Incentives, Social Learning and Economic Development

Experimental and Quasi-Experimental Evidence from Uganda

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Thesis

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To my family.

Contents

Chapter 1

Introduction

1.1 Overview

Technological innovations to address the adverse effects of climatic shocks on agriculture are widely promoted in sub-Saharan Africa (SSA). At least three primary reasons have motivated such efforts. First, a majority of the poor in developing countries, including SSA, continue to reside in rural areas where rain-fed agriculture is the main source of livelihoods (Ravallion et al., 2007). Reliance on rain-fed agriculture coupled with low adaptive capacity means that rural economies in SSA are highly vulnerable to climatic shocks (Shiferaw et al., 2014). Second, productivity growth in agriculture is widely seen as a driver of structural transformation and economic growth for developing countries (Evenson and Golin, 2003; Ligon and Sadoulet, 2007; de Janvry and Sadoulet, 2010; Christiaensen et al., 2011). Third, economic losses associated with climatic shocks in SSA are enormous: crop yields are projected to decline by 22 percent for maize, 17 percent each for sorghum and millet, and 18 percent for groundnuts by mid-century (Schelenker and Lobell, 2010). Moreover, farm revenues are expected to fall by about 39 US dollars per hectare for every degree centigrade rise in temperature (Hassan, 2010).

Damages to agricultural output due to climatic shocks, chiefly droughts and floods, in Uganda amounted to more than 900 million US dollars in 2010; corresponding to 77 percent of total damages across all sectors of the country’s economy (Republic of Uganda, 2012; 2016). Furthermore, the current and future increased climatic shocks are in areas of existing poverty and have serious consequences for local economies and food security (Republic of Uganda, 2015).

Technological innovations geared to addressing climatic shocks in SSA are increasingly promoted under the rubric of climate-smart agriculture (CSA)—predicated on the idea of achieving productivity growth and enhanced resilience, while contributing mitigation co-benefits where possible (Food and Agriculture Organisation (FAO), 2013). The popularity of CSA technologies is evident from, among others, the recent launch of the Alliance for Climate Smart Agriculture in Africa (ACSAA) spearheaded by New Partnership for Africa's Development (NEPAD) which intends to help catalyse the scaling up of CSA to 25 million farm households across SSA by 2025.

Two pertinent issues, however, remain. First, adoption rates for potentially beneficial agricultural technologies in SSA remain very low (Duflo et al., 2011; Suri, 2011; Bold et al., 2017). Informational constraints have been shown to contribute to low adoption of agricultural technologies (Foster and Rosenzweig, 1995; Bardhan and Udry, 1999). Other identified barriers to adoption include time-inconsistent preferences of farmers (Duflo et al., 2011), poor quality of agricultural inputs (Bold et al., 2017), heterogeneity of benefits (Suri et al., 2011) and inability to address downside risk (Emerick et al., 2016), the degree of risk aversion, and access to markets. The focus of this thesis is on informational constraints to technology adoption. Second, empirical evidence on the impact of recommended CSA technologies on downside risk (that is, the probability of crop failure or exposure to losses located in the lower tail of the distribution of yields) and resilience is inadequate (Arslan et al., 2015; Wossen et al., 2017). Together, these two issues make it difficult to conclude whether and in what contexts CSA technologies can help to address climatic shocks in SSA (Rosenstock et al., 2016).

Agricultural extension can help overcome informational constraints to technology diffusion (Bindlish and Evenson, 1997; Davis, 2008; Anderson and Feder, 2007). Through extension, farmers can be provided with context-specific information about crop cultivation practices hence familiarising themselves with the benefits of new technologies, and bridging the knowledge gaps (Lambrecht et al., 2014). Yet, despite large investment to foster agricultural transformation through different extension approaches, performance in SSA has been dismal and far below the expected levels of adoption and productivity increase. Disappointing extension outcomes have even led to disbandment of the national agricultural advisory services in some countries such as Uganda. Meanwhile, there is a ray of optimism that social learning can help to strengthen extension systems and expedite adoption of agricultural technologies in SSA (Bandiera and Rasul, 2006; Krishnan and Patnam, 2013; Kondylis et al., 2017). Social learning describes a process by which an individual learns from his neighbours' experiences, their previous decisions and outcomes, about a new technology (Munshi, 2004).

Human beings are inherently social. We not only interact and exchange information, but also observe and learn from each other's actions and outcomes. Social learning can, therefore, facilitate aggregation of dispersed and decentralised information (Acemoglu et al., 2011), shape people's beliefs and attitudes, and influence the decision to adopt agricultural technologies (Bandiera and Rasul, 2006; Conley and Udry, 2010; Magnan et al., 2015). Yet, our understanding of the mechanisms through which social learning happens in agricultural settings is far from perfect. The hypothesis of "passive" learning—implicitly assuming that farmers costlessly observe their neighbours' plots with little friction in the flow of information, and then update their beliefs about the technology's profitability—has recently been challenged. Ben Yishay and Mobarak (2018) indicated that technology diffusion within social networks could be sub-optimal in the absence of incentives for communication. Similarly, in their discussion about the reasons why providing direct training to contact farmers did not change the knowledge of and adoption by co-villagers, Kondylis et al. (2017) pointed to lack of incentives. Still, there is scant empirical evidence about incentives for agricultural knowledge and technologies diffusion via social learning.

Based on experimental and quasi-experimental evidence from northern Uganda, this thesis firstly studies the role of social learning in technology adoption, focusing on the effects of incentives on the diffusion of agricultural knowledge and technologies. Secondly, it studies the correlation between social distance and the likelihood of information exchange in the presence of an active intervention that provided direct agricultural training to a subset of the population. Social distance is defined as differences in socioeconomic and biophysical characteristics between disseminating farmers and their neighbours. The thesis further examines the effect of information exchange links on awareness exposure, that is, having heard about a technology; knowledge exposure, that is, understanding how to implement the technology; and adoption. Thirdly, the mechanisms through which social networks affect adoption of agricultural technologies are studied. Fourthly, the thesis examines the causal relationship between adoption of CSA technologies and yield, downside risk, food security, and resilience of livelihoods.

Each chapter of the thesis can be read as a standalone contribution to economic development literature. There are, however, important cross-cutting relationships between the chapters culminating into one message: Incentives, both private rewards and social recognition, are crucial in enhancing social learning and the diffusion of agricultural technologies, consequently increasing productivity, improving food security, and enhancing resilience of livelihoods to climatic shocks. The thesis generates an enhanced understanding of the cross-cutting relationships for policy, design and implementation of agricultural programs, and also for future research.

1.2 Agricultural Extension in Uganda

Several extension approaches have been implemented in Uganda since before independence. During the pre-independence period, extension services—mainly involving new crops and soil conservation practices—were delivered by the administration staff of the colonial government often using a coercive approach (Semana, 1998). While the practices and crops were beneficial to the farmers and communities, adoption was only short-lived and not sustainable once pressure was lifted. Furthermore, the extremely top-down approach alienated the beneficiaries and created resentment.

From 1956–1963, Uganda shifted to providing extension through progressive farmers. The intention was to encourage peer-to-peer farmer demonstrations about use of improved technologies. Although the approach was deemed effective in situations involving an inadequate number of trained extension staff, the selection criteria for progressive farmers were not clear (Semana, 1998; Barungi et al., 2016). Not only were progressive farmers reluctant to educate their peers in some instances (Ministry of Agriculture, Animal Industry, and Fisheries (MAAIF), 2017), but their co-villagers often also looked at them as a privileged group hence alienating them and rendering the initiative unproductive (Semana, 1998).

In 1964, the United States Agency for International Development (USAID) spearheaded a change in extension model towards educational approaches. The educational approach involved several activities to teach farmers including training at district farming institutes, exposure visits, field days, radio and television programs, film shows (cinema), leaflets, and posters (Barungi et al., 2016; MAAIF, 2017). These approaches generally helped to improve farming methods (MAAIF, 2017). The political turmoil that was experienced in 1972, however, left the country's extension services inactive from 1972–1980.

The Training and Visit (T&V) approach was piloted in Uganda from the mid-1980s. The approach involved a systematic planning, training of extension workers and visiting of farmers to deliver time-sensitive messages. To be effective, the approach required massive human, financial and logistical resources. It was, therefore, not sustainable and could not be scaled up to the rest of the country. Instead, a unified extension approach was adopted in an attempt to address the limited human resource at sub-county level and to enable diverse needs and challenges of the farmers to be addressed at the same time. In this unified approach, a technical officer at sub-county level was expected to deliver extension messages on all subject matters including crops, livestock, and fisheries. In most cases, however, the staff was not prepared for this approach right from their training. It was, therefore, a challenge to maintain the integrity of the technical content and methodology.

Backed by an Act of Parliament, the National Agricultural Advisory Services (NAADS) program was implemented from 2001 to 2014. The program was one of the seven pillars of the Plan for Modernization of Agriculture (PMA)—a multi-sectoral strategy under Uganda's strategic national planning and development framework. The NAADS program in Uganda was the first agricultural extension reform model in Africa that aimed at developing an alternative to the T&V system (Anderson et al., 2006), which had been criticised for its top-down supply-driven nature. The program adopted a decentralised, demand-driven, and farmer-led system. Public sector extension agents were replaced by contracted private service providers. Farmer groups at the village level participated in decision making processes including contracting of service providers.

Preliminary results showed positive results of the NAADS program (Benin et al., 2007). As the program matured, however, there were problems related to farmers' ambivalence towards the program (Musemakweri, 2007; Parkinson, 2009), mismanagement of public funds, questionable capacity of private service providers (Mangheni et al., 2003, Obaa et.al., 2004) and low technology uptake by farmers (Bua et al., 2004). In 2007, the NAADS program was suspended. When it was re-introduced in the same year, the NAADS program came with an expanded mandate. Under the "model farmer approach", input subsidies were provided to two individual "model farmers" per parish—group of villages—as incentives for experimentation with and diffusion of agricultural technologies. Model farmers were selected by a committee comprising politically elected local officials, the local chairperson of the ruling party (National Resistance Movement), and the local intelligence officer (MAAIF, 2010). Still, limited success of the NAADS led to its disbandment in 2014.

Following the disbandment of NAADS, the responsibility and function of delivering agricultural extension was transferred back to MAAIF by re-establishing a directorate of agricultural extension at national level. The current "single spine" agricultural extension system spearheaded by MAAIF began in June 2014. Its objective is to harmonise and coordinate all extension service delivery in the country to address the inefficiencies associated with its predecessor systems. Farmer-to-farmer technology transfer is recognised as an important component of the new extension system. Within this context, this thesis studies farmer-to-farmer technology transfer when disseminating farmers are selected by co-villagers themselves to be "representative" of the target population and incentivised to communicate knowledge about new technologies. Background details of the project design are provided in section 1.7 below.

1.3 Incentives, Social Learning, and Technology Diffusion

When individuals are exposed to diverse private information about the situation they face, they often base their decisions on those of others (Monzón, 2017). Social learning—processing of information gained by observing others—has received much attention, both in the theoretical (see Acemoglu et al., 2011 for a review)[1] and empirical (Bandiera and Rasul, 2006; Conley and Udry, 2010)[2] literature as a conduit for technology diffusion. Studies in agriculture have shown how farmers learn from their neighbours about the profitability of agricultural technologies (Besley and Case, 1993) and optimal input use (Foster and Rosenzweig, 1995). A few others have indicated that social learning might be as effective or even better than government extension (Krishnan and Patnam, 2013; Vasilaky and Leonard, 2018) in technology diffusion and impact on productivity.

Most recently, literature on the relationship between social learning and the diffusion of agricultural technologies identifies two important issues. The first issue relates to identification of disseminating farmers (DFs)—the first individuals in the population to receive the technology (Beaman et al., 2015). The second issue relates to incentives for the diffusion of agricultural technologies (Ben Yishay and Mobarak, 2018)—without incentives, selected optimal DFs may not expend costly effort to communicate new knowledge to their peers. Still, much less is known about the effect of incentives on the diffusion of agricultural technologies. While useful insights exist about the role of private material rewards, the effect of prosocial[3] preferences and social recognition has not been adequately examined. Yet behavioural studies indicate that there may be important interactions between the three types of incentives, namely prosocial preferences, private material rewards, and social recognition, with possibilities of "crowding-in" and "crowding-out" effects (Benabou and Tirole, 2006; Ariely et al., 2009). In *Chapter 2*, therefore, the thesis studies the effect of prosocial preferences, private material

[1] Early studies include Bikhchandani et al., 1992; Banerjee, 1992; Bala and Goyal, 1995; Smith and Sørensen, 2000; 2008; Banerjee and Fudenberg, 2004).
[2] Others include Besley and Case, 1993; Foster and Rosenzweig, 1995; Munshi, 2004; Maertens and Barrett, 2012; Krishnan and Patnam, 2013; Magnan et al., 2015).
[3] A prosocial task includes a range of individual actions that not only take into account individual benefits, but also those of others. A prosocial task is, therefore, one that creates benefits enjoyed by those other than the employer and employee (Ashraf et al., 2014a).

rewards, and social recognition on effort by the DFs to experiment with new agricultural technologies and communicate information to their peers.

While incentives may influence DFs' efforts to inform their peers, successful diffusion of agricultural technologies will further depend on the willingness of the peers to listen to and learn from the DFs. In Malawi, for example, Ben Yishay et al. (2015) found that although female DFs retained knowledge better and experienced higher yields than their male counterparts, neighbours were reluctant to listen to their messages. Few empirical studies have explicitly examined the effect of social distance on information exchange links in agriculture (Feder and Savastano, 2006; Santos and Barrett, 2010). Feder and Savastano (2006), for example, found that the probability of information exchange links increased with social distance, but decreased when the distance was excessive. Furthermore, heterogeneity in the benefits associated with technologies may influence information exchange (Munshi, 2004; Magnan et al., 2015)—agricultural technologies may not be welfare enhancing to all farmers everywhere. *Chapter 3* turns to these issues and examines systematically the role of social distance and differences in biophysical characteristics on the probability of link formation between directly trained DFs and their neighbours, and the subsequent effects on adoption of agricultural technologies.

1.4 Social Networks Effects on Adoption of agricultural Technologies

In developing countries, contact farmers are often used as messengers of agricultural information (Krishnan and Patnam, 2013; Kondylis et al., 2017). Trainings and demonstrations about new agricultural technologies target these contact farmers with the expectation that they will disseminate new information to neighbours in their villages. However, our understanding of how this actually happens is limited. A body of literature exists on the process of social network formation and underlying incentives (Bala and Goyal, 2000; Goyal et al., 2006;

Fafchamps and Gubert, 2007; Santos and Barrett, 2010). Equally, the role of social networks in technology diffusion has been extensively documented in empirical studies (Besley and Case, 1993, Bandiera and Rasul, 2006; Conley and Udry, 2010; Krishnan and Patnam, 2013). But these studies have largely taken pre-existing networks to be fixed, and do not address how existing networks change in response to exogenous shocks (Breza, 2015)—like training of a random node in the network.

A few studies have shown how external stimulus can change networks. Feigenberg et al. (2013) showed changes in the strength of ties through microfinance whereas Banerjee et al. (2018) analysed persistent changes in the number of links when a random subset of the population was exposed to microfinance. In a study that assessed how transfers between households changed in response to a randomised savings intervention, Comola and Prina (2014) found that treatment households increased the number of recipients relative to the control. Still, empirical evidence about the effect of external factors on networks in agricultural settings is missing. Furthermore, most studies do not indicate the underlying mechanisms through which information dissemination takes place. Neither do they address how incentives could affect social networks.

The main challenge in identifying the causal effect of social networks on adoption is the reflection problem (Manski, 1993). Individual behaviour may simply reflect the average behaviour of the reference group, but that does not necessarily mean that group behaviour causes the individual's behaviour (Manski, 1993). In the absence of learning, individuals may still behave like their neighbours as a result of interdependent preferences or because they are exposed to related unobservable shocks (Manski, 1993; Conley and Udry, 2010; Krishnan and Patnam, 2013). Therefore, disentangling learning from contextual and correlated effects may be problematic.

Therefore, having established in *Chapter 2* the effect of incentives on adoption decisions and networks of disseminating farmers (DFs), *Chapter 4* asks: (1) Does having an adopter DF in a neighbour's contacts for agricultural advice influence his or her own knowledge and decision to adopt an agricultural technology? (2) Do incentives change the networks of neighbours, and does it matter whether the rewards are private material or social recognition? The chapter employs several econometric techniques to address the reflection problem.

1.5 Technology Adoption, Food Security, Downside Risk, and Resilience

Achieving increased food security and enhanced resilience of livelihoods under climatic shocks is at the top on economic development agenda in sub-Saharan Africa (SSA). About 50 percent of household income in Uganda is spent on food (Uganda Bureau of Statistics, 2017). The World Food Programme (WFP) estimates that nearly half of all Ugandans consume fewer calories than they need every day. About 29 percent of children under five years suffers from stunting.

Adoption of agricultural technologies can help to reduce food insecurity and increase income hence improving the welfare of the rural poor in SSA (Kassie et al., 2011; Asfaw et al., 2012; Kabunga et al., 2014; Shiferaw et al., 2014). However, the increasing frequency and intensity of extreme weather events in the region primarily affects the risk profiles of agricultural technologies (Arslan et al., 2017). Although agriculture has always been subject to weather risks, these new challenges increase the importance of controlling for the effects of relevant weather related risks on adoption decisions as well as on productivity and resilience (Di Falco and Veronesi, 2013; Arslan et al., 2015). Empirical evidence about the effect of agricultural technologies on food security under climatic shocks is inadequate. A few exceptional studies include Arslan et al. (2015; 2017) and Di Falco and Veronesi (2013). These studies provide important insights suggesting that CSA technologies can help to increase crop yields and income.

Focusing on average crop yields is undoubtedly important, especially because an increase in yields tends to correlate with improved food security for households in many parts of SSA. Failure to adequately capture higher moments, such as variance and skewness of yields may, however, mask the effects of agricultural technologies on the downside risk brought by extreme weather events (Di Falco and Chavas, 2009; Shi et al., 2013; Wossen et al., 2017). Furthermore, evidence of the effect of agricultural technologies on resilience of livelihoods is missing. This is partly because of methodological limitations in measuring resilience. In *Chapter 5*, resilience is defined consistent with Barrett and Constas (2014) as, "the capacity of a household to avoid and escape from poverty over time and in the face of shocks. If and only if that capacity is and remains high over time, then the unit is resilient". Using a moment-based approach (Antle, 1987; Di Falco and Chavas, 2009; Barrett and Constas, 2014), the chapter examines the impacts of CSA technologies on yields, downside risk, and resilience. The chapter further looks beyond yields to assess effects on additional indicators of food security including number of months of food shortage and frequency of consumption of food.

1.6 Objectives

The empirical questions of this thesis are based on the following simplified theory of change. Training randomly selected and community-perceived "representative" disseminating farmers (DFs) and providing them with incentives will increase their probability of experimenting with climate-smart agricultural (CSA) technologies and effort to communicate to their peers. Incentives are further expected to positively influence changes in networks of other farmers subsequently improving their knowledge about CSA technologies. Reduced informational barriers and increased adoption by DFs is in turn expected to increase the likelihood of other farmers experimenting with the CSA technologies. Ultimately, adoption of the CSA technologies is expected to increase yield and food security, reduce downside risk, and enhance resilience of livelihoods.

The overarching objective of this thesis is to examine the effect of incentives on the diffusion of agricultural technologies through social learning, and to quantify the subsequent impacts of adoption on productivity, downside risk, food security, and resilience of livelihoods in the post-conflict northern Uganda. Specifically, the thesis addresses the following research questions throughout its four core chapters:

(1) *Chapter 2*: What effect does incentivised training of disseminating farmers (DFs) have on the diffusion of agricultural knowledge and technologies? Does the effect differ depending on whether DFs receive a private material reward or social recognition and is there a mediating role of prosocial preferences?

(2) *Chapter 3*: What is the effect of social distance and heterogeneity in biophysical soil characteristics on the probability of information exchange link formation between trained DFs and their peers? Do information exchange links subsequently influence awareness and knowledge exposure, and adoption of agricultural technologies?

(3) *Chapter 4*: What mechanisms underlie social network effects on adoption of CSA technologies?

(4) *Chapter 5*: What are the effects of adoption of CSA technologies on yields and downside risk, food security, and resilience of livelihoods?

1.7 Methodology

Both experimental and non-experimental approaches are used in this thesis to answer its research questions. Data come from three waves of household survey. A baseline survey was conducted in 2015 interviewing 1,320 randomly sampled households from 132 sub-villages.

The midline survey was conducted in 2016 to measure effort expended by DFs to train other farmers as well as knowledge of other farmers and experimentation with the technologies by both the DFs and the other farmers. During the midline, all the DFs and a random sample of 123 other farmers selected from the original list of farmers interviewed at baseline were revisited. An endline survey was implemented in 2017 involving all households that were interviewed at baseline. In addition to survey data, the thesis utilises georeferenced biophysical data, specifically on rainfall, temperature, and soil characteristics. Most of the georeferenced data are used in *Chapter 4*.

The research design is a randomised control trial (RCT). The experiment was designed to test incentives for the diffusion of agricultural knowledge and technologies. It involved random assignment of selected DFs into three groups, namely training only, private material reward, and social recognition. All DFs received training about some recommended CSA technologies. The experiment then varied the incentive for the DFs to share information with their neighbours.

In addition to the RCT, the thesis utilises artefactual field experiments (also called lab-in-the-field experiments) to measure social preferences. Specifically, the thesis utilises an augmented dictator game to measure prosocial preferences, that is, the intrinsic motivation of DFs to train their neighbours. Furthermore, incentive-compatible risk and time experiments were conducted to measure DFs' preferences for risk and time.

Under the conditions that the randomisation succeeds in achieving balance across the experimental arms and that the stable unit treatment value assumption (SUTVA) holds, identification of causal impacts is straightforward. This is the case for the approach followed in *Chapter 2* and (partly) *Chapter 4*. In *Chapters 3* and *5*, however, observational data are utilised raising issues of identification. Several approaches have been recommended in literature for use in the absence of experimental data. Commonly used estimators include instrumental variables

(IV), propensity score matching (PSM), difference-in-difference (DID), the standard fixed effects (FE), and regression discontinuity. This thesis employs panel data and utilises IV estimators as well as a combination of DID with matching techniques in *Chapter 3*. In *Chapter 5*, the standard FE model and matching techniques are used to identify causal effects.

Ethical issues are important in this thesis because it involves household interviews and experiments with human subjects. To address ethical issues, an informed consent was sought before commencing interviews and the experiments. Participation in the surveys and the field experiments was voluntary. Anonymity of interviewee's responses was preserved and data were kept confidential. The study was reviewed and approved by the ethics review board of Wageningen University and Research, prior to field implementation.

1.8 Outline

The rest of the thesis is organised as follows. *Chapter 2* examines incentives for agricultural knowledge and technology diffusion. *Chapter 3* studies the factors that shape information exchange links and the subsequent effects of links on adoption of agricultural technologies. *Chapter 4* examines the mechanisms through which social network effects on adoption of agricultural technologies occur. *Chapter 5* looks at the effects of adoption of agricultural technologies on yields, downside risk, food security, and resilience of livelihoods. Finally, *Chapter 6* presents a synthesis and discusses implications of the findings for policy and future research.

Chapter 2

Incentives and the Diffusion of Agricultural Knowledge

Experimental Evidence from Northern Uganda

Abstract

This chapter presents results of a randomised evaluation that assesses the effects of different incentives for diffusion of agricultural knowledge by smallholders in northern Uganda. Randomly selected disseminating farmers (DFs) from a large sample of villages are assigned to one of three treatment arms: (i) training about climate smart agriculture, (ii) training plus a material reward for knowledge diffusion, and (iii) training plus a reputational gain for knowledge diffusion. The chapter documents fairly robust evidence that leveraging somebody's reputation (or social recognition) has large effects on experimentation with new technologies and diffusion effort by DFs. The impact of providing private material gains is less robust.

This chapter is based on:

Shikuku, K.M., Pieters, J., Bulte, E., and Läderach, P. (2018). Incentives and the Diffusion of Agricultural Knowledge: Experimental Evidence from Northern Uganda. Revised manuscript in the *American Journal of Agricultural Economics*.

2.1 Introduction

Transforming smallholder agriculture in order to lift the majority of the population in sub-Saharan Africa out of poverty requires boosting agricultural productivity under increasingly volatile conditions. This requires diffusion of modern technologies (e.g., Evenson and Gollin, 2003; Minten and Barrett, 2008), but in many African countries adoption rates of innovations remain low (Pamuk et al., 2014). Several well-known reasons help to explain this. Benefits may be heterogeneous, reflecting variety in growing conditions and other factors, so adoption may be unprofitable for some smallholders (e.g., Suri, 2011; Magnan et al., 2015). Costs associated with innovations such as improved seeds or fertiliser may be an impediment to adoption if capital markets are imperfect. Low quality of agricultural inputs may help explain low take up (Bold et al., 2017), as does lack of information about the existence and proper implementation of agricultural innovations (e.g., Foster and Rosenzweig, 1995).

This chapter focuses on the diffusion of information. Development organisations and policy makers have long believed that information "travels easily" within social networks. Interventions reaching small target groups are expected to reach much larger populations as information diffuses from "treated individuals" to their peers. Interventions based on the assumption of automatic and extensive spreading of information, such as traditional extension efforts, have by and large produced unsatisfactory results and failed to reach large parts of the intended population (de Janvry et al., 2016). In some countries, such as Uganda, disappointing outcomes have led to disbandment of national agricultural advisory services systems. Current efforts to strengthen national extension systems in developing countries recognise the need to search for cost-effective complementary actions (Godtland et al., 2004).

Recent evidence suggests that knowledge does not diffuse automatically. Diffusion of information requires time and effort of agents on both the "supply" and the "demand" side. Allocation of effort to teaching and learning is akin to an investment by smallholders, so it makes sense for development agents to consider complementary measures to facilitate such investments. There are several dimensions to this issue. The first one is who to select as the "disseminating farmer (DF)" – the first individual in the target population to receive the technology (Banerjee et al., 2018). Not all individuals are equally likely to reach large numbers of co-villagers, or be in a position to convince others to follow their behaviour. Traditionally, extension efforts targeted better-off farmers, who typically are well-connected and expected to be role models for their peers. However, since such farmers may not be representative of their co-villagers, their experiences may be of limited value to others (e.g., Munshi, 2004; Conley and Udry, 2010; BenYishay and Mobarak, 2018). Although it is beyond the scope of this thesis to identify optimal DFs or map the network structure, a recent literature focuses on exploiting (social) network theory, and proposes to target individuals who occupy either a central (e.g., Kim et al., 2015), or clustered position in the network (Beaman et al., 2015, Chami et al., 2017). In this thesis, selected DFs are farmers comparable to their fellow villagers in terms of wealth and education.

A second dimension, which is the focus of this chapter, concerns how to motivate DFs to inform their peers and encourage them to adopt the technology (Ben Yishay and Mobarak, 2018). Following Benabou and Tirole (2006) the chapter distinguishes between three motives why farmers may invest time and effort in educating their peers. First, they may be altruistic and intrinsically motivated to help their co-villagers. Second, they may gain status and social recognition by helping others. Finally, they may engage in diffusion if there are private tangible rewards associated with knowledge diffusion. This could happen if there are externalities in adoption or use of new technologies (e.g. pest management), or if external rewards for diffusion are introduced. BenYishay and Mobarak (2018) demonstrated that incentivising DFs via material rewards may be an effective approach to promote diffusion. They trained DFs in Malawi to use new technologies (pit planting and composting), and promised some of them a bag of seeds in case knowledge and adoption of new technologies increased sufficiently among other farmers. They found that only with the incentive, DFs experiment with and communicate about the technologies, leading to increased adoption among other farmers. These findings underline the importance of understanding the motives for farmers to spread information to others.

The objectives of this chapter are twofold. First, an experimental approach is used to evaluate the effectiveness of approaches based on the above-mentioned motives for knowledge diffusion within one integrated framework: altruism or intrinsic motivation, social recognition and private rewards. The chapter asks whether social recognition and private rewards for diffusion affect DFs' effort to learn about the benefits of the new technology and subsequently diffuse information. Second, the chapter probes whether the impact of social recognition and private reward incentives varies with DFs' prosocial preferences. Social preferences of DFs are measured with an auxiliary lab-in-the-field game—an augmented dictator game with a local charity as the receiver.

A field experiment was designed in northern Uganda with three treatment arms: (i) a basic arm where DFs receive training about specific climate-smart agricultural technologies; (ii) another arm where they receive the same training plus a private reward (a weighing scale) in case of sufficient increase in knowledge among other farmers (to be specified below); and (iii) a final arm that combines the training with social recognition in case of sufficient increase in knowledge among other farmers. Specifically, in case a threshold level was reached, a public ceremony was organised in which the DF's contribution was highlighted and a weighing scale was given "to the community." As dependent variables, experimentation with the new technologies by the DFs and other farmers, effort devoted by DFs towards training other farmers, and the knowledge gained by other farmers are used. The chapter's main results are that (i) incentivising DFs by providing them with social recognition has a significant and large effect on diffusion effort and levels of knowledge diffusion; (ii) the effects of providing a private material reward are small; and (iii) the effect of both types of incentives is not mediated by prosocial preferences (see also Ashraf et al., 2014a).

The results speak to several literatures. First, and as mentioned above, they relate to the rapidly growing literature on social learning. Learning from others facilitates aggregation of dispersed information (Acemoglu et al., 2011; Alatas et al., 2016) and can generate social multiplier effects in diffusion of innovations (Hogset and Barrett, 2010). Social learning can, therefore, contribute to increased agricultural productivity (Vasilaky, 2012; Vasilaky and Leonard, 2018). Second, the findings contribute to the literature on incentives for prosocial behaviour or contributions to the common good. This literature has benefitted from recent insights in the field of behavioural economics, highlighting the potential interaction between motives (e.g., Benabou and Tirole, 2006; Ariely et al., 2009; Gneezy et al., 2011). For example, the provision of private rewards for prosocial behaviour may crowd out altruism or social recognition motives, by obscuring the (self)signal that someone is doing “good” – instead of simply doing “well.” Diffusion of agricultural knowledge is a prosocial task; the direct benefits created by the task are enjoyed by those other than the person who expends the costly effort (Ashraf et al., 2014a). The chapter’s inclusion of a social recognition incentive and analysis of the role of altruism further differentiates the current study from that of Ben Yishay and Mobarak (2018), who focus on the effect of private reward incentives. To our knowledge, the chapter provides the first evidence about the effects of social recognition on diffusion of agricultural knowledge.

The chapter is organised as follows. Section 2.2 describes the agricultural context, experimental design, and data. Section 2.3 discusses the identification strategy. Section 2.4 presents the findings, and Section 2.5 concludes.

2.2 Context, Experimental Design, and Data

2.2.1 Context

The experiment was implemented in Nwoya district, northern Uganda, a predominantly agrarian region characterised by low agricultural productivity. The region's poverty level is the highest in the country – about 44 percent of the population lives on less than one US dollar per day (Republic of Uganda, 2015). The region is expected to suffer more frequently from weather shocks in the future, including prolonged dry spells and uncertainty about the onset and cessation of rainfall (Mwongera et al., 2014). Damages to agricultural output due to weather shocks amounted to more than 900 million US dollars in 2010, or 77 percent of total damages across all sectors of the country's economy (Republic of Uganda, 2012; 2016). Although households tend to engage in off-farm activities such as weeding neighbours' plots, brick making and small businesses, diversification to non-farm activities in rural parts of northern Uganda remains minimal due to limited employment opportunities outside agriculture.

Efforts to sustain agricultural production in the region have focused on promoting adoption of climate-smart agricultural (CSA) technologies. The government of Uganda has identified CSA as an effective means of addressing challenges related to weather shocks. However, farmers lack knowledge about CSA technologies and perceive this as a major constraint to widespread adoption (Shikuku et al., 2015). Current efforts to restructure the extension system recognise the importance of working with DFs at the sub-county and village level to enhance dissemination of improved technologies (MAAIF, 2017). This chapter is part of these efforts, and it focuses on the performance of DFs that are more or less representative of the target population.

2.2.2 Sampling and intervention

A list of 310 sub-villages was first generated in Nwoya district, from which 132 sub-villages were randomly selected to participate in the study.[4] A census of all households and household heads was compiled for these selected sub-villages, and 10 households randomly sampled from each sub-village. One potential DF was then randomly picked from this sub-sample and a meeting organised with co-villagers to discuss whether the thus selected candidate was “not too different” (especially in terms of wealth and landholdings) from the rest of the village, and potentially interested to experiment with new technologies. Data on individual characteristics were not collected during the meeting. In more than 75 percent of the cases, the first candidate was selected as a DF. In the other villages another candidate was randomly picked and the process repeated. In one village three iterations were performed before the selected candidate was endorsed by his or her co-villagers.

Selected DFs were trained and had to decide whether or not to experiment with the new CSA technologies on their own farms. Importantly, the new technologies were not subsidised or “offered for free” to encourage farmers to try them out. Instead, farmers had to decide whether or not to purchase certain inputs from local agro-dealers, and whether or not to allocate labour (effort) to the construction of structures recommended during the training.[5] They also had to decide about the level of effort devoted to the diffusion of information. The main technologies, described below, were new and unfamiliar to the farmers so DFs had to spend time explaining the implementation of proposed activities as well as the potential benefits.

The 132 sub-villages were randomly assigned to one of three experimental arms of 44 sub-villages each: (i) training only, (ii) training plus a private material reward, and (iii) training

[4] A sub-village is equivalent to a hamlet. It is the lowest administrative unit in Uganda. The 132 sub-villages in our sample are located within four sub-counties.
[5] We verified that inputs that had to be purchased were actually available in local agro-dealers. This was invariably the case.

plus social recognition. Disseminating farmers in the first treatment arm received training about drought-tolerant maize variety and conservation farming basins and were subsequently asked to share the information with their co-villagers. Disseminating farmers in the second treatment arm received the same training, but after the training were informed they could earn a private reward. They were promised a weighing scale if they managed to share sufficient knowledge with their peers – to be established during a surprise visit at some unknown date in the future. They would earn the weighing scale in case the knowledge score of one randomly sampled co-villager exceeded a threshold. They were told the reward was private, that the weighing scale was theirs to keep, and that they were free to decide how to use it. Disseminating farmers in the third treatment arm also received the training, and were informed their community would receive a weighing scale if they managed to share sufficient knowledge with their peers – to be evaluated the same way as in the previous treatment arm. An announcement was made that, in case of sufficient knowledge diffusion, there would be a public celebration during which the "good performance" of the DF was publicly announced, and the weighing scale would be handed over to the village chief in the presence of other villagers. We do not have information on what the DFs told other farmers about the potential rewards. The chapter, therefore, acknowledges that in both the social recognition and the private reward treatment, it is possible that DFs told other farmers about the potential for getting access to a scale. If so, both the social recognition and private reward treatments may also have had an incentivising effect on other farmers (in addition to the DF).

Observe that DFs were not informed about the (private or social) reward until *after* completing the training. This design, therefore, deviates from BenYishay and Mobarak (2018), who informed their subjects about the potential reward *before* the training. Informing DFs after the training rules out the potential impact of incentives on two intermediate outcomes. First, incentives may change the composition of the group of DFs who attend the complete training.

Incentives may potentially stimulate invitees with low intrinsic motivation to attend (see Finan et al., 2017, on financial incentives and recruitment of public sector workers). Second, for a given pool of participating DFs, the incentives may affect their level of learning effort and hence the knowledge they accumulate during the training (Sseruyange and Bulte, 2018). It is not entirely clear, a priori, what the direction of these effects would be, and whether these effects increase or diminish the impacts on knowledge and technology adoption by other farmers. Since the chapter is primarily interested in the effect of incentives on DFs' knowledge diffusion efforts (and not selection effects or learning effort), we opted for a design in which the type of DF and his or her knowledge accumulation during the training is orthogonal to treatment status, that is, by informing DFs of their potential rewards *after* the training.

Interventions were rolled-out in March 2016. We partnered with researchers from the National Agricultural Research Organisation (NARO) and Tillers International – an NGO working with NARO to promote conservation farming in Uganda. A three-day training session was provided to the selected DFs. This training lasted five hours per training day. In addition to learning about the benefits and cultivation of drought-tolerant (DT) maize (Longe 10H), selected farmers learned how to construct so-called conservation farming (CF) basins which are 15 cm long, 15 cm wide, and 15 cm deep, and how to sow seeds of the improved varieties in these basins. Basins retain soil moisture, improve water infiltration (reducing surface water run-off) and minimise soil disturbance—similar as the "pit planting" technology studied in Malawi by BenYishay and Mobarak (2018). Experimental evidence suggests the existence of yield gains associated with this technology (Otim et al., 2015, see also Haggblade and Tembo, 2003; Gatere et al., 2013). The training also included crop management practices, such as correct spacing, row planting, and timely weeding. While the technology requires an upfront labour investment, the labour burden decreases in subsequent periods as the constructed basins are "permanent" (Haggblade and Tembo, 2003). As part of the training about conservation farming, farmers also learnt about proper use of herbicides to control weeds.

The trainings were organised in central locations, and DFs were invited to travel to these sites. Training sessions were organised per sub-county, with 11 farmers per session. In each sub-county, DFs from different treatment arms were trained in separate venues to minimise contamination. 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 farmers that were invited, 126 attended the full training.

2.2.3 Data and summary statistics

Data were collected during two household survey waves. A detailed baseline survey was conducted between September and December 2015. We visited 132 sub-villages and in every village surveyed the DFs as well as nine randomly selected co-villagers. In total we visited 1,320 households, and collected information on household demographics, crop and livestock production, off-farm income, assets ownership, exposure to weather shocks, sources of agricultural information and knowledge about farming practices, social networks, and food security. The "random villager" that was later used to evaluate the extent of knowledge diffusion was randomly drawn from this subsample (enabling us to control for *ex ante* knowledge levels in regression models, to increase precision of our estimates), but this was not communicated to DFs. It is possible that DFs suspected that we would interview the same co-villagers visited at baseline, so they might target diffusion efforts towards these individuals. If so, this may bias our estimates of diffusion in all treatment arms, and our estimates of treatment effects if DFs in different treatment arms responded differently in terms of their targeting effort.[6]

[6] This would be especially problematic if DFs were informed about the time of the evaluation visit or the content of the knowledge exam. However, DFs neither knew the date of the visit nor details of the knowledge exam.

Table 2.1 presents summary statistics of baseline data per treatment group, including demographic information, social network variables, exposure to weather shocks, and sources for agricultural information. Differences across the three groups are small in magnitude. Using the "orth_out" command in STATA, pre-treatment covariates are regressed on treatment dummies: an F-test that all treatment arm coefficients equal zero failed to reject. In addition, we perform an F-test of joint orthogonality using a multinomial logit, which tests whether the observable characteristics in Table 2.1 are jointly unrelated to treatment status. We cannot reject this null hypothesis (p-value = 0.227), suggesting that the randomisation succeeded in achieving balance across the experimental arms.

Most sample households are male-headed with an average age of 43 years and six years of completed formal education. The average size of a household is six with a dependency ratio of 54 percent. Ownership of both agricultural and livestock assets is very low. A household has on average two people from whom it seeks advice about crop production and two relatives. More than 90 percent of the sample households reported to have experienced drought. Access to government extension is very low: only two percent of the sample respondents had received agricultural advice from government extension.

The second survey wave was conducted in September 2016, after the first post-experimental cropping season, to measure performance of the DFs. We visited 246 farmers: 123 DFs (three of the initial sample of 126 farmers were not available for interview at the time of the survey)[7] and a random sub-sample of 123 "other farmers" (sampled from the original baseline sample of 1,188 households). We measured three types of dependent variables:

[7] Overall, attrition was low and not concentrated in a particular treatment arm. Specifically, only 4.5 percent of the selected disseminating farmers did not attend the training. Because DFs were only informed about the incentives (for those in the material reward and social recognition groups) at the end of the training, attrition ought not to be related to treatment assignment. Three more DFs (2%) were not available for interviews during data collection: one had got a temporary job at an electricity dam constructed by the government; another had migrated to neighboring Gulu town; and the third one had been hospitalised. These three DFs were from three different treatment arms.

knowledge levels (of the DFs and their co-villagers), on-farm experimentation (by the DFs and their co-villagers) and diffusion effort by the DFs.

Table 2.1. Baseline Characteristics by Treatment Group

	Training only (1)	Private reward (2)	Social recognition (3)
Panel A: Baseline individual and household characteristics			
Household head is male	0.820	0.791	0.817
	(0.384)	(0.407)	(0.387)
Age of household head (years)	44.084	44.548	42.778
	(16.080)	(15.644)	(14.216)
Household head's number of years of formal education	6.336	6.032	5.808
	(3.336)	(4.167)	(4.022)
Number of resident household members	5.603	5.870	5.841
	(2.317)	(2.576)	(2.331)
Dependency ratio	0.551	0.539	0.545
	(0.233)	(0.226)	(0.211)
The main activity of household head is farming	0.881	0.926	0.904
	(0.324)	(0.262)	(0.295)
Per capita household income	564,217	519,178	579,632
	(752,677)	(782,057)	(871,267)
Agricultural assets index	0.064	-0.010	-0.063
	(4.200)	(4.513)	(4.326)
Access to credit (1=yes; 0=no)	0.647	0.638	0.719
	(0.478)	(0.481)	(0.450)
Government extension	0.028	0.023	0.023
	(0.165)	(0.151)	(0.151)
Median social distance in education in the sub-village	2.938	3.269	3.409
	(1.272)	(1.307)	(1.382)
Median social distance in wealth index in the sub-village	3.023	3.052	3.377
	(0.908)	(0.952)	(0.991)
Panel B: Baseline social networks			
Number of agricultural information network links	2.018	1.907	1.857
	(1.009)	(1.066)	(1.445)
Number of kinship links outside the household but within the same sub-village	1.752	1.722	1.724
	(0.972)	(1.051)	(1.111)
Panel C: Baseline exposure to weather shocks			
Household has experienced droughts	0.956	0.944	0.953
	(0.206)	(0.230)	(0.212)
Number of sub-villages (total = 132)	44	44	44
Number of observations	428	431	427
p-value for joint orthogonality test		0.227	

Notes: Standard deviations are in parentheses. The *p*-value for joint orthogonality test is obtained from a multinomial logit regression of the treatment arms on the variables with robust standard errors clustered at the sub-village level.

To gauge knowledge levels we administered a simple test focusing on the content of the CSA training. Such exams are an effective approach of assessing knowledge retention by subjects (Kondylis et al., 2015), picking up effort during the training as well as effort to memorise the training content afterwards. We weigh correct answers by the inverse probability of a correct response so that difficult questions carry more weight in the final outcome (see Appendix C for the questions). Knowledge scores for DFs ranged between 0 and 33.0, with a mean of 20.0 (the mean knowledge score for “other villagers” was only 13.2).

We further measured uptake of other Longe maize varieties, also discussed during the trainings and more familiar to the farmers in our sample. About 8.3 percent of the DFs had tried out the Longe 10H maize variety, and 22 percent had constructed CF basins. In addition, about one-third had planted another Longe maize variety. Not surprisingly, experimentation by co-villagers was much lower: about two percent tried out Longe 10H maize; another two percent tried out CF basins; and 6.5 percent grew a different Longe maize variety of maize.

To measure diffusion effort chosen by DFs we used a binary outcome capturing whether or not the DF organised at least one activity in the sub-village intended to train co-villagers. Specifically, we asked the other farmer whether he or she knew of (or had attended) any activity organised by another farmer in their sub-village during the first season of 2016 to train co-villagers about agricultural technologies. If they answered affirmatively we asked the name of the farmer who had organised the activity by a series of follow up questions. We also asked about the content of the activity. On average, 18 percent of the other farmers indicated the DF from their villages had organised at least one meeting to train co-villagers during the previous season. It is possible, however, that DFs communicated with their neighbors via word of mouth. To capture this, we include an additional effort variable measuring the number of people with whom the DF communicated about improved farming methods (based on survey data provided by co-villagers, not the DFs).

Finally, we organised an artefactual field experiment to measure altruism. As mentioned, intrinsic motivation may interact with extrinsic and reputation motives. Following Ashraf et al. (2014a) we implemented a dictator game to elicit an incentive-compatible measure of prosocial motives. We assume prosocial preferences are exogenous and do not vary with exposure to the training or experiment. A formal test (Appendix Table 2.A.1) was performed to check whether the experiment affected the outcome of the prosocial preferences game. We cannot reject the null hypothesis that treatment did not affect the outcome of the games. Games were implemented during the second survey wave. Each disseminating farmer received 5,000 Ugandan shillings,[8] of which a fraction could be donated to a charity organisation helping farmers to increase agricultural productivity and improve their lives.[9] We interpret the amount donated as a proxy for the DF's intrinsic motivation for the cause (see also Carpenter and Myers, 2010). The average donation was UGX 1,900, with a median of UGX 2,000.

2.3 Identification and Empirical Estimation

First, the effect of incentives on the main outcomes of interest is examined, using the following equation:

$$y_{ivc} = \alpha + \sum_{j=1}^{2} \beta_j treat_v^j + \gamma_i W_{ivc} + C_c + \varepsilon_{ivc} \tag{2.1}$$

where y_{ivc} represents the outcome of interest for farmer i in sub-village v and sub-county c: the above-mentioned measures of *knowledge*, *experimentation*, or diffusion *effort*. The variable $treat_v^j$ denotes the two treatment dummies, with the training-only group as comparison group. Next, W_{ivc} is a vector of individual characteristics, and C_c captures sub-county fixed effects. Ordinary least squares regression (OLS) is used to explain variation in knowledge (by DFs and other farmers), and a probit model is used to analyse the DF's and other farmer's on-farm

[8] USD 1 = UGX 3,000 during the time of our experiment.
[9] The exact script used in the adapted dictator game is provided in the appendix.

experimentation. For DF's training effort, a probit model is used for the dummy effort variable and OLS for the number of people with whom the DF communicated. Throughout, robust standard errors are clustered at the sub-village level.

The decision to use the training-only group as comparison group instead of including a fourth arm (pure control) was informed by limitations in terms of statistical power, especially because the randomisation was done at sub-village and not individual level. Our experiment, therefore, provided training to all DFs, but varied the incentive received to expend costly effort. The experiment provides a convincing way of understanding effect of incentivised versus non-incentivised training of DFs on diffusion effort. We recognise, however, that use of the training-only group instead of a pure control as comparison group may underestimate effects of the incentives.

The coefficients β_j in equation (2.1) measure the causal effect of the incentive treatments on knowledge scores, experimentation and effort, under the identifying assumption that $treat_v^j$ is orthogonal to ε_{ivc}. Random assignment to treatment implies the identifying assumption is satisfied, unless there are substantial spillover effects (so that the SUTVA is violated). This might happen if DFs in the training-only group changed their behaviour as a result of knowing that others had been offered rewards. Two design features were employed to minimise this risk: (i) we selected only one DF from each sub-village and hence there was only one treatment per sub-village;[10] and (ii) DFs attended the training with others who were assigned to the same experimental arm (even if this was not announced to the DFs before the training). Training sessions for different treatment arms were organised at different venues. Furthermore, sub-villages in northern Uganda, and Nwoya district specifically, are geographically dispersed. Still, we use Global Positioning System (GPS) coordinates of the

[10] Only one of our DFs migrated after the training, and none moved to another sub-village with a different treatment.

sub-villages to test for evidence of spillovers across neighbouring sub-villages. We ask if the presence of a DF from another experimental arm in a neighbouring sub-village affects diffusion effort. Appendix Figure 2.B.1 (top panel) graphically shows the random assignment of treatments whereas the lower panel shows sub-villages receiving different treatments but neighbouring each other. We ask whether diffusion effort of DFs of the control group was affected by spillovers by comparing effort levels of control group DFs neighbouring a treated DF, and control group DFs further away from treated units. According to our estimates, summarised in Appendix Table 2.A.2, there are no spillovers. Using a border-to-treatment dummy variable, a *t*-test indicates that control group DF effort was not significantly affected by the presence of a neighbour from another experimental arm.

Finally, we assess heterogeneity in the treatment effect of incentives. To evaluate the mediating effect of altruism on the level of diffusion effort chosen by the DF we follow Ashraf et al. (2014a) and use donations in the dictator game to construct a continuous variable π. This variable represents the (standardised) level of donations. Using actual amounts donated may however be affected by outliers. Appendix Figure 2.B.2 shows the distribution of the actual amounts of money donated. As shown, the distribution is approximately normal. Nevertheless, we construct and use a dummy variable equal to one if the DF donated above the median amount and zero if otherwise. The *prosocial preference* variable was interacted with the treatment dummies and included in the DF effort equation:

$$effort_{ivc} = \alpha + \sum_{j=1}^{2} \vartheta_j treat_v^j + \sum_{j=1}^{2} \sigma_j treat_v^j * \pi_i + \lambda\pi_i + \rho W_{ivc} + C_c + $$
$$+ \varsigma_{ivc} \quad (2.2)$$

2.4 Results

2.4.1 Incentives and knowledge, experimentation, and diffusion effort

Table 2.2 presents results of a series of OLS and probit regressions assessing the effect of incentives on DFs' experimentation with the technologies (columns 1–3), their retained knowledge six months after the training (column 4), and their diffusion effort (columns 5–6).

Considering on-farm experimentation with the new technologies, we find that the social recognition treatment increases the propensity to experiment with Longe 10H DT maize (column 1)—compared to control group farmers, DFs incentivised with social recognition are 14 percentage points more likely to experiment with Longe 10H DT maize on their own farm. The impact of the private material reward is positive, but much smaller. Disseminating farmers in this group are as likely as un-incentivised DFs to grow Longe 10H DT maize.

Social recognition also increases the likelihood of using improved maize varieties (other than Longe 10H DT maize, column 2) and CF basins (column 3). On average, the probability of growing improved maize varieties increases by 17 percentage points more for the social recognition reward arm. Similarly, social recognition increases the probability of using CF basins by around 15 percentage points as compared to the comparison group. For these experimentation outcomes there are no differences between the private material reward and social recognition treatment, but again we observe that the effect of the private material reward incentive does not significantly differ from zero either.

Results in column 4 show that the incentive treatments did not affect DFs' level of knowledge. Remember that DFs were informed about the treatments after they completed their training, ruling out any impact on their knowledge accumulation during training. These results further indicate that knowledge levels did not change differentially during the subsequent six months. The training included a practical session where, for example, spacing, number of seeds to sow in a hole, and length, width, and height of the CF basins was demonstrated in the field. The knowledge questions in the test focused on this sort of information, not on the practical knowledge that farmers acquire through on-farm experimentation. Hence it is not surprising that test scores did not vary across treatment arms (that is, did not improve with own on-farm experimentation).

Table 2.2. Incentives and Disseminating Farmers' Knowledge, On-farm Experimentation, and Diffusion Effort

Incentive type	On-farm experimentation			Knowledge	Effort	
	DT maize	Improved maize	CF basin		Organised activity	Information exchange
	(1)	(2)	(3)	(4)	(5)	(6)
Training plus private reward (PR)	0.025	0.153	0.133	-0.118	0.209**	0.689**
	(0.073)	(0.097)	(0.085)	(0.231)	(0.089)	(0.282)
Training plus social recognition (SR)	0.136**	0.171*	0.147*	-0.064	0.244***	0.908***
	(0.057)	(0.096)	(0.082)	(0.231)	(0.083)	(0.300)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.340	0.168	0.158	0.037	0.139	0.169
Observations	123	123	123	123	123	123
Mean of dependent variable for non-incentivised DFs	0.025	0.150	0.125	0.090	0.075	1.225
	[0.158]	[0.362]	[0.335]	[1.086]	[0.267]	[1.050]
PR = SR (p-value)	0.067	0.836	0.857	0.814	0.674	0.513

Notes: DF means disseminating farmer. Dependent variables are as follows: column (1), (2), and (3) are dummy variables equal to one if disseminating farmer (DF) tried out the technology on at least one of the household's plots and zero otherwise; column (4) is the standardised knowledge score of the DF; column (5) is a dummy equal to one if DF held at least one meeting or activity to train other farmers and zero otherwise; column (6) measures the number of people in the sub-village with whom the DF communicated about improved farming methods. Robust standard errors corrected for sub-village level clustering are reported in parentheses. Square parentheses are the standard deviations of the control group means. Asterisks indicate the following: ***=$p < 0.01$, **=$p < 0.05$, *=$p < 0.1$. Household controls include sex, age, education, and main economic activity of the household head, dependency ratio, livestock ownership, agricultural assets ownership, and access to credit. Columns (4) and (6) are OLS estimates. Columns (1), (2), (3), (5), and (6) report average marginal effects from probit regression. DT maize means drought-tolerant maize; CF basin means conservation farming basin.

Column 5 shows that both incentive regimes increase the probability that a DF organised an activity to train other farmers, compared to the training-only group. Both types of incentives are effective in stimulating DFs' diffusion activity. Specifically, DFs incentivised by a private material reward are 21 percentage points more likely than un-incentivised DFs to train other farmers, and DFs incentivised by social recognition are 24 percentage points more likely to train other farmers. These outcomes are statistically identical. Observe that the size of the treatment effect, relative to the mean experimentation or effort level of the control group is large. We find similar evidence for the effect of the incentives on the number of people a DF communicated with about improved farming methods (column 6). Specifically, the DF's out degree—the number of people to whom information was communicated increased by 0.9 in the social recognition treatment arm and 0.7 in the private material arm, compared to the control group.

These findings support and extend insights by Ben Yishay and Mobarak (2018). Disseminating farmers respond strongly to incentives for diffusion. The findings are also consistent with Ashraf et al. (2014b) as well as Carpenter and Myers (2010) who found that social recognition incentives may be as effective as private material rewards for promoting prosocial behaviour. If anything, we find that social recognition may matter even more than private material rewards[11].

[11] we developed a small guide for data collection and went back to the field in May, 2018 to collect additional data on how the weighing scales were being used in the private and social recognition treatment groups. We found that in both groups, the weighing scales still existed and were in working condition. In the private arm, the DFs mostly used the weighing scales for weighing their own produce (mainly maize), rarely allowing others to access it—in very few isolated cases, access was allowed to close relatives and neighbours. Whereas relatives did not pay, neighbours were typically charged a small fee for using the scale. The story was different in the social recognition arm where the village chief was in charge of the scale. First, we found that the village chiefs were still in charge of keeping and maintaining the weighing scales—ruling out the possibility that the weighing scale ended up with the DFs in the social recognition arm. We further asked to see the weighing scales in order to verify that the village chief indeed was keeping the scale. Second, co-villagers were allowed to access the weighing scale at no fee, but

Results of the effect of incentives on knowledge of "other farmers" and experimentation with the technologies are presented in Table 2.3. Compared to respondents from training-only sub-villages, knowledge scores (column 1) increased by 0.41 standard deviations in the social recognition treatment arm (corresponding to an increase of 8.56 in the unstandardised knowledge score), significant at the 10 percent level, and by a statistically insignificant 0.27 standard deviations in the private material reward arm (corresponding to an increase of 5.42 in the unstandardised knowledge score). In terms of experimentation, we find no significant effects on Longe 10H DT maize (column 2) and CF basin (column 4). The probability of experimenting with an improved variety of maize, however, increased by 10 percentage points in the social recognition treatment arm (column 3), significant at the 10 percent level. Although our experiment was designed to test incentives for knowledge diffusion and experimentation by the DFs, actual implementation by other farmers is important for policy reasons.

Our small and insignificant effects for other farmers' experimentation are probably explained by the fact that outcomes were measured only one cropping season (six months) after the interventions were rolled out. While this is enough time for co-villagers to learn about new technologies (and sufficiently long for experimentation by DFs to occur), it may be too short to enable experimentation by other farmers.

with strict instructions to handle the scale with care. It is also important to mention that besides the weighing scales that we provided as rewards for DFs efforts, there were a few other individuals—in both the private and social recognition arms—who owned weighing scales. For these privately owned weighing scales access by co-villagers was limited.

Table 2.3. Incentives and Other Farmers' Knowledge and On-farm Experimentation

Incentive type	Other farmers' knowledge	On-farm experimentation		
		DT maize	Improved maize	CF basin
	(1)	(2)	(3)	(4)
Training plus private reward (PR)	0.267	0.033	0.031	-0.045
	(0.210)	(0.030)	(0.043)	(0.032)
Training plus social recognition (SR)	0.413*	0.052	0.102*	-0.046
	(0.232)	(0.033)	(0.055)	(0.033)
Baseline knowledge score	0.030	-	-	-
	(0.037)			
Household controls	Yes	No	No	No
Sub-county fixed effects	Yes	Yes	Yes	Yes
R-squared	0.100	0.065	0.040	0.043
Observations	123	123	123	123
Mean of dependent variable for other farmers in sub-villages where DFs were not incentivized	-0.211	0.000	0.025	0.050
	[0.729]	[0.000]	[0.158]	[0.221]
PR = SR (p-value)	0.529	0.617	0.236	0.908

Notes: DF means disseminating farmer. Dependent variables are as follows: column (1) is standardised knowledge scores of the other farmer (not DF); columns (2), (3), and (4) are dummy variables equal to one if another farmer (not the DF) tried out the technology on at least one of the household's plots and zero otherwise. Robust standard errors corrected for sub-village level clustering are reported in parentheses. Square parentheses are the standard deviations of the control group means. Asterisks indicate the following: ***=$p < 0.01$, **=$p < 0.05$, *=$p < 0.1$. Linear probability model (LPM) estimates for column (1) and average marginal effects from probit regression for columns (2–4). DT means drought-tolerant variety of maize (Longe 10H); CF basin means conservation farming basin.

2.4.2. Heterogeneous treatment effects of incentives

It is plausible that not all DFs are equally responsive to incentives. For example, in their study of promoting health-related prosocial behaviour, Ashraf et al. (2014a) found that the effects of private material rewards and social recognition were stronger for intrinsically altruistic subjects. We now analyse whether this result extends to the domain of agricultural knowledge diffusion. We first ask whether the impact of incentives on the propensity to invest effort in knowledge diffusion is mediated by prosocial preferences, and whether external incentives may "crowd out" altruism—as sometimes proposed in the literature. Specifically, if altruism leverages the impact of incentives then we expect the interaction of our altruism variable and the incentive (treatment) dummies to enter with a positive sign and significantly. Instead, if incentives crowd out altruism, then we expect that the altruism variable enters with a positive sign (level effect), but that the interaction between altruism and incentive dummies enters with negative signs.

Results are reported in Table 2.4, where we use a dummy variable equal to one if the DF donated above the median amount of money and zero if otherwise as a proxy for prosocial preferences or altruism. One might expect that altruistic farmers would have greater incentives to experiment because their utility goes up if they can help their peers with superior information in the future. We, however, find that the interaction between prosocial preferences and incentives—consider the terms *PR* × *donation* and *SR* × *donation*—is not significant at 10 percent level for DF's experimentation with the technologies (columns 3–5) and the knowledge of other farmers (column 6). Looking at effort expended by DFs to hold activities and train other farmers, the interaction between prosocial preferences and incentives is positive and statistically significant at one percent level (column 1). However, we also find a significant and negative *level effect* of prosocial preferences (column 1). More altruistic farmers spend, on average, less effort organising activities or holding meetings to demonstrate to their peers how to use new technologies. The interaction terms and level effect are statistically of the same magnitude, but have opposite signs meaning that the positive effect of the interaction terms is cancelled out by the negative effect of the level prosocial variable. The effect of incentives on DF's effort and actual experimentation with the technologies does not, therefore, seem to be mediated by prosocial preferences. The effect of the interaction terms on the number of people that the DF informed about the technologies is also not statistically significant at 10 percent level (column 2)[12].

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[12] First, consider the negative effect of altruism: in the absence of incentives, why are more altruistic DFs less likely to invest effort in training their peers? This finding is consistent with our understanding of heterogeneity in farm productivity and the low quality of agricultural inputs in Africa. Altruistic farmers who lack confidence in the profitability of new technologies for their co-villagers should not diffuse information. Such lack of confidence in overall profitability may follow from three reasons. (1) Heterogeneity in production conditions imply that the same technology will not be profitable for all farmers—even within the same village (Suri, 2011). This is especially likely for labour-intensive (or costly) innovations such as the construction of CF basins. (2) Drought-tolerant seeds might not have a yield advantage over other improved varieties, or might even have a yield penalty in normal years (Holden and Fisher, 2015). (3) There exists a major problem of counterfeit inputs in northern Uganda. In a recent study, Bold et al. (2017) find that 30 percent of nutrients are missing in chemical fertilizer, and samples of hybrid maize were estimated to contain less than 50 percent of improved seeds (presumably due to extensive adulteration).[12] They find that, on average, low quality inputs results in near zero average rates of return in Uganda.

In light of these observations it seems reasonable for DFs to question whether adopting these innovations is actually welfare-improving for all co-villagers. Instead, it may be optimal to delay transmission of the relevant information until after additional information has come available. Such a cautionary response can, however, be overwhelmed by incentives. If DFs are incentivised to diffuse information they choose *not* to delay transmission, and behave like their non-altruistic peers. In an effort to gain the material reward or social recognition, they seem willing to take the risk of spreading information that is potentially not useful to their peers. Extrinsic and intrinsic motives therefore work in opposite directions if the net benefits of new technologies are uncertain, and can offset each other.

The finding of a positive effect of prosocial preferences on the number of people that the DF talked with about the technologies perhaps suggests that while altruistic DFs may be reluctant to demonstrate the use of new technologies to their peers, they may see it harmless to make them aware of such technologies. Altruistic DFs may also talk to their peers about the new technologies because they enjoy interacting with them, or to "send a signal" that they are not withholding information that could potentially be relevant for them. The interaction terms are, however, not statistically different from zero.

Finally, we examine heterogeneous treatment effects of incentives by social distance. Motivated by the selection criteria for the DFs, we consider two social distance variables, namely wealth status and education. The social distance variables are measured based on baseline data as follows. First, we construct dyadic pairs for each of the respondents in a sub-village who were interviewed at baseline. Next, for each dyadic pair, we compute the absolute difference in wealth status (household assets index) and education. We then calculate the median distance for each sub-village and variable and observe how close or far the absolute distance between the DFs and their neighbours is from the median distance in the sub-village. This 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. Results are not statistically significant for wealth status (Table 2.5, columns 1 and 3). In terms of distance in education, we find an increased likelihood by 6.3 percentage points, of DFs holding an activity to discuss with their neighbours about the technologies, for the private rewards (Table 2.5, column 2). Heterogeneous treatment effects by distance in education are positive, for both private reward and social recognition, but not statistically significant in terms of the DFs' out-degree.

That prosocial preferences do not significantly affect the propensity to experiment (see columns 3–5 in Table 2.4) may reflect one of the lessons of Bold et al. (2017), who highlight the difficulty of Bayesian updating in the context of agricultural inputs and volatile production conditions. While Bayesian updating is relatively easy when counterfeit inputs are of either very low or very high quality, it is difficult and slow when adulteration of inputs occurs at intermediate levels—exactly as observed in actual Ugandan input markets. If farmers know that learning about the quality of inputs is slow and imperfect, the interaction between altruism and incentives is unlikely to have big effects on experimentation.

Table 2.4. Heterogeneous Treatment Effects: Pro-social Preferences

	Organised activity	Information exchange	DT maize	Improved maize	CF basin	Other farmers' knowledge
	(1)	(2)	(3)	(4)	(5)	(6)
Private reward (PR)	0.184**	0.754**	0.020	0.182	0.097	0.340
	(0.091)	(0.317)	(0.050)	(0.112)	(0.097)	(0.252)
Social recognition (SR)	0.188**	0.794**	0.156*	0.255**	0.090	0.277
	(0.087)	(0.340)	(0.084)	(0.108)	(0.093)	(0.241)
Donation (in dictator game)	-0.938***	0.677*	-0.074	0.182	0.013	0.039
	(0.161)	(0.382)	(0.050)	(0.162)	(0.147)	(0.228)
PR × donation	0.900***	-0.117	0.040	-0.124	0.150	-0.311
	(0.220)	(0.714)	(0.073)	(0.230)	(0.196)	(0.417)
SR × donation	1.010***	0.268	0.034	-0.317	0.170	0.471
	(0.209)	(0.620)	(0.129)	(0.206)	(0.184)	(0.498)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.156	0.220	0.178	0.184	0.163	0.136
Observations	123	123	123	123	123	123
p-value (PR × donation) = (SR × donation)	0.565	0.629	0.967	0.352	0.188	0.169

Notes: Average marginal effects. Household controls include sex, age, education, and main economic activity of the household head, dependency ratio, livestock ownership, agricultural assets ownership, and access to credit. Robust standard errors corrected for sub-village level clustering (123) are reported in parentheses. Asterisks indicate the following: ***=p < 0.01, **=p < 0.05, *=p < 0.1. DT means drought-tolerant variety of maize (Longe 10H); CF basin means conservation farming basin.

Table 2.5. Heterogeneous Treatment Effects: Social Distance

	Organised activity		Information exchange	
	(1)	(2)	(3)	(4)
Private reward (PR)	0.200	0.076	1.149***	0.157
	(0.125)	(0.131)	(0.434)	(0.524)
Social recognition (SR)	0.215*	0.183*	0.960**	0.982*
	(0.110)	(0.108)	(0.421)	(0.506)
DistHHassets index	-0.019		-0.011	
	(0.022)		(0.087)	
PR × DistHHassets index	0.002		-0.174	
	(0.036)		(0.133)	
SR × DistHHassets index	0.007		-0.031	
	(0.035)		(0.146)	
DistHHHeduc		-0.048**		-0.164**
		(0.024)		(0.079)
PR × DistHHHeduc		0.063*		0.199
		(0.037)		(0.165)
SR × DistHHHeduc		0.039		0.013
		(0.027)		(0.102)
Controls	Yes	Yes	Yes	Yes
Sub-county fixed effects	Yes	Yes	Yes	Yes
R-squared	0.146	0.155	0.192	0.210
Observations	123	123	123	123
p-value (PR × social distance) = (SR × social distance)	0.911	0.488	0.363	0.258

Notes: Average marginal effects. DistHHassets index and DistHHHeduc measure social distance in terms of household assets (wealth status) and education, respectively. Household controls include sex, age, education, and main economic activity of the household head, dependency ratio, livestock ownership, agricultural assets ownership, and access to credit. Robust standard errors corrected for sub-village level clustering (123) are reported in parentheses. Asterisks indicate the following: ***=p < 0.01, **=p < 0.05, *=p < 0.1.

2.5 Discussion and conclusions

Effective approaches to alleviate poverty in sub-Saharan Africa will require rural development and agricultural intensification. A key concern is how to promote the adoption of modern production techniques that are more productive and resilient. Conventional extension efforts have by and large failed to reach large swaths of the rural population, and the search is on for innovative approaches to stimulate the diffusion of information about agricultural innovations. Social learning has long since been an important component of such efforts, but the insight is sinking in that diffusion of information within social networks may neither be easy nor "automatic." In contexts where individual farmers stand to gain little from spreading information but expect to pay a positive (effort) cost, diffusion is often slow and imperfect. Incentivising farmers to engage in diffusion represents one potential solution.

In this chapter we use an experimental approach to study the effects of incentivising farmers to allocate effort to the diffusion of information. Incentivising can happen in different forms, and we consider two types of "extrinsic rewards" for effective information sharing; a private material reward for the disseminating farmer and an intervention that aims to build the reputation of the disseminating farmer within his or her community ("social recognition"). As a material reward we used a weighing scale, and we focus on the diffusion of knowledge about climate-smart agricultural practices. We find that reputation building may be a particularly effective way to promote diffusion—while a private material reward had small effects on diffusion, the same reward given to "the community" in a public ceremony celebrating the efforts of the contact farmer effectively pushed up own experimentation by the disseminating farmer, his diffusion effort, and actual information transmission. We believe this result speaks to the importance of community structures for rural livelihoods in Africa.

A large literature studies the interaction between different motives for prosocial behaviour, and in particular asks whether extrinsic motives (private rewards or "reputation building") may interact with intrinsic motives. Indeed, in theory it would be possible that providing extrinsic rewards reduces the diffusion of information if the "crowding out effect" is sufficiently large and dominates the direct incentive effect. However, our data are not consistent with such outcomes. We show that altruistic farmers are *more* responsive to extrinsic rewards than non-altruistic farmers when required to demonstrate use of improved technologies. Altruistic disseminating farmers are more likely to communicate by word of mouth to their neighbors, but reluctant to demonstrate implementation of improved technologies than non-altruistic dissemination farmers. However, extrinsic incentives attenuate this reluctance. While it seems paradoxical that altruistic farmers invest less in demonstrating technology use than their non-altruistic counterparts, we speculate this finding is due to fundamental uncertainty about the value of new technologies. This uncertainty follows from heterogeneity in production conditions, or from uncertainty about the quality of the inputs. Altruistic farmers appear reluctant to expose their peers to new technologies with unproven welfare effects.

We hope the results in this chapter can guide thinking about effective ways to promote the diffusion of information. The main policy message is that including incentives in extension schemes may be welfare-enhancing. However, this begs the question 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? Additional experimenting with innovative approaches is presumably necessary for this. An auxiliary policy message concerns the perceived low quality of agricultural inputs. Bold et al. (2017) correctly identify that poor handling and adulteration reduce the rate of return of adopting these inputs. Our results suggest low input quality may also attenuate incentives to share information in social networks. Addressing the issue of low-quality inputs may therefore have beneficial effects along multiple dimensions.

Appendix 2.A: Tables

Table 2.A.1. Did the Experiment Affect the Outcome of the Donations Game?

Dependent variable: amount of money donated in the pro-social preferences game		
	Coefficient	p-value
Training plus private reward (PR)	-0.285	0.188
	(0.215)	
Training plus social recognition (SR)	-0.062	0.780
	(0.221)	
Intercept	0.112	0.454
	(0.150)	
R-squared	0.015	
Observations	123	

Notes: Robust standard errors corrected for sub-village level clustering (123) reported in parentheses.

Table 2.A.2. Testing for Spillover Effects

	Close but different treatment	Otherwise	Difference	t-value	p-value
Effort	0.091	0.198	0.107	1.441	0.157
	(0.063)	(0.040)	(0.074)		
Observations	101	22			

Notes: In parentheses are standard errors.

Appendix 2.B: Figures

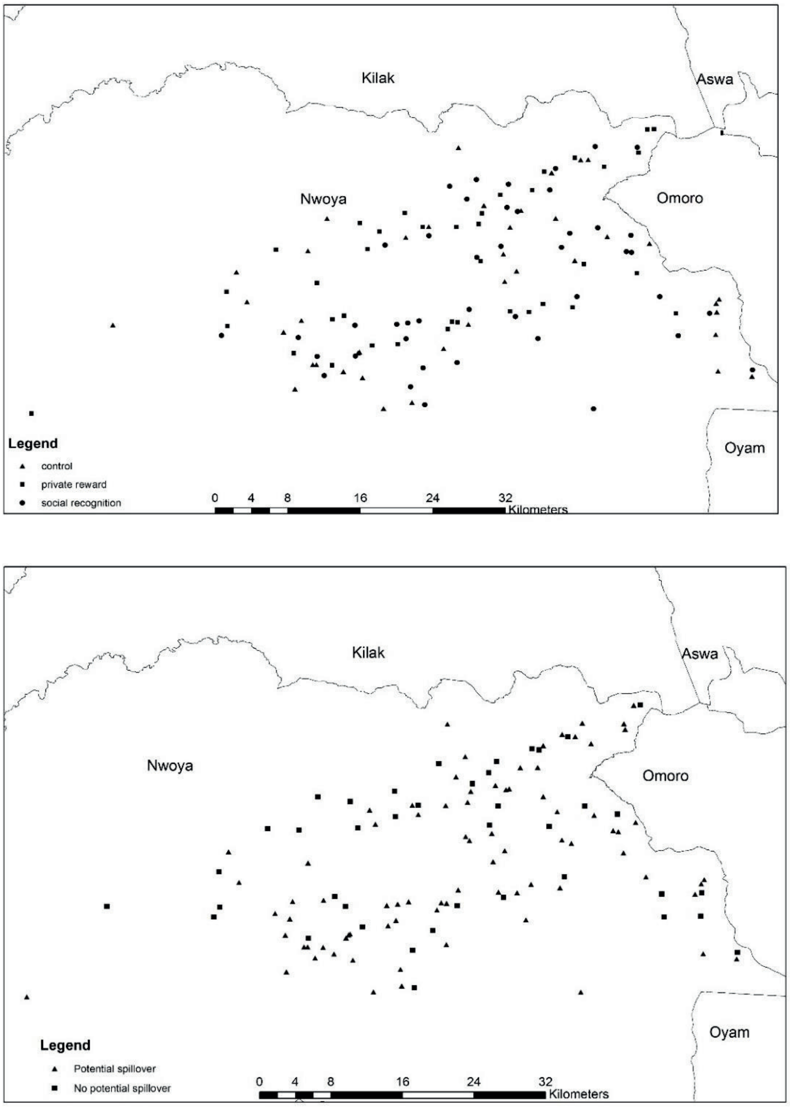

Figure 2.B.1. Location of disseminating farmers (top panel) and potential for spillover (bottom panel)

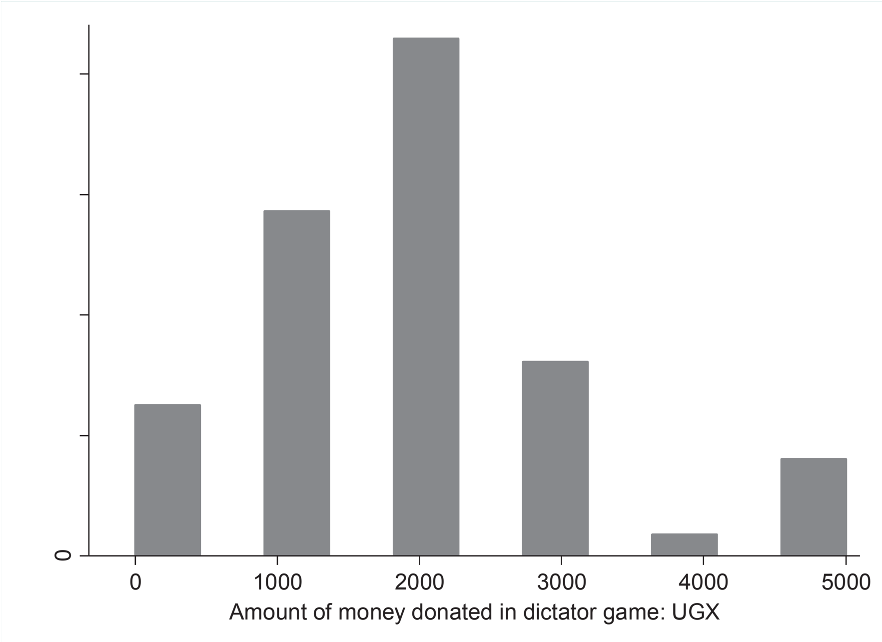

Figure 2.B.2. Distribution of amount donated by disseminating farmers in the augmented dictator game

Appendix 2.C. Knowledge questions

Q1. Have you ever heard about improved varieties of crops? (1mk if the farmer has heard about improved varieties of crops)

Q2. What improved varieties of maize have you heard about? (1mk if the farmer mentions at least one name of an improved variety of maize)

Q3. What improved varieties of groundnuts have you heard about? (1mk if the farmer mentions at least one name of an improved variety of groundnuts)

Q4. What benefits do improved varieties of crops have? (1mk if the farmer mentions at least one benefit of an improved variety of crop)

Q5. Have you ever heard about conservation farming basins? (1mk if the farmer has heard about conservation farming basins)

Q6. How long should a conservation farming basin be? (1mk if the farmer answers 30cm–40cm; estimated using length of a straight stick and measured by enumerator using a ruler)

Q7. How wide should a conservation basin be? (1mk if the farmer answers 10cm–15cm; estimated using length of a straight stick and measured by enumerator using a ruler)

Q8. How deep should a conservation farming basin be? (1mk if the farmer answers 10cm–15cm; 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? (1mk if farmer answers three)

Q10. When planting groundnuts in a conservation farming basin, how many seeds should a farmer plant? (1mk if farmer answers 6–8 seeds)

Appendix 2.D. Instructions for the Augmented Dictator Game

We recently had a meeting in which farmers were trained about new farming methods. During the meeting, each participant was provided with transport fee. After the meeting, we found out that we had some funds remaining. The funds that remained are enough to allow us to give you 5,000 UGX. Therefore, I have with me here, 5,000 UGX [SHOW THE 5,000 UGX TO THE RESPONDENT] that I will give to you. You can choose how much of this sum to keep for yourself and how much to donate to African Revival or Charity for Rural Development (CHAFORD), local charities that work with farmers to train them about new farming methods. I will give you this envelope [GIVE THE ENVELOPE TO THE RESPONDENT]. With me I have this collection box [SHOW THE BOX TO THE RESPONDENT]. If you wish to donate, please put your donation in the envelope and drop it in the collection box. Note that the amount you donate is totally up to you: you can give nothing, part of the 5,000 UGX, or the entire thing. The amount you contribute will be kept completely confidential. I will give you a few minutes to think about it. When you've taken a decision, please drop your envelope in the box. Is it clear? [IF THE RESPONDENT HAS UNDERSTOOD THE INSTRUCTIONS] I will now give you 5,000 UGX and allow you a few minutes to make your decision [GIVE THE RESPONDENT 5,000 UGX in 1,000 notes].

AFTER THE GAME

Thank you for your donation

Appendix 2.E. Theoretical Model

To guide our empirical analysis, we summarise a framework that combines insights from the standard target input model commonly used in diffusion studies (e.g. Bardhan and Udry, 1999; Bandiera and Rasul, 2006) and a model of incentives for communication proposed by BenYishay and Mobarak (2018).

The basic set-up is as follows. There is a continuum of farmers distributed on a line, with mean revenues equal to zero and variance equal to one. Farmers can produce output using a conventional technology, producing known profit q, or a new technology. While the basics of the new technology are observable and known to all farmers, one parameter is random and *ex ante* unknown. This parameter is the target level of a variable input (say, labour), denoted by y^*.[13] Payoffs of the new technology for farmer i depend on the distance between the applied input level and the target: $Q_i = 1 - (y_i - y^*)^2$. For simplicity we assume both the target value and productivity of the new technology is homogenous across farmers. Nevertheless, payoffs may depend on the location of farmers in the distribution. The reason is that farmers receive signals about the profitability and implementation of the new technology by observing their peers, but the signal of "neighbouring farmers" is more informative than signals received from farmers further away in the distribution.

Assume there is an *ex ante* common belief about the target input level, which is normally distributed with mean 0 and variance σ^2. If farmers adopt the new technology their expected payoff equals $1-\sigma^2$, so in the absence of additional information farmers will choose not to adopt when $q > 1-\sigma^2$. Next assume there is one informed farmer, the disseminating farmer, who knows the target level y^*. This farmer is located at x in the distribution and can choose to send a signal with precision ρ to her peers at a cost $c(\rho)$. We assume these costs are increasing in the precision of the signal, $c'(\rho) > 0$ and $c''(\rho) > 0$. Following BenYishay and Mobarak (2018), we assume that if the disseminating farmer sends a signal, farmer i receives a noisy message with the noise level increasing in the distance between x and i:

[13] The original diffusion model developed by Bardhan and Udry (1999) and Bandiera and Rasul (2006) assumes that the target level y^* varies across farms (i.e. y_i^*). This approach captures differences in agronomic conditions between farms. However, since our data do not enable quantification of "proximity" (or similarity) between farmers, and our analysis does not consider the question "who learns from whom?", we ignore such heterogeneity in production in the theoretical model.

$$s_{xi} = y^* + \frac{|x-i|}{\rho} \quad (2.E.1)$$

After receiving signal s_{xi} the receiving farmer uses Bayesian updating to update his beliefs about the target level. The *ex post* mean and variance are now given by:

$$E[y^*|s_{xi}, \rho] = \frac{\sigma^2\rho^2 s_{xi}}{\sigma^2\rho^2+(x-i)^2} \quad (2.E.2)$$

$$VAR[y^*|s_{xi}, \rho] = \frac{1}{\frac{1}{\sigma^2}+\frac{\rho^2}{(x-i)^2}} \quad (2.E.3)$$

Farmers further away from the disseminating farmer receive a more noisy signal; their updated beliefs are more biased and variable than the updated beliefs of farmers closer to the disseminating farmer. Since farmers will only adopt if their expected payoffs of the new technology are higher than their profits under the traditional technology, farmer i will adopt the new technology if the following condition is satisfied:

$$q < Q_i = 1 - \frac{1}{\frac{1}{\sigma^2}+\frac{\rho^2}{(x-i)^2}} \quad (2.E.4)$$

While diffusion of the new technology in the absence of signal-sending by the disseminating farmer only occurs if $q < 1-\sigma^2$, the probability that adoption occurs increases after receiving a signal. Since the variance of the target level is decreasing in the distance between sending and receiving farmers ($x-i$), diffusion is most likely to occur among "similar farmers" exposed to the signal. The variance is also decreasing in the precision of the signal, so disseminating farmers willing to incur greater signalling costs will also promote diffusion.

The level of signal-sending chosen by the disseminating farmer will vary with marginal benefits and costs of increasing the precision of the signal. In the absence of any benefits, farmers will not invest in information diffusion and choose $\rho = 0$. We distinguish between two reasons why disseminating farmers may choose a precision level that is greater than 0 and incur positive signalling costs.

First, altruistic disseminating farmers may invest in signalling to increase the payoffs of their peers (e.g. Ashraf et al., 2014a). Specifically, assume farmer x internalises the payoffs of farmer i and knows that (i) adopting the technology would be welfare-increasing for farmer i and (ii) that sending a signal would convince that farmer to adopt the new technology. Farmer x's full payoff function reads as:

$$\pi_x = Q_x + \beta[Q_i - q] - c(\rho) \qquad (2.E.5)$$

where Q_x are the own material payoffs for farmer x and $\beta \leq 1$ is the parameter used to weigh the payoffs of farmer i. For $Q_i - q > 0$, an altruistic disseminating farmer will set $\rho > 0$. For $Q_i > q$, the optimal precision level of the signal solves:

$$\frac{\frac{2\beta\rho}{(x-i)^2}}{\left(\frac{1}{\sigma^2}+\frac{\rho^2}{(x-i)^2}\right)^2} = c'(\rho). \qquad (2.E.6)$$

Importantly, altruistic disseminating farmers should *not* send a signal to their peers if they believe the distance to others is "too large" so that the resulting signal for the receivers will be "too noisy."[14]

Second, disseminating farmers may invest in signalling to secure private payoffs – either in the form of a private material reward *PR* or in the form of social recognition *SR*. Following Ben Yishay and Mobarak (2018), assume the disseminating farmer receives a reward *PR* (or *SR*) if a certain mass of peer farmers knows about the new technology or adopts the new technology. From (2.E.4), adoption will occur by the mass of farmers i satisfying the following condition:

$$(x-i)^2 \leq \frac{\rho^2}{\frac{1}{1-q}-\frac{1}{\sigma^2}}. \qquad (2.E.7)$$

Suppose the reward is given if a mass *z* of farmers adopts. To obtain the reward, disseminating farmer *x* should send signal with precision ρ^* such that condition (2.E.7) is satisfied for all farmers located on the interval $[x-½z, x+½z]$. Of course this signal will only be sent if $c(\rho^*)<PR$ (or if $c(\rho^*)<SR$).

According to this model, farmers who are motivated by *both* altruism and a desire for (social) rewards are more likely to send a signal than farmers who are *either* altruistic or signalling for rewards. However, this result depends on two simplifications. First, as discussed above, engaging in an activity because of an extrinsic private or social recognition reward may

[14] Observe that this finding depends on the assumption that disseminating farmers discount the future. Her neighbours, after receiving a precise signal about input use, may subsequently decide to send a signal to their own neighbours (located further away from the disseminating farmer). This would allow information about the new technology to gradually and accurately spread. We assume such second-order diffusion is ignored by the disseminating farmers.

undermine altruistic benefits (e.g. Benabou and Tirole, 2006). Second, we have assumed the new technology is equally productive for all farmers (upon applying the same level of input y). If heterogeneity in production conditions—due to agronomic circumstances or farming skills, say—implies a range of payoffs from adoption (as documented by Suri, 2011), then an altruistic disseminating farmer may decide to *not* send a signal if she suspects a fraction of her peers will be worse off after adoption – even if they choose the optimal target y^*. Altruistic disseminating farmers should only work hard to diffuse knowledge if they believe the net payoffs of the new technology are positive for their peers.

Mutatis Mutandis, the theoretical model is also applied in *Chapter 4* where it implies a potential for changes in information networks coming from two sources. First, DFs may be motivated to reach out to more neighbours either to optimise their altruistic behaviour or to achieve the critical mass of peer farmers who know about the new technology to secure getting the reward. In the end, this leads to an increase in the number of people with whom the DF shares information about the new technology. Second, providing training to DFs exogenously makes them potentially important nodes as a source of information about a highly relevant new technology in the context of rural Uganda. Neighbours, including those who were not in the DFs' networks at the baseline, may realise this, and actively seek to be connected with DFs, ultimately implying changes in information networks of neighbours.

Chapter 3

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

Abstract

Using panel data from northern Uganda and employing quasi-experimental econometric techniques, this chapter systematically studies the relationship between social distance and the likelihood of information exchange, subsequently evaluating effects on awareness, knowledge, and adoption of agricultural technologies. We find an increased likelihood of information exchange when the disseminating farmer (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 higher than the median in the sub-village and when distance in non-agricultural assets index was lower than the median in the sub-village. 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".

This chapter is based on:

Shikuku, K.M. (2018). Information exchange links, knowledge exposure, and adoption of agricultural technologies in northern Uganda. Accepted for publication in *World Development*.

3.1 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 leveraging social networks for knowledge diffusion (Kondylis et al., 2016).

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 (FAO, 2013; Arslan et al., 2015; Kimaro et al., 2015; Lamanna et al., 2016). 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 (see *Chapter 2* for a comprehensive explanation of the selection procedure of DFs and details of the training). 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 chapter 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., 2015; Chami et al., 2017) and the increasingly recognised role of incentives for knowledge diffusion (*Chapter 2* of this thesis, Ben Yishay 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 (Ben Yishay et al., 2015). 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 chapter, 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 chapter 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 chapter 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 chapter is organised as follows. Section 3.2 discusses the conceptual framework underlying the study. Section 3.3 describes the data and variables used in the analysis. Section 3.4 discusses the empirical approach and estimation procedure. Section 3.5 presents the results while section 3.6 concludes.

3.2 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[15]. 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 Ben Yishay and Mobarak (2018). 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 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[16].

[15] 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).

[16] 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,

Suppose further that there is an informed farmer k who has been trained about the new technology and understands the possibilities. Leveraging 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 (Ben Yishay 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 Ben Yishay 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 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:

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

however, that several other motives, such as minimisation of risks, might drive the adoption behaviour of farm households.

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.

3.3 Data and description of variables

3.3.1 Data

Analysis is performed on a panel dataset that was collected through two waves of household surveys. The baseline survey was conducted in 2015 (see *Chapter 2* for a detailed explanation about the baseline survey). 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 3.A.1, 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.

3.3.2 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[17]) 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 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[18].

3.3.3 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

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

[18] 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.

social distance. The following steps were followed in constructing the social distance variables. In step one, dyadic pairs were generated for each of the respondents interviewed at baseline. Step two, involved computing (for each dyadic pair) the absolute difference in the continuous variable (education, age, area under maize, agricultural assets index, non-agricultural assets index, 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 3.1.

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

$$+I_{(x_{DFneighbour}-x_{villagemedian}>0)} \text{ x } \left|x_{DFneighbour} - x_{villagemedian}\right| \qquad (3.1)$$

where $I_{(\cdot)}$ is an indicator variable equal to one if true and zero if otherwise; for a continuous variable, $\left(x_{DFneighbour} - x_{villagemedian}\right)$ 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 3.A.2 presents a description of all the variables used to measure social distance including their summary statistics.

3.4 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.

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

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

$$\Pr\left(l_j = 1 | \boldsymbol{z_j}, \boldsymbol{x_j}\right) = \Phi\left(\boldsymbol{z_j'\beta 1} + \boldsymbol{x_j'\beta 2}\right) \tag{3.2}$$

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 (3.2), by probit, 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:

$$y_{jt} = \alpha + \lambda D_t + \theta l_{jkt} D_t + \mu_{jt} \qquad (3.3)$$

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 (3.3), 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. In the second step, therefore, the estimated propensity scores from equation (3.2) are used as weights in the DID equation (3.3). In other words, equation (3.3) 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 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 chapter, 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 3.2 and 3.3. 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.

3.5 Results

3.5.1 Descriptive statistics

Summary statistics of the sample households at baseline, with and without weighting, are presented in Table 3.1. 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[19] 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.

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 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 3.1, however, show that weighting observations according to the propensity score actually eliminates difference in average group characteristics.

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

Turning to the outcome variables, descriptive statistics in Table 3.2 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 3.2, 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.

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 3.2, 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.

Table 3.1. 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.

Table 3.2. 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	0.0522	0.0948	0.0456	0.0493*	0.1079	0.5086	0.0456	0.4630***
Heard about DT maize in general	0.2030	0.3362	0.1823	0.1539***	0.2285	0.7155	0.1528	0.5627***
Heard about improved variety of maize	0.3608	0.5086	0.3378	0.1708***	0.3329	0.8276	0.2560	0.5716***
Heard about serenut 5R or 14R	0.0046	0.0172	0.0027	0.0146	0.0290	0.1121	0.0161	0.0960***
Heard about Serenut groundnuts	0.0882	0.1379	0.0804	0.0575*	0.0661	0.2328	0.0402	0.1925***
Heard about conservation farming basins	0.0000	0.0000	0.0000	NA	0.1311	0.3276	0.1005	0.2271***
Knowledge score (standardized)	-0.2355	0.0095	-0.2735	0.2831***	0.0175	1.1755	-0.1626	1.3381***
Panel B: Adoption variables								
Grow Longe 10H	0.0128	0.0517	0.0067	0.0450**	0.0394	0.1897	0.0161	0.1736***
Grow any drought-tolerant variety of maize	0.0580	0.1552	0.0429	0.1123***	0.1427	0.4655	0.0925	0.3730***
Grow an improved variety of maize	0.1265	0.1983	0.1153	0.0830**	0.1647	0.5086	0.1113	0.3974**
Grow Serenut 5R or 14R	0.0023	0.0086	0.0013	0.0073	0.0058	0.0259	0.0027	0.0232
Use conservation farming basins	0.0000	0.0000	0.0000	NA	0.0070	0.0172	0.0054	0.0119
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.

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.

3.5.2. Determinants of information exchange links

Table 3.3 presents results of probit regression (equation 3.2) 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; Ben Yishay et al., 2015), 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.

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 IPs also empowers male farmers to seek agricultural advice is in contrast with Ben Yishay et al. (2015). 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 neighbors 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. 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 9.7 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 an 8.1 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; Ben Yishay 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.

Table 3.3. 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	0.127^{***} (0.037)
DF is female; neighbour is male	0.138^{***} (0.040)
Both DF and neighbour are male	0.034 (0.043)
Difference in age ≤ sub-village median distance	-0.002 (0.003)
Difference in age > sub-village median distance	-0.002 (0.002)
Difference in education ≤ sub-village median distance	0.001 (0.009)
Difference in education > sub-village median distance	0.010 (0.008)
Difference in maize area ≤ sub-village median distance	0.040 (0.045)
Difference in maize area > sub-village median distance	0.040^{**} (0.016)
Difference in agricultural assets index ≤ sub-village median distance	0.041 (0.060)
Difference in agricultural assets index > sub-village distance	0.008 (0.038)
Difference in non-agricultural assets index ≤ sub-village median distance	0.097^{**} (0.046)
Difference in non-agricultural assets index > sub-village median distance	0.081^{*} (0.041)
Both DF and neighbour belong to a farmers' group	0.025 (0.183)
Only DF belongs to a farmers' group	0.044 (0.185)
Only neighbour belongs to a farmers' group	0.088 (0.185)
Difference in soil pH ≤ sub-village median distance	0.166 (0.407)
Difference in soil pH > sub-village median distance	0.215 (0.266)
Private reward	0.029 (0.029)
Social recognition	0.069^{**} (0.033)
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.

Differences in terms of age, education, 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).

3.5.3. 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 3.A.3. 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 3.B.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 3.B.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.

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 3.A.4). 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 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.

Table 3.4 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 similar 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 3.4, information exchange links increased awareness about improved varieties of maize and CF basins. According to IPW-DID estimates (Table 3.4, 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).

Table 3.4. 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.

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 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; Kondylis et al., 2016; 2017; Ben Yishay and Mobarak, 2018).

Information exchange links did not only increase awareness and knowledge, but also adoption. Table 3.5 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.

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 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.

Table 3.5. IPW-DID Estimates of the Effect of Information Exchange Links on Adoption of Improved Varieties and Conservation Farming

	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.

3.6 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 leveraging 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 chapter 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 or 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 chapter 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 chapter 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.

Appendix 3.A: Tables

Table 3.A.1. 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.

Table 3.A.2. 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.

Table 3.A.3. 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 3.A.2 were also included in the covariates balancing test (as instruments).

Table 3.A.4. 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 standardized bias before matching	Mean standardized 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

Table 3.A.5. 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.

Appendix 3.B: Figures

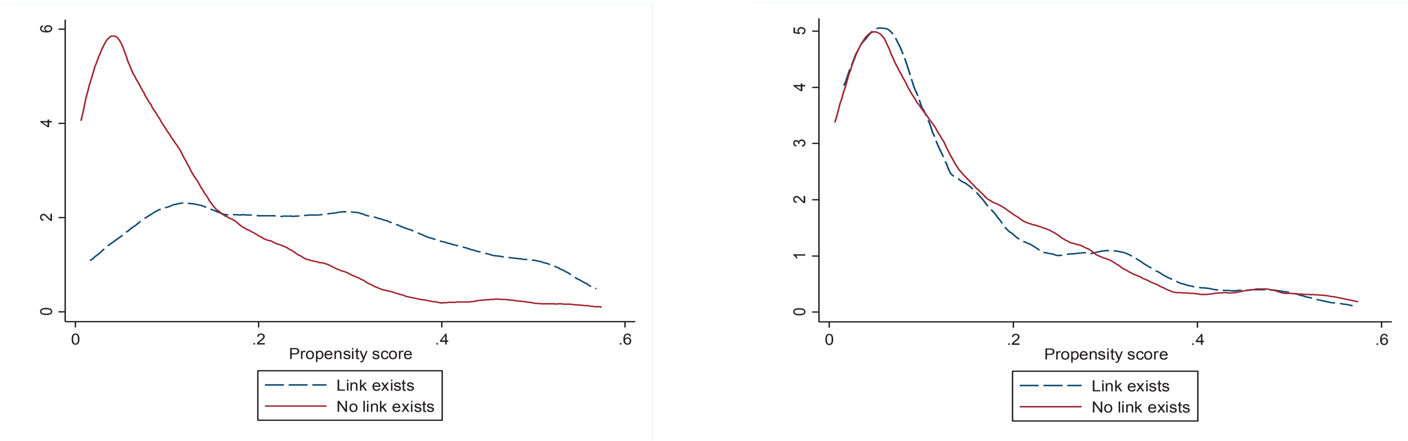

Figure 3.B.1. Propensity score weighting

Notes: Left panels shows distribution of propensity scores for the un-weighted sample whereas the right panels shows the same distribution for weighted sample.

Chapter 4

Information Networks, Incentives and Technology Adoption

Experimental Evidence from Uganda

Abstract

The role of social networks in agricultural technology diffusion has increasingly been studied. However, policy implications of previous findings have been limited, as less attention has been paid to understanding drivers of network changes. We use data from a randomised experiment in northern Uganda to examine effects of information networks on the decision to adopt drought-tolerant maize varieties (DTMVs) and the mechanisms through which the effects occur. The experiment provides training to a random subset of farmers—disseminating farmers (DFs). A random sub-sample of the trained DFs receive either a private material reward or social recognition for their efforts to share knowledge with neighbours. We find that incentives change both DFs' and neighbours' networks, and increase the likelihood of the former to adopt DTMVs. Information networks substantially increase knowledge and the likelihood of growing DTMVs among neighbours who mentioned trained and adopter DFs as contacts for crop production advice.

This chapter is based on:

Shikuku, K.M. and Mequanint, M.B. (2018). Information Networks, Incentives and Technology Adoption: Experimental Evidence from Uganda. *Under review in the Journal of Development Economics*.

4.1 Introduction

In developing countries, contact farmers are often used as messengers of agricultural information. Trainings and demonstrations about new agricultural technologies target these contact farmers with the expectation that they will disseminate new information to neighbours in their villages (Kondylis et al., 2017). However, our understanding of how this actually happens is limited. A body of literature exists on the process of social network formation and underlying incentives (Bala and Goyal, 2000; Goyal et al., 2006; Fafchamps and Gubert, 2007; Santos and Barrett, 2010). Equally, the role of social networks in technology diffusion has been extensively documented in empirical studies[20]. But these studies have largely taken networks as exogenous, and do not address how existing networks change in response to interventions, like training of a random node in the network (Breza, 2015). Most studies do not indicate the underlying mechanisms through which information dissemination takes place. Neither do they address how incentives could affect social networks and information dissemination within such networks. This chapter aims to contribute to the literature by endogenising networks, and looking into how training and incentives affect information networks as important conduits to influence knowledge about and adoption of new technologies.

Understanding how social networks could be changed can facilitate identifying the mechanisms through which information networks affect technology adoption. Such knowledge has direct implications for the design of agricultural extension and training programs in developing countries. Such understanding is also important to identify strategies for nudging adoption of optimal behaviour and designing incentives for better communication within networks. Recent

[20] Early contributions to the literature on social learning and technology adoption include Bikhchandani et al. (1992); Bikhchandani et al. (1998); Banerjee (1992); Ellison and Fudenberg, 1993; Besley and Case (1994); Foster and Rosenzweig (1995); Bala and Goyal (1998); Udry and Conley (2001); Munshi (2004); Acemoglu et al. (2011).

efforts studying network effects on adoption examine diffusion from a few starting points (seed nodes) to the larger target population. The focus is often on settings in which seed nodes' effort to communicate to their neighbours about a new technology is voluntary[21]. Networks may, however, interact with incentives subsequently influencing effort to communicate with peers about a new technology (Ben Yishay and Mobarak, 2018) and worker performance (Bandiera et al., 2005).

Theoretically, several reasons can motivate why the effect of social networks on adoption of a new technology may be mediated by incentives. When a task is prosocial, meaning that its benefits are enjoyed by those other than the seed nodes themselves, incentives may encourage efforts to reach out to more neighbours with information about a technology (Ashraf et al., 2014a). Incentives may, therefore, increase the seed node's degree—the number of people with whom information about a technology is discussed. Furthermore, incentives may induce seed nodes to experiment with a new technology (Ben Yishay and Mobarak, 2018). Several studies have shown increased propensity of a neighbour to adopt a technology when his or her network comprises adopters (Bandiera and Rasul, 2006; Conley and Udry, 2010; Matuschke and Qaim, 2009; Krishnan and Patnam, 2013). In the presence of an adopter seed node, social networks can influence adoption decision of neighbours by sending information about the adoption decision of the seed node or through diffusion of knowledge (Cai et al., 2015).

Informed by these insights, we conduct an experiment in northern Uganda in which a random sample of households—disseminating farmers (DFs)—are invited to receive training on growing of new drought-tolerant maize varieties (DTMVs). Drought-tolerant varieties are increasingly seen as interventions that can help to boost yields, while reducing downside risk

[21] See, for example, Kim et al. (2015) and Chami et al. (2018) for health-improving technologies; Cai et al. (2015) for insurance products; and Kondylis et al. (2017) and Vasilaky and Leonard (2018) for agricultural technologies.

associated with droughts (Wossen et al., 2017). A random sub-sample of the DFs then receive incentives to encourage them to expend effort to share information with their neighbours. The experiment varies whether subjects receive a private material reward or social recognition for their effort to share the knowledge learnt.

The overarching objective of this chapter is to assess social network effects on adoption of DTMVs and the main channels through which such effects occur. We observe whether a trained DF i is mentioned among neighbour $j's$ contacts for crop production advice as well as the frequency of interaction via the information exchange link. The former allows us to measure network effects at the extensive margin, whereas the latter captures the intensive margin. We then test whether social networks diffuse knowledge about DTMVs or transfer adoption decisions of DFs to neighbours. Further, we answer four questions: (1) do information networks in rural Uganda contribute to technology adoption? (2) does providing an incentive to DFs affect their information networks and adoption behaviour? (3) does incentivised training of DFs affect neighbours' information networks? and (4) does incentivised training of DFs affect neighbours' knowledge about DTMVs?

Our design has different distinctive aspects that sharpen the analysis of the paper. The technology (i.e., DTMV) that we use in our experiment is a recently introduced one, and people in the study communities have not formed their own experiences, subjective opinions and beliefs about the technology that might play a confounding role. This is corroborated by quite low adoption and knowledge of farmers at the baseline. Our social network is uniquely defined. We define the relevant social network as the farmers from whom the respondent seeks advice on crop production. These informational networks are further defined based on unidirectional links from DFs to the neighbours, because information is more likely to flow from the DFs rather than in the opposite direction, especially since the technology is a new one and directly "injected" into the DFs but not the neighbours (Cai et al., 2015).

The main results of the chapter are as follows. Compared to conventional training, incentivised training increases the likelihood of a DF being mentioned as a contact and the frequency of interaction for agricultural advice. Particularly, we find that both private material rewards and social recognition are equally effective in influencing neighbours' information networks. Altruism of DFs does not, however, significantly influence information networks. Having a trained and adopter DF in a neighbour's information network for crop production advice increases adoption of DTMVs by 28 percentage points and knowledge by 1.9 points more than when such networks are absent. Information networks, therefore, not only transfer information about the functions and benefits of DTMVs but also convey DFs' adoption decisions, in our context—suggesting that the main mechanisms through which social networks affect decision making are social learning about benefits of DTMVs and the influence of peers' adoption decisions.

This chapter contributes to the existing literature on social networks in several important ways. First, the chapter contributes to the literature studying the effects of social networks on adoption of agricultural technologies. While several studies have shown that a critical mass of adopters in a neighbour's existing network—suggesting passive learning—influences technology diffusion (Bandiera and Rasul, 2006; Matuschke and Qaim, 2009; Conley and Udry, 2010; Krishnan and Patnam, 2013), we show that having a directly trained and adopter disseminating farmer in a neighbour's network for crop production advice increases his or her likelihood of adopting a technology. Second, the chapter contributes to the small but growing literature examining changes in social networks in response to exposure to an external stimulus. Feigenberg et al. (2013) randomised microfinance borrowers into either weekly or monthly group meetings, and showed that borrowers randomised into the weekly group meetings continued interacting more even outside of group meetings, suggesting a change in the strength of ties through microfinance. Vasilaky and Leonard (2018) matched female farmers in Uganda and encouraged them to exchange agricultural information. They observed continued interaction between the matched pairs which resulted in greater increases in crop yields compared to conventional government extension. Banerjee et al. (2018) also analysed persistent changes in the number of links when a random subset of the population was exposed to microfinance. In a study that assessed how transfers between households changed in response to a randomised savings intervention, Comola and Prina (2014) found that treatment households increased the number of recipients relative to the control. While these studies generally suggest that networks respond to external stimulus, they provide evidence in very specific contexts, where prosocial behaviour is limited. We provide evidence about how information networks change in response to an agricultural extension intervention that provided direct training to a random subset of seed nodes, and in a setting where individuals are expected to engage in a prosocial task to disseminate agricultural information to their neighbours.

Third, the chapter explicitly shows how three different types of motivations, namely private material rewards, social recognition, and altruism influence information networks at the extensive and intensive margins. Prosocial preferences of disseminating farmers are measured with an auxiliary lab-in-the-field game—an augmented dictator game with a local rural development charity as the receiver. Lack of incentives may explain why direct training of contact farmers might not improve knowledge and adoption behaviour of neighbours (Kondylis et al., 2017). For example, Ben Yishay and Mobarak (2018) showed that private material rewards influenced communication within social networks. Additionally, the previous literature does not make a clear distinction between the roles of the extensive and intensive margins in social networks.

The chapter is organised as follows. Section 4.2 describes the experimental design. Section 4.3 formalises our empirical estimation approach. Section 4.4 presents and discusses results of the empirical analysis, while Section 4.5 concludes the chapter.

4.2 Experimental Design and Data

4.2.1 Experimental design

The experimental design is described in greater detail in *Chapter 2*. In this section a few elements of the experiment are repeated to maintain focus. A total of 132 sub-villages—a sub-village is equivalent to a hamlet—were randomly assigned to one of three experimental arms of 44 sub-villages each: (1) training only ("conventional" control), (2) training plus a private material reward (PR), and (3) training plus social recognition (SR). Target farmers in the first treatment arm received training about DTMVs and were subsequently asked to share the information with their co-villagers. Target farmers in the second treatment arm received the same training, but after the training were informed they could earn a private reward. They were promised a weighing scale if they managed to share sufficient knowledge with their peers—to be established during a surprise visit at some unknown date in the future. They would earn the weighing scale in case the knowledge score of nine randomly sampled co-villager exceeded a threshold. They were told the reward was private, that the weighing scale was theirs to keep, and that they were free to decide how to use it. Disseminating farmers in the third treatment arm also received the training, and were informed their community would receive a weighing scale if they managed to share sufficient knowledge with their peers—to be evaluated the same way as in the previous treatment arm. We announced that, in case of sufficient knowledge diffusion, there would be a public celebration during which the "good performance" of the DF was publicly announced, and the weighing scale would be handed over to the village chief in the presence of other villagers.

The trainings were organised in central locations, and DFs were invited to travel to these sites. Training sessions were organised per sub-county[22], with 11 farmers per session. In each sub-county, DFs from different treatment arms were trained in separate venues to minimize contamination. 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 who we invited, 126 attended the full training.

4.2.2 Data and summary statistics

Data were collected during two household survey waves. A detailed baseline survey was conducted between September and December 2015 covering 132 sub-villages. In every sub-village the DF as well as nine randomly selected co-villagers were interviewed. In total we visited 1,320 households, and collected information on household demographics, crop and livestock production, off-farm income, assets ownership, exposure to weather shocks, sources of agricultural information, knowledge about farming practices, and food security. The second survey wave was conducted in February–May 2017. During the follow up survey, 126 sub-villages whose selected DFs had actually attended the training were revisited. Effort was made to interview the same respondents that had been interviewed at the baseline. In total, 1,036 respondents (122 DFs and 914 other farmers) were interviewed in the follow-up survey. We administered a similar questionnaire to that used at baseline. This shows that attrition is non-negligible, and we turn to addressing it below.

[22] A sub-county is the second administrative unit in Uganda, after the district. At the time of the study, Nwoya district had four sub-counties including Anaka, Alero, Purongo, and Koch goma. Below the sub-county there are parishes, villages, sub-villages, and households.

Panel A in Table 4.1 presents summary statistics of selected household characteristics at baseline (2015) and endline (2017). Household heads were predominantly male. On average a household head was 45 years old and had completed six years of formal education. The average household size was six. The main source of livelihood for most households was farming. Households cultivated on average one-half of a hectare under maize. Less than three percent of the sample households, both at baseline and endline, had access to formal government extension.

In both survey waves, a specific module collected data on social networks. Previous studies have defined social networks in different ways. For example, some earlier studies defined social networks as comprising the entire village (e.g. Besley and Case, 1993; Foster and Rosenzweig, 1995; Munshi, 2004). The advantage of using the village as the relevant social network is that many of a farmer's contacts would be captured. The limitation, however, is that many who are not in the farmer's contacts are also included (Maertens and Barrett, 2012). Therefore, other studies have recently elicited farmer network links directly (Maertens and Barrett, 2012; Krishnan and Patnam, 2013; Magnan et al., 2015; Cai et al., 2015). Respondents are asked about the people with whom they interact for a specific purpose, such as information exchange, risk-sharing, and friendship. Once each individual's connections are determined, links can be classified as unidirectional (i is in j's network if j claims i), bidirectional (i is in j's network if j claims i or i claims j), or reciprocal (i is in j's network if j claims i and i claims j).

We elicit network links directly along several dimensions: names of individuals from whom the respondent gets advice about crop production, those to whom the respondent gives advice about crop production, those from whom the respondent gets advice about livestock production, those to whom the respondent gives advice about livestock production, those from whom the respondent would borrow money, those to whom the respondent would lend money, those from whom the respondent would borrow material goods (for example, kerosene and salt), those to whom the respondent would lend material goods, those who visit the respondent's home regularly, those whose homes the respondent visits regularly, relatives in the village, nonrelatives with whom the respondent socialises, those from whom the respondent receives medical advice, those to whom the respondent would go if hit with a disaster, those considered as neighbours, and those with whom they belong to the same farmers' group.

We required the respondent to mention a fixed number of names (i.e., five names) in a specific network type. The advantage of this approach is that it helps respondents to understand what is required of them and to consider only very relevant nodes of their specific network (Newman, 2010). The drawback is that imposing a threshold limits the out-degree—the number of people nominated by the respondent (Cai et al., 2015). Our pilot study before the survey, however, showed that none of the respondents named more than five people for all networks when the number was not limited. Similar results were also observed at the baseline, with the average household effectively consulting only another partner (Table 4.1).

We use six types of household-level social network measures for our main analysis. The first measure is a dummy variable equal to one if the household mentions a trained DF among its network of crop production advice, and zero if otherwise. The second social network variable is based on the intensity of the link between households (Granovetter 1973) and measures the frequency of interaction of a household with the trained DFs through a bilateral link. This measure ranges from zero (no interaction at all between the neighbour and a DF) and three (daily interaction with the DF). We use unidirectional links because information is more likely to flow from the DF to the farmer claiming him or her (Magnan et al., 2015). The third measure captures weak ties and is defined as a dummy variable equal to one if a household is connected to the DF for agricultural advice through second-order links and zero if otherwise. A second-order linked household is one that is named as a contact by a given household's neighbours if that neighbour is linked to the DF (Cai et al., 2015). The fourth measure is the neighbour's out degree—a structural characteristic of the social network defined as the number of listed agricultural advice contacts for a household. The fifth social networks variable is based on membership to financial or risk-sharing neighbourhood. Two farmers—the DF and the neighbour—belong to the same financial or risk-sharing neighbourhood if they lend to, borrow from, or exchange material goods in common with each other at any point during the two-year survey period. The sixth variable captures non-crop production advice networks, and is based on co-membership of a DF and a neighbour to networks for medical or livestock advice. Baseline household social network variables are reported in panel B of Table 4.1.

Panel C of Table 4.1 gives our main outcome variables. Knowledge is measured as a sum of correct responses on a ten-question knowledge exam. The details of the questions are presented in the appendix. The questions included general awareness of improved varieties, names of improved varieties of maize, and the benefits of growing improved varieties of maize. Adoption is a dummy variable equal to one if a household grew a DTMV on any of its farming plots between the baseline and the endline.

Finally, we organised an artefactual field experiment to measure altruism. Following Ashraf et al. (2014a), we implemented a dictator game to elicit an incentive-compatible measure of prosocial motives (see *Chapter 2* for details about the dictator game). Using the amount donated in the dictator game, we generate a dummy altruism variable equal to one if a DF donated above the median amount of money and zero if otherwise. About one-quarter of the DFs donated above the median amount of money.

Table 4.1. Summary Statistics

	2015 (baseline)		2017 (endline)	
	Mean	SD	Mean	SD
Panel A: *Household Characteristics*				
Sex of the household head (1=male, 0=female)	0.815	0.388	0.806	0.396
Age of the household head (years)	44.610	15.189	44.510	14.883
Household size (number of resident members)	5.789	2.374	6.346	2.623
Main activity of household head is farming (1=yes, 0=no)	0.913	0.282	0.954	0.210
Education of household head (years)	5.621	3.360	5.593	3.390
Area of maize production (Hectares)	0.451	0.883	0.477	0.757
Received credit (1=yes, 0=no)	0.683	0.466	0.526	0.500
Own a radio (1=yes, 0=no)	0.505	0.500	0.525	0.500
Own a phone (1=yes, 0=no)	0.535	0.499	0.566	0.496
Received advice from government extension (1=yes, 0=no)	0.025	0.157	0.010	0.099
Altruism (1=DF donated above median amount)			0.236	0.425
Panel B: *Social networks*				
Mentioned a DF as contact (1=yes, 0=no)	0.014	0.119	0.159	0.366
Mentioned DF is an adopter (1=yes, 0=no)	0.000	0.000	0.075	0.264
Frequency of interaction with DF (0=no interaction, 1=rarely, 2=at least monthly, 3=daily)	0.023	0.216	0.352	0.889
Neighbour's out-degree (size of information network)	0.767	1.169	2.014	1.109
Risk sharing network (1=DF is a member)	0.073	0.260	0.098	0.298
Weak ties (1=household has a second-order link)	0.004	0.066	0.050	0.217
Other information network (1=DF is a member)	0.020	0.140	0.024	0.154
Panel C: *Knowledge and adoption*				
Knowledge about DTMVs (score)	3.340	1.831	2.485	2.783
Adopt DTMV—Longe maize (1=yes, 0=no)	0.122	0.327	0.165	0.371
Observations	905		905	

Notes: DF=Disseminating farmer; DTMV=drought-tolerant maize variety.

Only 1.4 percent of the households mentioned a DF among its contacts for agricultural advice at baseline compared to 15.9 percent at endline. The average out-degree for neighbours was 0.77 at baseline and 2.01 at endline. Whereas there was no adopter DF at baseline, 7.5 percent of the sample households reported having an adopter DF in their contacts at endline. The frequency of interaction between a mentioned DF and the neighbour was 0.33 points higher at endline compared to the baseline (0.02). Only seven and 10 percent of the sample households mentioned a DF as a contact for risk sharing at baseline and endline, respectively. The proportion of farmers connected via second-order links to the DFs was only 0.4 percent at baseline. This increased to five percent at endline. The proportion of farmers who are linked to the DFs for information other than crop production advice was two percent at baseline; this number did not change much at endline.

Unfortunately, attrition in our sample is considerable as outlined above. Six out of the selected 132 DFs did not attend the training. This means that six sub-villages representing 60 households or 4.5 percent of the original total sample dropped from the study. Attrition as a consequence of DFs not attending training was not concentrated in a particular treatment arm. Because DFs were only informed about the incentives (for those in the material reward and social recognition groups) at the end of the training, attrition ought not to be related to treatment assignment. Four more DFs (0.3% of the total sample) were not available for interviews during the endline survey: two had separated with their husbands and we could not track them; one had migrated to the neighbouring Gulu town; and another one had been hospitalised. These four DFs were not concentrated in one experimental arm once again.

Finally, we were unable to administer the endline survey to some households (220 households, or about 17% of the original sample), as these farmers were absent even after three callback visits. We have no particular reason to believe that potential causes of attrition are systematically linked to specific treatments (something that is confirmed by the data). Attrition rates are rather equal across the three experimental arms. High attrition is potentially problematic, as it could introduce selection bias in our randomised experiment.

We examine the implication of this attrition for our results in several ways. First, we test whether our remaining sample is (still) balanced along key observable dimensions—18 variables in total. Using the "orth_out" command in STATA, pre-treatment covariates are regressed on treatment dummies: an F-test that all treatment arm coefficients equal zero failed to reject existence of balance. In addition, we perform randomisation checks comparing each treatment arm to the other. As presented in Table 4.2 (for a selection of the variables), there was pre-treatment balance across the randomly assigned groups for all but three variables, namely age and education of the household head and household income. But, even for the three variables, differences are small: education of the household head is 6.32 in the conventional control group and 5.80 in the private material reward group; age of the household is 44.79 in the private material reward group and 42.30 in the social recognition group.

The second approach is to explain attrition with observable household characteristics. Appendix Table 4.A.1 presents the results of a probit regression where we regress attrition status on the treatment dummies and household characteristics. As shown, treatment assignment is not correlated with attrition. An F-test (p-value=0.632) rejected the null hypothesis that the treatment dummies jointly influenced attrition. None of the other variables is correlated with our attrition-dummy, except for the sex and education of the household head, and experience with floods. Again, except for education, these two variables were not significantly different across our three groups (Table 4.2). Nevertheless, we cannot completely rule out the possibility that external validity of the impact analysis might be compromised by non-random attrition. For example, when attrition is based on unobservables like ability, we could perhaps systematically over- or underestimate the effect of incentives on networks.

As a third approach, therefore, we attempt to control for potential selection concerns by a weighting procedure as a robustness analysis (Gerber and Green, 2012; Bulte et al., 2014). Specifically, we follow a two-stage procedure. In the first stage, a probit regression is used to estimate the predicted probability of having non-missing measures for our outcomes given treatment assignment and a vector of observable covariates (see Table 2). In the second stage, we weight each observation using the inverse of the thus estimated probability of having a non-missing measure of our outcomes. Our main results remain robust to all these robustness tests (see Section 4.5.2).

Table 4.2. Randomisation Balance on Observables at Baseline

	Whole sample	Training only	Private reward	Social recognition	*F*-test (*p*-value)	*p*-value (2)=(3)	*p*-value (2)=(4)	*p*-value (3)=(4)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Household head is male	0.82	0.84	0.80	0.82	0.528	0.261	0.629	0.482
Age of household head	43.49	43.41	44.79	42.30	0.105	0.246	0.328	0.035**
Household size	5.85	5.68	5.93	5.93	0.320	0.195	0.170	0.991
Dependency ratio	0.55	0.55	0.54	0.54	0.846	0.664	0.591	0.924
Education of household head	5.99	6.32	5.80	5.86	0.203	0.094*	0.155	0.847
Main activity is farming	0.91	0.89	0.92	0.92	0.553	0.300	0.367	0.837
Household income per AE	467,504.00	471,500.00	425,300.00	505,334.00	0.172	0.270	0.483	0.072*
Participation in casual job	0.29	0.31	0.29	0.28	0.529	0.497	0.269	0.644
Participation in self-employment	0.10	0.10	0.10	0.11	0.493	0.802	0.250	0.433
Credit amount received (UGX)	86,000.00	82,200.00	82,700.00	92,800.00	0.738	0.975	0.477	0.549
Agricultural assets index	0.01	0.15	-0.05	-0.06	0.690	0.570	0.409	0.965
Non-agricultural assets index	0.08	0.14	-0.08	0.18	0.731	0.586	0.910	0.444
Contacts for crop production advice	2.00	2.00	2.00	2.00	0.885	0.781	0.629	0.806
Kinship network	1.73	1.76	1.70	1.73	0.841	0.559	0.839	0.759
Experienced floods	0.03	0.04	0.02	0.02	0.301	0.127	0.509	0.412
Experienced droughts	0.68	0.66	0.66	0.73	0.346	0.354	0.773	0.154
Observations	1,025	330	345	350				

Notes: DF means disseminating farmer; AE means adult equivalents. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

4.3 Empirical strategy

Adoption of DTMVs is low among farmers in our study communities. Perhaps, this could be due to limited information about its benefits. In our context, the effect of networks on adoption of DTMVs by neighbours may depend on whether incentivised training changed the DFs' own networks and adoption decisions relative to conventional training. We thus begin our empirical analysis by examining the effect of incentives on adoption decision of DFs and their in-degree—the number of neighbors with who the DF shared agricultural advice. Formally, we estimate:

$$y_{ivc} = \beta_0 + \beta_1 PR_{ivc} + \beta_2 SR_{ivc} + \gamma_i X_{ivc} + C_c + \varepsilon_{ivc} \qquad (4.1)$$

where y_{ivc} is the outcome of interest: for adoption, y_{ivc} indicates whether a DF i in sub-village v and sub-county c grew a DTMV or not whereas for DF's in-degree, y_{ivc} measures the number of people with whom the DF shared agricultural advice. PR_{ivc} and SR_{ivc} are dummy treatment variables: PR_{ivc} is equal to one if the DF was randomly assigned to receive a private material reward and zero if otherwise whereas SR_{ivc} is equal to one if the DF was randomly assigned to receive social recognition and zero if otherwise. X_{ivc} includes household characteristics, and C_c captures sub-county fixed effects. We estimate equation (4.1) using OLS and report robust standard errors clustered at the sub-village level.

The coefficients β_1 and β_2 in equation (4.1) measure the causal effect of incentive treatments on the DFs' in-degree and adoption decisions, under the identifying assumption that PR_{ivc} and SR_{ivc} are orthogonal to ε_{ivc}. Random assignment to treatment implies the identifying assumption is satisfied, unless there are substantial spillover effects (see the discussion about spillovers and the SUTVA in *Chapter 2*, including the design features included in the experiment to minimise spillovers). We further formally test for evidence of spillovers across neighboring sub-villages using Global Positioning System (GPS) coordinates of the DFs. To check whether information networks of the control group neighbours were affected by spillovers, we compare information networks of control group neighbours who are close to a treated neighbour, and control group neighbours further away from treated units. According to our estimates, summarised in Table 4.A.2 in the appendix, there are no spillovers. Using a border-to-treatment dummy variable, a *t*-test also indicates that control group neighbours' information networks were not significantly affected by the presence of a neighbour from another experimental arm.

To test the social network effect on adoption of DTMVs, we focus on the sample of other farmers (neighbours). Consistent with previous studies, we identify two main channels through which social networks may influence the adoption of a new technology: (i) neighbours may gain knowledge about the availability and benefits of the technology (e.g., Conley and Udry, 2010), and (ii) people are influenced by the decisions of others (e.g., Bandiera and Rasul, 2006; Matuschke and Qaim, 2009). We, therefore, ask: (1) suppose that incentives change networks of trained DFs and that (2) DFs respond to incentives by adopting DTMVs, do networks transfer adoption decision of the DFs or help to diffuse knowledge or both?

Identifying the causal effect of social networks on adoption is, however, not trivial. The first challenge involves defining the relevant reference group—the set of neighbours from whom an individual can learn. Secondly, assuming that the reference group can be defined appropriately, disentangling learning from contextual and correlated effects may be problematic. Individual behaviour may simply reflect the average behaviour of the reference group, but that does not necessarily mean that group behaviour causes the individual's behaviour (Manski, 1993). In the absence of learning, individuals may still behave like their neighbours as a result of interdependent preferences or because they are exposed to related unobservable shocks (Manski, 1993; Conley and Udry, 2010; Krishnan and Patnam, 2013).

Our experiment and rich dataset allows us to address the problems mentioned above as follows. First, we collected detailed data on whom individuals know and discuss with about farming. Within this reference group, we identify whether a trained DF is mentioned as a contact for crop production advice both at baseline and endline. We then ask whether the mentioned DF is an adopter of a DTMV. Second, we collect data about the characteristics of both the DFs and neighbours, allowing us to control for contextual effects. Third, we estimate a difference-in-difference regression with fixed effects, which allows controlling for time-invariant unobserved heterogeneity. Although several techniques are used to identify the effect of networks on the adoption decisions of neighbours, we cannot completely rule out that there might still be a concern for endogeneity. Our results, however, survive a number of robustness checks (presented later in Section 4.4.2). Formally, we estimate:

$$y_{ivt} = \beta_0 + \beta_1 Network_{ivt} + \beta_2 Network_{ivt} * D_t + \beta_3 D_t + \beta_4 X_{ivt} + \tau_{ivt} + \varepsilon_{ivt} \quad (4.2)$$

where y_{ivt} represents our outcomes of interest: (1) a dummy variable equal to one if a household i in sub-village v adopted a DTMV at time t and zero if otherwise and (2) the score that a household obtained on an eight-question knowledge test. $Network_{ivt}$ is a dummy variable equal to one if an adopter DF is mentioned among the household i's contacts for agricultural advice and zero if otherwise, D_t is an indicator variable equal to one at endline and zero at baseline, and τ_{ivt} are individual fixed effects. Included in X_{ivt} are incentives treatment dummy variables and time-varying characteristics of the DF and the neighbour. Equation (4.2) is estimated with robust standard errors ε_{ivt} clustered at the sub-village level.

Next, we ask: suppose social networks influence neighbours' decisions to adopt DTMVs, does incentivised training of DFs change networks of the neighbours? To answer this question empirically, we causally estimate the intent-to-treat (ITT) effects of a sub-village being assigned to incentivised DF training (relative to conventional DF training) on neighbours' networks and knowledge scores using equations (4.3) and (4.4):

$$y_{ivc} = \beta_0 + \beta_1 Incentivised_{ivc} + \gamma_i X_{ivc} + C_c + \varepsilon_{ivc} \tag{4.3}$$

$$y_{ivc} = \beta_0 + \beta_1 PR_{ivc} + \beta_2 SR_{ivc} + \beta_3 A_{ivc} + \gamma_i X_{ivc} + C_c + \varepsilon_{ivc} \tag{4.4}$$

where the outcomes of interest y_{ivc} in both equations measure whether or not a DF is mentioned in a neighbour's contacts for agricultural advice, the frequency of interaction between a DF and his or her neighbours, and a weak tie defined as an indirect link between a DF and a neighbour through another neighbour. $Incentivised_{ivc}$ is a dummy variable equal to one if the farmer resides in a sub-village in which a DF was assigned to receive a reward and zero if otherwise. In equation (4.4), we distinguish between the effect of private reward (PR_{ivc}), social recognition (SR_{ivc}), and altruism (A_{ivc}) on neighbours' networks. The rest of the variables are as defined in equation (4.1).

4.4 Empirical Results

4.4.1 Main results

To set the stage, we first look at the impact of training on social networks. The motivation is simple. Underlying incentives for network formation are generally related to resource sharing—be it information or risk sharing and social learning. The DFs received training on a highly relevant technology in the context of rural Uganda. Such training exogenously changes the relative importance of the DFs as a source of information with respect to the technology and makes them potentially relevant nodes in their networks. Table 4.3 presents results of a descriptive analysis about changes in networks at both the extensive and intensive margins before and after training of the DFs by comparing the baseline and endline data. With the exception of other information networks including contacts for medical and livestock advice, results show significantly higher values of network variables after training of DFs than before training.

Table 4.3. Test of Change in Neighbours' Networks with and without Training of Disseminating Farmers (DFs)

Variable	Before training of DFs (1)	After training of DFs (2)	*t*-statistic (3)	*p*-value (4)
DF is mentioned by neighbour (DF mentioned)	0.014	0.159	-6.664	0.000
Frequency of interaction with mentioned DF (Intensity)	0.023	0.353	-5.608	0.000
Weak link: DF linked to neighbour for agricultural indirectly through another neighbour	0.004	0.050	-4.053	0.000
DF mentioned in risk sharing networks	0.012	0.043	-3.002	0.003
DF mentioned in medical or livestock advice network	0.006	0.013	-1.424	0.156
Observations	1,810			

Notes: *t*-test with clustering at sub-village level. Because all DFs received training after baseline, the variable DF trained equals one at endline and zero at baseline.

Results in Table 4.4 show that incentivised training influenced the likelihood of DFs to adopt DTMVs and changed their in-degree. While columns (1), (3), and (6) indicate positive and significant effects of incentives, we are interested to understand what types of incentives drive the effects. Results in column (2) shows that social recognition increased the likelihood of adopting a DTMV by 14 percentage points relative to conventional training. The effect was significantly larger (*p*-value = 0.067) than that of private rewards (2.5 percentage points). In column (4) we find that social recognition also increased the likelihood of growing improved varieties of maize, in general, by 17 percentage points as compared with conventional training. This latter effect is statistically the same as that of private reward. In terms of networks, results in column (5) show that incentives significantly increased the DFs' in-degree by 0.69 points for private rewards and 0.91 points for social recognition. That incentives affect adoption decisions of DFs is consistent with the findings of Ben Yishay and Mobarak (2018), who examined the responsiveness of DFs—selected using a criterion similar to the one used in the current study—to incentives for technology diffusion. These authors showed that material rewards motivate DFs to experiment with new technologies. In our context, however, we distinguish between private rewards and social recognition, and find that only the latter significantly influenced adoption decision of DFs.

The changes in DFs' in-degree and adoption decisions suggest possible network effects on neighbours' adoption decisions. We now ask: does having a trained and adopter DF in a neighbour's list of contacts for agricultural advice affect his or her own adoption decision? Table 4.5 presents results of network effects on neighbours' adoption of DTMVs. Columns (1 and 2) present results at the extensive margin as measured by the presence of an adopter DF in a neighbour's network whereas columns (3 and 4) show results at the intensive margin as captured by the frequency of interaction of a neighbour with an adopter DF. We present DID fixed effects results, with and without controlling for characteristics of the neighbours and the DFs. The results are reported as marginal effects.

Table 4.4. Incentives and Disseminating Farmers' Adoption and Networks

	Adoption				Network	
	DT maize		Improved maize		Information exchange	
Incentive type	(1)	(2)	(3)	(4)	(5)	(6)
Incentivized training	0.110*		0.164*			0.804***
	(0.060)		(0.086)			(0.238)
Training plus private reward (PR)		0.025		0.153	0.689**	
		(0.073)		(0.097)	(0.282)	
Training plus social recognition (SR)		0.136**		0.171*	0.908***	
		(0.057)		(0.096)	(0.300)	
Household controls		Yes		Yes	Yes	
Sub-county fixed effects		Yes		Yes	Yes	
R-squared	0.278	0.340	0.168	0.168	0.169	0.166
Observations	123	123	123	123	123	123
Mean of dependent variable for non-incentivized DFs	0.150	0.025	0.150	0.150	1.225	1.225
	[0.362]	[0.158]	[0.362]	[0.362]	[1.050]	[1.050]
PR = SR (p-value)		0.067		0.836	0.513	

Notes: DF means disseminating farmer. Dependent variables are as follows: columns (1—4) are dummy variables equal to one if disseminating farmer (DF) tried out the technology on at least one of the household's plots and zero otherwise; columns (5 and 6) measure the number of people in the sub-village with whom the DF communicated about improved farming methods. Robust standard errors corrected for sub-village level clustering are reported in parentheses. Square parentheses are the standard deviations of the control group means. Household controls include sex, age, education, and main economic activity of the household head, dependency ratio, livestock ownership, agricultural assets ownership, and access to credit. Columns (5 and 6) report OLS estimates. Columns (1—4) report average marginal effects from probit regression. DT maize means drought-tolerant maize. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4.5. Effect of Social Networks on Neighbours' Decisions to Adopt Drought-tolerant Maize Varieties (DTMVs)

Dependent variable:	Adoption of DTMV (1=yes, 0=no)			
	Extensive		Intensive	
Explanatory variables:	(1)	(2)	(3)	(4)
Endline dummy	0.017	0.014	0.024	0.019
	(0.030)	(0.030)	(0.031)	(0.030)
Adopter DF in agricultural advice	0.319***	0.279***	0.103***	0.084**
network x Endline dummy	(0.070)	(0.069)	(0.032)	(0.032)
Incentive treatment dummies	Yes	Yes	Yes	Yes
Household controls	No	Yes	No	Yes
DF controls	No	Yes	No	Yes
Constant	0.122***	0.068***	0.122	0.055
	(0.008)	(0.050)	(0.008)	(0.052)
R-squared	0.042	0.080	0.026	0.077
Observations	1,810	1,810	1,810	1,810

Notes: Difference-in-difference (DID) fixed effects (FE) estimates. DF means disseminating farmers. DTMV means drought-tolerant maize variety. In parentheses are robust standard errors clustered at the sub-village level. DTMV=drought-tolerant maize variety. *Extensive* (columns 1 and 2) indicates that an adopter DF is mentioned in the neighbour's network whereas *intensive* (columns 3 and 4) indicates the frequency of interaction with an adopter DF. Household and DF controls include farm size under maize, farm size under groundnuts, ownership of radio, ownership of mobile phone, access to government extension, agricultural and non-agricultural assets indices, livestock ownership in tropical livestock units, and access to credit. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The results suggest that there is a strong relationship between the adoption decisions of trained DFs and neighbours' own decisions to adopt DTMVs, both at the extensive and intensive margin. Having an adopter DF as a contact for agricultural advice increases the likelihood of a neighbour adopting a DTMV by 32 percentage points more without controlling for characteristics of neighbors and DFs, and 28 percentage points when the characteristics are controlled for (column 2), between the baseline and endline compared to neighbours who lack adopter DFs in their networks.

At the intensive margin, a unit increase in the frequency of interaction with adopter DFs increased the likelihood of neighbours adopting DTMVs by 10 percentage points between the baseline and the endline. These results agree with findings from previous studies that use similar estimation procedures (e.g., Krishnan and Patnam, 2013), and are consistent with DFs transmitting key information via their own actions. This suggests that DFs were not only teaching others about how to use the technology, but also trying to signal its profitability. In this context, the findings on dissemination and learning, therefore, relate to the social learning literature (Foster and Rosenzweig 1995; Munshi 2004; Bandiera and Rasul, 2006; Conley and Udry 2010). In the current context, however, we pursue an active intervention strategy rather than rely on passive learning. Our approach closely relates to that of Cai et al. (2015) and Magnan et al. (2015).

Throughout, the effects of the intensive margin are generally found to be smaller than the extensive margin. This is a bit contrary to our expectation. Our measure of intensive margin captures whether the DFs and their neighbour never interacted, interacted daily, at least weekly, at least monthly, or less often. First, with a caveat that the current study cannot definitively explain this effect, we speculate that if neighbours who interacted with their DFs at the extensive margin discussed for longer hours within one visit, it is plausible that the effect could be greater compared to less hours of interaction during several period of discussion at the intensive margin. Second, while our network questions about the frequency of interactions were very specific and clearly intended to reflect only information about crop production, social networks in developing countries are multi-tasked so that (some) interactions might also capture other aspects. Future research can benefit from explicitly addressing these caveats.

Although we have so far shown that networks transfer the adoption decision of DFs to their neighbours, we have not succinctly illustrated network effects on knowledge of neighbours about DTMVs. We now turn to this issue. Do networks affect adoption through diffusion of knowledge? Results of fixed effects DID estimates in Table 4.6 indicate that networks influenced knowledge of neighbours about DTMVs: having a trained and adopter DF in a neighbour's list of contacts for agricultural advice increases knowledge of the neighbour by 1.92 points more at the extensive margin and 0.63 points at the intensive margin between the baseline and the endline than when such DFs are absent.

Table 4.6. Networks Effects on Knowledge of Neighbours

Dependent variable:	Neighbour's knowledge			
	Extensive		Intensive	
Explanatory variables	(1)	(2)	(3)	(4)
Endline dummy	-1.038***	-0.923***	-0.994***	-0.894***
	(0.160)	(0.160)	(0.159)	(0.159)
Adopter DF in agricultural advice	2.194***	1.924***	0.765***	0.627***
network x Endline dummy	(0.346)	(0.355)	(0.178)	(0.177)
DF was incentivized	0.026	0.018	0.031	0.026
	(0.187)	(0.181)	(0.184)	(0.178)
Household controls	No	Yes	No	Yes
DF controls	No	Yes	No	Yes
Constant	3.340***	2.496***	3.340***	2.424***
	(0.041)	(0.283)	(0.041)	(0.283)
R-squared	0.154	0.204	0.136	0.188
Observations	1,810	1,810	1,810	1,810

Notes: Fixed effects (FE) estimates. DF means disseminating farmers. Adopter DF is a dummy variable equal to one if the mentioned DF grew a DTMV, and zero if otherwise. Endline is a post-treatment dummy variable equal to one if survey period is endline, and zero if otherwise. *Extensive* (columns 1 and 2) indicates that an adopter DF is mentioned in the neighbour's network whereas *intensive* (columns 3 and 4) indicates the frequency of interaction with an adopter DF. Household and DF controls include farm size under maize, farm size under groundnuts, ownership of radio, ownership of mobile phone, access to government extension, agricultural and non-agricultural assets indices, livestock ownership in tropical livestock units, and access to credit. In parentheses are robust standard errors clustered at the sub-village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

We have successfully shown that incentives changed (positively) the networks and adoption decision of DFs, consequently increasing the probability of a neighbour to adopt a DTMV. It is possible, therefore, that incentivised training affected neighbours' networks. Results of OLS regression to empirically test the effect of incentives on networks of neighbours are presented in Table 4.7. We find that providing incentives to DFs increases the likelihood of the DF being mentioned as a contact for agricultural advice by eight percentage points (column 1) compared to conventional training without incentives. Similarly, results in column (3) show that DFs interact 0.22 points more frequently with their neighbours when incentivized than when they do not receive an incentive. Incentives did not, however, significantly influence formation of weak ties (i.e. farmers connected to the DF for agricultural advice through second-order links) between DFs and their neighbours (column 5). Results are robust when we control for sub-county fixed effects (columns 2, 4, and 6).

Incentives may affect neighbours' networks differently depending on whether DFs receive a private reward or social recognition. We, therefore, extend our analysis of effects of incentives on neighbours' networks to compare private rewards versus social recognition. Results are reported in Table 4.8. We find that both private rewards and social recognition increase the likelihood of mentioning DFs as contacts for agricultural advice (columns 1 and 2). Specifically, the probability of a neighbour mentioning a DF as a contact for agricultural advice increased by 7.5 percentage points more for private reward and 8.7 percentage points more for social recognition compared with conventional training of DFs. The corresponding increase in the intensity of information exchange link was 0.23 points more for private reward and 0.22 points more for social recognition (column 3). Neither private rewards nor social recognition significantly influenced formation of weak ties. Throughout, we find that the effect of private reward and social recognition on networks is statistically the same.

Table 4.7. Effect of Incentivized Versus Conventional Training on Neighbours' Networks

	Network					
	DF is mentioned		Frequency of interaction		Weak link	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
DF is trained and incentivized	0.081***	0.076**	0.225***	0.212***	0.008	0.010
	(0.030)	(0.031)	(0.073)	(0.074)	(0.018)	(0.019)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county fixed effects	No	Yes	No	Yes	No	Yes
Constant	0.016	0.061	0.097	0.171	0.017	0.055
	(0.071)	(0.081)	(0.162)	(0.191)	(0.039)	(0.051)
Observations	905	905	905	905	905	905
Control group mean	0.110	0.110	0.209	0.209	0.045	0.045
	[0.313]	[0.313]	[0.674]	[0.674]	[0.207]	[0.207]
R-squared	0.032	0.036	0.024	0.030	0.005	0.018

Notes: OLS regression. DF means disseminating farmers. The outcome in columns (1) and (2) is an indicator variable equal to one if a DF is mentioned among the neighbour's contacts for agricultural advice, zero if otherwise whereas in columns (3) and (4) the outcome measures the frequency of interaction between a neighbour and the mentioned DF. The outcome in columns (5) and (6) is an indicator variable equal to one if a DF is not linked to the neighbour directly for agricultural advice but through another neighbour, zero if otherwise. In parentheses are robust standard errors clustered at the sub-village level. In square parentheses are the standard deviations for the control group. Treatment group comprises sample households residing in sub-villages in which a DF received an incentive—either private reward or social recognition—whereas control group comprises households in sub-villages in which a DF was not incentivized. Household controls include sex, age, and education of household head, household size, size of land cultivated with maize, ownership of radio, ownership of mobile phone, access to government extension, and access to credit. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4.8. Private Reward versus Social Recognition: Effect on Neighbours' Networks

	Network					
	DF is mentioned		Frequency of interaction		Weak link	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Private reward (PR)	0.076**	0.070*	0.241***	0.219**	0.005	0.011
	(0.036)	(0.037)	(0.092)	(0.094)	(0.020)	(0.022)
Social recognition (SR)	0.083**	0.083**	0.209**	0.215**	0.006	0.006
	(0.038)	(0.039)	(0.097)	(0.096)	(0.022)	(0.021)
Altruism (A)	0.007	0.013	0.116	0.125	-0.003	0.009
	(0.042)	(0.042)	(0.124)	(0.122)	(0.020)	(0.020)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county effects	No	Yes	No	Yes	No	Yes
Constant	0.011	0.048	0.069	0.143	0.017	0.055
	(0.072)	(0.081)	(0.170)	(0.190)	(0.041)	(0.052)
Observations	905	905	905	905	905	905
R-squared	0.036	0.040	0.029	0.036	0.006	0.020
Control group mean	0.110	0.110	0.209	0.209	0.045	0.045
	[0.313]	[0.313]	[0.674]	[0.674]	[0.207]	[0.207]
p-value: PR = SR	0.862	0.752	0.781	0.973	0.961	0.818
p-value: PR = A	0.164	0.265	0.371	0.521	0.791	0.943
p-value: SR = A	0.119	0. 173	0.442	0.485	0.784	0.930

Notes: OLS regression estimates. DF means disseminating farmers. The outcome in columns (1) and (2) is an indicator variable equal to one if a DF is mentioned among the neighbour's contacts for agricultural advice, zero if otherwise whereas in columns (3) and (4) the outcome measures the frequency of interaction between a neighbour and the mentioned DF. The outcome in columns (5) and (6) is an indicator variable equal to one if a DF is not linked to the neighbour directly for agricultural advice but through another neighbour, zero if otherwise. In parentheses are robust standard errors clustered at the sub-village level. In square parentheses are the standard deviations for the control group. Control group comprises households in sub-villages in which a DF was not incentivized. Household controls include sex, age, and education of household head, household size, size of land cultivated with maize, ownership of radio, ownership of mobile phone, access to government extension, and access to credit. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The effect of altruism of DFs on neighbours' networks was positive, but small and not statistically significant at 10 percent level. Consistent with our theoretical model, we speculate that uncertainty about the quality of DTMVs might explain the null result of altruism. Bold et al. (2017) reported the presence of a high prevalence of low quality seeds in Uganda. Such low quality seeds substantially reduced the yields of crops and discouraged farmers' investment behaviour. On the one hand, in the presence of aggregate uncertainty about the quality of seeds, farmers may not only herd on inferior "traditional" crop varieties (Monzón, 2017) but may also be reluctant to listen to advice related to cultivation of improved new seeds. On the other hand, DFs may delay contacting their neighbours about something that could potentially be harmful to avoid both societal damage and negative reputation consequences. Both mechanisms would, therefore, tend to diminish the effect of altruism on network change.

4.4.2 Robustness checks

To bolster further confidence in our estimates of network effects on neighbours' adoption of DTMVs, we undertake several robustness checks. First, we perform a placebo test by regressing neighbours' baseline adoption decisions—revealed before training of DFs—on the network variable in equation (4.2). A similar approach was used by Magnan et al. (2015). If the coefficient on the network variable is significantly positive (or negative), it would indicate the presence of unobservable variables correlated to both DTMV adoption and network variable, which could introduce bias (Magnan et al., 2015). Results in Table 4.9 indicate no statistically significant effect of social networks on adoption decisions of neighbours before DFs were trained, suggesting that our estimates are not affected by such a bias.

Table 4.9. Placebo Test for Spurious Network Effects

Dependent variable:	Adoption of DTMV at baseline (1=yes, 0=no)	
Explanatory variables	(1)	(2)
Adopter DF in agricultural advice network	0.054	0.040
	(0.035)	(0.033)
Incentive dummy variables	Yes	Yes
Household controls	No	Yes
DF controls	No	Yes
Sub-county fixed effects	yes	Yes
R-squared	0.009	0.081
Observations	905	905

Notes: Average marginal effects from probit regression. DF=disseminating farmer; DTMV=drought-tolerant maize variety. In parentheses are robust standard errors clustered at the sub-village level. Household controls include sex, age, and education of household head, household size, ownership of radio and phone, access to government extension and credit, and farm size under maize. DF controls include sex, age, and education of the DF, household size, main activity of DF is farming, and access to credit.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Second, we combine the fixed effects DID estimation in equation (4.2) with inverse probability weighting (IPW). Three different matching algorithms are used, namely Radius matching, Kernel-based matching, and Nearest neighbour matching (with three neighbors). Given that we use adequate baseline data for matching, this enables us to rule out biases that stem from heterogeneity in behaviour and potential sources of self-selection biases, which would not be possible in an ordinary matching approach. Results in Table 4.10 are consistent with our estimates for fixed effects DID.

Table 4.10. Combined Difference-in-Difference (DID) with Inverse Probability Weighting (IPW) Estimates of Network Effects on Neighbours' Adoption and Knowledge

Variable	Adoption of DTMV (1=yes, 0=no)		
	Matching algorithm		
	Radius	Kernel-based	Nearest neighbour
	Panel A: Adoption		
Endline dummy	0.018	0.015	-0.012
	(0.016)	(0.017)	(0.037)
Adopter DF in agricultural advice	0.265^{***}	0.269^{***}	0.294^{***}
network x Endline dummy	(0.098)	(0.098)	(0.099)
Constant	0.178^{***}	0.181^{***}	0.218^{***}
	(0.025)	(0.026)	(0.041)
R-squared	0.133	0.136	0.177
Observations	1,810	1,688	446
	Panel B: Knowledge		
Endline dummy	-0.971^{***}	-0.983^{***}	-1.656^{***}
	(0.242)	(0.251)	(0.427)
Adopter DF in agricultural advice	1.820^{***}	1.783^{***}	2.321^{***}
network x Endline dummy	(0.278)	(0.271)	(0.401)
Constant	3.717^{***}	3.754^{***}	4.904^{***}
	(0.430)	(0.456)	(0.810)
R-squared	0.266	0.268	0.419
Observations	1,798	1,682	443

Notes: DF means disseminating farmers. DTMV=drought-tolerant maize varieties. Endline is a post-treatment dummy variable equal to one if survey period is endline, and zero if otherwise. In parentheses are robust standard errors clustered at the sub-village level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Third, we test whether co-membership of adopter DFs and neighbours in networks other than the agricultural advice affects adoption decisions of neighbours. Two additional network variables are constructed. The first variable is based on membership to financial or risk-sharing neighbourhood. Two farmers—the DF and the neighbour—belong to the same financial or risk-sharing neighbourhood if they lend to, borrow from, or exchange material goods in common with each other at any point during the two-year survey period. The second variable captures non-agricultural advice networks, and is based on co-membership of a DF and a neighbour to networks for medical or livestock advice. Our focus on these two additional network variables is motivated by alternative explanations that would suggest that a significant effect of agricultural advice network on uptake might be caused by omitted variable bias because of information that neighbours share from common access to other arrangements (Conley and Udry, 2010). As shown in Table 4.11, we do not find significant effects of alternative networks on adoption of DTMVs, and hence ruling out that neighbours may have changed their adoption decision because they shared membership to other arrangements with DFs.

In addition, robustness analysis of the effect of incentives on networks was performed using an inverse probability score weighting procedure to formally assess the sensitivity of the main results to the attrition problem as described in Section 4.2. Results are presented in Tables 4.12 and 4.13. As shown, the attrition-weighted estimates remain robust and are similar to those reported in Tables 4.7 and 4.8, suggesting the robustness of our results to the level of attrition in our sample.

Table 4.11. Difference-in-Difference (DID Estimates of Effects of Alternative Network on Adoption of Drought-tolerant Maize Varieties (DTMVs)

Dependent variable:	Adoption of DTMV (1=yes, 0=no)	
	(1)	(2)
Endline	0.023	0.026
	(0.020)	(0.020)
Adopter DF in risk sharing network	0.146	
	(0.092)	
Adopter DF in risk sharing network x Endline	-0.124	
	(0.113)	
Adopter DF in medical or livestock advice network		0.010
		(0.035)
Adopter DF in medical or livestock advice network x Endline		0.022
		(0.114)
Household controls	Yes	Yes
DF characteristics	Yes	Yes
Constant	0.023	0.026
	(0.052)	(0.052)
R-squared	0.054	0.054
Observations	1,810	1,810

Notes: DF=disseminating farmer; Endline is a dummy variable equal to one if endline and zero if baseline. In parentheses are robust standard errors clustered at the sub-village level. Household and DF controls include farm size under maize, farm size under groundnuts, ownership of radio, ownership of mobile phone, access to government extension, agricultural and non-agricultural assets indices, livestock ownership in tropical livestock units, and access to credit.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4.12. Attrition-Weighted Effect of Incentivised versus Conventional Training on Neighbours' Networks

	Network					
	DF is mentioned		Frequency of interaction		Weak link	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
DF is trained and incentivized	0.080***	0.075**	0.223***	0.211***	0.009	0.012
	(0.030)	(0.031)	(0.073)	(0.074)	(0.017)	(0.019)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county effects	No	Yes	No	Yes	No	Yes
Constant	0.024	0.066	0.114	0.181	0.018	0.054
	(0.071)	(0.081)	(0.162)	(0.190)	(0.039)	(0.051)
Observations	905	905	905	905	905	905
Control group mean	0.110	0.110	0.209	0.209	0.045	0.045
	[0.313]	[0.313]	[0.674]	[0.674]	[0.207]	[0.207]
R-squared	0.032	0.036	0.024	0.030	0.005	0.018

Notes: OLS regression. DF means disseminating farmers. The outcome in columns (1) and (2) is an indicator variable equal to one if a DF is mentioned among the neighbour's contacts for agricultural advice, zero if otherwise whereas in columns (3) and (4) the outcome measures the frequency of interaction between a neighbour and the mentioned DF. The outcome in columns (5) and (6) is an indicator variable equal to one if a DF is not linked to the neighbour directly for agricultural advice but through another neighbour, zero if otherwise. In parentheses are robust standard errors clustered at the sub-village level. In square parentheses are the standard deviations for the control group. Treatment group comprises sample households residing in sub-villages in which a DF received an incentive—either private reward or social recognition—whereas control group comprises households in sub-villages in which a DF was not incentivised. Household controls include sex, age, and education of household head, household size, size of land cultivated with maize, ownership of radio, ownership of mobile phone, access to government extension, and access to credit. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4.13. Attrition-Weighted Effect of Private Material Reward versus Social Recognition: Effect on Neighbours' Networks

	Network					
	DF is mentioned		Frequency of interaction		Weak link	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Private reward (PR)	0.073**	0.068*	0.235***	0.214**	0.006	0.012
	(0.036)	(0.037)	(0.092)	(0.094)	(0.020)	(0.022)
Social recognition (SR)	0.083**	0.083**	0.211**	0.217**	0.008	0.008
	(0.038)	(0.039)	(0.098)	(0.098)	(0.022)	(0.021)
Altruism (A)	0.008	0.013	0.118	0.127	-0.003	0.009
	(0.042)	(0.042)	(0.124)	(0.121)	(0.020)	(0.020)
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Sub-county effects	No	Yes	No	Yes	No	Yes
Constant	0.019	0.053	0.085	0.152	0.018	0.055
	(0.072)	(0.081)	(0.171)	(0.190)	(0.040)	(0.051)
Observations	905	905	905	905	905	905
R-squared	0.036	0.040	0.029	0.036	0.006	0.020
Control group mean	0.110	0.110	0.209	0.209	0.045	0.045
	[0.313]	[0.313]	[0.674]	[0.674]	[0.207]	[0.207]
p-value: PR = SR	0.823	0.714	0.833	0.976	0.948	0.840
p-value: PR = A	0.179	0.281	0.402	0.552	0.766	0.911
p-value: SR = A	0.123	0.174	0.451	0.488	0.753	0.975

Notes: OLS regression estimates. DF means disseminating farmers. The outcome in columns (1) and (2) is an indicator variable equal to one if a DF is mentioned among the neighbour's contacts for agricultural advice, zero if otherwise whereas in columns (3) and (4) the outcome measures the frequency of interaction between a neighbour and the mentioned DF. The outcome in columns (5) and (6) is an indicator variable equal to one if a DF is not linked to the neighbour directly for agricultural advice but through another neighbour, zero if otherwise. In parentheses are robust standard errors clustered at the sub-village level. In square parentheses are the standard deviations for the control group. Control group comprises households in sub-villages in which a DF was not incentivized. Household controls include sex, age, and education of household head, household size, size of land cultivated with maize, ownership of radio, ownership of mobile phone, access to government extension, and access to credit. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.5 Conclusion

Social networks continue to play a central role in the diffusion of new technologies. In many developing countries, technology diffusion through social networks offers an opportunity to strengthen national extension systems. This chapter examines network effects on adoption of drought-tolerant maize varieties (DTMVs) in northern Uganda and the mechanisms through which the effects occur. We conduct an experiment in which a random subset of households receives training about DTMVs. A random sample of the trained individuals receive incentives for sharing the knowledge learnt with their neighbours—we distinguish between a private material reward and social recognition incentive schemes.

Incentives increased the likelihood of DFs to experiment with DTMVs and the number of people with whom they discussed about farming, suggesting a change in the networks of neighbors. Relative to conventional training, incentivised training increased the likelihood of a neighbour mentioning a DF in his or her own contacts for agricultural advice and the frequency of interaction with a DF for information exchange, but not second-order linkages through friends of neighbors. Altruism of DFs, however, did not influence changes in networks. Having an adopter DF in a farmer's own network not only increased his or her knowledge but also the likelihood of adopting DTMVs. The results are robust to several robustness checks, and controlling for spillover effects and the problem of attrition in our sample.

Our results generate several important implications for policy. First, the findings suggest that an active intervention in the form of direct training provided to a few selected individuals can help to disseminate new agricultural technologies. This is in contrast with Kondylis et al. (2017), who found that providing direct training to contact farmers might not significantly influence knowledge and adoption decision of neighbors. However, among factors that were identified by Kondylis et al. (2017) as potential explanation for their null effects of direct DFs training was lack of incentives. In our context, we find that incentivised training of DFs substantially increase interaction within networks. The second implication of our findings, therefore, is that incentives matter for technology diffusion within social networks. Ben Yishay and Mobarak (2018) showed that private rewards influenced social learning. In addition to private rewards, we find that social recognition by announcing “good” performance of DFs in public plays an important role to substantially improve social learning. Our findings demonstrate that private reward and social recognition are equally important in affecting information networks.

Appendix 4.A: Tables

Table 4.A.1. Determinants of Attrition: Probit Regression

Variable	Coefficient	Standard error	*p*-value
Private material reward (PR)	0.115	0.288	0.690
Social recognition (SR)	-0.163	0.250	0.514
Household head is male	-0.476	0.220	0.030**
Age of household head	-0.002	0.006	0.736
Size of the household	-0.058	0.045	0.192
Education of the household head	0.039	0.020	0.049**
Household income (natural log)	-0.064	0.104	0.538
Participation in casual employment	-0.434	0.456	0.341
Participation in self-employment	0.299	0.532	0.575
Amount of credit received (natural log)	-0.091	0.085	0.285
Agricultural assets index	0.026	0.021	0.224
Non-agricultural assets index	0.025	0.027	0.363
Housing index	-0.224	0.233	0.336
Crop production advice network	-0.056	0.082	0.497
Kinship network	0.010	0.074	0.891
Experience with floods	-0.318	0.186	0.088*
Experience with droughts	0.601	0.417	0.150
Constant	0.148	0.694	0.832
P-Value of test: PR + SR = 0	0.632		
Wald Chi-square (17)	49.33***		
Pseudo R-squared	0.029		
Observations	1,286		

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4.A.2. Test for Spillover Effects: *t*-Test Using a Border-to-Treatment Dummy Variable

	Without potential spillover	With potential spillover	*p*-value of difference in means
DF is mentioned	0.092	0.088	0.773
	(0.011)	(0.009)	
	[0.288]	[0.283]	
Frequency of interaction	0.179	0.205	0.417
	(0.023)	(0.023)	
	[0.634]	[0.710]	
Weak link	0.032	0.024	0.339
	(0.006)	(0.005)	
	[0.176]	[0.154]	
Observations			

Notes: Standard errors are reported in parentheses. In square parentheses are standard deviations.

Chapter 5

Food Security, Downside Risk, and Resilience Effects of Agricultural Technologies in Northern Uganda

Abstract

This chapter examines the effects of drought-tolerant maize varieties (DTMVs) and maize-legume intercropping (MLI) on yield and downside risk, food security, and resilience of livelihoods in northern Uganda. Both technologies are increasingly promoted as being climate-smart. Using panel survey and georeferenced climate data, causal impacts are estimated via fixed effects estimation. The chapter finds that adoption of DTMVs increased mean yields and reduced variance of yields suggesting that the varieties boosted productivity and addressed production risks under heat stress. Neither DTMVs nor MLI, however, reduced exposure to downside risk. Furthermore, the hunger period shortened while income, frequency of food consumption, and resilience increased with adoption of DTMVs and MLI. Our findings underscore the importance of DTMVs and MLI in increasing food security, reducing production risks, and enhancing resilience of livelihoods. In order to minimise the trade-offs of downside risk, however, investment in complementary interventions may be required.

This chapter is based on:

Shikuku, K.M. and Mwongera, C. (2018). Food security, downside risk, and resilience effects of agricultural technologies in northern Uganda. Under review in *Agricultural Economics*.

5.1. Introduction

The majority of the poor in sub-Saharan Africa (SSA) are projected to continue residing in rural areas until 2040 (Ravallion et al., 2007). Rural populations in SSA mostly rely on rain-fed agriculture for their livelihoods and are often characterised by persistently high poverty rates, widespread food insecurity, and prevalent malnutrition (Hyman et al., 2008). Livelihoods are, therefore, highly sensitive to climatic shocks while the adaptive capacity is weak (Shiferaw et al., 2014). Together, these two factors increase vulnerability of rural households to climatic shocks (Hassan, 2010; Di Falco and Veronesi, 2013).

Increasing productivity growth in agriculture is widely seen as an effective strategy to improve the wellbeing of the poor in developing countries (Evenson and Golin, 2003; Ligon and Sadoulet, 2007; Christiaensen et al., 2011). Without adequate measures to address the adverse effects of climatic shocks in SSA, however, the costs of agricultural and economic development are enormous. An estimated 70 percent of economic losses in the region are attributed to droughts and floods alone (Bhavnani et al., 2008). Studies indicate a 2–4 percent reduction in the annual growth of gross domestic product (GDP) (Brown et al., 2011); a substantial decline of about 22 percent in yields of maize, 17 percent each for sorghum and millet, and 18 percent for groundnuts (Schlenker and Lobell, 2010); a reduction in farm revenues by about 39 US dollars per hectare for every degree centigrade rise in temperature (Hassan, 2010); and a reduction in food security (Parry et al., 2005; Lybbert and Sumner, 2012; Wheeler and von Braun, 2013) as a consequence of climatic shocks.

The agriculture sector of Uganda, which employs 66 percent of the population and contributes about 22 percent to the total GDP (Uganda Bureau of Statistics, 2013), faces threats from climate change. For example, damages to agricultural output due to climatic shocks amounted to more than 900 million US dollars in 2010; corresponding to 77 percent of total damages across all sectors of the country’s economy (Republic of Uganda, 2012; 2016). Furthermore, the current and future increased risks are in areas of existing poverty and have serious consequences for local economies and food security (Republic of Uganda, 2015). Climatic shocks not only exacerbate food insecurity, but may also lead to sustained long-term asset poverty traps if farmers are induced to sell their key assets as a coping measure (Wossen et al., 2017). Furthermore, the general equilibrium effects of covariate climatic shocks imply that farmers may not find employment in neighbouring farms due to widespread crop failure. Clearly, identifying and promoting options that will help to address the problems posed by climatic shocks is an imperative towards achieving Uganda’s target of 8.2 percent growth rate in GDP by 2040.

An option that has received considerable attention is climate-smart agriculture (CSA). By definition, CSA is a three-pillar approach targeted towards achieving a sustained increase in food security, enhancing resilience of livelihoods to climatic shocks, and providing co-benefits of greenhouse gases (GHGs) mitigation (Food and Agriculture Organisation of the United Nations (FAO), 2013). The popularity of the approach, both globally and in SSA, is evident from among others, the launch of a Global Alliance for Climate Smart Agriculture (GACSA) in 2014 with the goal of helping 500 million smallholder farmers practice CSA, and the Alliance for Climate Smart Agriculture in Africa (ACSAA) spearheaded by New Partnership for Africa’s Development (NEPAD) which intends to help catalyse the scaling up of CSA to 25 million farm households across the continent by 2025. Agricultural technologies that reduce variance of yields and address downside risk can contribute towards improved welfare of the poor and food insecure farm households in SSA (Kostandini et al., 2013; Wossen et al., 2017).

Yet few studies have examined the impacts of recommended CSA technologies in SSA. Cost-benefit analysis by Ngángá et al. (2017a; 2017b) showed positive net present values and high internal rates of return associated with adoption of CSA technologies in western Kenya and coastal savannah agro-ecological zone of Ghana suggesting that such technologies are worth investing in. Arslan et al. (2015) showed that yields increased and the probability of lower yields decreased with adoption of recommended CSA technologies in Zambia. *Ex-ante* analysis by Shikuku et al. (2017) indicated that adoption of improved livestock feeding in rural Tanzania increased milk yield and reduced methane emission. A large part of these previous studies focuses on yields.

The focus on average yields has several implications for food security in SSA. First, whereas increased mean yields tend to correlate with improved food security status of rural households in SSA, downside risk will negatively affect households' welfare (Di Falco and Chavas, 2009). Empirical evidence about the impact of recommended CSA technologies on downside risk is inadequate. Understanding impacts of agricultural technologies on downside risk requires analysis beyond average yields: such analysis should consider impacts on higher moments such as variance and skewness of yields (Di Falco and Chavas, 2009; Shi et al., 2013; Wossen et al., 2017). Second, increased focus on yields as a proxy for food security has left much less attention paid to the effects of recommended CSA technologies on other indicators of food security, especially dietary diversity. A notable exception is Smale et al. (2015) who showed the positive impact of hybrid maize varieties on dietary diversity, but did not take into account the effect of climatic shocks. Although there is still a major focus on increasing food supply in developing country policies, there is also increasing interest in supporting consumption of more diverse and nutritious food. Third, very few studies have examined heterogeneous treatment effects of adopting agricultural technologies under climatic shocks on yields (e.g., Arslan et al., 2015; 2017; Wossen et al., 2017) and an explicit assessment of the impact of agricultural technologies on resilience of livelihoods is largely missing.

Focused on two pillars of CSA, namely food security and resilience, and two technologies including DTMVs and maize-legume intercropping (MLI), this chapter attempts to fill the gaps in literature by addressing four specific objectives: (1) to assess the relationship between climatic variables and the probability of growing DTMVs and practicing MLI; (2) to assess the effect of DTMVs and MLI on yield of maize, production risk, and downside risk; (3) to assess the effect of DTMVs and MLI on food security; (4) to assess the effect of DTMVs and MLI on resilience of livelihoods. The chapter's assessment of a wide range of outcomes enables us to identify synergies and trade-offs associated with implementation of the two technologies.

The rest of the chapter is organised as follows. Section 5.2 explains the methodology followed including the theoretical framework, empirical approach, data, description of variables, and summary statistics. Section 5.3 presents the empirical results while in Section 5.4, the chapter concludes.

5.2 Methodology

5.2.1 Theoretical framework

The theoretical framework is motivated by a moment-based specification of the stochastic production function (Antle, 1983) as empirically applied by Di Falco and Chavas (2009) and Wossen et al. (2017). Consider a maize producing household using inputs $\boldsymbol{x}$ (including DTMVs and MLI) under risk. The household faces a production function $q = g(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w})$, where $\boldsymbol{s}$ is a vector of climatic variables (rainfall and temperature) and $\boldsymbol{w}$ includes household and farmer characteristics. The output q produced can either be consumed by the household or sold, that is, $q = c_1 + m$, where c_1 is the amount out of q that is consumed, and m is the marketed surplus that can be sold at price p_1. Furthermore, most farm households in Uganda are risk averse (Harrison et al., 2010) and operate under conditions characterised by imperfect markets. In that case, production and consumption decisions are inseparable (Singh et al., 1986; de Janvry et al., 1991). Households combine farm resources and family labour to maximise utility over leisure and consumption goods produced on the farm c_1 or purchased on the market c_2. Utility is maximised subject to a full income constraint, where income includes farm and off-farm income. A dietary diversity constraint defines the optimal bundle of food attributes or combination of foods consumed by the household (Smale et al., 2015).

Let $U(c_1, c_2)$ be a von Neumann-Morgenstern utility function representing households preferences under risk. Under the expected utility model, the household makes decisions so as to solve the optimisation problem:

$$Max(EU[c_1, \pi(\boldsymbol{x})]) \tag{5.1}$$

where E is the expectations operator and π represents all incomes received by the household. Following Di Falco and Chavas (2009), the choice of $\boldsymbol{x}$ in equation (5.1) can be written in terms of the certainty equivalent (CE), satisfying:

$$U(c_1, CE) = EU(c_1, \pi) = U(c_1, E(\pi) - R) \tag{5.2}$$

where $E(\pi)$ is the expected income, and R is a risk premium measuring the cost of private risk bearing (Di Falco and Chavas, 2009). Equation (5.2) shows that, under risk aversion, risk exposure will tend to reduce welfare.

Risk-averse farm households have an incentive to reduce their risk exposure. We assess how DTMVs and MLI included in $\boldsymbol{x}$ affect exposure to risks. To do that we follow the moment-based approach (Antle, 1983). Consider the following econometric specification for the production function $g(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w})$:

$$g(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w}) = f_1(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w}, \beta_1) + u \tag{5.3}$$

where $f_1(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w}, \beta_1) \equiv E[g(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w})]$ is the mean of $g(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w})$, and $u = g(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w}) - f_1(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w}\ \beta_1)$ is a random variable with mean zero. The higher moments of $g(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w})$ are given by:

$$E\{[g(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w}) - f_1(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w}, \beta_1)]^k | \boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w}\} = f_k(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w}, \beta_k)\ \forall\ k \geq 2 \tag{5.4}$$

Denoting the first moment (mean), $\mu_1 = E[g(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w})]$, the second moment (variance), $\mu_2 = E\{[g(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w}) - f_1(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w}, \beta_1)]^2\}$, and the third moment (skewness), $\mu_3 = E\{[g(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w}) - f_1(\boldsymbol{x}, \boldsymbol{s}, \boldsymbol{w}, \beta_1)]^3\}$, equation (5.1) can be rewritten as:

$$E\ Max(EU[c_1, \pi(\boldsymbol{x})]) = U(c_1, \mu_1, \mu_2, \mu_3) \tag{5.5}$$

The optimum condition for the adoption of DTMVs and MLI in elasticity form is then given by:

$$\mu_1^* - \frac{1}{2}\left(\frac{U''(\pi)}{U'(\pi)} m_2\right) \mu_2^* + \frac{1}{6}\left(\frac{U'''(\pi)}{U'(\pi)} m_3\right) \mu_3^* = 0 \tag{5.6}$$

where $\mu_j^* = \frac{\partial \mu_j}{ds}$, m_2 is the variance of π, and m_3 is the skewness of π (Antle, 1987; Di Falco and Chavas, 2009). From Equation (5.6), μ_1^* captures the marginal returns of using DTMVs and MLI and the term $-\frac{1}{2}\left(\frac{U''(\pi)}{U'(\pi)} m_2\right) \mu_2^* + \frac{1}{6}\left(\frac{U'''(\pi)}{U'(\pi)} m_3\right) \mu_3^*$ represents the marginal risk premium of adopting DTMVs and MLI (Di Falco and Chavas, 2009; Wossen et al., 2017). A profit-maximising farm household would adopt DTMVs and MLI when the returns from using these technologies are higher than the returns from not using the technologies. However, the expected increases in weather extremes under climate change can be conceptualised as an increase in downside risk, which would, on one hand, lead to decreasing incentives to adopt risky new technologies (Arslan et al., 2017). If DTMVs and MLI are perceived as risk-decreasing, on the other hand, it can be expected that their adoption will increase. A few recent studies have shown that adoption of stress-tolerant crop varieties can mitigate downside risks (Emerick et al., 2016; Wossen et al., 2017).

The framework described above, allows us to test several hypotheses. First, we hypothesis that adoption of DTMVs and MLI will increase under high variability in rainfall and perceived heat stress. Related to this, and as our second hypothesis, we test that the mean and skewness of yields of maize will increase whereas the variance will decrease with adoption of DTMVs and MLI. This would mean increased productivity with reduced downside risk. Third, we hypothesise that adoption of DTMVs and MLI will improve the food security situation of households and increase dietary diversity. Finally, and consistent with the objective of the climate-smart agriculture approach, we test the hypothesis that resilience of livelihoods will improve as a result of growing DTMVs and practicing MLI.

5.2.2 Estimation strategy

Our interest lies first, in understanding the correlation between variability in rainfall and perceived increase in heat stress and the probability of growing DTMVs and practicing MLI, and second, in evaluating subsequent effects of adoption on yield, downside risk, food security, and resilience of livelihoods. We begin our analysis by estimating two separate linear probability models: one for DTMVs and another one for MLI using panel data and in fixed effects[23]. The fixed effects model is formulated as follows:

$$y_{it} = \beta_0 + \beta_1 D_{\mathrm{t}} + \beta_2 \mathbf{CLIMATE_{it}} + \beta_3 \mathbf{X}_{it} + c_i + \varepsilon_{it}, \qquad i = 1, \dots, \mathrm{N}; t = 1,2, \quad (5.7)$$

where y_{it} is the binary adoption variable equal to one if the household i implemented the CSA technology at time t, and zero if otherwise; $\mathbf{CLIMATE}_{it}$ is a vector of climatic variables; D_t is an indicator variable equal to one at endline and zero at baseline; $\mathbf{X}_{it}$ comprises time-varying

[23] A few studies consider adoption of agricultural technologies in combinations (see for example, Kassie et al. (2015) and Arslan et al. (2017). In our case, however, the number of observations for combined DTMVs plus MLI was very small: 5 percent at baseline and 7 percent at endline making it difficult to assess impacts of the combination of technologies.

household characteristics; c_i captures time-invariant unobserved heterogeneity and ε_{it} is the error term (Imbens and Wooldridge, 2007). Equation (5.7) was estimated with robust standard errors clustered at the sub-village level.

Next, we estimate the impacts of adoption of DTMVs and MLI on yield, downside risk, food security, and resilience. Let Y_{1i} be the value of a given outcome variable for household i with adoption of a CSA technology, and let Y_{0i} be the household's outcome without adoption of a CSA technology. At a given point in time, a household either adopts a CSA technology $(T_i = 1)$ or does not $(T_i = 0)$. Thus the observed outcome, Y_i is

$$Y_i = T_i Y_{1i} + (1 - T_i) Y_{0i} \tag{5.8}$$

The treatment effect of adopting a CSA technology for household i is

$$\tau_i = Y_{1i} - Y_{0i} \tag{5.9}$$

but this effect is not directly observable because the household can only be in one state of nature (adopter or non-adopter) at a given time. The population parameters we seek to estimate are the average treatment effect (ATE) or average treatment effect on the treated (ATT) of CSA adoption, where

$$\tau_{\mathrm{ATE}} = E(Y_1 - Y_0) \tag{5.10}$$

$$\tau_{\mathrm{ATT}} = E(Y_1 - Y_0 | T = 1) \tag{5.11}$$

If CSA technologies were randomly assigned, then the potential outcomes would be independent of treatment (that is, $(Y_1, Y_0) \perp T$, $E(Y_1|T = 1) = E(Y_1|T = 0)$, $E(Y_0|T = 1) = E(Y_0|T = 0)$), $\tau_{\mathrm{ATE}} = \tau_{\mathrm{ATT}}$, and we could estimate τ_{ATE} by comparing the mean outcomes of CSA technology adopters and non-adopters. In the current case, CSA technologies were not randomly assigned, so selection bias is a major concern. We employ various econometric and quasi-experimental approaches to address the endogeneity problem and obtain unbiased estimates of the ATT of CSA technology adoption.

We first estimate fixed effects (FE) regression according to:

$$y_{it} = \beta_0 + \beta_1 D_{\mathrm{t}} + \beta_2 \mathbf{CSA_{it}} + \beta_3 \mathbf{X}_{it} + c_i + \varepsilon_{it}, \qquad i = 1, \dots, \mathrm{N}; t = 1,2, \tag{5.12}$$

where y_{it} again indicates the outcome of interest (yield, food security, and resilience indicators); $\mathbf{CSA_{it}}$ represents two adoption dummy variables: (1) equal to one if the household i grew a DTMV at time t, and zero if otherwise; and (2) equal to one if the household i practiced MLI at time t, and zero if otherwise; D_{t} and $\mathbf{X}_{it}$ are as defined in equation (5.7); and ε_{it} is the random error term.

An alternative approach to controlling for differences between adopters and non-adopters of CSA technologies to obtain unbiased estimates of the ATT is combined inverse-probability weighting (IPW) with FE, that is IPW-FE. Propensity score matching (PSM) is first used to obtain matched treatment and control observations based on the probability of adopting a CSA technology. Two assumptions are, however, crucial for PSM, namely ignorability of treatment and common support. The ignorability assumption requires that conditional on observed covariates $(\mathbf{X})$, adoption of CSA technology, (T) and the potential outcomes are independent: $(Y_1, Y_0) \perp T|\mathbf{X}$ (Rosenbaum and Rubin, 1983). The assumption of common support requires that there is substantial overlap: $0 < P(T = 1|\mathbf{X}) < 1$, that is, households with the same covariates have positive probabilities of both adopting and not-adopting a CSA technology.

We estimate a probit model of CSA technology adoption in the 2017 survey wave as a function of household and village characteristics at baseline (2015). Adopters and non-adopters of CSA technologies are then matched using three matching algorithms, namely radius, kernel-based, and nearest-neighbour matching. We use the estimated propensity scores to generate weights (φ)

as follows: for adopters, $\varphi = \frac{1}{p}$ whereas for non-adopters $\varphi = \frac{1}{1-p}$ where p represents estimated propensity scores. Equation 5.12 is then estimated incorporating weights from PSM.

Several tests were conducted to assess the quality of our matching procedure. Results of the covariates balancing test for the matched sample are presented in the Appendix Table 5.A.1. There are no significant differences in pre-treatment covariates between adopters and non-adopters of DTMVS and similarly between adopters and non-adopters of MLI after matching. Furthermore, bias was substantially reduced after matching. Figure 5.B.1 in the Appendix shows the distribution of the estimated propensity scores by adoption status for DTMVs and MLI. As shown, the weighting procedure was successful in generating matched treated and control observations. After estimating the propensity scores for the "adopter" and "non-adopter" households we check the common support condition. There is considerable overlap in common support. Among households that adopted DTMVs, the predicted propensity score ranges from 0.080 to 0.879, with a mean of 0.299, while among those that did not adopt DTMVs, it ranges from 0.080 to 0.667, with a mean of 0.221. Similarly, among households that adopted MLI, the predicted propensity score ranges from 0.056 to 0.358, with a mean of 0.201, while among those that did not adopt MLI, it ranges from 0.058 to 0.339, with a mean of 0.172. Thus, the common support assumption is satisfied in the region of (0.080, 0.879) for DTMVs and (0.056, 0.358) for MLI, with no loss of observations from treatment households.

The standardized mean difference for overall covariates used in the propensity score (19.6% for DTMVs and 7.6% for MLI before matching) is reduced to about 3.9 percent for DTMVs and 1.7 percent for MLI after matching (see Appendix Table 5.A.2). This substantially reduces mean bias by 80 percent for DTMVs and 77.6 percent for MLI 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 13.7 percent for DTMVs and 3.2 percent for MLI before matching to 0.8 percent for DTMVs and 0.1 percent for MLI after matching. Therefore, the low pseudo- R-squared, 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.

5.2.3 Data

The panel dataset comes from two waves of household surveys which were implemented in Nwoya district, northern Uganda. The first survey (baseline) was implemented in 2015 whereas the second one (endline) was conducted in 2017. Both survey rounds covered a total of four sub-counties and 126 randomly selected sub-villages. The sample used in this study is a balanced panel of 747 randomly selected maize growing households, hence 1,494 observations for which we have complete data. Data were collected on a broad range of topics including household demographic characteristics, crops and livestock production and marketing activities, varieties of crops grown, access to credit and information, participation in farmers' associations, food security, off-farm income activities, social networks, and assets ownership.

In addition to the survey data, georeferenced data on rainfall, temperature, and soil characteristics were collected. Rainfall data and temperature data were obtained from WorldClim version 2 (WorldClim2). The interpolated WorldClim2 rainfall and temperature data have a spatial ground resolution of 1km for the period 1970–2000 (Fick and Hijmans, 2017). In order to generate variation in rainfall data between baseline and endline, additional data were obtained from the daily Africa Rainfall Climatology version 2 (ARC2) of the National Oceanic and Atmospheric Administration's Climate Prediction Center (NOAACPC) for the period 2014–2016. These additional data are important to allow our fixed effects estimation not to drop the climate variables. The ARC2 rainfall database contains raster data at a spatial ground resolution of 1/10 of degree for African countries. Georeferenced data on soil pH were obtained from the Harmonized World Soil Database version 1.2 (HWSD) (Hengl et al., 2017). The HWSD has a resolution of 30 arc-seconds. The collected survey and georeferenced data were used to construct outcome and explanatory variables for analysis as follows.

5.2.4 Variables and descriptive statistics

5.2.4.1 Adoption

We define adoption as a binary variable taking a value of one if a household implemented the technology on at least one of its plots (irrespective of the area covered) and zero if otherwise. Specifically, two adoption dummy variables are created: (1) equal to one if a household grew DTMVs (Longe 10H, Longe 7H, or Longe 5) and zero if otherwise; and (2) equal to one if a household practiced MLI and zero if otherwise. The grain legumes included in the MLI variable are beans and groundnuts. Table 5.1 presents descriptive statistics on the use of the technologies. On the one hand, the share of households growing DTMVs doubled from 11 percent in 2015 to 22 percent in 2017. On the other hand, 8.5 percent less households practiced MLI in 2017 compared to the proportion in 2015 (26 percent).

Table 5.1. The Proportion of Adopting Households at Baseline (2015) and Endline (2017)

	2015	2017
Variable	Mean (SD)	Mean (SD)
Drought-tolerant maize varieties (DTMVs)	0.11 (0.31)	0.22 (0.42)
Maize-legume intercropping (MLI)	0.26 (0.44)	0.177 (0.38)
Number of observations	747	747

5.2.4.2 Mean, variance, and skewness of yields

Construction of outcome variables used in the estimation of impacts of DTMVs and MLI on mean, variance, and skewness of yields followed the following steps. First, yield of maize (kg/ha) was measured as total quantity of maize harvested divided by the size of land cultivated with the crop and summed for two cropping seasons. Yields were winsorised at one percent to account for outliers. In the second step, conditional mean yields were obtained by regressing the natural log of yields on a set of explanatory variables including use of inputs other than DTMVs and MLI, soil characteristics, climatic variables, and household characteristics via ordinary least squares (OLS) regression with robust standard errors clustered at sub-village level. In the third step, residuals from the second step were obtained, squared and regressed on the same set of explanatory variables. Similarly, for skewness the residuals obtained from the second step were raised to the power of three and regressed on the same set of covariates. Table 5.2 shows that both at baseline and endline, adopters of DTMVs and MLI obtained substantially higher yields than non-adopters.

5.2.4.3 Food security outcomes

The first outcome of food security is the months of inadequate household food provisioning (MIHFP) (Bilinsky and Swindale, 2010). Households were asked to indicate the months, in the 12 months preceding the survey, when they experienced a shortage of food. Our MIHFP index, therefore, equals the sum of the number of months of food shortage. The index ranges from 0 (maximum food security) to 12 (maximum food insecurity). The second measure of food security is the food consumption score (FCS) (World Food Programme (WFP), 2009). Using seven-day food frequency data, all food items were grouped into eight specific food groups, namely main staples, pulses, vegetables, fruits, meat and fish, milk, sugar, and oil. All consumption frequencies of food items of the same group were then summed – values of each group above seven were recoded to seven. For each food group, the value obtained was then multiplied by its weight to create weighted food group scores. Weights come from WFP (2009) as follows: main staples = 2; pulses = 2; vegetables = 1; fruit = 1; meat and fish = 4; milk = 4; sugar = 0.5; and oil = 0.5. A sum of the weighted food groups produced the FCS. Summary statistics in Table 4.2 show that adopters of DTMVs are significantly better in terms of food security outcomes compared with non-adopters both at baseline and endline.

A similar pattern is observed for MLI (Table 5.2, panel B). Furthermore, there is an improvement in all outcomes at endline (2017) compared to baseline (2015). The differences in outcomes at baseline support our empirical estimation approaches. Construction of the income variable is described in the next section.

Table 5.2. Summary Statistics of Yield and Food Security Outcomes, by Adopter Category at Baseline (2015) and Endline (2017)

Variable	2015		2017	
	Adopters	Non-adopters	Adopters	Non-adopters
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
	(1)	(2)	(3)	(4)
Panel A: Drought-tolerant (DT) varieties				
Maize yield (kg/ha)	1,169.41 (986.99)	597.44 (862.82)***	1,653.46 (1,145.04)	651.77 (882.31)***
MIHFP	2.41 (0.94)	2.89 (1.48)***	2.52 (0.99)	3.14 (1.53)***
Income (US$/AE)	162.83 (113.62)	120.83 (123.28)***	302.69 (261.97)	192.31 (214.89)***
FCS	41.76 (12.13)	38.34 (9.92)***	44.90 (14.16)	41.06 (14.68)***
Observations	79	668	166	581
Panel B: Maize-legume (M-L) intercropping				
Maize yield (kg/ha)	875.48 (962.76)	580.54 (855.28)***	1,075.95 (1,005.00)	831.10 (1,035.66)**
MIHFP	2.71 (1.44)	2.89 (1.43)	2.61 (1.42)	3.09 (1.44)***
Income (US$/AE)	133.93 (113.34)	122.19 (126.08)	260.15 (222.65)	207.55 (231.43)**
FCS	39.68 (10.72)	38.35 (10.03)	44.47 (14.72)	41.37 (14.58)**
Observations	196	551	132	615

Notes: FCS=food consumption score; MIHFP =months of inadequate household food provisioning. AE=Adult equivalents; ***, **, * means statistically significant difference between adopters and non-adopters at 1%, 5%, and 10% level, respectively.

5.2.4.4 Resilience outcome variables

Two moment-based indices of resilience were constructed following Barrett and Constas (2014) and Upton et al. (2016). Barrett and Constas (2014) defined resilience as “the capacity of a household to avoid and escape from poverty over time and in the face of shocks. If and only if that capacity is and remains high over time, then the unit is resilient”. This is the definition used in the current study. We begin the construction of our moment-based resilience indices by choosing two livelihoods indicators, namely household income per adult equivalents and household dietary diversity score (HDDS)[24]. Income was measured as the total sum of cash received from sale of crops, sale of livestock and livestock products, salaried and wage employment, business and other types of self-employment, and remittances. This total sum was then divided by the number of adult equivalents for a household and converted to US dollars using purchasing power parity adjusted exchange rates for 2015 and 2016. Next, we set a threshold value of one US dollar for income and follow Swindale and Bilinsky (2006) to set the minimum HDDS threshold equal to the mean HDDS of the wealthiest third of our sample, that is 7.65.

We then estimated the conditional mean income econometrically as a function of exposure to climatic shocks as well as community, household, and individual characteristics using OLS regression with robust standard errors clustered at sub-village level. Residuals from the conditional mean income equation were then obtained, squared, and regressed on the same covariates to estimate conditional variance. A similar estimation procedure was followed separately for conditional mean HDDS and conditional variance HDDS. Our dependent variable in the conditional mean income equation was the natural log of income per adult equivalents whereas in the mean HDDS equation we used HDDS as the dependent variable. The HDDS index is based on

[24] Upton et al. (2016) also used HDDS as a livelihoods indicator in their estimation of resilience.

twelve food groups including cereals; roots and tubers; vegetables; fruits; meat (including poultry and offals); eggs; milk and milk products; fish; pulses legumes and nuts; oil and fats; sugar and honey; condiments (Swindale and Bilinsky, 2006). Each group is a binary variable equal to one if a household member consumed the food seven days before the survey date and zero otherwise. The score is thus a summation across the 12 food groups and ranges from zero to 12. In addition to mean and variance, we further estimated the skewness of income. As shown in Appendix Figure 5.B.2, whereas the distribution of HDDS is normal, that of income is skewed.

The probability of meeting a threshold level of well-being, $\underline{y}$ (1 US dollar per day) for income was then derived using the conditional mean, variance, and skewness estimates, and similarly the probability of meeting $\underline{q}$ (7.65) for HDDS using conditional mean and variance. As a final step, resilience scores were computed as a function of the estimated probability that the household will meet or surpass the income threshold and similarly for HDDS. This procedure, therefore, gives us two moment-based resilience variables; an income-based and an HDDS-based index.

Furthermore, it is important to understand how resilience changed over time. In order to perform this analysis, terciles were created from each of the two indices (income-based and HDDS-based). We then examine the proportion of people who moved from "least resilient" in 2015 to "average resilient" and "most resilient" in 2017. Table 5.3 presents summary statistics of the resilience outcome variables. As shown in panel A, values for the two resilience variables were higher for households which grew a DTMV compared with their non-adopting counterparts, both at baseline and endline. For example, the income-based index was 21 percent higher at baseline and 26 percent higher at endline for adopters of DTMVs than for non-adopters. Whereas the index rose by about three percent for farmers who grew a DTMV, the index fell by the same magnitude for non-adopters, between the baseline and the endline. Similar to DTMVs, the resilience indices were higher for adopters of MLI compared with non-adopters (panels B).

Table 5.3. Summary Statistics of Resilience Outcome Variables, by Adopter Category

Variables	Baseline (2015)		Endline (2017)	
	Adopters	Non-adopters	Adopters	Non-adopters
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
	Panel A: Drought-tolerant (DT) varieties			
Income-based index	0.138 (0.144)	0.083 (0.092)***	0.257 (0.210)	0.118 (0.146)***
HDDS-based index	0.404 (0.156)	0.327 (0.139)***	0.562 (0.188)	0.383 (0.188)***
Observations	79	668	166	581
	Panel B: Maize-legume (M-L) intercropping			
Income-based index	0.111 (0.0126)	0.080 (0.087)***	0.194 (0.190)	0.140 (0.166)***
HDDS-based index	0.372 (0.0152)	0.322 (0.137)***	0.489 (0.205)	0.409 (0.198)***
Observations	196	551	132	615

Notes: HDDS=household dietary diversity score; Income-based and HDDS-based indices are moment-based following Barrett and Constas (2014). *, **, *** means statistically significant difference between adopters and non-adopters at 10%, 5%, and 1% level, respectively.

5.2.4.5 Explanatory variables

The choice of explanatory variables that would influence the decision to adopt DTMVs and MLI, and the outcomes was informed by economic theory, empirical literature, and availability of data. The explanatory variables are mainly drawn from studies on adoption of agricultural technologies (Kassie et al., 2011; 2013; Asfaw et al., 2012; Shiferaw et al., 2014), those that focus on adoption of risk-mitigating technologies (Di Falco and Bulte, 2012; Di Falco and Veronesi, 2013), those that estimate resilience of households and its determinants (Barrett and Constas, 2014; Upton et al., 2016), and those that examine the effect of agricultural technologies on agricultural productivity (Di Falco and Chavas, 2009; Arslan et al., 2017; Wossen et al. 2017) and food security (Smale et al., 2015; Kabunga et al., 2014).

Variables commonly considered to influence adoption behaviour of rural households include households' human capital (sex, age, and education of the household head, and household's dependency ratio); productive capital (household assets-based wealth index); agricultural knowledge; access to credit and markets; social networks; and exposure to climatic shocks. Four climatic variables are included: (1) coefficient of variation in seasonal rainfall; (2) total amount of seasonal rainfall; (3) perception about prolonged droughts; and (4) perception about increasing temperature. We further controlled for biophysical (soil) characteristics by including soil organic carbon and soil pH. Furthermore, estimation of the production function as described in section 5.2.1 requires that we control for use of external inputs, other than DTMVs. We, therefore, constructed three dummy variables measuring use of fertiliser, manure, and agro-chemicals (pesticides and herbicides). Table 5.4 provides summary descriptive statistics of the explanatory variables for the whole sample at baseline and endline.

Households were predominantly male-headed with an average of 43 years of age and six years of completed formal education. About 40 percent of the household heads had completed primary level of education (primary 7). A household had on average six members and a dependency ratio of 55 percent. Close to 60 percent of households reported to have received credit and more than 80 percent had at least one member participating in a farmers' association in 2017. On average, a household had two other households in the same village with whom they were related by blood or marriage.

Table 5.4. Summary Statistics for Explanatory Variables

Variable	2015	2017
	Mean (SD)	Mean (SD)
HHH is female (1=yes; 0=otherwise)	0.18 (0.38)	0.19 (0.39)
Age of HHH (years)	42.00 (14.39)	43.00 (14.25)
Education of HHH (years)	5.71 (3.34)	5.64 (3.38)
HHH has education above primary seven (1=yes; 0=otherwise)	0.44 (0.50)	0.41 (0.49)
Dependency ratio (%)	55.60 (21.84)	55.27 (0.20)
Knowledge about agricultural technologies (score)	4.33 (1.91)	5.67 (3.57)
Number of different sources of income for the HH	3.00 (0.99)	3.50 (1.45)
HH received credit (1=yes; 0=otherwise)	0.71 (0.45)	0.56 (0.50)
HH has a member participating in a farmers' association(1=yes; 0=otherwise)	0.76 (0.43)	0.83 (0.37)
Kinship network (number of relatives in same village)	2.00 (1.05)	3.00 (1.40)
Farm size (amount of cultivated land in ha)	1.89 (1.52)	2.02 (1.96)
Ownership of agricultural assets (index)	0.30 (0.50)	1.29 (0.50)
Ownership of non-agricultural assets (index)	0.74 (0.65)	0.85 (0.65)
Livestock ownership (TLU)	0.70 (1.51)	0.92 (1.70)
Self-reported willingness to take risks (score 0-10)	5.57 (2.71)	5.57 (2.71)
Total seasonal rainfall (mm)	799.18 (50.50)	799.18 (50.50)
Coefficient of variation in seasonal rainfall (%)	26.83 (1.56)	26.83 (1.56)
Household perceives prolonged drought	0.688 (0.464)	0.482 (0.500)
Household perceives rising temperature	0.232 (0.422)	0.510 (0.500)
Distance to the nearest main road (walking minutes)	11.73 (18.19)	11.73 (18.19)
Distance to the nearest main market (walking minutes)	43.32 (34.07)	43.32 (34.07)
Soil pH	5.84 (0.15)	5.84 (0.15)
Soil organic carbon	22.66 (4.07)	22.66 (4.07)
Number of observations	747	747

Notes: HH=Household; HHH=household head; TLU=Tropical Livestock Units.

Ownership of assets including livestock was very low both in 2015 and 2017. On a scale of zero (does not take risks at all) to 10 (always takes risks), the average willingness to take risks was 5.6. Households walked, on average, about 12 minutes to the nearest main road and close to 45 minutes to the nearest main market. Use of external input was very low; only 0.6 percent of households applied fertilisers at baseline while seven percent used agrochemicals. At endline, 1.2 percent had used fertilisers while the percentage of households that applied agrochemicals increased to 15 percent. In terms of climatic variables, the average amount of total seasonal rainfall received was 800mm. The coefficient of variation in seasonal rainfall was 26.8 percent. The maximum seasonal temperature for 72 percent of our sample households exceeded 28˚C. The average soil pH was 5.8 and the soil organic carbon content was 23 percent.

5.3 Empirical results

5.3.1 Determinants of adoption

Results of fixed effects regression to assess the determinants of adoption of DTMVs and MLI are presented in Table 5.5, expressed in terms of marginal effects. Column (1) presents effects on adoption of DTMVs whereas column (2) shows results for MLI. Households that had experienced increasing temperature were more likely to grow a DTMV, suggesting that farmers perceived such varieties as a strategy to mitigate the effects of heat stress. Specifically, experiencing warmer days correlated with a 7.2 percentage points increase in the likelihood to adopt DTMVs relative to households that did not report changes in temperature. The likelihood to use DTMVs also correlated positively, although not significantly, with the coefficient of variation in seasonal rainfall.

Results further show that the decision to adopt DTMVs is influenced by education of the household head and agricultural knowledge. A one point increase in the knowledge score correlated significantly with a 5.2 percentage points increase in the likelihood to grow a DTMV. The finding that knowledge exposure correlated positively with the adoption decision is consistent with previous studies and supports efforts targeting to increase diffusion of agricultural knowledge among farmers in SSA (Lambrecht et al., 2014; Kondylis et al., 2017; Ben Yishay and Mobarak, 2018). Better educated household heads may have an increased ability to search for and apply agricultural knowledge.

Table 5.5. Determinants of Adoption of Drought-Tolerant Maize Varieties (DTMVs) and Maize-Legume Intercropping (MLI): Fixed Effects Regression Model

Variable	DTMVs	MLI
	(1)	(2)
Total seasonal rainfall (mm)	0.006 (0.021)	-0.054*** (0.020)
Coefficient of variation in seasonal rainfall (%)	0.009 (0.015)	-0.007 (0.013)
Household perceives prolonged drought	-0.004 (0.025)	-0.022 (0.033)
Household perceives rising temperature	0.058** (0.029)	0.084*** (0.031)
Household head is female	-0.042 (0.055)	0.053 (0.081)
Age of household head	-0.011 (0.103)	-0.028 (0.137)
Household head has education above primary	0.122** (0.059)	0.152** (0.070)
Dependency ratio	-0.032 (0.071)	0.055 (0.093)
Income sources for the household	0.005 (0.011)	0.026** (0.013)
Agricultural assets index	0.053* (0.030)	0.042 (0.036)
Household assets index	-0.046* (0.024)	0.064* (0.032)
Farm size (ha)	-0.009 (0.008)	0.008 (0.010)
Number of relatives	0.018 (0.012)	0.037*** (0.013)
Group membership	-0.046 (0.034)	0.044 (0.039)
Knowledge score	0.052*** (0.005)	0.004 (0.006)
Endline	0.047 (0.160)	-0.493*** (0.147)
Constant	-1.283 (2.706)	7.832*** (2.728)
Observations	1,494	1,494
Diagnostics		
R-squared	0.235	0.563
Proportion of variance due to fixed effects	0.349	0.102

Notes: Average marginal effects are reported. In parentheses are robust standard errors clustered at sub-village level. All variables are as defined in Table 4.4. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Ownership of assets influence adoption of DTMVs. Whereas the agricultural assets index correlated with an increased likelihood to adopt DTMVs, there was a negative relationship between non-agricultural assets index and the probability of growing DTMVs. A possible explanation is that households endowed with agricultural assets may find it easier to experiment with DTMVs (Langyntuo and Mungoma 2008). Those with a greater endowment of non-agricultural assets may, however, have other means to cope with shocks hence a reduced likelihood to adopt DTMVs.

Results in column (2) show that several factors influence the likelihood to practice MLI. An increase in the long run seasonal rainfall by one millimetre correlated with a reduced likelihood of practicing MLI by 8.4 percentage points whereas a rise in temperature increased the probability of implementing the practice. The practice of MLI in northern Uganda is largely a diversification strategy. In anticipation of climate related shocks, households practice MLI to mitigate the risk of total crop failure—should one crop fail, farmers could still harvest the second crop (Shikuku et al., 2015). Similar to DTMVs, education of the household head correlated with an increased likelihood of practicing MLI.

The number of kinship links was significantly correlated with an increased probability of adopting MLI. Contrary to the findings of Di Falco and Bulte (2013), this positive relationship suggests that kinship networks are a complementary risk-mitigating strategy that may not attenuate incentives to adopt recommended CSA technologies. The possibility of complementarities in risk-mitigating strategies can further be observed from the positive correlation of the diversity of income sources with the decision to adopt MLI. Diversification is widely recognised as a strategy for adapting to climatic shocks (Kankwamba et al., 2018).

Wealth status of households correlate with the decision to practice MLI. We find a positive correlation between the non-agricultural assets index and the probability of practicing MLI.

Households with a greater endowment of assets may be able to smoothen consumption by selling or leasing out some of its assets when hit by shocks. The positive correlation between non-agricultural assets and the likelihood of practicing MLI possibly suggests that both strategies are perceived as risk-minimizing and consumption smoothing options.

5.3.2 Impact of DTMVs and MLI on mean, variance, and skewness of maize yields

Table 5.6 presents results of econometric analysis to assess the effect of DTMVs and MLI on maize productivity (mean of yields), production risk (variance of yields), and downside risk (skewness of yields). Columns (1), (3), and (5) present results of fixed effects (FE) regression analysis whereas columns (2), (4), and (6) show results of combined FE with inverse-probability weighting (IPW). In general, increasing productivity, reducing variance, and increasing skewness are seen as desirable. A lower variance of yields means lower risk exposure. Similarly, a higher skewness means reduced exposure to unfavourable events located in the lower tail of the yield distribution (Shi et al., 2013; Wossen et al., 2017).

Results show that adoption of DTMVs and MLI had a significant positive effect on average yields of maize. Mean yields increased by 18 percent more for adopters of DTMVs and seven percent more for adopters of MLI relative to non-adopters (column 1). The regression results for the variance function are shown in columns (3 and 4). Both DTMVs and MLI are found to be statistically significant. Adoption of DTMVs and MLI reduces the variance of yield. Specifically, the variance of maize yield fell by seven percent with adoption of DTMVs and three percent with MLI, although for the latter technology, the effect is only statistically significant at 10 percent level under the IPW-FE estimation. If the variance were taken to be the only measure of risk, results in columns (3) and (4) suggest that DTMVs and MLI are risk-reducing technologies. Risk reduction is welfare-enhancing for risk-averse farmers (Di Falco and Chavas, 2006). Together, the findings that DTMVs increased productivity and reduced production risks are consistent with previous studies such as Wossen et al. (2017). Variance does not, however, distinguish between unexpected good and bad outcomes (Di Falco and Chavas, 2009). We, therefore, extend our analysis to assess the effect of DTMVs and MLI on skewness of yields.

The regression results for the skewness function are presented in columns (5) and (6) in Table 5.6. The effect of DTMVs on skewness of yields is not statistically significant at 10 percent level (see also Figure 5.B.3 in the Appendix). The effect of MLI is negative and statistically significant at five percent level under the FE estimation. This effect, which would suggest that MLI increases downside risks, however disappears when differences in observable time-varying characteristics of households are controlled for using IPW-FE. The finding that DTMVs did not reduce the probability of obtaining yields in the lower tail of the distribution contradicts that of Wossen et al. (2017) in rural Nigeria. The finding is, however, in line with the on-going debate about CSA technologies and specifically speaks to the argument that such technologies are context-specific. The finding further supports that in order to understand the impacts of CSA technologies on productivity and risk, there is need to move beyond mean yields and to consider variance and skewness of yields.

In order to understand whether and how the effects of DTMVs and MLI on yields change under climatic shocks, heterogeneous treatment effects are estimated. Table 5.7 presents IPW-FE estimates of the heterogeneous treatment effects of DTMVs and MLI by climatic shocks on mean, variance, and skewness of yields. We find strongly significant effects of DTMVs on mean and variance of yields. Adoption of DTMVs increased yields and reduced variance of yields under climatic shocks.

Table 5.6. Impact of Drought-Tolerant Maize Varieties (DTMVs) and Maize-Legume Intercropping (MLI) on Mean, Variance, and Skewness of Yield

Variable	Average yield		Variance of yield		Skewness of yield	
	FE	IPW-FE	FE	IPW-FE	FE	IPW-FE
	(1)	(2)	(3)	(4)	(5)	(6)
DTMV	0.175***	0.183***	-0.066***	-0.071***	-0.013	-0.026
	(0.026)	(0.030)	(0.013)	(0.017)	(0.022)	(0.023)
MLI	0.072***	0.078***	-0.015	-0.029*	-0.041**	-0.002
	(0.019)	(0.028)	(0.012)	(0.015)	(0.018)	(0.026)
Endline	0.223***	0.226***	-0.076***	-0.081***	-0.171***	-0.162***
	(0.016)	(0.019)	(0.009)	(0.011)	(0.014)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	6.398***	6.428***	0.809***	0.794***	-0.436***	-0.297**
	(0.073)	(0.131)	(0.038)	(0.086)	(0.073)	(0.145)
Observations	1,007	863	1,007	863	1,007	863
R-squared	0.536	0.659	0.474	0.464	0.448	0.463
Fraction of variance due to fixed effects	0.631	0.630	0.668	0.683	0.690	0.704

Notes: FE=fixed effects; IPW-FE combined inverse probability weighting (IPW) with fixed effects (FE), that is, fixed effects estimation on matched treatment and control observations. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Figures in parentheses are robust standard errors clustered at sub-village level.

Table 5.7. Heterogeneity of Yield Impacts by Weather Shock

Variable	Average yield (1)	Average yield (2)	Variance of yield (3)	Variance of yield (4)	Skewness of yield (5)	Skewness of yield (6)
	Panel A: Coefficient of variation in rainfall					
	1st quintile	3rd quintile	1st quintile	3rd quintile	1st quintile	3rd quintile
DTMV	0.114**	0.108***	-0.104***	-0.044**	-0.052	-0.016
	(0.049)	(0.040)	(0.024)	(0.019)	(0.036)	(0.052)
MLI	0.081*	0.121**	-0.012	0.010	-0.021	-0.063
	(0.081)	(0.056)	(0.026)	(0.022)	(0.034)	(0.065)
Observations	283	295	283	295	283	295
	Panel B: Perception about occurrence of prolonged drought					
	Yes	No	Yes	No	Yes	No
DTMV	0.122***	0.172**	-0.077***	-0.109***	0.020	-0.032
	(0.042)	(0.084)	(0.022)	(0.032)	(0.046)	(0.041)
MLI	0.050	-0.057	-0.022	0.008	0.014	-0.021
	(0.032)	(0.070)	(0.020)	(0.026)	(0.036)	(0.037)
Observations	520	343	520	343	520	343
	Panel C: Perception about rising temperature					
	Yes	No	Yes	No	Yes	No
DTMV	0.188***	0.237***	-0.082***	-0.085***	0.009	-0.048
	(0.068)	(0.054)	(0.025)	(0.024)	(0.048)	(0.033)
MLI	-0.005	0.019	-0.014	0.022	0.017	0.031
	(0.060)	(0.046)	(0.032)	(0.022)	(0.046)	(0.035)
Observations	351	512	351	512	351	512

Notes: Combined inverse probability weighting (IPW) with fixed effects (FE) estimates, that is, fixed effects estimation on matched treatment and control observations. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Figures in parentheses are robust standard errors.

The effect of DTMVs on skewness of yield is also positive under the perceived prolonged droughts and increased temperature (Panels B and C), suggesting a reduction of downside risks. The effects are, however, not statistically significant at 10 percent level. The effects of MLI is not statistically significant under the self-reported perceived prolonged droughts and increased temperature (Panels B and C). Results in Panel A, that is, under increased uncertainty in rainfall indicate that MLI increased mean of yields but had no significant effect on the variance and skewness of yields.

5.3.3 Impact of DTMVs and MLI on Food Security and Resilience

Results of FE and IPW-FE estimation of the impacts of DTMVs and MLI on food security are presented in Table 5.8. As shown in columns (1) and (2) adoption of DTMVs and MLI significantly improved food security. Specifically, the period of food shortage reduced by 7–8 days for DTMVs adopters and 8–12 days for MLI adopters compared with non-adopters. Furthermore, results show an increase in household income per adult equivalents (columns 3–4). Specifically, income increased by 25–34 percent with DTMVs adoption and by 20–25 percent with adoption of MLI. The frequency of food consumption also improved with adoption of DTMVs and MLI (columns 5–6) . The food consumption score increased between 2.3–3.1 points more with DTMVs and by 2.4 points more with MLI compared with non-adoption. The findings that DTMVs improved food security are consistent with Wossen et al. (2017).

Table 5.8. Impact of Drought-Tolerant Maize Varieties (DTMVs) and Maize-Legume Intercropping (MLI) on Food Security Outcomes

	Months of food shortage		Household income		Food consumption score	
	FE	IPW-FE	FE	IPW-FE	FE	IPW-FE
Variable	(1)	(2)	(3)	(4)	(5)	(6)
DTMV	-0.282**	-0.227**	0.343***	0.251**	2.319*	3.083*
	(0.112)	(0.141)	(0.083)	(0.101)	(1.367)	(1.562)
MLI	-0.406***	-0.257**	0.200***	0.251***	2.441**	2.236**
	(0.126)	(0.128)	(0.077)	(0.078)	(1.105)	(1.579)
Endline	0.133*	0.180**	0.462***	0.519***	3.121***	3.687***
	(0.078)	(0.082)	(0.055)	(0.064)	(0.663)	(0.802)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.345***	2.828***	4.918***	5.181***	37.025***	38.745***
	(0.503)	(0.662)	(0.355)	(0.446)	(4.112)	(5.944)
Observations	1,494	1,278	1,494	1,494	1,494	1,494
R-squared	0.035	0.037	0.187	0.272	0.056	0.102
Fraction of variance due to fixed effects	0.346	0.398	0.456	0.473	0.387	0.384

Notes: FE=fixed effects; IPW-FE combined inverse probability weighting (IPW) with fixed effects (FE), that is, fixed effects estimation on matched treatment and control observations. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Figures in parentheses are robust standard errors clustered at sub-village level.

Although results of heterogeneous treatment effects of DTMVs and MLI on yield under climatic shocks showed positive impacts, we are further interested to explicitly examine effects on resilience. Table 5.9 presents FE and IPW-FE estimates of the effects of DTMVs and MLI on resilience. We find that both technologies increased resilience of livelihoods. In terms of the income-based resilience indicator, results in columns (1) and (2) show that resilience increased by 3–5 percentage points more for adopters of DTMVs and by 3–4 percentage points more for adopters of MLI compared with non-adopters. The results are consistent when we use HDDS as an indicator for livelihood. Specifically, results in columns (3) and (4) indicate that the HDDS-based index rose by 0.07–0.08 points for DTMVs and 0.06–0.07 points for MLI.

Table 5.9. Impact of Drought-Tolerant Maize Varieties (DTMVs) and Maize-Legume Intercropping (MLI) on Resilience

	Income-based indicator		HDDS-based indicator	
	FE	IPW-FE	FE	IPW-FE
Variable	(1)	(2)	(3)	(4)
DTMV	0.053***	0.031***	0.080***	0.071***
	(0.011)	(0.012)	(0.011)	(0.013)
MLI	0.030***	0.041***	0.056***	0.066***
	(0.008)	(0.012)	(0.009)	(0.013)
Endline	0.091***	0.104***	0.140***	0.147***
	(0.005)	(0.007)	(0.006)	(0.007)
Controls	Yes	Yes	Yes	Yes
Constant	0.027	0.080	0.293***	0.300***
	(0.025)	(0.049)	(0.034)	(0.053)
Observations	1,494	1,278	1,494	1,278
R-squared	0.556	0.594	0.556	0.594
Fraction of variance due to fixed effects	0.460	0.461	0.460	0.461

Notes: FE=fixed effects; IPW-FE combined inverse probability weighting (IPW) with fixed effects (FE), that is, fixed effects estimation on matched treatment and control observations; HDDS=household dietary diversity score. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Figures in parentheses are robust standard errors clustered at sub-village level.

Figure 5.B.4 shows the transition from lower terciles of resilience scores to highest terciles. The upper panel shows the transition for the income-based index whereas the lower panel shows transition for the HDDS-based index. Both panels display a similar pattern. In 2015, majority of the households were in the lower and intermediate terciles. The percentage of households in the

highest terciles, however, increased in 2017 whereas that in the lower and intermediate terciles reduced.

5.5. Conclusion

At the centre of agricultural and economic development policy debates in sub-Saharan Africa (SSA) today is the question of how to sustainably increase yield, reduce downside risks, improve food security, and enhance resilience of livelihoods to climatic shocks. Climate-smart agriculture (CSA) is increasingly promoted as an approach that can help to answer this question. This chapter focused on two pillars of CSA, namely food security and resilience, and sought to specifically address the following objectives: (1) to assess the relationship between climatic variables and the probability of growing drought-tolerant maize varieties (DTMVs) and practicing maize-legume intercropping (MLI); (2) to assess the effect of DTMVs and MLI on yield of maize, production risks, and downside risks; (3) to assess the effect of DTMVs and MLI on food security; (4) to assess the effect of DTMVs and MLI on resilience of livelihoods.

The study combined a panel survey dataset from northern Uganda with georeferenced climatic data and employed fixed effects estimation and inverse probability weighting technique to assess causal impacts. We found an increased likelihood to adopt DTMVs and to practice MLI when households perceived rising temperatures. The likelihood to practice MLI correlated negatively with an increase in total amount of seasonal rainfall. These results suggest that farmers perceive DTMVs and MLI as risk-mitigating technologies. Furthermore, adoption of DTMVs and MLI increased mean and reduced variance of maize yield suggesting positive impacts on productivity and production risks. The impact of DTMVs on skewness of yields was positive under climatic shocks, but not statistically significant meaning that the technology did not reduce downside risks. Similarly, MLI did not reduce downside risks under climatic shocks. Finally, we found that both DTMVs and MLI improved food security and increased resilience of livelihoods.

The findings of this study have several important implications for policy and future research. First, under conditions characterised by increasing climatic shocks, efforts to promote adoption of DTMVs and MLI can help to achieve increased yield, food security, and resilience of smallholder farmers' livelihoods. Promoting adoption of DTMVs will require increased investment in the diffusion of accurate knowledge about the technology including its benefits and proper implementation. Leveraging social networks may increase knowledge diffusion through social learning. Secondly, there is need for further research to assess impacts of DTMVs and MLI on downside risks in diverse contexts.

Appendix 5.A: Tables

Table 5.A.1. Balancing tests

Variable	DTMVs		Bias reduction (%)	MLI		Bias reduction (%)
	Adopters	Non-adopters		Adopters	Non-adopters	
Total seasonal rainfall	143.23	142.66	-128.5	143.64	143.74	82.2
Coefficient of variation in seasonal rainfall	23.03	23.09	82.6	23.60	23.57	94.5
Household experienced prolonged drought	0.66	0.67	45.1	0.73	0.74	86.8
Household experienced warmer days	0.21	0.25	-23.8	0.23	0.23	69.8
Household head is female	0.10	0.10	98.4	0.19	0.20	69.8
Age of the household head (log)	3.62	3.61	88.0	3.62	3.61	97.6
Household head has primary education	0.55	0.54	95.1	0.43	0.44	8.4
Dependency ratio	0.53	0.54	75.3	0.55	0.55	28.8
Number of different income sources	3.27	3.25	58.7	3.25	3.24	-21.6
Agricultural assets index	1.34	1.33	82.4	1.26	1.27	83.7
Non-agricultural assets index	0.88	0.88	97.0	0.68	0.67	90.1
Farm size	2.09	2.23	77.8	1.88	1.80	-174.9
Number of relatives	1.83	1.78	46.3	1.76	1.77	-25.0
Membership to farmers' group	0.80	0.80	89.8	0.78	0.77	50.6
Knowledge score about improved crop varieties	5.00	4.90	91.0	4.35	4.31	-431.1

Notes: DTMVs=drought-tolerant maize varieties; MLI=maize-legume intercropping.

Table 5.A.2. Matching quality indicators before and after matching (Matching algorithm = Kernel-based 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 standardized bias before matching	Mean standardized bias after matching	Total % |bias| reduction
DTMVs	0.093	0.008	73.64 (0.000)	3.66 (0.999)	19.6	3.9	80.00
MLI	0.032	0.001	22.15 (0.104)	0.54 (1.000)	7.6	1.7	77.63

Notes: DTMVs=drought-tolerant maize varieties; MLI=maize-legume intercropping.

Appendix 5.B: Figures

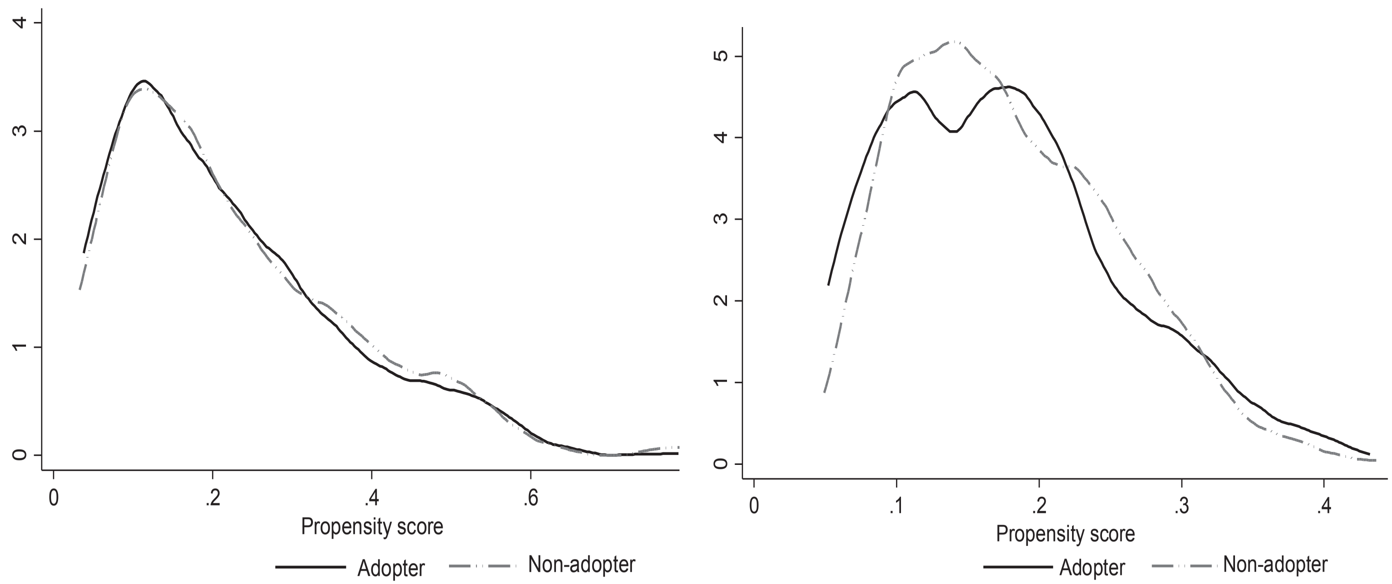

Figure 5.B.1. Distribution of propensity scores

Notes: Left panel = drought-tolerant maize varieties (DTMVs); right panel = maize-legume intercropping (MLI).

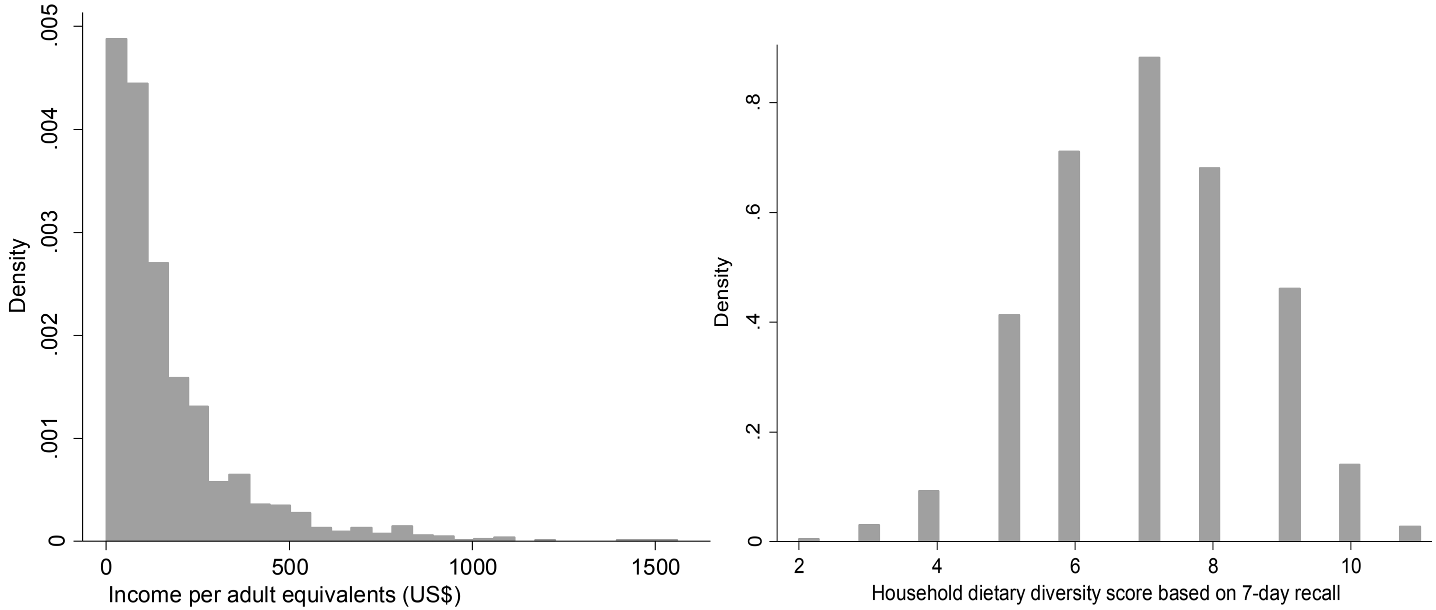

Figure 5.B.1. Distribution of income and household dietary diversity score

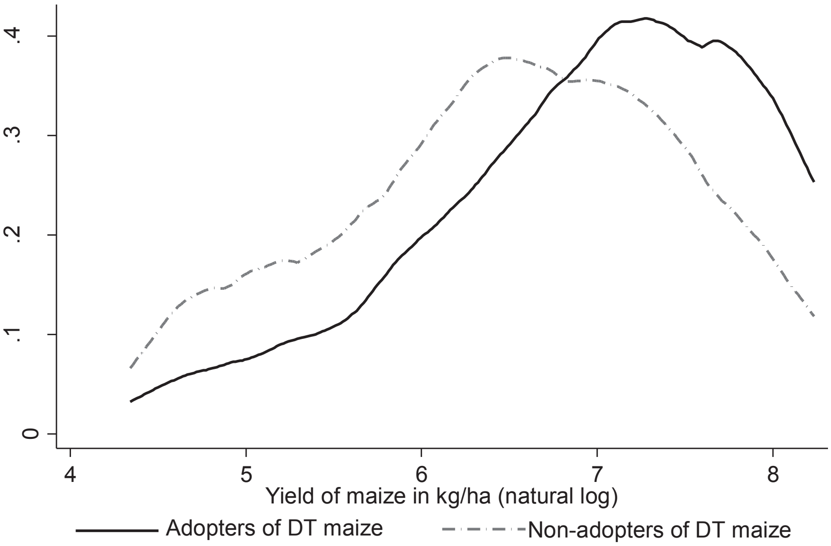

Figure 5.B.3. Distribution of maize yield among adopters and non-adopters of drought-tolerant (DT) maize varieties

Notes: Kolmogorove-Smirnov equality-of-distributions test p-value = 0.000.

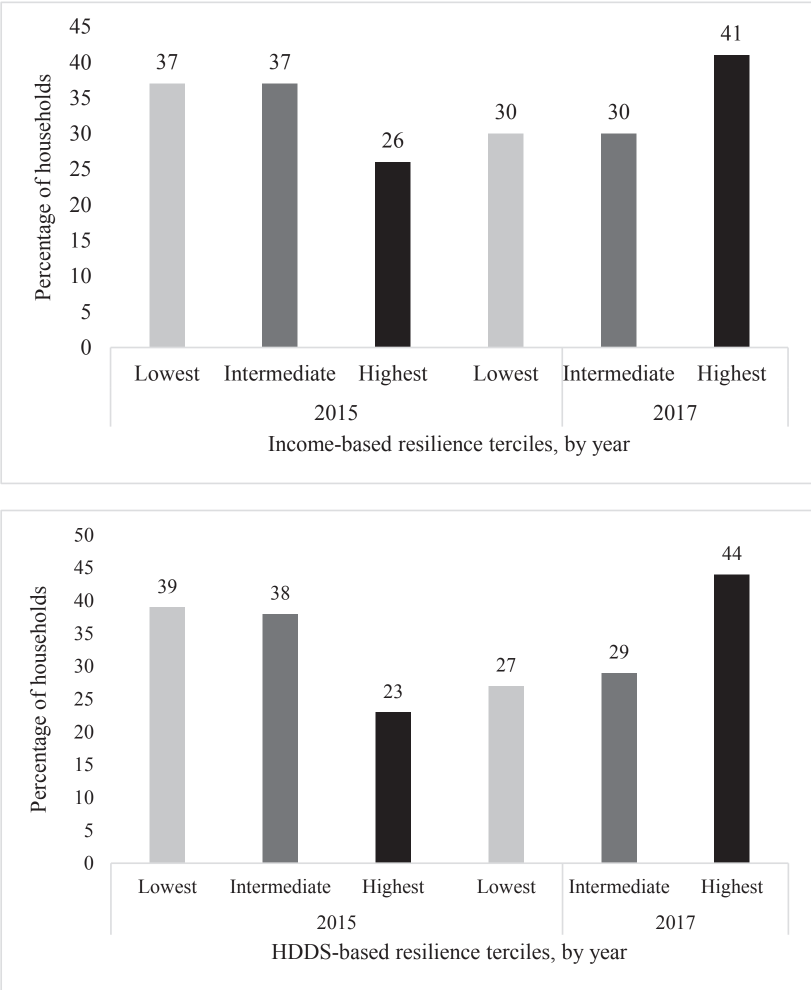

Figure 5.B.4. Transition across terciles of resilience indices, by year

Chapter 6

Synthesis

6.1 Introduction

Central to agricultural transformation and economic development in poor countries of sub-Saharan Africa (SSA), especially in the face of increasing climatic shocks, are technological innovations. Insights from economist Theodore W. Schultz tell us that smallholder farmers in SSA may be poor because they have used the state of art at their disposal to the fullest, so that to realise any meaningful change in their livelihoods, they would require technological innovations. But why is it that rational farmers continue to rely on low-yielding technologies, often producing below their subsistence means, even in situations where welfare-enhancing technologies exist? In many countries of SSA, there tends to be a huge gap between yields at research stations and actual yields in farmers' fields (Tittonell and Giller, 2013). High-yielding technologies "lie on the shelves" at research stations while the intended beneficiaries live in squalor as a consequence of depressed yields. Poverty traps tend to be well-established in many rural areas of SSA. A formidable challenge for policy in this region, therefore, is finding ways of breaking such poverty traps and inducing virtuous circles through increased diffusion of technological innovations. Social learning can help towards that end (Bandiera and Rasul, 2006). Yet, our understanding of the mechanisms through which social learning happens is limited.

This thesis analyses and discusses the role of incentives in the diffusion of agricultural knowledge and technologies. The thesis not only sheds light on how incentives shape information exchange networks and the subsequent effects on adoption of agricultural technologies, but also provides important insights about the impact of "recommended" climate-smart agricultural (CSA) technologies on yields and food security, downside risk, and resilience of livelihoods. The insights generated come from a combination of household survey panel data and economic lab-in-the-field experiments. The main message of the thesis is that incentives directed at randomly selected "seed nodes" within the target population influence knowledge and technology diffusion through social learning subsequently improving the welfare of the rural poor. In the following sections, the main lessons learnt from each chapter are presented, including discussions of the resulting policy implications and recommendations for future research.

6.2 Key lessons and implications for policy

6.2.1 Incentives and the diffusion of agricultural knowledge

While literature has long established the importance of incentives in inducing worker effort (Lazear, 1982; Nalebuff and Stiglitz, 1983; Shearer, 2004; Charnes et al., 2010), the focus has mainly been on the effect of financial rewards in settings in which employee effort only benefits the employer (Bandiera et al., 2011). Our understanding of incentives for prosocial behaviour, especially in agricultural settings is limited. Prosocial behaviour includes a range of individual actions that not only take into account individual benefits, but also those of others. A prosocial task is, therefore, one that creates benefits enjoyed by those other than the employer and employee (Ashraf et al., 2014).

Prosocial behaviour is a function of extrinsic, intrinsic, and image motivation (Benabou and Tirole, 2006). Extrinsically motivated individuals would expend costly effort in completing a task only when provided with private material rewards. In agriculture, for example, Ben Yishay and Mobarak (2018) showed that communication within social networks about new technologies is more effective when knowledgeable individuals are incentivised with small bags of agricultural inputs. Intrinsically motivated individuals exhibit others-regarding behaviour and believe that doing something "good" for others is good (Ariely et al., 2009). Image motivation means that individuals behave the way they do in order to seek social approval of their behaviour (Gneezy et al., 2011). Insights from behavioural economics indicate that interaction of extrinsic motivation with intrinsic and image motivation may create potential crowding-in or crowding-out effects suggesting the need to consider the three types of motivations in analysing prosocial behaviour (Benabou and Tirole, 2006; Ariely et al., 2009; Gneezy et al., 2011).

A few authors have examined the effect of the three types of motivation on prosocial behaviour. Ashraf et al. (2014) studied the diffusion of a health intervention—condoms—and found that altruism, material rewards, and image motivation influenced effort to sell condoms in Zambia. Very few studies have examined incentive effects on worker performance in agricultural settings (Bandiera et al., 2005; Ben Yishay and Mobarak, 2018). Empirical evidence on the effect of altruism and image motivation on prosocial behaviour in agriculture is missing.

Chapter 2 distinguished between private material rewards and social recognition and generated an incentive-compatible measure of altruism using an auxiliary lab-in-the field experiment. The chapter studies the incentive effects on the diffusion of agricultural knowledge from randomly selected and trained disseminating farmers (DFs) to their neighbours. We learnt that both material rewards and social recognition induced DFs to expend costly effort to communicate with their neighbours about the new technologies, but only social recognition influenced the likelihood of DFs to experiment with the technologies. Without incentives, altruistic DFs did not communicate with their neighbours about the new technologies.

The main policy implication of these findings is that efforts promoting the diffusion of agricultural technologies through social networks would benefit from carefully selecting a subset of individuals in the target population, and providing direct training and incentives to them hence encouraging communication with neighbours. Several studies have recently indicated that without incentives communication within social networks may be sub-optimal (Kondylis et al., 2017; Ben Yishay and Mobarak, 2018). Kondylis et al. (2017), for example showed that although direct training of contact farmers increased their own knowledge and experimentation with new agricultural technologies, this did not translate into improved knowledge and adoption rates of other farmers. In discussing their results, the authors indicate that lack of incentives was an impediment to technology diffusion. One of the main reasons attributed to the failure of national extension systems in developing countries is the high cost of implementation (Anderson and Feder, 2007). We show that recognising the effort of DFs in public has a similar effect in inducing communication effort as does private material rewards, and even greater impact on experimentation with agricultural technologies.

The findings further imply that when networks are dispersed and benefits associated with a technology are heterogeneous, incentives matter even to the most altruistic disseminating farmers. Heterogeneity of benefits depends not only on the biophysical environment, but may also be caused by differences in the quality of agricultural inputs. Bold et al. (2017) showed a large presence of adulterated agro-inputs in Uganda which depressed yields and discouraged investment by farmers. The aggregate uncertainty introduced by fake seeds may lead to 'incorrect herds' when the inferior technology is chosen in the long run with positive probability (Monzón, 2017). Designing optimal incentives for prosocial behaviour in agricultural settings will, therefore, require a better understanding of the context in which farmers operate and addressing market imperfections related to poor quality of inputs.

6.2.2 Social distance and information exchange

Homophilous individuals have a tendency to associate disproportionately with others who are similar to themselves (Lazarsfeld and Merton, 1954). Although studies that examine social learning in agriculture recognise this fact, very few have actually empirically examined the correlation between social distance and information exchange. The studies that have attempted to address this gap have generated inconclusive evidence on the effect of social distance on communication within networks. Whereas the general conclusion so far is that individuals tend to learn more from neighbours with whom they have similar characteristics or face similar agronomic constraints (Munshi, 2004; Bandiera and Rasul, 2006; Santos and Barrett, 2010; Magnan et al., 2015; Ben Yishay and Mobarak, 2018), some authors have shown that information diffusion only diminishes if the social distance is excessive (Feder and Savastano, 2006). But does social distance matter in agricultural knowledge and technology diffusion when the community is involved in selecting "perceived" representative disseminating farmers (DFs) and when the thus selected DFs are provided with direct agricultural training?

Chapter 3 of this thesis attempts to answer this question. We learn that social distance matters for information exchange even when the community itself is involved in the selection process of the DFs. There is an increased likelihood of information exchange from female DFs, regardless of the sex of the recipient neighbour. We further find that the likelihood of information exchange increases when the difference between DFs and their neighbours in farm size cultivated with maize is greater than the median distance in the sub-village. In terms of wealth, results show an 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. Information exchange links with trained DFs increased knowledge for improved varieties and conservation farming basins, but only increased adoption for improved varieties.

In terms of policy, the findings of *Chapter 3* suggest that including more female "seed nodes" among individuals selected to help with communication about new agricultural technologies will enhance diffusion by increasing outreach to both male and female farmers. In Mozambique, for example, Kondylis et al. (2016) found that female farmers were more likely to visit male messenger demonstration plots monthly only in communities with female messengers. Involving the community in selecting DFs may increase trust in the motive and competence (Buck and Alwang, 2011) of female messengers subsequently increasing acceptance of their messages among men and women. As indicated by Kondylis et al. (2016), female messengers may increase female farmer awareness of the technology and hence their demand for information—consistent with women becoming empowered in the presence of female leadership (Chattopadhyay and Duflo, 2004).

If the positive correlation between farm size under maize and information exchange can be interpreted to imply more experience in cultivating the crop, targeting experienced DFs may enhance social learning. Indeed, Barrett and Santos (2010) showed increased likelihood of information exchange within networks when the messenger was more experienced in farming. Furthermore, DFs whose endowment of assets is close to that of co-villagers may be more effective to disseminate agricultural technologies because their messages are likely to be relevant to the decision-making of their neighbours. Those with a greater endowment might, however, cover experimentation costs hence have an increased ability to demonstrate use of the technologies. As indicated by Feder and Savastano (2006), however, information exchange may stop if social distance is excessive. Future research should, therefore, examine the non-linear impacts of these variables on information exchange when the distance is excessive.

The finding that increased knowledge did not translate into increased adoption of conservation farming basins imply that additional constraints might exist. Technologies that mean simply substituting a new variety into an existing production system require little overall change (although albeit some extra investment). Farmers are likely to face many more barriers in adopting technologies that require a major change in the production system – these barriers can be lack of knowledge, a reluctance to change if the benefits are not clear – as well as extra investment required in labour or inputs. Several studies have indicated that if not accompanied with increased application of herbicides, implementation of conservation farming might be labour burdensome (Andersson and Giller, 2012; Andersson and D'Souza, 2014; Giller et al., 2015; Rusinamhodzi, 2015; Brown et al., 2017a, 2017b). In Nwoya district, use of herbicides is very low. Efforts promoting climate-smart agricultural technologies must, therefore, take into consideration that appropriateness of such technologies will not only depend on their potential to address climatic shocks but also possible trade-offs related to increased labour-burdens. In other words, what is perceived as "climate-smart" might not be "farmer-smart".

6.2.3 Information networks, incentives, and adoption of agricultural technologies

An extensive body of work has studied network effects on adoption of agricultural technologies (Besley and Case, 1993; Foster and Rosenzweig, 1995; Udry and Conley, 2001; Bandiera and Rasul, 2006; Matuschke and Qaim, 2009; Conley and Udry, 2010; Krishnan and Patnam, 2013). The main finding of most of these studies is that having an adopter in one's own network enhances his or her likelihood of adopting a technology. But what mechanisms drive network effects on adoption? Does incentivised training of disseminating farmers (DFs) play a role in influencing the networks of their neighbours? Given that incentives not only increase the likelihood of DFs adopting drought-tolerant maize varieties (DTMVs) but also change their own networks (*Chapter 2* of this thesis), does having an adopter DF as a contact for agricultural advice influence the adoption decisions of the neighbours? If so, do networks influence adoption by transferring the adoption decision of the DFs or through knowledge diffusion?

In *Chapter 4*, the thesis turns to the questions mentioned above. We learn that incentivised training of DFs changes networks of neighbours, and that this change in networks subsequently enhances the likelihood of neighbours adopting DTMVs by transferring the adoption decisions of DFs and through diffusion of knowledge about the varieties.

Two main policy implications can be drawn from these results. First, our study suggests that providing direct training about DTMVs to a subset of farmers and relying on social networks to rapidly multiply their effect on knowledge by others can be an effective strategy to increase the adoption of the varieties in similar contexts. Nudging such individual "seed nodes" to adopt the varieties can make a significant difference in adoption by others. Second, our finding that farmers' networks transfer adoption decisions of the 'seed nodes' suggests that encouraging a subset of individuals in the population to take-up a new technology with the hope that others will follow their behaviour might actually achieve expected outcomes. This is consistent with the idea of observational learning (Bandiera and Rasul, 2006; Conley and Udry, 2010). In the current context, however, individuals learn from their peers who are selected to be representative of the community.

6.2.4 Technology adoption, downside risk, food security, and resilience

There has been tremendous progress in understanding farmers' adoption behaviour in developing countries. Among factors identified as determinants of adoption of agricultural technologies include informational constraints (*Chapter 2* and *Chapter 3* of this thesis, Foster and Rosenzweig, 1995; Conley and Udry, 2010; Vasilaky and Leonard 2018), inconsistent preferences for time (Duflo et al., 2011), profitability (Suri, 2011) and appropriateness (Emerick et al., 2016) of the technology, quality of agricultural inputs (Bold et al., 2017), the degree of risk aversion, credit constraints, and access to markets. Similarly, another vast strand of literature has examined impacts of agricultural interventions on productivity and households' welfare (Kassie et al., 2011; Asfaw et al., 2012; Shiferaw et al., 2014). Only few studies, however, take into account climatic factors when assessing adoption and impacts of agricultural technologies (Di Falco and Veronessi, 2013; Arslan et al., 2015; 2017).

Under conditions characterized by increasing climatic shocks, the suitability of agricultural technologies can be assessed through its impacts on not only food security but also downside risks and resilience of livelihoods. A natural starting point in assessing impacts of agricultural technologies under climatic shocks is to consider yields. This is because for many households in developing countries, especially in sub-Saharan Africa (SSA), higher yields tend to correlate with improved food security status of households which in turn contributes to labour productivity. Furthermore, higher yields might imply an increase in marketable surpluses and hence income. As most households in SSA tend to spend a larger share of their budgets on food, increased income might indicate an improvement in food security through lower food prices. Frequent occurrence of climatic shocks, however, means that it might not be enough to produce more yields. Efforts must be made to promote interventions that ensure stable yields while reducing the probability of crop failure—that is, minimizing downside risks.

In *Chapter 5*, the thesis first examines the correlation between climate variables and the likelihood of adopting drought-tolerant maize varieties (DTMVs) and maize-legume intercropping (MLI). The impacts of DTMVs and MLI on yield and downside risk, food security, and resilience of livelihoods are then evaluated. We learn that there is a positive correlation between farmers' perceptions about rising temperature and the likelihood of adopting DTMVs, on one hand, and a negative correlation between the total amount of seasonal rainfall and the probability of practicing MLI, on the other hand. Whereas both DTMVs and MLI increased mean yields and reduced the variance of yields, only the former technology had a statistically significant impact under climatic shocks. Neither DTMVs nor MLI, however, significantly reduced downside risk although both technologies substantially increased food security and enhanced resilience of livelihoods.

The findings of *Chapter 5* provide several important implications for policy. Firstly, promoting adoption of DTMVs and MLI could help farm households to adapt to climatic shocks. We found a strongly positive correlation between agricultural knowledge and the probability of adopting DTMVs suggesting the need for increased investment in knowledge diffusion. Secondly, interventions to address drought stress through crop genetic improvements will have a paramount role to play in terms of increasing yields, reducing variability in yields, improving food security, and enhancing resilience of livelihoods. Thirdly, although resilience increased with adoption of DTMVs and MLI, failure of both technologies to address downside risk suggests the need to identify and promote complementary interventions in order to minimize trade-offs. Future research should, therefore, help to fill this gap.

6.3 Concluding remarks and implications for future research

The role of agriculture in economic development has greatly evolved. The evolution is largely as a result of rapidly changing contexts characterised by climate change, increasingly integrated value chains, changing dietary patterns, and globalization. Consequently, agriculture in most developing countries, is now increasingly seen as contributing towards several dimensions of economic development. These include, among others, accelerating economic growth at early stages of development, reducing poverty and vulnerability, narrowing rural-urban income disparities, releasing scarce resources such as water and land for use by other sectors, and delivering a multiplicity of environmental services (Byerlee et al., 2009; de Janvry and Sadoulet, 2010).

The capacity of agriculture to deliver on these roles will require technological innovations and hence finding ways to accelerate adoption of agricultural technologies is an imperative. This thesis explored the role of incentives and social learning in the diffusion of agricultural technologies increasingly promoted under the rubric of climate-smart agriculture (CSA) because of their perceived potential to increase yields and hence food security, enhance resilience to climatic shocks, and contribute mitigation co-benefits where possible. The thesis has shown that incentives matter in the diffusion of CSA technologies through social networks and that such technologies have an important role to play in improving food security and increasing resilience of livelihoods.

While, to our knowledge, the thesis provides first evidence on the effect of intrinsic, extrinsic, and image motivation on the diffusion of agricultural knowledge and technologies, a number of issues remain. First, the social recognition treatment group of the experiment publicly announced the performance of the disseminating farmers and awarded the *community* a material reward. Would the results have been different if we only announced the "good" performance of the disseminating farmers? Second, limited by statistical power, the experiment provided training to all disseminating farmers but varied the incentive for communication effort. We do not know what the results would have looked like had we included a pure control without training. Third, the thesis focused on the effect of incentivising disseminating farmers, but the question remains whether and how first order beneficiaries can in turn be incentivised to reach out to second-order beneficiaries, and so on.

Similarly, we find a win-win situation where the technologies increased food security and enhanced resilience. However, we made no attempt to look at mitigation—for obvious reasons that the time duration of the study was too short to measure changes in greenhouse gas emissions in a meaningful way. Our finding that downside risk did not reduce suggests a possibility of trade-offs within a specific dimension of CSA, in the current case, the food security dimension. Taking mitigation into account would, however, enhance our understanding of the trade-offs and synergies across the three dimensions of CSA, namely food security, resilience, and mitigation. We hope future research will address these caveats.

My final reflection relates to the external validity of the findings of this thesis. Specifically, to what extent are results generated from one experiment in a single locality in Uganda applicable to other contexts in sub-Saharan Africa (SSA). Firstly, the problem of weak extension systems is not unique to Uganda—most countries in SSA face a similar problem. Secondly, our results about incentives effects on social learning agree with those of Ben Yishay and Mobarak (2018) whose context and sample summary statistics were very close to those of this thesis. Furthermore, recent studies conducted in other parts of SSA including, for example, Kondylis et al. (2017) have recognised the role of incentives in social learning. Hence, I believe that the lessons derived from this research are applicable and relevant to many similar contexts in SSA.

Related to this final reflection is that artefactual field experiments remain an abstraction of reality. Still, lab-in-the field experiments were used in this thesis. Why? To the extent that people's behaviour in an experimental setting predicts their real life behaviour (see for example, Armantier and Boly, 2012), they enhance our understanding of how decisions are made in real life (Beekman, 2015). By implementing lab-in-the-field experiments, this thesis contributes to enhanced understanding about how prosocial preferences influence decision making at the individual level. This approach also lends credibility to the identification of causal effects of prosocial preferences on agricultural knowledge and technology diffusion.

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Summary

This thesis examines the effect of incentives on the diffusion of agricultural technologies through social learning, and evaluates the subsequent impacts of adoption on yield and food security, downside risks, and resilience of livelihoods in the post-conflict northern Uganda. The thesis fits in three broader strands of literature: (1) empirical work on the relationship between social learning and adoption of new technologies; (2) the role of incentives on communication within social networks and prosocial behaviour; (3) impacts of agricultural technologies on productivity, food security, and resilience of rural livelihoods under increasing climatic shocks.

Chapter 1 presents an overview of the importance of technological innovations on agricultural development under increasingly changing climate, highlights the key concepts in the thesis, namely incentives, social learning, productivity and food security, downside risk, and resilience, and describes the research problem. This discussion logically leads to a formulation of the research questions guiding the main chapters of the thesis. Specifically, the research questions include: What effects do prosocial preferences, private material rewards, and social recognition have on the diffusion of agricultural knowledge and technologies (*Chapter 2*)? What is the relationship between social distance and the probability of information exchange between trained disseminating farmers (DFs) and their peers (*Chapter 3*)? What are the effects of adoption of recommended climate smart agricultural (CSA) technologies on yields and food security, downside risk, and resilience of livelihoods (*Chapter 4*)? What mechanisms explain network effects on adoption of CSA technologies (*Chapter 5*)?

In *Chapter 2*, the effects of incentives on agricultural knowledge and technology diffusion are examined. In each sub-village and for all the DFs who attended full training, each DF was paired with one neighbour randomly selected from the list of 10 households interviewed at baseline. In addition to the data from the RCT, an augmented dictator game was used to measure prosocial preferences of the DFs. Results showed that both private material rewards and social recognition increased (by the same magnitude) the effort expended by the DFs to communicate with their neighbours about the technologies, but only social recognition influenced experimentation by the DFs. Unless incentivised, altruistic DFs did not share knowledge with their neighbours. The results provide evidence that incentives matter in agricultural knowledge and technology diffusion via social learning even among the most altruistic DFs.

In *Chapter 3*, quasi-experimental approaches are used to study the correlation between information exchange and social distance, and the subsequent impacts on neighbours' awareness, knowledge, and technology adoption. Results show that female DFs are more likely to share information with their neighbours—both male and female. Distance in ownership of agricultural assets and the size of farm cultivated with maize and also correlated with an increased probability of information exchange. Information exchange increased awareness and knowledge of the neighbour about CSA technologies, but the increase in knowledge only translated in increased up-take of drought-tolerant maize varieties.

In C*hapter 4*, the mechanisms through which social networks influence adoption of agricultural technologies are tested. Combining experimental data from the RCT with detailed social networks survey data, the chapter assesses the effect of incentives on neighbours' information exchange networks, and how changes in networks influence neighbours' knowledge and adoption decision. Results show that social networks influence adoption of drought-tolerant maize varieties through the diffusion of knowledge and by transferring information about the adoption decisions of the DFs.

Chapter 5 examined the correlation between climate variables and the likelihood of growing drought-tolerant maize varieties (DTMVs) and maize-legume intercropping (MLI). The chapter further quantifies the impacts of DTMVs and MLI on yields, downside risk, food security, and resilience of livelihoods. The results indicate that farmers' perceptions about rising temperature correlates with an increased probability of growing DTMVs whereas an increase in total seasonal rainfall correlates with a reduced likelihood of implementing MLI. Adoption of DTMVs increased yields and reduced variance of yields with climatic shocks. Both DTMVs and MLI improved food security and enhanced resilience of livelihoods, but the effect on downside risk was not statistically significant. The findings suggest that both technologies are promising adaptation strategies for farmers and highlight the need to find complementary interventions that would help to address downside risk.

Finally, *Chapter 6* presents a synthesis of the core chapters. The main findings are discussed and insights for policy implications as well as future research discussed. The thesis concludes with a few general remarks.

Samenvatting

Dit proefschrift onderzoekt het effect van prikkels op de verspreiding van landbouwtechnologieën door middel van sociaal leren. Ook evalueert het het effect van eventuele adoptie op opbrengst en voedselzekerheid, financiële risico's en veerkracht in het noorden van Oeganda, waar conflict heeft plaatsgevonden. Het proefschrift past in drie delen van de literatuur: (1) empirisch werk over de relatie tussen sociaal leren en de adoptie van nieuwe technologieën; (2) de rol van financiële prikkels voor communicatie binnen sociale netwerken en sociaal gedrag; (3) Het effect van landbouwtechnologieën op de productiviteit, voedselzekerheid en veerkracht van het boeren tijdens klimaatverandering.

Hoofdstuk 1 geeft een overzicht van het belang van technologische innovaties voor landbouwontwikkeling tijdens klimaatverandering, benadrukt de kernbegrippen in het proefschrift, namelijk prikkels, sociaal leren, productiviteit en voedselzekerheid, financiële risico's en veerkracht, en beschrijft het onderzoeksprobleem. De discussie leidt logischerwijs tot een formulering van de onderzoeksvragen die de kern zijn van de belangrijkste hoofdstukken van het proefschrift. Concreet zijn de onderzoeksvragen: welk effect hebben sociale voorkeuren, beloningen en sociale erkenning op de verspreiding van agrarische kennis en technologieën (hoofdstuk 2)? Wat is de relatie tussen sociale afstand en de waarschijnlijkheid van informatie-uitwisseling tussen opgeleide verspreidende boeren (VB's) en andere boeren(hoofdstuk 3)? Welke mechanismen verklaren netwerkeffecten bij de toepassing van KSL-technologieën (hoofdstuk 4)? Wat zijn de effecten van de toepassing van aanbevolen klimaat slimme landbouwtechnologieën (KSL) op opbrengsten en voedselzekerheid, financiële risico's en veerkracht van kostwinning (hoofdstuk 5)?

In Hoofdstuk 2 worden de effecten van prikkels op agrarische kennis en technologiediffusie onderzocht. In elk subdorp en voor alle VB's die volledige training volgden, werd elke VB samen gezet met één buur die willekeurig was geselecteerd uit een lijst met 10 eerder geïnterviewde huishoudens. Naast de gegevens van de RCT werd een uitgebreide dictator game gebruikt om de sociale voorkeuren van de VB's te meten. De resultaten toonden aan dat zowel fysieke beloningen als sociale erkenning de inspanningen vergrootte (met dezelfde omvang) die de VB's gebruikten om met hun buren over de technologieën te praten, maar alleen sociale erkenning beïnvloedde experimenteren door de VB's. Tenzij gestimuleerd, deelden altruïstische VB's geen kennis met hun buren. De resultaten leveren bewijs dat prikkels van belang zijn in landbouwkundige kennis en technologische diffusie via sociaal leren, zelfs bij de meest altruïstische VB's.

In Hoofdstuk 3 worden quasi-experimentele methodes gebruikt om de correlatie tussen informatie-uitwisseling en sociale afstand te onderzoeken, en het effect daarvan op het bewustzijn, de kennis en de technologie-acceptatie door buren. De resultaten laten zien dat vrouwelijke VB's vaker informatie delen met hun buren, ongeacht het geslacht van de ontvanger. Afstand tot de boerderij en de grootte van de maisboerderij zijn ook gecorreleerd met een verhoogde kans op informatie-uitwisseling. Informatie-uitwisseling verhoogde het bewustzijn en de kennis van de buurman over KSL-technologieën, maar de toename van kennis vertaalde zich alleen in een toename van het gebruik van droogte-tolerante maisvariëteiten.

In Hoofdstuk 4 worden de mechanismen getest waarmee sociale netwerken de adoptie van landbouwtechnologieën beïnvloeden. Door de combinatie van experimentele gegevens van de RCT met gedetailleerde sociale netwerkgegevens, beoordeelt het hoofdstuk het effect van prikkels op de informatie-uitwisselingsnetwerken van buren en hoe veranderingen in netwerken de kennis en adoptiebeslissingen van buren beïnvloeden. Uit de resultaten blijkt dat sociale netwerken de adoptie van droogtetolerante maisvariëteiten beïnvloeden door de verspreiding van kennis en door informatie over de adoptiebeslissingen van de VB’s over te dragen.

Hoofdstuk 5 onderzoekt de correlatie tussen klimaatvariabelen en de waarschijnlijkheid van het gebruik van droogtetolerante maïsvariëteiten (DTMV's) en mais-peulvruchten combinatieteelt (MPC). Het hoofdstuk kwantificeert de impact van DTMV's en MPC op het rendement, het financiële risico, de voedselzekerheid en de veerkracht van de kostwinning. De resultaten geven aan dat de perceptie van boeren over stijgende temperatuur correleert met een verhoogde kans op het groeien van DTMV's, terwijl een toename van de totale seizoensgebonden regenval correleert met een verminderde waarschijnlijkheid van het implementeren van MPC. Gebruik van DTMV's verhoogde opbrengsten en verminderde variatie van opbrengsten tijdens klimaatschokken. Zowel DTMV's als MPC verbeterden de voedselzekerheid en verbeterde de veerkracht van de kostwinning, maar het effect op het financieële risico was niet statistisch significant. De bevindingen suggereren dat beide technologieën veelbelovende strategieën voor boeren zijn en benadrukken de noodzaak om aanvullende strategieën te vinden die zouden helpen om het financiële risico verminderen.

Tenslotte presenteert hoofdstuk 6 een synthese van de kernhoofdstukken. De belangrijkste bevindingen, een aantal beleidsimplicaties en toekomstig onderzoek worden besproken. Het proefschrift concludeert met een aantal algemene opmerkingen.

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Completed Training and Supervision Plan

Name of the learning activity	Department/Institute	Year	ECTS*
A) Project related competences			
Advanced Microeconomics (ECH 32306)	Wageningen University	2015	6
Advanced Macroeconomics (ENR 30806)	Wageningen University	2014	6
Advanced Econometrics (AEP 60306)	Wageningen University	2016	6
Experiments in Developing Countries: Methods and Application	University of Groningen	2016	2
B) General research related competences			
WASS Introduction Course	WASS	2014	1
Research Proposal	WASS	2014	6
Techniques for Writing and Presenting a Scientific Paper	Wageningen Graduate School	2015	1.2
Reviewing a Scientific paper	Wageningen Graduate School	2017	0.1
'Incentives and the Diffusion of Agricultural Knowledge: Evidence from a Randomized Evaluation in Northern Uganda'	XV European Association of Agricultural Economists Congress (EAAE), Parma, Italy	2017	1
'Information Exchange Links, Knowledge Exposure, and Adoption of Agricultural Technologies in Northern Uganda'	30th Conference of the International Association of Agricultural Economists (ICAE), Vancouver, Canada	2018	1
C) Career related competences/personal development			
Interpersonal Communication for PhD students	Wageningen Graduate School	2018	0.6
Project and Time Management	Wageningen University	2018	1.5
Total			**32.4**

*One credit according to ECTS is on average equivalent to 28 hours of study load

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