Information Exchange Links, Knowledge Exposure, and Adoption of Agricultural Technologies in Northern Uganda

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Abstract

Direct training of selected individuals as disseminating farmers (DFs) can help to implement a farmer to farmer extension approach. This study systematically examines the relationship between social distance and the likelihood of information exchange, subsequently evaluating effects on awareness, knowledge, and adoption of drought-tolerant (DT) varieties of maize, disease-resistant varieties of groundnuts and conservation farming. Using a panel dataset from northern Uganda, the study combines matching techniques with difference-in-difference (DID) approach and employs two-stage least squares regression (2SLS) to identify causal effects. The study finds an increased likelihood of information exchange when the DF is female, regardless of the sex of the neighbour. The likelihood of information exchange increased when distance in farm size cultivated with maize was larger than the median in the sub-village. In terms of non-agricultural assets index, there was an increased likelihood of information exchange both when the distance was smaller and greater than the village median. Information exchange links improved awareness and knowledge for all of the technologies, but only increased adoption of maize varieties. Together, these findings suggest that social distance shapes the diffusion of agricultural knowledge even when DFs are selected by the community to be "representative" and reinforces that social learning can help to address informational constraints to adoption of agricultural technologies.

Key words: Farmer to farmer extension, information exchange links, social learning, adoption, climate smart agriculture, Uganda

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. Lack of information about a technology impedes 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 disseminating farmers (DFs)—and using social networks for knowledge diffusion (Kondylis et al., 2016).

Empirical evidence suggests that social learning can be as effective as formal extension in transferring agricultural information (Krishnan and Patnam, 2013). In a few cases, it has been shown that social learning can generate greater productivity gains compared to formal extension (e.g., Vasilaky and Leonard (2018)). Effectiveness of farmer to farmer extension depends, however, on how the DFs are identified (Beaman et al., 2018) and whether or not such individuals are incentivised (BenYishay and Mobarak, 2018). Cost-benefit analysis of providing direct training to DFs has indicated that farmer to farmer technology transfer could be cost-effective (Kondylis et al., 2017). Similarly, BenYishay and Mobarak (2018) found that provision of training accompanied by small performance-based incentives to DFs was a cost-effective approach for disseminating agricultural knowledge. In Uganda, where previous formal extension approaches have yielded unsatisfactory performance triggering efforts to restructure the system (Barungi et al., 2016; Ministry of Agriculture, Animal Industry and Fisheries [MAAIF], 2017), farmer to farmer extension could play an important complementary role. Hogset and Barrett (2010) indicated that learning from others could generate important social multiplier effects in the diffusion of agricultural technologies, required to complement formal extension systems.

In 2016, we partnered with the National Agricultural Research Organisation (NARO) and Tillers International—an NGO promoting conservation farming in northern Uganda to train 126 randomly selected DFs about agricultural technologies that are increasingly seen to be climate-smart (Food and Agriculture Organization [FAO], 2013). The technologies considered in this study include drought-tolerant (DT) varieties of maize, disease-resistant varieties of groundnuts, and conservation farming (CF) basins. Each of the selected DFs represented a sub-village. The DFs were selected by the community not to be too wealthy. The training, which lasted for three days, included both classroom sessions and practical demonstration in the field. At the end of the training, DFs were asked to share the knowledge learnt with their fellow sub-villagers (whom we refer to as neighbours).

The specific objectives of this study are twofold: (1) to assess relationship between social distance and information exchange links; and (2) to evaluate the impacts of information exchange links on awareness, knowledge, and adoption of agricultural technologies. Interest is growing in understanding the effect of "active" interventions that provide direct agricultural training to DFs on adoption behaviour of their neighbours (e.g., Kondylis et al., 2016; 2017). The motivation stems largely from an enhanced understanding of the selection criteria for DFs (Banerjee et al., 2014; Kim et al., 2015; Beaman et al., 2018; Chami et al., 2017) and the increasingly recognised role of incentives for knowledge diffusion (BenYishay and Mobarak, 2018; Sseruyange and Bulte, 2018).

In addition to selection and incentives, diffusion of agricultural technologies through social networks could be influenced by social distance—differences in socioeconomic and biophysical characteristics between network nodes (Feder and Savastano, 2006; Santos and Barrett, 2010). For example, farmers may not learn from DFs of the opposite sex if they viewed their messages as inferior to those of the same sex (BenYishay et al., 2016). Similarly, heterogeneity in growing conditions might generate varied benefits among farmers meaning that messages of DFs may not be relevant to the decision making of their neighbours (Munshi, 2004; Magnan et al., 2015).

Literature has long established that individuals tend to associate disproportionately with others who are similar to themselves (McPherson et al., 2001; Goeree et al., 2010). This tendency is referred to as homophily—a term coined by Lazarsfeld and Merton (1954). 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. Genius et al. (2013) indicated, however, that in addition to "homophilic neighbours" 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. Studies that assess neighbourhood effects on the behaviour of economic agents, therefore, consider average characteristics of an individual's reference group (Matuschke and Qaim, 2009; Krishnan and Patnam, 2013). These studies do not, however, measure the differences in the characteristics between network nodes and, therefore, fail to assess effects of social distance. Those that have attempted to assess effects of social distance focused on information exchange within existing social networks (Feder and Savastano, 2006; Santos and Barrett, 2010). Santos and Barrett (2010) also did not assess effects of information exchange links on adoption of agricultural technologies.

This study, therefore, contributes to the literature on social learning and technology adoption (Bandiera and Rasul, 2006; Matuschke and Qaim, 2009; Conley and Udry, 2010; Krishnan and Patnam, 2013; Vasilaky and Leonard, 2018) in three important ways. First, the study focuses on differences in both socioeconomic and soil characteristics between a trained DF in a sub-village and his or her neighbours. Such neighbours may be "homophilous" or "heterophilous" to the DF in terms of social distance and/or soil characteristics. Second, we study information exchange in the context of an active intervention in which DFs are directly trained and encouraged to communicate with their neighbours. The study, therefore, departs from previous studies which examined the effect of social distance on information exchange under the assumption of "passive" learning (Feder and Savastano, 2006; Santos and Barrett, 2010). Third, we distinguish between awareness exposure, that is, having heard about a technology and knowledge exposure, that is, knowing how to implement the technology, and study the effect of information exchange links on awareness, knowledge, and adoption of agricultural technologies. A few authors have highlighted the importance of distinguishing between awareness and knowledge in adoption analysis (Lambrecht et al., 2014). The study shows that: (1) differences in sex, ownership of non-agricultural assets, and size of land cultivated with maize, influence information exchange links; and (2) information exchange links generated through an active intervention increase awareness and knowledge exposure, and adoption of drought-tolerant varieties of maize.

The paper is organised as follows. Section 2 describes the context. Section 3 discusses the conceptual framework underlying the study. Section 4 describes the data and variables used in the analysis. Section 5 discusses the empirical approach and estimation procedure. Section 6 presents the results while section 7 concludes.

2. CONTEXT AND SELECTION OF DISSEMINATING FARMERS

(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, 2015). 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 recognise 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 recognise the role of farmer to farmer knowledge and technology transfer. It is, therefore, important to understand the factors that 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 disseminating farmers*

The procedure for selecting DFs 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 DF 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 a DF who was endorsed by co-villagers was three and in more than 75% of sub-villages the first name was endorsed.

Selected DFs were provided a three-day training session. The trainings were organised in central locations, and DFs 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 DFs that we invited, 126 attended the full training. Sub-villages for which selected DFs did not attend the training are excluded from the analysis.

3. CONCEPTUAL FRAMEWORK

The fundamental issue that training of DFs seeks to address is the notion that use of recommended climate-smart agricultural (CSA) technologies which could potentially increase productivity and enhance resilience to weather shocks is very low because of inadequate exposure of farmers to knowledge about the technologies[1]. 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 yield potential due to many years of experimentation with the variety but might experience a major crop failure if 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 BenYishay and Mobarak (2018). The target input model presupposes

[1] A fundamental assumption here is that the 'CSA' technology being promoted is better, under climate change, than what the farmers have already. Whereas this may be true for the new varieties—they have some better traits in terms of disease resistance or drought-tolerance—farmers may not prefer such varieties if they are inferior in terms of other traits such as colour and taste compared with the local varieties. For example, the two varieties of groundnuts (Serenut 5R and Serenut 14R) that we studied were denoted R meaning Red seeded but they are generally not as deep red as Red Beauty (a local variety).

the existence of a new technology whose required target inputs for implementation are not known to farmers. Farmer j chooses the amount 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, because of the gap between the farmer's inputs and the target inputs. The farmer will, therefore, seek to learn in order to maximise payoffs from the new technology[2].

Suppose further that there is an informed farmer k who has been trained about the new technology and understands the possibilities. Using social networks could help with diffusion of knowledge from this informed farmer to neighbours (Conley and Udry, 2010). Communicating the information to other farmers requires that the informed farmer sends a signal, incurring a cost that is increasing with precision of the message (BenYishay and Mobarak, 2018). Proximity between farmers j and k not only in terms of similarity in agricultural practices but also capacity to implement such 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 BenYishay and Mobarak (2018), expected payoffs from learning decrease with the distance between the communicator and the receiver of the message.

Disseminating farmers in this study were selected to be not very wealthy—as perceived by neighbours. As such, it can be expected that DFs will be closer to some neighbours and far from others in terms of social distance. Furthermore, the selection criterion was not restrictive in terms of other socioeconomic factors such as age, education, membership of farmer associations, or

[2] The assumption of profit maximisation is central to the theory of the firm and producer behaviour. Most adoption studies, therefore, assume that farmers' adoption behaviour is motivated by profit maximization. We acknowledge, however, that several other motives, such as minimisation of risks, might drive the adoption behaviour of farm households.

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:

> H1: Proximity in terms of social distance and soil characteristics between DFs and their neighbours increases the formation of information exchange links.
>
> H2: Information exchange links between trained DFs and their neighbours increase neighbours' awareness, knowledge, and adoption of drought-tolerant (DT) maize and disease-resistant groundnut varieties and conservation farming (CF) basins.

4. DATA AND DESCRIPTION OF VARIABLES

(a) *Data*

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 DF and nine other households. In each selected household, personal interviews with either the household head or spouse (in case the household head was not available) were conducted. The baseline survey was conducted 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 DFs had actually attended the training about the CSA technologies were revisited. Effort was made to interview the same respondents who had been interviewed at the baseline. In total, 1,036 respondents (122 DFs 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 organised 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. Existence of an information exchange link is defined as a dummy variable equal to one if a farmer had contact with or attended an activity organised by the DF in the respective sub-village and zero otherwise.

Next, we distinguish between awareness, knowledge, and adoption of the "recommended" CSA technologies. For each of the crop 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[3]) 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. Because questions differ in difficulty and farmers differ in their ability to respond (Lagerkvist et al., 2015), we generate the probability of answering correctly to a question, that is, $p = (q/Q)$ where q captures the number of people

[3] This latter category includes not only Serenut 5R and Serenut 14R, but also Serenut 2, Serenut 3, and Serenut 4).

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 technologies considered, 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. Adoption as measured here is, therefore, use of technologies at one point in time[4].

(c) *Definition of explanatory variables*

Although evidence on social distance as a determinant of information exchange links in agricultural settings is scant, Santos and Barrett (2010) provide some guidance on measuring social distance. The following steps were followed in constructing the social distance variables. In step one, dyadic pairs were generated for each of the respondent interviewed at baseline. Step two, involved computing (for each dyadic pair) the absolute difference in the continuous variable (education, age, area under maize, area under groundnuts, agricultural assets index, non-agricultural assets index, soil pH). In step three, the median village distance was obtained for each variable. Step four then calculated the distance between the village median and the absolute difference (for each variable) between the DF and the neighbour using equation 1.

[4] We are, however, aware of the suggestion by literature that adoption is not a simple on-off but a gradual process that can go up and down depending on circumstances (e.g. Glover et al., 2016). We also did not look at the intensity of adoption.

$$I_{(x_{DFneighbour}-x_{villagemedian}\leq 0)} \text{ x } \left|x_{DFneighbour}-x_{villagemedian}\right| +$$

$$+I_{(x_{DFneighbour}-x_{villagemedian}>0)} \text{ x } \left|x_{DFneighbour}-x_{villagemedian}\right| \qquad (1)$$

where $I_{(\cdot)}$ is an indicator variable equal to one if true and zero if otherwise; for a continuous variable, $(x_{DFneighbour}-x_{villagemedian})$ measures the absolute distance between the village median $x_{villagemedian}$ and the absolute difference between the DF and the neighbour $x_{DFneighbour}$. Measuring social distance using this approach allows us to capture heterogeneity in distance in the sub-village: in other words, we control for the possibility that in a sub-village, a wide social distance between the DF and the neighbour might simply reflect an existing wide median distance in the sub-village.

Social distance between DF i and neighbour j was measured for categorical variables (sex and membership to a farmers' group) by a set of dummy variables that consider the several possible characterizations of the match (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–non-member, non-member–member, and non-member–non-member). Table 1 presents a description of all the variables used to measure social distance including their summary statistics.

<< Please insert Table 1 about here >>

4. EMPIRICAL APPROACH

In order to 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, a two-step procedure combining difference-in-difference (DID) approach with inverse probability weighting (IPW) technique is employed.

In the first step, the probability for farmer j to have formed an information exchange link with the DF in his or her sub-village is estimated, using the following model.

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

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

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

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 DF 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 social distance at baseline; and $\boldsymbol{x_j}$ is a vector of additional baseline covariates and sub-county fixed effects). $\Phi(\cdot)$ 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 model, allows us to analyse the correlation between social distance and the likelihood of information exchange between DFs and their neighbours. Furthermore, it generates propensity scores which are required to match treatment and control observations—these matched observations 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 DFs, the ultimate impact of interest here comes from the effect of diffusion of DFs' knowledge on other farmers' knowledge and use of the technologies. In the second step, therefore, DID estimation is used 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 DF.

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

$$y_{jt} = \alpha + \lambda D_t + \theta l_{jkt} D_t + \mu_{jt} \quad (3)$$

where y_{jt} is the outcome variable of interest for farmer j at time t (baseline or endline)—in the current case awareness, knowledge, and adoption; l_{kj} is the treatment dummy variable (equals 0 at baseline and for those farmers who did not form a link at endline, and 1 for those farmers who formed a link at endline); D_t is an indicator variable equal to one at endline and zero at baseline.

In equation (3), the coefficient θ on the interaction between link formation l_{kj} and endline dummy D_t gives the average difference-in-difference (DID) effect of the information exchange link. The internal validity of DID estimator depends on the crucial assumption of parallel trends. Parallel trends assumes that the average change in the outcome variable for the "treated" in the absence of treatment is equal to the observed average change in the outcome variable for the "controls". This assumption implies that differences between the controls and the treated if untreated are assumed time-invariant. Therefore, parallel trends assumption is consistent with unobservable group-specific time-invariant heterogeneity. Although the assumption cannot be tested directly, with several periods of data before the treatment it is possible to visually observe trends. A few authors have also tested for parallel trends prior to treatment by regressing the difference in the outcome variables between two periods preceding treatment implementation on a binary variable equal to one for treated observations at endline (see for example, Mason et al., 2017).

In the current study, data are only available for two periods: the baseline and endline. We are not, therefore, able to test the parallel trend assumption. In order to allow the possibility of time-variant selection bias due to initial observables, we therefore use the predicted probability of link formation (that is, the propensity score) to match the treatment units with observationally similar control units. Clearly, farmers who form a link with the DF 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 neighbours, even after adjusting for differences in observed covariates (Imbens and Wooldridge, 2009).

By combining IPW with DID, our empirical estimation allows us to correct for 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[5]. 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 ATT represents average treatment effects on the treated, $\Delta y = y^{t1} - y^{t0}$ 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 a DF, 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

[5] Although propensity score matching plays an important role to generate comparable treatment and control groups, we acknowledge that the approach is not without limitations. For example, two matched groups with same land size does not necessarily mean they have same quality of land. Same is true for variables such as education.

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 DFs 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).

In addition to the IPW-DID approach, an instrumental variable two-stage least squares (2SLS) regression is estimated in panel data. 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 not correlated 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. In this study, three instruments are used, namely difference in education when the DF is less educated than the neighbour, difference in agricultural assets when both the DF and neighbour are less endowed, and difference in non-agricultural assets when both DF and neighbour have a lower endowment. To evaluate the suitability of the 2SLS approach, we conduct several tests, results of which are presented at the bottom of Tables 5 and 6. Specifically, using the Kleibergen-Paap test for under-identification we reject the null hypothesis that our models are under-identified. We further test for weak identification using the Cragg-Donald F-statistic. Our values for this statistic exceed the critical 10 percent value for weak instruments proposed by Stock and Yogo (2001) that stands at 13.91 for our specifications. Furthermore, the Hansen J test cannot reject the hypothesis that our instruments are uncorrelated with the error term. Overall, these tests confirm the adequacy of our three instruments. We, therefore, discuss results of both IPW-DID and 2SLS.

6. RESULTS

(a) *Descriptive statistics*

Summary statistics of the sample households at baseline, 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 percent of the household heads have completed primary level of formal education. The dependency ratio is 57 percent; on average, a household has two members aged between 16–60 years old. The average index for housing condition—constructed using principal component analysis[6] 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. Seven out of ten (68%) of the households reported to have borrowed and actually received credit.

<< Please insert Table 2 about here >>

About one-third of the sample households had not received weather-related information. On average, households are about 42 walking minutes away 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). Comparing these

[6] Several studies have used a similar approach to construct asset indices (see for example, Booysen et al. (2008); and Échevin (2013)).

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; travelled a shorter distance to the nearest main road; and had a more extensive 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 CF basins (Table 3, panel A). Awareness, however, increased at endline; 10.6 percent of farmers knew about Longe 10H maize, 2.7 percent knew about Serenut 5R/14R groundnut varieties, and 13 percent had heard about the CF basins in 2017.

>> Please insert Table 3 about here >>

In both years (2015 and 2017) the proportion of farmers who had heard about the technologies was higher when an information exchange link was formed after baseline compared to when no link was formed. The baseline differences between treatment and control farmers point out the importance of using a DID approach. Adoption rates for the technologies were similarly very low at baseline (Table 3, panel B). Specifically, 1.3 percent of the households grew Longe 10H DT maize variety in 2015. This figure increased to 3.9 percent in 2017. Similarly, the proportion of those who grew DT maize in general increased from 5.8 percent in 2015 to 14.3 percent in 2017.

Adoption of Serenut 5R/14R groundnut varieties and CF basins remained low both at baseline and endline. In both years, farmers who formed an information link with a DF after baseline were more likely to know about and grow the DT varieties of maize as well as the disease-resistant groundnut varieties than their counterparts who did not form 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 CF basins.

(b) *Determinants of information exchange links*

Table 4 presents results of probit regression (equation 2) to assess the correlation between social distance variables and the likelihood of an information exchange link. Results are very similar if we use logit or linear probability model estimation. Average marginal effects are reported. The model is estimated with bootstrapped standard errors to account for heteroscedasticity.

Gender composition of the DF-neighbour pair correlates with the likelihood of information exchange links. The reference group here is the male DF–male neighbour pair. Results indicate that link formation is more likely if the DF is female compared to when the DF is male, regardless of the sex of the neighbour. Link formation is 13 percentage points more likely when both the DF and the neighbour are female. The corresponding magnitude for the female DF–male neighbour pair is 14 percentage points more compared to the male DF–male neighbour pair. Although previous studies have shown that male farmers are generally less likely than female farmers to seek advice of others (Santos and Barrett, 2010; BenYishay et al., 2016), our findings suggest greater willingness to learn *from* female DFs. Because formation of links depends not only on the neighbour but also the DF's effort, our results perhaps suggest that female DFs expended more effort to reach out to their neighbours than their male counterparts. When we compare effort level expended by female versus male DFs, our findings show that about 12 percent more female DFs than male DFs contacted their neighbours about the technologies. Providing direct training to female DFs might enhance trust by other farmers in their competence while involvement of the community in the process of selecting DFs 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 not only other women, but also men to overcome barriers to adoption posed by limited access to extension advice.

>> Please insert Table 4 about here >>

The higher likelihood of a link between female DFs and female neighbours compared with when the DF is male and neighbour is female is consistent with Kondylis et al. (2016) who also argued that including women among selected DFs 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 DF more relevant (Quisumbing and Pandolfelli, 2010). The finding that including women among the DFs also empowers male farmers to seek agricultural advice is in contrast with BenYishay et al. (2016). It is possible that male farmers, in our context, did not view female DFs as less able than their male counterparts in disseminating agricultural knowledge and therefore consider the messages of the former as important.

Differences between DFs and their neighbours in the amount of land cultivated with maize influence information exchange links. Specifically, the probability of link formation increased when the difference in farm size under maize between DFs and their neighbours exceeded the median distance in the sub-village. More specifically, an increase in distance between DFs and their neighbours in farm size under maize by one hectare relative to the median distance for the sub-village correlated with a four percentage points increase in the probability for link formation. Santos and Barrett (2010) also found that differences in amount of land cultivated influenced information exchange links. Kondylis et al. (2017) indicated that DFs with greater endowments of land were more likely to convince other farmers to adopt sustainable land management practices. They explained their finding as stemming from credibility in the source of information; farmers with larger farms may command more trust and respect within the community as seeing is believing (Kondylis et al., 2017). In the current case, a larger difference in farm size relative to the sub-village median may indicate more experience in the cultivation of maize.

We further found that distance in ownership of non-agricultural assets determine whether or not farmers will establish a link with trained DFs. Results show increased likelihood of information exchange both when differences in the non-agricultural assets index between DFs and their neighbours is less than the sub-village median and when the differences exceed the sub-village median. On the one hand, a one unit *decrease* in the difference between DFs and their neighbours in non-agricultural assets index relative to the sub-village median distance correlated with a 9.5 percentage points *increase* in the likelihood of information exchange. On the other hand, a one unit *increase* in the difference between DFs and their neighbours in non-agricultural assets index relative to the sub-village median distance correlated with a 7.9 percentage points *increase* in the likelihood of information exchange. Whereas similarity in wealth status may imply more relevance of the DFs messages to the decision making of their neighbours (Bandiera and Rasul, 2006; BenYishay and Mobarak, 2018), a greater endowment with non-agricultural assets may suggest an increased ability to experiment with the technologies and to demonstrate their implementation to neighbours.

Differences in terms of age, education, area under groundnuts, and agricultural assets index did not significantly influence information exchange links. The estimated marginal effects are very small and not statistically significant at 10 percent level. Similarly, differences in terms of participation in farmers' organisations did not significantly influence link formation at 10 percent level.

In summary, our evidence about the effect of social distance on information exchange is inconclusive. For some variables such as farm size under maize, distance greater than the median for a sub-village correlates with an increased likelihood of information exchange. For others such as ownership of non-agricultural assets, the likelihood of information exchange increases regardless of whether the distance is greater or less than the sub-village median. Yet for others such as sex, the likelihood of information exchange increases as long as the DF is female. Although very few studies have explicitly examined the effect of social distance on knowledge diffusion, these findings perhaps suggest the need to examine the magnitude of the distance (Feder and Savastano, 2006).

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

Before turning to the effects of information exchange links on other outcomes, we discuss the quality of the matching process as applied in the first step of our empirical analysis. Results of the covariates balancing test for the matched sample are presented in the Appendix Table A2. There are no significant differences in pre-treatment 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 DFs. 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 Figure 1 about here >>

After estimating the propensity scores for the "link" and "no-link" households, we check the common support condition. There is considerable overlap in common support. Among households with an information exchange link, the predicted propensity score ranges from 0.033 to 0.957, with a mean of 0.221, while among those without a link, it ranges from 0.002 to 0.636, with a mean of 0.121. Thus, the common support assumption is satisfied in the region of (0.030, 0.967), with no loss of observations from treatment households.

The standardised mean difference for overall covariates used in the propensity score (14–16% before matching) is reduced to about 2.1–2.5 percent after matching (see Appendix Table A3). This substantially reduces mean bias by 84–85 percent 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*-squared also dropped significantly from 11–13 percent before matching to 0.5–0.7 percent after matching. Therefore, the low pseudo-*R*-squared, low mean standardised 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.

Table 5 presents results of IPW-DID and 2SLS estimates of the mean impact of information exchange links between DFs and their neighbours on awareness and knowledge about 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. IPW-DID analysis estimates mean impacts comparing matched treated and matched untreated households' outcomes in the baseline and follow up. Treatment is defined as equal to one if an information exchange link exists between sampled respondents in a sub-village and the selected DF for that sub-village, and zero if otherwise. Panel A presents results with Radius matching whereas panel B presents results with Kernel-based matching. Results of IPW-DID with both matching algorithms are very similar indicating robustness to the different matching methods. Results of 2SLS are consistent to those of IPW-DID in terms of direction of influence, but the estimated causal effects are larger in magnitude for most of the outcomes.

As shown in Table 5, information exchange links increased awareness about improved varieties of maize and CF basins. According to IPW-DID estimates (Table 5, Panels A and B), two cropping seasons after baseline, the probability of knowing about Longe 10H DT maize significantly increased by about 32 percentage points more (column 1) among farmers having information exchange links with a trained DF compared to those in the control group. The corresponding increase according to 2SLS estimates was 34 percentage points more (Panel C, column 1). The likelihood to have heard about DT maize varieties overall (Longe 10H plus Longe 5) rose by 35 percentage points more for households with information exchange links compared to those without such links (Panels A and B, column 2); the corresponding increase for 2SLS was 54 percentage points (Panel C, column 2). According to IPW-DID estimates, the probability of having heard about improved varieties of maize generally increased between 36–39 percentage points more (Panels A and B, column 3), for farmers who had an information exchange link at endline; corresponding to a 42 percentage points increase for 2SLS (Panel C, column 3).

>> Please insert Table 5 about here >>

Whereas the IPW-DID estimates show no significant effect of information exchange links on awareness about improved groundnut varieties, 2SLS estimates indicate that awareness about Serenut 4R and Serenut 14R disease-resistant groundnut varieties increased by about 20 percentage points (Panel C, column 4) more relative to the control group between the baseline and endline. Relative to the control group, the likelihood to hear about CF basins rose by 28–29 percentage points more with information exchange links, according to IPW-DID estimates (Panels A and B, column 6) and about 53 percentage points more according to 2SLS estimates (Panel C, column 6).

In addition to having heard about a technology, knowledge about how the technology works including its benefits is important. Results of IPW-DID show that knowledge increased by 0.81–0.85 standard deviations above the mean (Panels A and B, column 7) for farmers who had an information exchange link with trained DFs relative to the control group between the baseline and endline. The corresponding increase according to 2SLS estimates was 1.61 standard deviations above the mean (Panel C, column 7). This means that information exchange links with trained DFs 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 using 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; Kondylis et al., 2016; 2017; BenYishay and Mobarak, 2018).

Information exchange links did not only increase awareness and knowledge, but also adoption[7]. Table 6 presents estimated effects on adoption for both IPW-DID (Panels A and B) and 2SLS (Panel C). According to IPW-DID estimates, the probability of growing Longe 10H DT maize increased by 11 percentage points more for farmers who had information exchange links with trained DFs compared to those in the control group between the baseline and the endline; the corresponding increase for DT maize as a whole and improved varieties of maize generally was 25 percentage points and 26–28 percentage points more, respectively.

Results of 2SLS show a 12, 53, and 54 percentage points increase in the probability of "treatment" households adopting Longe 10H DT maize, DT maize overall, and improved varieties of maize as a whole, respectively between the baseline and the endline. These findings perhaps suggest that farmers who learnt about improved varieties of maize from trained DFs found the information useful and subsequently used it to improve their farming methods. The increase in adoption of improved groundnut varieties and CF basins was, however, very low and statistically not significant at 10 percent level both for IPW-DID and 2SLS estimates. For these technologies, therefore, it seems that the increase in awareness among farmers did not translate into adoption.

>> Please insert Table 6 about here >>

Construction of conservation basins is labour-intensive. In a context where limited availability of labour is a binding constraint to productivity, increased knowledge might not be enough to induce adoption of CF basins. The direct training that the DFs received included proper usage of herbicides. Yet, this knowledge did not result in increased adoption of CF basins. Usage

[7] Disseminating farmers may not be trusted if themselves do not adopt the technologies. Our data show that before the training only 0.8% of the DFs were growing Longe10H drought-tolerant (DT) maize, 9% grew DT maize generally, 0.8% grew Serenut 5R/14R, and 0% used CF basins. After the training 18% grew Longe 10H, 36% grew DT maize generally, 9% grew Serenut 5R/14R, and 26% used CF basins. These are great increases in adoption rates among DFs relative to the baseline

of herbicides in northern Uganda is very low largely explained by lack of effective demand. At the same time, Bold et al. (2017) showed that most herbicides in Uganda are of poor quality—this might further discourage usage by farmers. Limited usage of herbicides means that the labour burdens both in constructing the CF basins and for weeding are very high (see also Andersson and Giller, 2012; Andersson and D´Souza, 2014; Giller et al., 2015; Rusinamhodzi, 2015; Brown et al., 2017a, 2017b). There seems, therefore, to be a trade-off in terms of appropriateness of CF basins as a CSA technology—a perceived CSA technology may not be appropriate in the immediate term if it brings with it increased labour burdens and huge upfront investment costs while the benefits are only expected later.

The larger estimates for 2SLS compared with those of IPW-DID suggest that there may be a downward bias in the IPW estimates. This means that the unobserved variables that drive link formation are negatively related to changes in awareness and adoption. It is possible therefore that the IPW-DID approach does not adequately address the endogeneity concerns.

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 disseminating farmers (DFs) – in the target population and using social networks for technology diffusion. Central to the success of this approach, however, is understanding how information exchange links form between trained DFs and their neighbours. Using a panel dataset collected in northern Uganda during 2015–2017, the objectives of this study were twofold. First, we assessed determinants of information exchange links between DFs selected to be representative of the target population and their neighbours, focusing on the role of differences in socioeconomic and soil characteristics. Second, we assessed 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 (CF) basins.

The first part of our analysis estimates a probit regression model to assess the determinants of information exchange links. For most of the variables considered in the study, we find inconclusive evidence about the effect of social distance on information exchange. The likelihood of information exchange increased when the DF was female regardless of the sex of the neighbour. Information exchange further increased when the difference between the DFs and their neighbours in farm size cultivated with maize exceeded the sub-village median distance. In terms of wealth, we find a positive correlation between non-agricultural assets index and the likelihood of information exchange both when the sub-village median distance exceeds and when is below the difference between the DFs and their neighbours. There is, however, need for future research to study the extent to which social distance influences diffusion of agricultural knowledge. It is possible that effectiveness of DFs to disseminate agricultural knowledge might diminish when social distance is excessive (Feder and Savastano, 2006).

The second part of our analysis estimated the effect of information exchange links on awareness, knowledge, and adoption. Results showed that information exchange links increased awareness and knowledge of neighbours about the DT and improved varieties of maize as a whole, disease-resistant groundnut varieties, and CF basins. Information exchange links also influenced adoption of the maize varieties, but neither groundnut varieties nor CF basins.

We acknowledge, however, that our results cannot be generalised 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 DFs, factors that influence information exchange links, and impacts on adoption of agricultural innovations. Together the findings of this study suggest that even with careful selection of "representative" DFs, social distance influences information exchange. Furthermore, providing direct training to DFs can help to diffuse agricultural knowledge and technologies. There is, however, need to understand the contexts in which farmers operate (Andersson and D´souza, 2014)—increased labour burdens associated with CF basins, especially when use of herbicides is very low suggests that although the technology is perceived to be climate-smart, acceptance among farmers will be low. Efforts to promote CF basins may be successful if accompanied with strategies to promote usage of herbicides for weeds control and if complemented with increased access to rippers. The latter will also depend on whether herd sizes of oxen, currently very low, will increase. Although our findings have shown that providing direct training accompanied with small performance-based incentives can enhance technology diffusion, questions remain about scalability—can extension approaches based on incentives be scaled across larger landscapes, and how can first-order beneficiaries in turn be incentivised to reach out to second-order beneficiaries, and so on? We hope that future research can help to generate further insights on these issues.

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Table 1. Description and summary statistics for social distance variables at baseline

Variables	Description	Mean (SD)
Female, Female	1= both respondent and DF are female; 0=otherwise	0.294 (0.456)
Female, Male	1= DF is female and respondent is male; 0=otherwise	0.225 (0.418)
Male, Female	1= DF is male and respondent is female; 0=otherwise	0.276 (0.447)
Male, Male	1= both respondent and DF are male; 0=otherwise	0.206 (0.405)
Social distance in age	Median village distance in age minus the absolute age difference (years) between DF and respondent	8.543 (6.874)
Social distance in education	Median village distance in education minus the absolute education difference (years) between DF and respondent	2.175 (1.816)
Social distance in area under maize	Median village distance in farm size under maize minus the absolute farm size difference (ha) between DF and respondent	0.386 (0.725)
Social distance in agricultural assets index	Median village distance in agricultural assets index minus the absolute difference in agricultural assets index between DF and respondent	0.332 (0.313)
Social distance in non-agricultural assets index	Median village distance in non-agricultural assets index minus the absolute difference in non-agricultural assets index between DF and respondent	0.437 (0.335)
Both are group members	1= both respondent and DF are group members; 0=otherwise	0.593 (0.492)
Both are not group members	1= both respondent and DF are not group members; 0=otherwise	0.069 (0.254)
Only DF is a group member	1= DF is a group member whereas the respondent is not; 0=otherwise	0.205 (0.404)
Only neighbour is a group member	1= respondent is a group member whereas the DF is not; 0=otherwise	0.133 (0.340)
Distance in soil pH	Median village distance in soil pH minus the absolute difference in soil pH between DF and respondent	0.044 (0.043)
Observations		855

Notes*: DF means disseminating farmer.*

Source: 2015 baseline survey in northern Uganda.

Table 2. Baseline sample statistics by link status for non-weighted and weighted sample: matching algorithm = Kernel-Based

	Pooled sample	Non-weighted sample			Weighted sample		
		Link	No link	Diff.	Link	No link	Diff.
Variable	(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
Soil pH	5.834	5.846	5.832	0.014	5.819	5.833	0.014
Number of observations	862	116	746		84	510	

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

Source: 2015 baseline survey in northern Uganda.

Table 3. Differences in outcome variables by link status

Variables	Baseline (2015)				Endline (2017)			
	All	Link	No link	Difference	All	Link	No link	Difference
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Awareness and knowledge variables								
Heard about Longe 10H DT maize	0.052	0.095	0.046	0.049*	0.108	0.509	0.046	0.463***
Heard about DT maize in general	0.203	0.336	0.182	0.154***	0.229	0.716	0.153	0.563***
Heard about improved variety of maize	0.361	0.509	0.338	0.171***	0.333	0.828	0.256	0.572***
Heard about serenut 5R or 14R	0.005	0.017	0.003	0.015	0.029	0.112	0.016	0.096***
Heard about Serenut groundnuts	0.088	0.138	0.080	0.058*	0.066	0.233	0.040	0.193***
Heard about conservation farming basins	0.000	0.000	0.000	NA	0.131	0.328	0.101	0.227***
Knowledge score (standardised)	-0.236	0.010	-0.274	0.283***	0.018	1.176	-0.163	1.338***
Panel B: Adoption variables								
Grow Longe 10H	0.013	0.052	0.007	0.045**	0.039	0.190	0.016	0.174***
Grow any drought-tolerant variety of maize	0.058	0.155	0.043	0.112***	0.143	0.466	0.093	0.373***
Grow an improved variety of maize	0.127	0.198	0.115	0.083**	0.165	0.509	0.111	0.397**
Grow Serenut 5R or 14R	0.002	0.009	0.001	0.007	0.006	0.026	0.003	0.023
Use conservation farming basins	0.000	0.000	0.000	NA	0.007	0.017	0.005	0.012
Observations	862	116	746		862	116	746	

Notes: ****, **, * indicate statistically significant difference at 1%, 5%, and 10% level. Drought-tolerant (DT) maize varieties include Longe 10H, Longe 7, and Longe 5.
Source: 2015 baseline and 2017 endline household surveys in northern Uganda.

Table 4. Determinants of link formation between disseminating farmers (DFs) and neighbours: average marginal effects from probit regression

Dependent variable = 1 if an information exchange link exists at endline and 0=otherwise	
Variable	Marginal effect
Both DF and neighbour are female	0.128*** (0.043)
DF is female; neighbour is male	0.140*** (0.039)
Both DF and neighbour are male	0.038 (0.046)
Difference in age ≤ sub-village median distance	-0.002 (0.002)
Difference in age > sub-village median distance	-0.002 (0.002)
Difference in education ≤ sub-village median distance	0.001 (0.008)
Difference in education > sub-village median distance	0.008 (0.006)
Difference in maize area ≤ sub-village median distance	0.053 (0.060)
Difference in maize area > sub-village median distance	0.040** (0.020)
Difference in groundnut area ≤ sub-village median distance	-0.124 (0.112)
Difference in groundnut area > sub-village median distance	-0.000 (0.023)
Difference in agricultural assets index ≤ sub-village median distance	0.04 (0.059)
Difference in agricultural assets index > sub-village distance	0.006 (0.046)
Difference in non-agricultural assets index ≤ sub-village median distance	0.095** (0.047)
Difference in non-agricultural assets index > sub-village median distance	0.079* (0.041)
Both DF and neighbour belong to a farmers' group	0.022 (0.123)
Only DF belongs to a farmers' group	0.040 (0.132)
Only neighbour belongs to a farmers' group	0.084 (0.115)
Difference in soil pH ≤ sub-village median distance	0.105 (0.418)
Difference in soil pH > sub-village median distance	0.197 (0.246)
Private reward	0.030 (0.033)
Social recognition	0.070*** (0.025)
R-squared	0.135
Observations	855

Notes: Figures in parentheses are bootstrapped standard errors. Additional control variables include sex, age, and education of the household head; household members between 16 and 60 years of age; access to credit and weather-related information; size of friendship and kinship network; distance to nearest main market and road; and sub-county fixed effects. : ***=p < 0.01, **=p < 0.05, *=p < 0.1.
Source: 2015 baseline and 2017 endline household surveys in northern Uganda.

Table 5. Effect of information exchange links on awareness and knowledge about improved varieties and conservation farming

	Dependent variable: awareness and knowledge about agricultural technologies						
	Longe 10H DT	Any DT maize	Improved maize	Serenut 5/14	Any Serenut	CF basin	knowledge
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A: IPW-DID with Radius matching						
Post-program dummy*information link	0.319***	0.354***	0.362**	0.037	0.016	0.282**	0.808***
	(0.107)	(0.122)	(0.141)	(0.026)	(0.085)	(0.113)	(0.282)
Number of observations	1,312	1,316	1,316	1,316	1,316	1,316	1,316
	Panel B: IPW-DID with Kernel-Based matching						
Post-program dummy*information link	0.312***	0.354**	0.388**	0.040	0.025	0.292**	0.848***
	(0.109)	(0.139)	(0.150)	(0.025)	(0.089)	(0.125)	(0.281)
Number of observations	1,166	1,166	1,166	1,166	1,166	1,166	1,166
	2SLS estimates						
Information exchange link	0.341**	0.544**	0.424**	0.199*	0.256	0.428***	1.607***
	(0.167)	(0.220)	(0.216)	(0.111)	(0.216)	(0.154)	(0.509)
Kleibergen-Paap LM statistic	15.974***	15.974***	15.974***	15.974***	15.974***	15.974***	15.974***
Cragg-Donald Wald F-statistic	18.877	18.877	18.877	18.877	18.877	18.877	18.877
Hansen J statistic (*p*-value)	0.354	0.354	0.354	0.354	0.354	0.354	0.354
Number of observations	1,318	1.318	1,318	1.318	1,318	1.318	1,318

Notes: Average marginal effects are reported, except for column (3). Robust standard errors clustered at sub-village level are in parentheses. Asterisks indicate the following: ***=p < 0.01, **=p < 0.05, *=p < 0.1. IPW-DID means combined inverse probability weighting with difference-in-difference; 2SLS means two-stage least square regression.

Source: 2015 and 2017 household surveys in northern Uganda.

Table 6. IPW-DID estimates of the effect of information exchange links on adoption of improved varieties

	Adoption outcome variables: 1=adopted; 0=did not adopt				
	Longe 10H	All DT maize	All improved maize	Serenut 5/14	Any Serenut
	(1)	(2)	(3)	(4)	(5)
Panel A: IPW-DID with Radius matching					
Post-program dummy*information link	0.115	0.245*	0.255*	0.007	0.005
	(0.072)	(0.075)	(0.131)	(0.010)	(0.013)
Number of observations	1,312	1,312	1,312	1,312	1,312
Panel B: IPW-DID with Kernel-Based matching					
Post-program dummy*information link	0.111	0.248*	0.276*	0.009	0.016
	(0.074)	(0.143)	(0.145)	(0.011)	(0.032)
Number of observations	1,166	1,166	1,166	1,166	1,166
Panel C: 2SLS estimates					
Information exchange link	0.124	0.528***	0.537**	0.015	0.006
	(0.102)	(0.197)	(0.223)	(0.019)	(0.025)
Kleibergen-Paap LM statistic	15.974***	15.974***	15.974***	15.974***	15.974***
Cragg-Donald Wald F-statistic	18.877	18.877	18.877	18.877	18.877
Hansen J statistic (*p*-value)	0.318	0.217	0.432	0.222	0.535
Number of observations	1,318	1.318	1,318	1.318	1,318

Notes: Average marginal effects are reported, except for column (3). Robust standard errors clustered at sub-village level are in parentheses. Asterisks indicate the following: ***=p < 0.01, **=p < 0.05, *=p < 0.1. IPW-DID means combined inverse probability weighting with difference-in-difference; 2SLS means two-stage least square regression.

Source: 2015 and 2017 household surveys in northern Uganda.

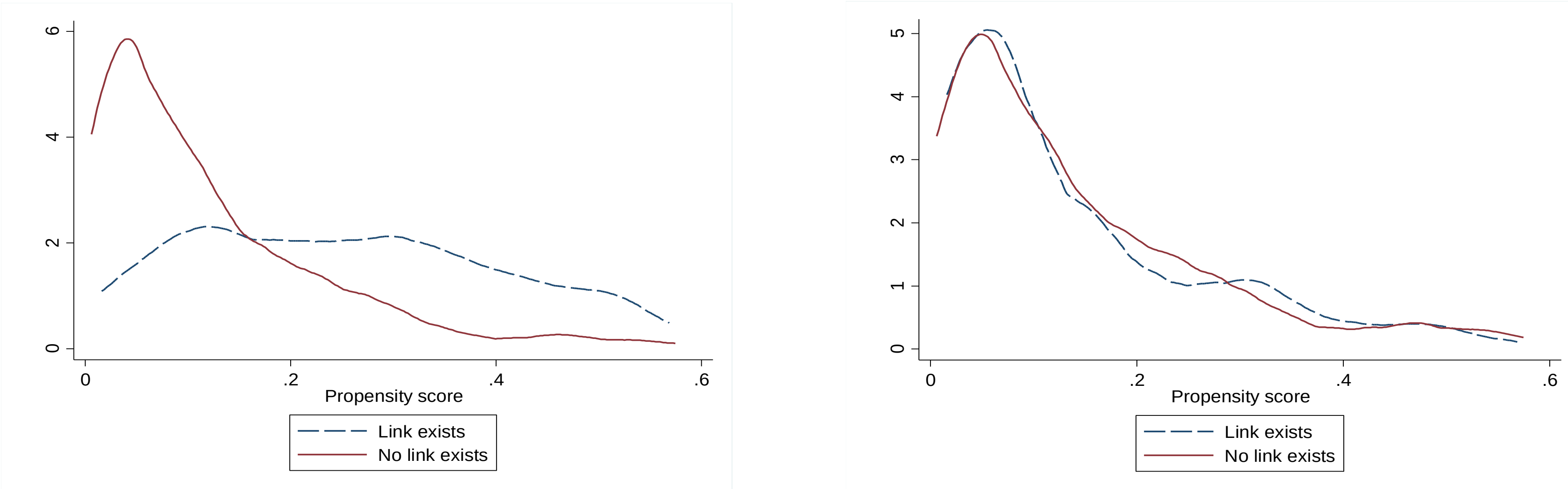

Figure 1. Propensity score weighting

Notes: Left panels shows distribution of propensity scores for the un-weighted sample whereas the right panels shows the same distribution for weighted sample.
Source: 2015 baseline survey in northern Uganda.

Appendix

Table A1. Baseline summary statistics without attrition

Variables	Whole sample (1)	Link (2)	No-link (3)	Diff (4)
Household head is male	0.818	0.879	0.808	0.071
Respondent is male	0.430	0.470	0.424	0.045
Household head completed primary education	0.420	0.543	0.401	0.142***
Age of the household head (years)	43.691	41.664	44.007	2.343
Dependency ratio	0.567	0.568	0.567	0.001
Housing condition (index)	-0.866	-0.860	-0.867	0.007
Livestock asset (TLU)	0.698	0.845	0.676	0.169
Household received credit	0.682	0.810	0.662	0.148***
Received climate-related information	0.737	0.802	0.727	0.075*
Distance to main market (walking minutes)	41.592	43.767	41.253	2.514
Distance to main road (walking minutes)	12.350	9.000	13.000	4.000***
Friendship network (number of friends)	2.023	2.172	2.000	0.172*
Kinship network (number of relatives)	1.730	1.879	1.706	0.173
Soil pH	5.834	5.846	5.832	0.014
Number of observations	862	746	116	

Notes: *, **, *** indicate statistically significant difference at 10%, 5%, and 1% level.
Source: 2015 baseline survey in northern Uganda.

Table A2. 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).

Source: 2015 baseline survey in northern Uganda.

Table A3. Matching quality indicators before and after matching

Matching algorithm	Pseudo R^2 before matching	Pseudo R^2 after matching	LR χ^2 (p-value) before matching	LR χ^2 (p-value) after matching	Mean standardised bias before matching	Mean standardised bias after matching	Total % |bias| reduction
Radius	0.126	0.005	85.24 (0.000)	1.62 (1.000)	13.8	2.1	84.78
Kernel-Based	0.109	0.007	186.84 (0.000)	4.17 (1.000)	15.6	2.5	84.00

Source: 2015 baseline survey in northern Uganda.

Table A4. Two-stage least squares regression to assess effect of information links on awareness, knowledge, and adoption of improved varieties and conservation farming basins: first stage regression results

Variable	Coefficient	*p*-value
	(1)	(2)
DF is less educated than the neighbour	0.028	0.000
	(0.007)	
Both DF and neighbour have less agricultural assets	0.084	0.039
	(0.041)	
Both DF and neighbour have less non-agricultural assets	-0.105	0.004
	(0.036)	
Endline dummy	0.106	0.000
	(0.025)	
Number of observations	1,318	

Notes: DF means disseminating farmer.

Source: 2015 and 2017 household surveys in northern Uganda.

Knowledge questions

Q1. Have you ever heard about improved varieties of crops?

Q2. What improved varieties of maize have you heard about?

Q3. What improved varieties of groundnuts have you heard about?

Q4. What benefits do improved varieties of crops have?

Q5. Have you ever heard about conservation farming basins?

Q6. How long should a conservation farming basin be? (Estimated using length of a straight stick and measured by enumerator using a ruler)

Q7. How wide should a conservation basin be? (Estimated using length of a straight stick and measured by enumerator using a ruler)

Q8. How deep should a conservation farming basin be? (Estimated using length of a straight stick and measured by enumerator using a ruler)

Q9. When planting maize in a conservation farming basin, how many seeds should a farmer plant?

Q10. When planting groundnuts in a conservation farming basin, how many seeds should a farmer plant?