs, providing direct training can help to diffuse agricultural knowledge and technologies. Efforts targeting to incorporate farmer-to-farmer technology transfer within national extension systems in order to enhance information exchange and adoption could benefit by taking into consideration 'proximity' between IPs and other farmers in terms of social distance.

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Table 1. Description and summary statistics for social distance variables

Variables	Description	Mean (SD)	Observations
Sex: both female	1= both respondent and IP are female; 0=otherwise	0.321 (0.467)	313
Sex: female, male	1= IP is female and respondent is male; 0=otherwise	0.197 (0.398)	192
Sex: male, female	1= IP is male and respondent is female; 0=otherwise	0.242 (0.429)	236
Sex: male, male	1= both respondent and IP are male; 0=otherwise	0.240 (0.427)	234
Age: younger	Age difference (years) between IP and respondent if the IP is younger than the respondent, 0 otherwise	6.935 (11.241)	414
Age: older	Age difference (years) between IP and respondent if the IP is older than the respondent, 0 otherwise	6.682 (10.485)	424
Education: more educated	Education difference between IP and respondent if the IP is more educated than the respondent, 0 otherwise	1.861 (2.831)	402
Education: less educated	Education difference between IP and respondent if the IP is less educated than the respondent, 0 otherwise	1.507 (2.602)	340
Maize area: more	Farm size difference if the IP cultivated more land under maize than the respondent, 0 otherwise	0.235 (0.413)	424
Maize area: less	Farm size difference if the IP cultivated less land under maize than the respondent, 0 otherwise	0.237 (0.785)	312
Agricultural assets: both more	1=both IP and respondent have a greater endowment of agricultural assets, 0 otherwise	0.223 (0.416)	217
Agricultural assets: both less	1=both IP and respondent have a lower endowment of agricultural assets, 0 otherwise	0.371 (0.483)	362
Agricultural assets: more, less	1=IP has a greater endowment of agricultural assets than the respondent, 0 otherwise	0.201 (0.401)	196
Agricultural assets: less, more	1=IP has a lower endowment of agricultural assets than the respondent, 0 otherwise	0.205 (0.404)	200
Non-agricultural assets: both more	1=both IP and respondent have a greater endowment of non-agricultural assets, 0 otherwise	0.208 (0.406)	203
Non-agricultural assets: both less	1=both IP and respondent have a lower endowment of non-agricultural assets, 0 otherwise	0.176 (0.382)	392
Non-agricultural assets: more, less	1=IP has a greater endowment of non-agricultural assets than the respondent, 0 otherwise	0.194 (0.396)	189
Non-agricultural assets: less, more	1=IP has a lower endowment of non-agricultural assets than the respondent, 0 otherwise	0.196 (0.397)	191

Group: both members	1= both respondent and IP are group members; 0=otherwise	0.617 (0.486)	602
Group: both non-members	1= both respondent and IP are not group members; 0=otherwise	0.602 (0.490)	84
Group: member, not member	1= IP is a group member whereas the respondent is not; 0=otherwise	0.179 (0.384)	175
Group: not member, member	1= respondent is a group member whereas the IP is not; 0=otherwise	0.117 (0.321)	114
Soil pH: more	Difference in pH if IP's soil pH is higher than that of the respondent's farm, 0 otherwise	0.030 (0.059)	336
Soil pH: less	Difference in pH if IP's soil pH is lower than that of the respondent's farm, 0 otherwise	0.030 (0.054)	422
Silt content: more	Difference in silt content if IP's soil has more silt than that of the respondent's farm, 0 otherwise	0.360 (0.733)	355
Silt content: less	Difference in silt content if IP's soil has less silt than that of the respondent's farm, 0 otherwise	0.433 (0.727)	357

Notes: IP means knowledge injection point. For age, education, and farm size, absolute value is computed.

Source: 2015 baseline survey in Northern Uganda.

Table 2. Baseline sample statistics by link status

Variable	Pooled sample	Non-weighted sample			Weighted sample		
		Link	No link	Diff.	Link	No link	Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Household head is male	0.818	0.879	0.808	0.071	0.797	0.802	0.005
Respondent is male	0.430	0.470	0.424	0.045	0.381	0.417	0.036
Household head completed primary education	0.420	0.543	0.401	0.142***	0.479	0.420	0.059
Age of the household head (years)	43.691	41.664	44.007	2.343	43.881	44.334	0.453
Dependency ratio	0.567	0.568	0.567	0.001	0.544	0.571	0.027
Housing condition (index)	-0.866	-0.860	-0.867	0.007	-0.837	-0.858	0.021
Livestock asset (TLU)	0.698	0.845	0.676	0.169	0.588	0.702	0.114
Household received credit	0.682	0.810	0.662	0.148***	0.774	0.703	0.071
Received climate-related information	0.737	0.802	0.727	0.075*	0.701	0.719	0.018
Distance to main market (walking minutes)	41.592	43.767	41.253	2.514	44.000	42.000	2.000
Distance to main road (walking minutes)	12.350	9.000	13.000	4.000***	10.000	11.000	1.000
Friendship network (number of friends)	2.023	2.172	2.000	0.172*	2.000	2.000	0.000
Kinship network (number of relatives)	1.730	1.879	1.706	0.173	2.000	2.000	0.000
Number of observations	862	116	746		84	510	

Notes: *, **, *** indicate statistically significant difference at 10%, 5%, and 1% level.

Source: Household survey, 2015.

Table 3. Differences in outcome variables by link status

Variables	Baseline (2015)				Endline (2017)			
	All	No link	Link	Difference	All	No link	Link	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Awareness and knowledge variables								
Heard about Longe 10H DT maize	0.0522	0.0456	0.0948	-0.0493*	0.1079	0.0456	0.5086	-0.4630***
Heard about DT maize in general	0.2030	0.1823	0.3362	-0.1539***	0.2285	0.1528	0.7155	-0.5627***
Heard about improved variety of maize	0.3608	0.3378	0.5086	-0.1708***	0.3329	0.2560	0.8276	-0.5716***
Heard about serenut 5R or 14R	0.0046	0.0027	0.0172	-0.0146	0.0290	0.0161	0.1121	-0.0960***
Heard about Serenut groundnuts	0.0882	0.0804	0.1379	-0.0575*	0.0661	0.0402	0.2328	-0.1925***
Heard about conservation farming basins	0.0000	0.0000	0.0000	NA	0.1311	0.1005	0.3276	-0.2271***
Knowledge score (standardized)	-0.2355	-0.2735	0.0095	-0.2831***	0.0175	-0.1626	1.1755	-1.3381***
Panel B: Adoption variables								
Grow Longe 10H	0.0128	0.0067	0.0517	-0.0450**	0.0394	0.0161	0.1897	-0.1736***
Grow any drought-tolerant variety of maize	0.0580	0.0429	0.1552	-0.1123***	0.1427	0.0925	0.4655	-0.3730***
Grow an improved variety of maize	0.1265	0.1153	0.1983	-0.0830**	0.1647	0.1113	0.5086	-0.3974**
Grow Serenut 5R or 14R	0.0023	0.0013	0.0086	-0.0073	0.0058	0.0027	0.0259	-0.0232
Use conservation farming basins	0.0000	0.0000	0.0000	NA	0.0070	0.0054	0.0172	-0.0119
Observations	862	746	116		862	746	116	

Notes: *, **, *** indicate statistically significant difference at 10%, 5%, and 1% level. *Source*: 2015 baseline and 2017 endline household surveys in Northern Uganda. Drought-tolerant (DT) maize varieties include Longe 10H and Longe 5.

Table 4. Determinants of link formation between knowledge injection points (IPs) and neighbors

Dependent variable = 1 if an information exchange link exists and 0=otherwise	
Variable	(1)
Both IP and neighbor are female	0.089** (0.043)
IP is female; neighbor is male	0.089* (0.052)
Both are male	-0.036 (0.046)
IP is younger than neighbor	-0.002 (0.001)
IP is older than neighbor	0.002 (0.001)
IP is more educated than neighbor	0.002 (0.006)
IP is less educated than neighbor	0.010** (0.005)
IP cultivates more land under maize	0.074*** (0.029)
IP cultivates less land under maize	0.024 (0.015)
IP has more agricultural assets	-0.032 (0.034)
IP has less agricultural assets	0.005 (0.044)
Both have less agricultural assets	0.067* (0.040)
IP has more non-agricultural assets	-0.032 (0.039)
IP has less non-agricultural assets	-0.003 (0.034)
Both have less non-agricultural assets	-0.091** (0.039)
Both belong to a group	0.035 (0.159)
Only IP belongs to a group	0.076 (0.148)
Only neighbor belongs to a group	0.117 (0.162)
Soil pH: more	0.060 (0.208)
Soil pH: less	0.473** (0.222)
Silt content: more	-0.002 (0.208)
Silt content: less	-0.063*** (0.019)
Control variables	Yes
Sub-county fixed effects	Yes
R^2	0.176
Observations	855

Notes: IP=Injection point. Average marginal effects are reported. Figures in parentheses are bootstrapped standard errors. *, **, *** indicate statistically significant difference at 10%, 5%, and 1% level.

Source: 2015 baseline household surveys in Northern Uganda.

Table 5. Balancing tests for individuals with a link and matched controls

Variable	Mean		Bias reduction (%)	*t*-Test	
	Link	No link		*t*-Stat	*p*-value
Household head is male	0.857	0.855	96.10	0.04	0.971
Household head completed primary education	0.548	0.579	79.00	-0.04	0.688
Age of the household head (natural log)	3.688	3.688	100.00	0.00	1.000
Dependency ratio	0.581	0.581	100.00	0.00	1.000
Housing condition (index)	-0.842	-0.794	-144.10	-0.82	0.416
Livestock asset (TLU)	0.858	0.828	83.80	0.09	0.929
Household received credit	0.821	0.819	98.40	0.04	0.970
Received climate-related information	0.774	0.768	94.30	0.09	0.927
Distance to main market (walking minutes)	43.000	45.000	29.30	-0.47	0.642
Distance to main road (walking minutes)	10.000	9.000	70.80	0.60	0.553
Friendship network	2.214	2.243	86.60	-0.19	0.847
Kinship network	1.857	1.938	66.80	-0.48	0.630

Notes: Variables on social distance as presented in Table 1 were also included in the covariates balancing test (as instruments) – we do not present results here because of space limitation, but they are available upon request from the author.

Source: 2015 baseline survey in Northern Uganda.

Table 6. Matching quality indicators before and after matching

Matching algorithm	Pseudo R^2 before matching	Pseudo R^2 after matching	LR chi-square (*p*-value) before matching	LR chi-square (*p*-value) after matching	Mean standardized bias before matching	Mean standardized bias after matching
RM	0.148	0.007	100.82^{***} (0.000)	2.09 (1.000)	17.5	2.8
KBM	0.114	0.008	198.03^{***} (0.000)	4.59 (1.000)	15.2	3.0

Notes: RM=Radius matching and KBM=Kernel-Based matching. *** Significant at 1% level.

Table 7. Effect of information exchange links on awareness, knowledge, and adoption of improved varieties and conservation farming

Treatment / dependent variable	IPW-DID with Radius matching	IPW-DID with Kernel-Based matching	Two-stage least square fixed effects model	Kleibergen-Paap test	Cragg-Donald test	Hansen J statistic	Endogeneity test
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Treatment 1 ($LINK_F$)							
Awareness							
Longe 10H DT maize	0.011 (0.019)	0.009 (0.020)	0.413*** (0.150)	33.661**	4.775	25.617*	0.123
Any DT maize including Longe 10H	0.354*** (0.122)	0.354** (0.139)	0.577*** (0.181)	33.661**	4.775	20.586	0.949
Improved maize variety	0.362** (0.141)	0.388** (0.150)	0.452** (0.207)	33.661**	4.775	17.857	0.108
Serenut 5R or Serenut 14R groundnut	0.037 (0.026)	0.040 (0.025)	0.141* (0.074)	33.661**	4.775	18.164	2.828*
Any Serenut groundnut variety	0.016 (0.085)	0.025 (0.089)	0.230 (0.170)	33.661**	4.775	20.105	0.174
Conservation farming basins	0.282** (0.113)	0.292** (0.125)	0.428*** (0.141)	33.661**	4.775	16.309	1.103
Knowledge	0.808*** (0.282)	0.848*** (0.281)	1.441***(0.427)	33.661**	4.775	26.590*	1.145
Number of observations	1,316	1,166	1,318				
Adoption							
Longe 10H DT maize	0.115 (0.072)	0.111 (0.074)	0.132* (0.079)	33.661**	4.775	15.102	0.227
Any DT maize including Longe 10H	0.245* (0.075)	0.248* (0.143)	0.544*** (0.163)	33.661**	4.775	22.302	8.703***
Improved maize variety	0.255*(0.131)	0.276*(0.145)	0.506*** (0.174)	33.661**	4.775	23.423	8.239***
Serenut 5R or Serenut 14R groundnut	0.007 (0.010)	0.009 (0.011)	0.016 (0.032)	33.661**	4.775	3.013	0.057
Conservation farming basins	0.005(0.013)	0.006 (0.013)	0.027 (0.032)	33.661**	4.775	5.720	0.079
Number of observations	1,312	1,166	1,318				

Table 7. Continued

Treatment / dependent variable	IPW-DID with Radius matching (1)	IPW-DID with Kernel-Based matching (2)	Two-stage least square fixed effects model (3)	Kleibergen-Paap test (4)	Cragg-Donald test (5)	Hansen J statistic (6)	Endogeneity test (7)
Panel B: Treatment 2 ($LINK_V$)							
Awareness							
Longe 10H DT maize	0.063*** (0.024)	0.047** (0.024)	0.205** (0.081)	28.800*	7.084	18.286	2.929*
Any DT maize including Longe 10H	0.082** (0.037)	0.062* (0.037)	0.172** 0.092)	28.800*	7.084	19.503	2.173
Improved maize variety	0.045 (0.044)	0.045 (0.048)	0.163 (0.132)	28.800*	7.084	22.501	0.969
Serenut 5R or Serenut 14R groundnut	0.026* (0.015)	0.023 (0.014)	0.024 (0.031)	28.800*	7.084	17.681	0.258
Any Serenut groundnut variety	0.033 (0.021)	0.021 (0.021)	-0.009 (0.084)	28.800*	7.084	17.549	0.908
Conservation farming basins	0.044 (0.030)	0.047 (0.030)	0.123 (0.082)	28.800*	7.084	21.460	0.742
Knowledge	0.082 (0.088)	0.059 (0.091)	0.315 (0.238)	28.800*	7.084	33.814***	0.396
Number of observations	1,298	1,172	1,326				
Adoption							
Longe 10H DT maize	0.022 (0.013)	0.021 (0.013)	0.048 (0.042)	28.268*	7.390	17.573	0.476
Any DT maize including Longe 10H	0.089*** (0.028)	0.082*** (0.029)	0.163* (0.089)	28.268*	7.390	27.857**	5.938**
Improved maize variety	0.097*** (0.031)	0.095*** (0.035)	0.191* (0.102)	28.268*	7.390	28.017**	3.703*
Serenut 5R or Serenut 14R groundnut	-0.001 (0.006)	-0.000 (0.006)	-0.005 (0.014)	28.268*	7.390	5.418	0.007
Conservation farming basins	0.001 (0.004)	0.003 (0.005)	0.001 (0.021)	28.268*	7.390	7.005	0.002
Number of observations	1,684	1,522	1,710				

Notes: Average marginal effects are reported, except for column (3). Robust standard errors clustered at sub-village level are in parentheses. *, **, *** indicate statistically significant difference at 10%, 5%, and 1% level.

Source: 2015 and 2017 household surveys in Northern Uganda.

Table A1. Comparison of baseline characteristics for full sample and sample after attrition

Variable (2015 values)	Full sample	Sample after attrition
	(1)	(2)
Age of the household head (natural log of years)	44.084	43.691
Years of formal education of the household head	6.059	5.680
Sex of the household head (1=male; 0=female)	0.809	0.818
Dependency ratio	0.545	0.567
Livestock ownership (TLU)	0.693	0.698
Household received credit	0.668	0.682
Friendship network	2.152	2.023
Kinship network	1.733	1.730
Observations	1286	862

Notes: Sample in column (2) excludes knowledge injection points.

Source: 2015 baseline household surveys in Northern Uganda.

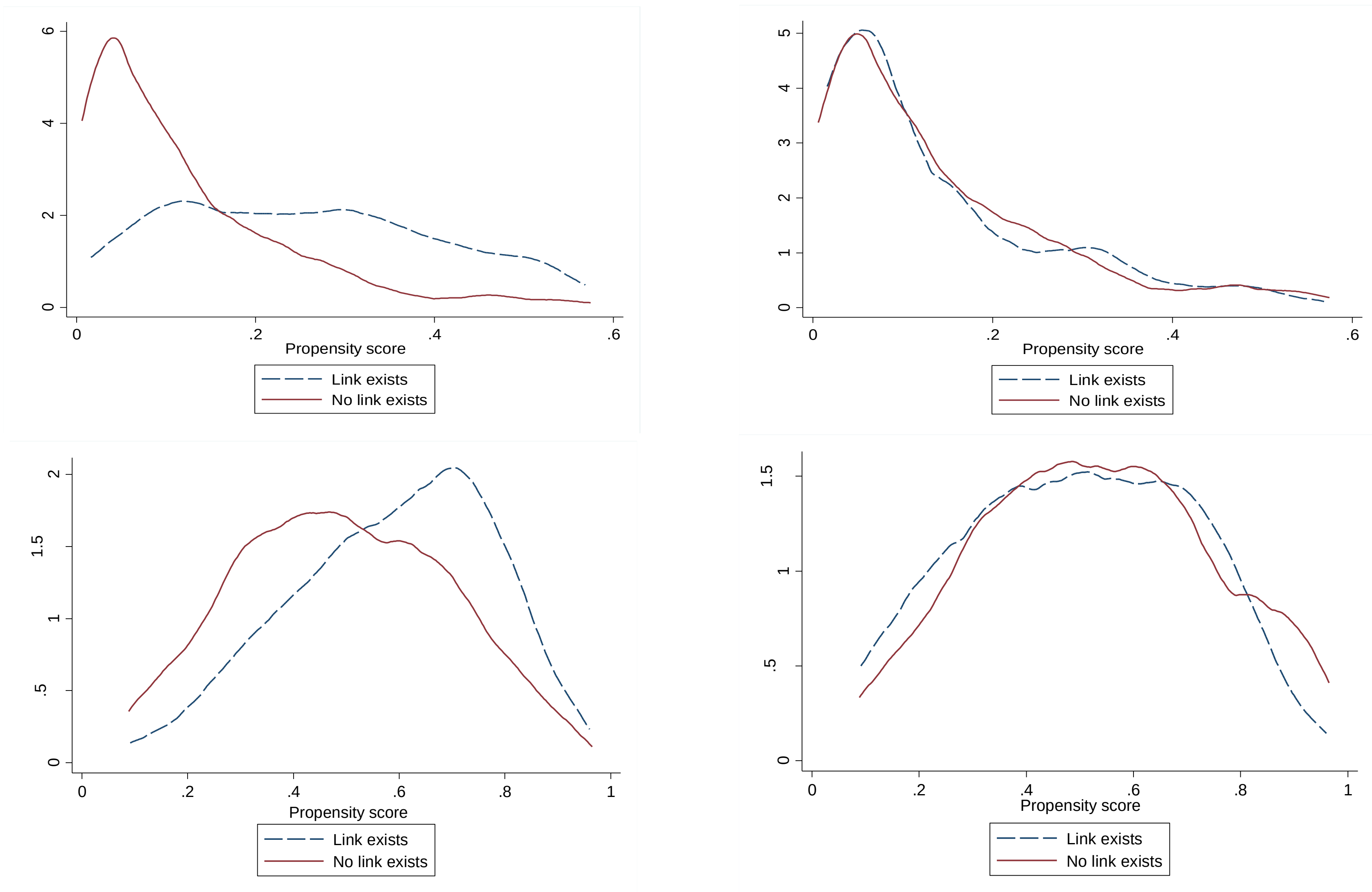

Figure 1. Propensity score weighting

Notes: Left panels shows distribution of propensity scores for the un-weighted sample whereas the right panels shows the same distribution for weighted sample. Top panel is based on treatment defined as existence of a link between an IP and individual farmer whereas bottom panel is based on treatment defined as a sub-village in which an IP trained at least one farmer.

Source: 2015 baseline survey data from Northern Uganda.