

**Social Networks, Technology Adoption and Technical Efficiency in
Smallholder Agriculture: The Case of Cereal Growers in Central Tanzania**

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Summary

Global demand for food and agricultural products is on the rise. There is hence the need to increase production to meet this growing demand and smallholders will play a significant role. One strategy for smallholders to sustainably increase agricultural production is the use of modern productivity-enhancing technologies such as improved crop varieties. Investments in global agricultural research have resulted in the development and release of thousands of new varieties since the first Green Revolution. However, especially in Sub-Saharan Africa, traditional varieties still dominate smallholder farming, limiting the envisaged output and productivity gains. Lack of agricultural information is often cited as a major constraint to adoption of improved varieties, and the role of social networks in diffusion of information relevant for adoption of these varieties is increasingly being studied.

This research contributes to the growing literature by looking at a number of elements that to the best of our knowledge have not been studied before. First, most studies on social network effects in agricultural technology diffusion tend to focus on networks within villages (intra-village networks). In this study, we look at effects of social networks across villages (intra-village networks) as well. Furthermore we explore other types of networks, in particular to community leaders (village administrators), who are part of formal information dissemination channels. Second, while the role of social networks in cereal farming has been investigated in the context of well-developed private seed markets, we do not find any studies assessing the role of social networks in situations where seed markets are underdeveloped. This study investigates effects of social networks in two contexts: one with developed seed markets and the other with frequently failing seed markets. Third, studies linking social networks to new agricultural technologies tend to focus on technology diffusion. However, information conveyed through social networks might also affect other farming practices and hence we investigate also the effects of social networks on technical efficiency.

The main objective of this dissertation is to assess social networks and their explicit role in technology adoption and technical efficiency in smallholder agriculture. Using data collected from 345 cereal growers in Central Tanzania between September and November 2012, we focus on improved varieties of sorghum and maize, the staple cereals in the study area. Improved varieties of sorghum in Tanzania are characterized by underdeveloped private seed markets, while those of maize have mostly functioning private seed markets. This enabled us to make interesting comparisons that have not been made before. Our specific objectives are (1) to assess the factors that determine the existence of network links for the

exchange of agricultural information between farmers, (2) to examine the role of social networks in exposing farmers to improved sorghum and maize varieties and hybrids (as a precondition for adoption of the technologies), (3) to assess the effects of social networks on adoption of improved varieties, and (4) to investigate the role of social networks for technical efficiency. In addition to descriptive analyses, a number of econometric tools were developed and used to achieve the objectives. These include dyadic regressions to identify determinants of network links, Poisson regressions to assess exposure to improved varieties, and the average treatment effect (ATE) framework to analyze adoption while controlling for non-exposure bias. To analyze technical efficiency, a stochastic frontier framework was applied. Propensity score matching techniques were used to control for endogeneity in the stochastic frontier analysis.

We find that even at the lowest administrative unit, the sub-village, not all farmers know each other. Interestingly, even in the cases where farmers know one another, only about one third of randomly drawn pairs of such farmers exchange agricultural information. The exchange of relevant information is more likely between farmers who have similar levels of education, different farm sizes, are members of the same community association, live in the same village, have known each other for a longer time, have kinship ties, and if one of them is a community leader or has a direct link to a public extension officer. These patterns are almost the same for sorghum and maize, meaning that if farmers exchange farming information, they are unlikely to limit this exchange to certain crops.

Farmer-to-farmer networks are important sources of first information on improved sorghum and maize varieties, with neighbors and friends playing a bigger role than relatives. Moreover, controlling for other farmer characteristics, we find that increasing the size of a farmer's network increases the farmer's intensity of exposure (number of varieties known) to improved varieties of sorghum, but not to those of maize. Further disaggregation of maize varieties shows that while larger social networks increase farmers' exposure to open pollinated varieties (OPVs), the result remains insignificant for hybrids. Seed markets for hybrids are more developed than those of OPVs. Hence, the flow of information through informal networks is more important for seed technologies for which formal markets fail. Strikingly, inter-village networks play a larger role in creating awareness about new varieties than intra-village networks. Other results show that by networking with public extension officers and village administrators, farmers increase their exposure to improved varieties considerably. We conclude that informal information channels complement, but do not substitute awareness creation through formal channels.

Consistent with expectations, we find evidence that for both crops, lack of exposure is indeed a constraint to the adoption of improved varieties, signaling a need to create more awareness. Interestingly, even after accounting for the role of social networks in exposure, and controlling for the intensity of exposure, we find that social networks for sorghum have a positive effect on variety adoption. We do not find significant social network effects on adoption of improved maize varieties, implying that the influence of social networks on adoption is greater for improved varieties whose markets often fail. Contrary to the influence of social networks on exposure, it is the intra-village and not inter-village networks that produce this effect in the case of sorghum. It means that while inter-village networks are more important for learning about new varieties as shown above, intra-village networks play a more important role in adoption. Network links with village administrators or extension officers do not influence adoption significantly, meaning that in the adoption process, formal channels are more relevant for the first step, which is, raising awareness.

Finally, while the total and intra-village network sizes do not significantly influence technical efficiency, the inter-village sorghum network size has a positive effect on technical efficiency of improved but not of traditional varieties of sorghum. When comparing between improved varieties of the two crops, we conclude that social network effects are more relevant for varieties that do not have functioning private seed markets, consistent with the findings for exposure and adoption. Networking with village administrators did not have any significant effect on technical efficiency, but having links to the public extension officers and attending technology and information dissemination events organized through the officers had a positive effect on technical efficiency for improved varieties of maize. This shows that efficiency-enhancing production information for the largely commercialized seed technologies may be much more technical, hence requiring more specialized dissemination.

The findings raise a number of implications for policy and future research. First, social networks matter for the spread and efficient utilization of new agricultural technologies. Hence, technology dissemination programs should try to make use of such networks. Second, inter-village networks matter for farmers' exposure to and technical efficiency of improved varieties; hence facilitation of information exchange across village boundaries may improve awareness creation and the spread and productivity of new technologies. Third, the power of farmer networks with community leaders and village administrators can be exploited for increased awareness of improved technologies. Fourth, extension officers facilitate discussions about crop farming, and help in increasing awareness and technical efficiency of improved technologies. Therefore, new extension models could be

developed that explicitly build on the synergies between formal and informal information channels.

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1. General Introduction

1.1 Background

Global demand for food and agricultural products is on the rise as human population and incomes increase (FAO, 2014). Moreover, food insecurity remains a major development challenge for many agrarian economies, especially in Sub-Saharan Africa (World Bank, 2007). Projections show that aggregate agricultural production should increase by about 60% between 2005/2007 and 2050 to meet the world's consumption demand (Alexandratos and Bruinsma, 2012). Such increase calls for growth in productivity, implying that available production resources would have to be used much more efficiently. Smallholders, who form the majority of farmers around the world, will play a significant role in this regard (FAO, 2014). By increasing their production, smallholders will improve not only the availability of food and agricultural products, but also their incomes and those of others employed directly or indirectly by the agriculture sector. This will contribute further to poverty reduction in rural areas of developing countries, where farming is the main source of livelihood.

1.2 The role and adoption of improved technologies

One strategy for increasing agricultural productivity is the development and use of modern technologies such as improved crop varieties (ICVs) (World Bank, 2007). Studies show that ICVs account for 50-90 percent of global crop yield increase (Bruins, 2009), can increase farmer's incomes and also reduce rural poverty (Krishna and Qaim, 2008; Alene *et al.*, 2009; Nguetzet *et al.*, 2011). Since the Green revolution, investments in global agricultural research have seen the development and release of thousands of ICVs for cultivation by farmers (CGIAR, 2011). However, especially in the predominantly smallholder farming communities in Sub-Sahara Africa, the adoption of improved varieties remains relatively low (Gollin *et al.*, 2005; Smale *et al.*, 2011). Recent estimates show that improved varieties of 20 key crops grown by farmers in Africa occupy just about 35% of the area cultivated with the crops (Walker *et al.*, 2014). The low use of improved variety limits envisaged productivity gains for farmers, especially in this region, where crop productivity and productivity growth have been low relative to global trends and the continent's population growth (Rakotoarisoa, Iafrate and Paschali, 2012).

Lack of farmer exposure to new varieties has been identified as one major constraint for wider adoption (Doss *et al.*, 2003; Diagne, 2006; Simtowe *et al.*, 2011; Kabunga *et al.*,

2012). The argument in these studies is that farmers cannot adopt technologies that they are unaware of, in the first place. Such lack of exposure may surprise, given that variety development and testing often involve farmer participation (Bellon and Reeves, 2002; Heinrich and Mgonja, 2002). The philosophy behind participatory breeding approaches is that the farmers involved would adopt superior varieties themselves and further disseminate information and seeds through their social networks, leading to wider diffusion and adoption.

1.3 Social networks and their potential role in agriculture

A social network is a set of actors that have relationships with one another (Marin and Wellman, 2011). Social networks are seen as an important mechanism for the spread of information and technology (Baerenklau, 2005). The theory of social networks has been applied to study general behavior, as well as outcomes that have social and economic implications, such as employment, prices and firm productivity and profitability (Granovetter 2005, Borgatti *et al.*, 2009 and Kimura, 2011). In the recent past, there has been growing interest in the use this theory to assess participation in and impacts of development initiatives, such as health programs, and adoption and diffusion of technological innovations (Dufhues *et al.* 2006).

Social networks can influence diffusion and productivity of agricultural technologies by providing an opportunity for farmers to gather more information about the technologies from each other – through social learning, or merely copying their colleagues (Young, 2009). The networks help to reduce risks associated with adoption of new technologies by providing information on how to use the technologies and the expected benefits (Kimura, 2011). This can be especially useful in contexts where agricultural extension services or technology and information markets are weak or missing. In many developing countries, the lack of seeds has often been cited as a key constraint to adoption of improved varieties (Asfaw *et al.*, 2011). Moreover, for some crops, improved varieties lack reliable seed markets. In these contexts, social networks could facilitate awareness and adoption of improved varieties when farmers share information and seeds with their fellows (Tripp, 2006).

The exchange of information on farming practices and trust between small-holders can also influence behavior of farmers with respect to the choice of other farming practices, resulting in changes in the use of available resources and consequently technical efficiency and productivity. For instance, information and trust could influence farmers to adjust the type and timing of crop husbandry methods used, such as seedbed preparation, sowing, and management of soil fertility, pests and diseases, factors that as Bindraban *et al.* (2009) show,

have great influence on agricultural productivity in Sub-Saharan Africa. Christoplos (2010) demonstrates that extension services to smallholders will play a critical role if the farmers are to increase their productivity and meet the demand for food and agricultural products in 2050. Moreover, Anandajayasekeram *et al.* (2008) argue that future agricultural extension services will be more successful if the approaches employed would involve farmers as well. In this study, we hypothesize that informal information exchange through social networks can complement formal agricultural extension services. Hence, a better understanding of how social networks function, and their role in agriculture, can contribute to the design of participatory farmer advisory policies and services that improve performance of the sector.

1.4 Statement of problem

The development and use of improved crop varieties is seen as a key to increasing agricultural output and productivity. However, especially in the predominantly smallholder farming communities in Sub-Sahara Africa, adoption of improved varieties remains relatively low, limiting the envisaged productivity gains. Lack of farmer exposure to new varieties has been identified as one major constraint for wider adoption. Social networks are seen as an important mechanism for the spread of information and technology, and developers of improved varieties usually tap into these informal institutions by employing participatory breeding approaches. The philosophy underlying such approaches is that the farmers involved would adopt superior varieties and further disseminate information and seeds through their social networks. However, the concrete role of these networks is still a subject of research.

A few recent studies looked at the role of social networks in agricultural technology diffusion. In general, these studies find that social networks and social learning promote technology awareness and adoption among smallholders, but the strengths of the effect seem to vary by technology and context. Most of these studies focus on cash crops such as sunflower (Bandiera and Rasul, 2006) and pineapples (Conley and Udry, 2010), while the few that analyzed technologies in food crops focused on hybrids, for which private seed markets exist (Matuschke and Qaim, 2009). Hence, to our knowledge, the role of social networks in food crop production in contexts where seed markets are weak or missing has not been investigated. Moreover, a comparison of the role of social networks in contexts where both market conditions prevail has not been done. This analysis is of critical importance especially in Sub-Saharan Africa, where seed markets are not equally well-developed for all key crops. We hypothesize that the roles played by social networks may differ between varieties with developed markets and those without.

Strikingly, most empirical studies assessing the role of informal information in agricultural technology diffusion investigate their effects only on technology adoption, yet it has long been shown that the role of information may extend to influencing the productivity of, or efficiency with which farmers use these technologies (Müller, 1974). Technical efficiency is an important determinant of productivity differences among producers (Fried *et al.*, 2008), and understanding its drivers can help policymakers in designing programs that increase efficiency and ultimately productivity, among smallholder farmers. However, empirical literature on the concrete role of social networks in technical efficiency of crop producers is hard to find.

Furthermore, although past social network studies often report that these networks cross geographical boundaries (De Weerd, 2004; Fafchamps and Gubert, 2007), most analyses of network effects in agricultural technology diffusion tend to focus on intra-village links, ignoring inter-village networks that may play an important role. In addition to farmer-to-farmer networks, farmer links with other actors may also matter for agricultural outcomes. For instance, agricultural research and development actors in Africa usually involve community leaders and public extension staff in disseminating information about their activities and technologies (Rusike *et al.*, 2006; Saka *et al.*, 2008). While farmers with closer network ties to such leaders may be expected to have access to more information about these activities and technologies, effects of such ties have not been concretely analyzed from a social network perspective.

1.5 Objectives and justification of the study

The main objective of the study is therefore to assess social networks and their explicit role in technology adoption and technical efficiency in smallholder agriculture. We do so by using data collected from 345 cereal growers in Central Tanzania between September and November 2012, as an example (see Table 1.1 for surveyed areas). We focus on improved crop varieties, and Tanzania as one of the Sub-Saharan African countries where partnerships between national and international agricultural research institutions and private seed sector have led to development and release of many improved varieties, but where variety adoption rates and crop productivity are still low. Specifically, we look at sorghum and maize, the two main staple cereals grown in Central Tanzania. Official records from the variety list updated in 2008 show that 6 improved varieties of sorghum and 72 of maize are released in the country (Ngwediagi *et al.* 2010). In Singida and Dodoma, the two administrative regions of central Tanzania where this study was carried out, improved varieties occupy only 11% and

14% of cultivated area respectively. Moreover, average productivity of sorghum in the regions is 0.7-1.1 tons/ha while that of and maize is 1.0-1.3 tons/ha (United republic of Tanzania, 2012). This is quite low compared to potential yields of 1.6-3.5 tons/ha for improved sorghum and 3-8 tons/ha for most dryland maize varieties contained in the official variety list. Hence, studies on diffusion and productivity of improved varieties are still relevant in Tanzania.

Improved varieties of sorghum available in Tanzania are open pollinated varieties (OPVs) whose seeds farmers usually recycle and exchange among themselves, while those of maize are OPVs and hybrids. Seeds of improved maize varieties are available in the private market, but the market for hybrids is much more developed (Shiferaw, Kebede and You, 2008). Thus, with this heterogeneity in seed market conditions, interesting comparisons can be made. Moreover, farming communities in Tanzania are open, with social interactions occurring even across geographically defined boundaries (Van den Broeck and Dercon, 2011). This allows us to assess effects of social networks both within and across villages.

Our specific objectives are to:

- i. assess the factors that determine the existence of network links for the exchange of agricultural information between farmers,
- ii. examine the role of social networks in exposing farmers to improved sorghum and maize varieties and hybrids,
- iii. assess the effects of social networks on adoption of improved varieties,
- iv. investigate the role of social networks in technical efficiency.

Table 1.1: Surveyed areas

Village clusters	Ward	Villages surveyed
<i>Kondoa District</i>		
Cluster 1	Kingale	Kingale, Iyoli, Chemchem, Tampori
Cluster 2	Kwa Mtoro	Ndoroboni, Kurio, Porobanguma, Msera, Kwamtoro
Cluster 3	Sanzawa	Gumbu, Gungi, Sanzawa, Motto
<i>Singida Rural District</i>		
Cluster 1	Mungaa	Mungaa, Makiungu, Unyaghumpi
Cluster 2	Mungaa	Minyinga, Kimbwi, Kinku
Cluster 3	Ntutntu	Ntuntu, Ntewa

1.6 Outline of the study

The rest of the study is organized into three main chapters that address the study objectives, and a concluding chapter. The study is based on the same dataset and hence the sampling methods and most key variables are described in a similar manner. In Chapter 2 entitled “Social networks and farmer exposure to improved crop varieties in Tanzania”, we first define social networks and discuss measurement challenges and how they are addressed in the study. We then assess the factors that determine the existence of network links for the exchange of agricultural information between farmers, and proceed to examine the role that social networks play in exposing farmers to improved sorghum and maize varieties. Chapter 3 is entitled “Social networks and the adoption of agricultural innovations: The case of improved cereal cultivars in Central Tanzania”. Here, we critically assess what farmers know about improved varieties with respect to some key agronomic and utilization characteristics, and examine the current adoption rates and constraints. We then investigate the effects of social networks on the adoption of improved varieties, after controlling for biases arising from non-random exposure. Some of the information and results in this chapter overlap with those of Chapter 2. The analytical framework we use to assess adoption in Chapter 3 corrects for non-exposure bias, hence it was necessary to discuss exposure also in this chapter, and in a manner similar to Chapter 2, for consistency. In Chapter 4, which is entitled “Effects of social networks on technical efficiency in smallholder agriculture: The case of cereal producers Tanzania”, we investigate the role of social networks in technical efficiency, after correcting for potential selectivity problems in variety adoption. The results are compared between sorghum and maize, and between traditional and improved varieties, for each crop. Chapter 5 concludes by discussing implications of the study for policy and further research.

2. Social networks and farmer exposure to improved crop varieties in Tanzania¹

Abstract

In Sub-Saharan Africa, adoption rates of improved crop varieties remain relatively low, which is partly due to farmers' limited access to information. In smallholder settings, information often spreads through informal networks. Better understanding of such networks could potentially help to spur innovation and farmers' exposure to new technologies. This study uses survey data from Tanzania to analyze social networks and their role for the spread of information about improved varieties of maize and sorghum. Regression models show that network links for the exchange of agricultural information are more likely between farmers who have similar educational but different wealth levels. Moreover, network links are more likely when farmers have direct contacts to extension officers, suggesting that information flows through informal channels can support but not replace formal channels. Social networks play a significant role for the spread of information about open-pollinated varieties. This is not the case for maize hybrids, which are sold by private seed companies.

Key words: social networks, exposure, improved varieties, sorghum, maize, gender

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2.1 Introduction

The development and use of improved crop varieties is an important strategy to increase food production and food security. However, especially in Sub-Saharan Africa, the adoption of improved varieties remains relatively low (Gollin *et al.*, 2005; Smale *et al.*, 2011). Lack of farmer exposure to new varieties has been identified as one major constraint for wider adoption (Doss *et al.*, 2003; Diagne, 2006; Simtowe *et al.*, 2011; Kabunga *et al.*, 2012). Such lack of exposure may surprise, given that variety development and testing often involve farmer participation (Bellon and Reeves, 2002; Heinrich and Mgonja, 2002). The philosophy behind participatory breeding approaches is that the farmers involved would adopt superior varieties themselves and further disseminate information and seeds through their social networks. Hence, social networks are seen as an important mechanism for the spread of information and technology, but the concrete role of these networks has rarely been investigated.

A few recent studies looked at the role of social networks for agricultural technology diffusion (Bandiera and Rasul, 2006; Matuschke and Qaim, 2009; Conley and Udry, 2010; Hogset and Barrett, 2010; Maertens and Barrett, 2013). In general, these studies find that social networks and social learning promote technology awareness and adoption among smallholders, but the strengths of the effect seems to vary by technology and context. Most existing studies focused on cash crops such as pineapples (Conley and Udry, 2010), sunflower (Bandiera and Rasul, 2006), and cotton (Maertens and Barrett, 2013). The few studies that analyzed technologies in food crops focused on hybrids, for which formal seed markets exist (Matuschke and Qaim, 2009). As hybrid seeds are often promoted by private companies, one may expect that informal social networks are less important than for open-pollinated varieties (OPVs), for which formal seed markets frequently fail. To our knowledge, a comparison of the role of social networks between hybrids and OPVs has never been made. Moreover, previous technology-related studies primarily examined farmers' networks within villages, although social networks are known to cross geographical boundaries (Fafchamps and Gubert, 2007).

We add to the literature by looking at both intra-village and inter-village networks for the exchange of information on improved crop varieties, building on a survey of smallholders in Central Tanzania. In the study region, many farmers grow sorghum and maize, which differ in terms of technology and seed market conditions. While sorghum is only grown as OPVs, for maize, improved OPVs and hybrids are available in the market. Hence, interesting

comparisons can be made. Specifically, we address two questions. First, what factors determine network links for the exchange of agricultural information between farmers? Second, what effects do social networks have on farmer exposure to improved sorghum and maize varieties and hybrids?

2.2 Methodology

2.2.1 Conceptual framework

We define a *social network* as a set of actors or nodes (individuals, agents, or groups) that have relationships with one another (Hanneman and Riddle, 2005; Marin and Wellman, 2011). Social networks evolve due to *ties* between actors, which may arise because of kinship, affection, or familiarity between them (Easley and Kleinberg, 2010). The simplest social network is a *dyad* (pair of linked actors), in which one actor (whose network is being studied), is referred to as the *ego*, and the other as the *alter* (Smith and Christakis, 2008). This raises two fundamental questions for our study. First, what factors contribute to placing farmers in each other's information exchange network? Second, does the size and structure of the individual network influence farmers' exposure to improved crop varieties?

We illustrate the idea behind the first question using two farmers *A* (not exposed to an improved variety) and *B* (exposed). By invoking elements of *social contagion* theories, which focus on dyadic relationships in the social system (Burt, 1987), we hypothesize that there are characteristics of both *A* and *B* that position them close enough to each other (social proximity) for *A* to socially learn from *B*, thereby also getting exposed to the improved variety. We summarize these characteristics in two categories, as shown in Figure 2.1. First are similarities, such as living in same geographical location, having common membership in associations, and personal attributes such as gender, education, and wealth. In the second category, we consider social relationships, including kinship ties, friendship, and cognitive relations such as shared knowledge. These characteristics determine the nature and intensity of interactions between the ego and alter (such as doing things together, discussing issues, and advising each other) and the flow of information, beliefs, and resources necessary for exposure to improved varieties.

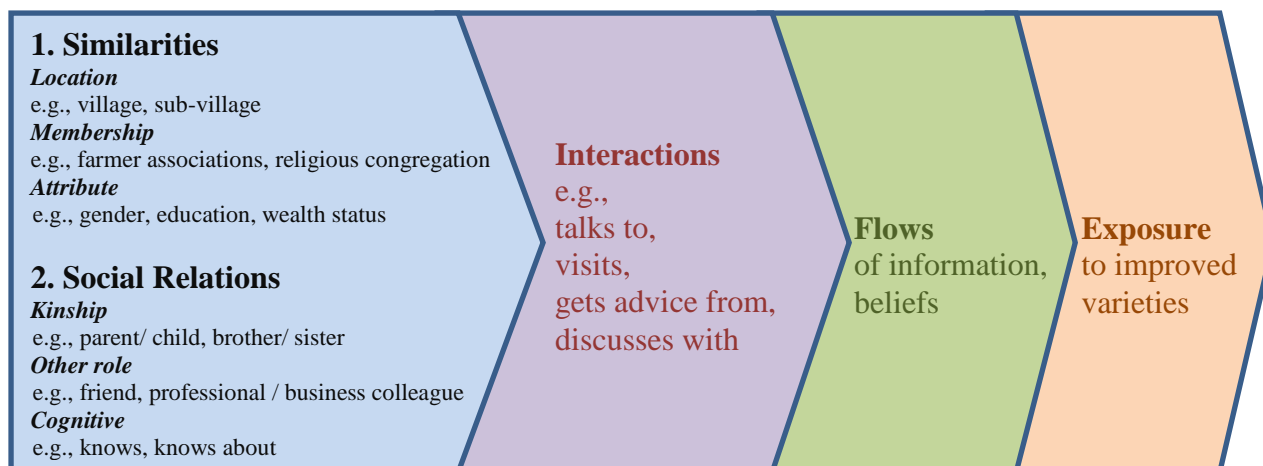


Figure 2.1: A framework for understanding drivers of learning about improved varieties

Source: Adapted from Borgatti *et al.* (2009).

To address the second question, we apply the concept of node-level properties of social networks, particularly *centrality* measures (Borgatti, 2005). These measures determine *positions* and *power* of network actors, contributing to opportunities and constraints that determine outcomes (House *et al.*, 2007; Borgatti *et al.*, 2009). Key among the centrality measures is *degree*, which refers to the number of alters to which an ego is directly connected (Newman, 2010). We hypothesize that respondents with a higher network degree occupy positions that predispose them to more learning opportunities about improved varieties; hence they are more likely to have a higher intensity of exposure than those with a lower degree.

2.2.2 Measurement of social networks

Empirical measurement of social networks is an evolving topic. When designing a network study, two particular challenges need to be addressed. The first involves selection of actors to be studied. Some researchers use a *complete network* approach, which involves a census of the population being studied (Barroga-Jamias and Brien, 1996; Goswami and Basu, 2010; van den Broeck and Dercon, 2011). While theoretically appealing, this approach is of limited practical use in studying large populations. Besides, even with a complete census, it is impossible to capture all of an individual's social links, because some may remain unreported, while others may span out of the geographical boundary (Fafchamps and Gubert, 2007; Handcock and Gile, 2010). Researchers therefore often use samples to study social networks in large populations. However, Santos and Barrett (2010) and Chandrasekhar and Lewis (2011) argue that little can be learned about the real networks if individuals in the

network are sampled, and recommend the sampling of paired actors (dyads). We follow this recommendation and use the sampling of dyads approach.

The second challenge is how to establish which actors constitute an individual's network. Three main approaches have been used in past studies. In one approach, each individual is asked to name a certain number of people with whom they interact (Barroga-Jamias and Brien, 1996; Bandiera and Rasul, 2006; Tatlonghari *et al.*, 2012). The weakness of this approach is that individuals are likely to name only persons to whom they are strongly linked, leading to estimates of network properties that are biased towards strong links. The second method, called *matches within sample*, asks each individual about their ties and interactions with every other individual in the sample, while the third approach, called *random matching within sample*, pairs each individual in the sample with only a specified number of individuals randomly selected from the sample (Santos and Barrett, 2008). The *matches within sample* approach suffers the same limitations as the census method if the sample is large (Fafchamps and Gubert, 2007). Santos and Barrett (2008) demonstrate that the *random matching within sample* approach produces parameters that represent the real network more efficiently. We use this latter approach in our study.

When using the random matching approach, there is no clear rule regarding the number of matches per respondent. More than seven random matches have rarely been used in previous studies. We paired each farmer with six others in the sample: three from the respondent's village and three from neighboring villages. Most previous studies considered only intra-village networks. We decided to also consider possible inter-village links, because social networks do not necessarily stop at village boundaries.

In the survey, respondents were asked whether they know their random matches and for how long they have known them, whether and how often they talk about agricultural issues in general and specific crop aspects in particular, and whether they have kinship ties or common membership in a group or association. In addition, respondents were asked about the frequency of interactions with village administrators (chair or other executives at village or subvillage level) and public extension officers. This was done to compare the influence of formal and informal information channels on farmers' exposure to improved varieties. Further details about the survey are presented below.

2.2.3 Estimating determinants of information exchange networks

To analyze the factors that determine information exchange networks, we use an econometric framework similar to Conley and Udry (2010) and Maertens and Barrett (2013). Following the random matching approach discussed above, each farmer i is paired with six other farmers j . We define farmer j (the alter) to be in the sorghum or maize information network of farmer i (the ego) if the two exchange information about these crops, as reported by the ego. Two different approaches can be used to elicit these kind of data (Santos and Barrett, 2008). The first, referred to as *potential network* approach, involves asking the ego whether he/she could approach the alter for information regarding the specific crop. Alternatively, in the *real network* approach, the ego is asked whether he/she has ever sought such information from the alter. Since our aim is to assess exposure to improved varieties, which is a function of actual information flows in the past, the latter approach is more useful in our context. Hence, we define j to be in i 's sorghum/maize information network if i reports that he/she discusses farming issues related to these crops with j .

For each crop, c , we estimate the following probit model to assess the determinants of an information network link in a random pair of farmers i and j (or random dyad, d):

$$P(Y_{dc} = 1 | \mathbf{x}_d) = \Phi(\beta_0 + \sum_{k=1}^K \beta_k x_{kd}) \quad d=1, 2, \dots, D \quad (2.1)$$

where, the outcome $P(Y_{dc} = 1 | \mathbf{x}_d)$ is the probability of detecting an information network link, conditional on a set of observable characteristics, \mathbf{x} , defined for each dyad, d .² Key among these characteristics are similarities in personal attributes of ego and alter (such as age, sex, education level, wealth status, and religion), membership in the same association, kinship ties, and geographical proximity. Φ is a standard normal cumulative distribution function that forces predicted probabilities to be between zero and one, β_0 and β_k are parameters to be estimated, K is the total number of explanatory variables, while D is the total number of dyads used in the regression.

A potential problem associated with estimating equation (2.1) is that the stochastic errors for each dyad are not independent (Fafchamps and Gubert, 2007; Cameron *et al.*, 2011). Given that each respondent is paired with several others, the error terms for all dyads involving the same respondent are correlated in two dimensions. The first dimension refers to

² Since matching is random, not all of a farmer's matches are necessarily known to the respondent. We do not expect a network link between matches who do not know each other; hence we restrict this regression analysis to the subsample of pairs where the respondent knows the match (Fafchamps and Gubert, 2007; Santos and Barrett, 2010).

dyads where the respondent is the ego, and the second to dyads where the respondent is the alter. We account for such correlation by clustering the probit standard errors in these dimensions, following Petersen (2009).

2.2.4 Estimating determinants of exposure to improved varieties

In a next step, we are interested to understand whether information flows through social networks influence farmers' exposure to improved sorghum and maize varieties. Previous studies defined farmers to be exposed if they are aware of at least one variety (Diagne and Demont, 2007). This makes sense when looking at broader technologies or traits that are incorporated in different varieties. In our case, different improved varieties are more distinct, so that it makes more sense to consider each variety as a separate technology. Hence, instead of using a binary exposure variable, we consider the intensity of exposure in terms of the number of improved varieties a farmer is aware of. In our dataset, this intensity of exposure is closely correlated with the adoption of improved varieties.

To determine the effect of social networks on exposure, we regress exposure intensity, V , on a set of explanatory variables, including a social network measure, assuming a Poisson distribution:

$$Pr(V = v_i | \mathbf{z}_i, \mathbf{w}_i) = \frac{e^{-\mu_i} \mu_i^{v_i}}{v_i!} \quad v_i = 0, 1, 2 \dots \quad (2.2)$$

where μ is a loglinear function that can be expressed as:

$$\ln \mu_i = \mathbf{z}'_i \boldsymbol{\beta} + \mathbf{w}'_i \boldsymbol{\delta} \quad (2.3)$$

Based on this specification, intensity of exposure is given by

$$E[v_i | \mathbf{z}_i, \mathbf{w}_i] = Var[v_i | \mathbf{z}_i, \mathbf{w}_i] = \mu_i = e^{\mathbf{z}'_i \boldsymbol{\beta} + \mathbf{w}'_i \boldsymbol{\delta}} \quad v_i = 0, 1, 2 \dots \quad (2.4)$$

For each farmer i , v is the intensity of exposure to improved varieties, \mathbf{z} is a set of personal and household characteristics such as age, education, sex, and wealth, and \mathbf{w} is a set of variables that capture the quantity of information about improved varieties available to the farmer through social networks, village administrators, and government agricultural extension officers. $\boldsymbol{\beta}$ and $\boldsymbol{\delta}$ are vectors of parameters to be estimated, denoting the partial effects of personal and household characteristics, and social networks, respectively. We hypothesize that controlling for \mathbf{z} , social networks influence a farmer's exposure directly through discussions about improved varieties between the farmer and network members, or indirectly when the farmer is invited or persuaded in some other way by network members to

attend forums where improved varieties are discussed, such as extension meetings and field days.

One critical assumption of the Poisson distribution in equation (2.4) is that the expected value of the dependent variable is equal to its expected variance (equidispersion), a condition that is violated if the latter exceeds the former (overdispersion) (Cameron and Trivedi, 1998). We tested for this using the likelihood ratio test for on-boundary values described by Gutierrez, Carter and Drukker (2001), and failed to reject the null hypothesis that the over-dispersion parameter was zero. Furthermore, results of a negative binomial regression model, which accounts for overdispersion, produced almost identical estimates. The assumption of a Poisson distribution is therefore appropriate in our study.

2.3 Data

2.3.1 Farm survey

This study uses farm survey data collected in Singida Rural and Kondoa Districts in Central Tanzania between September and November 2012. Central Tanzania is mainly semi-arid. Farmers in this region are smallholders who cultivate sorghum and maize, often in addition to millets, pulses, oil crops, and roots and tubers. Many also keep livestock. While maize is more popular among farmers and consumers, sorghum has recently been promoted by the government due to its larger tolerance to drought situations. Of the survey respondents, 88% grew maize, while 71% grew sorghum. Eighty-nine percent of the maize growers also cultivated sorghum, while 72% of the sorghum growers also cultivated maize. Until the late-1960s, sorghum and maize varieties in the study area were mainly landraces. Since then, public and private agricultural research organizations have developed improved varieties, which were transferred to farmers through approaches such as on-farm trials, participatory variety selection, field days, direct seed distribution by government and non-governmental organizations, and farmer field schools (Heinrich and Mgonja, 2002; Mgonja and Monyo, 2002; Erenstein *et al.*, 2011).

The data were collected through a survey involving 345 farmers from 21 villages. In both districts, three village clusters (each consisting of 2-5 villages) were purposively selected. Within the villages, respondents were randomly selected. Face-to-face interviews with the household heads were conducted using a structured questionnaire. A broad set of agricultural and socioeconomic variables were captured. To elicit data on social network links, survey respondents were asked questions about their six random matches in this sequence: “Do you know j (the match)?” If the answer was “no”, no further network

questions about the particular match were asked. If the answer was “yes”, the respondent was asked: “Do you discuss sorghum (maize) farming issues with j ?” Based on these answers, we interpret a “yes” response as presence of a network link between ego and alter for sorghum (maize), and a “no” response as absence of such a link. Similar information about the respondent was not sought from his/her alters, implying that we assess undirected networks. We also collected data on dyadic attributes by asking the respondent: “Since when have you known j ?” “How is j related to you?”, “Are you member of an association that j is also member of?” Other dyadic attributes used in the models were constructed from personal and household characteristics of ego and alter, since both are in our sample.

2.3.2 Farmers’ sources of information

We are particularly interested in the flow of information about improved sorghum and maize varieties. Table 2.1 shows the sources of first information about improved varieties, as stated by farmers. Since many respondents were exposed to more than one improved variety, and sources of first information are not necessarily the same for all varieties, we report the percentage of ‘responses’ rather than ‘respondents’. For sorghum varieties, government extension officers are the main source of first information, followed by other farmers. For maize varieties, this order is reversed. Besides, more than 20% of the farmers receive their first information about improved maize varieties from the mass media (radio, newspaper) and grain or seed traders, while these sources hardly play a role for sorghum varieties. The last two columns in Table 2.1 differentiate between maize OPVs and hybrids. Mass media as a source of information are especially important for hybrids. Unlike OPVs, hybrids are sold by private seed companies that advertise their products through commercial media channels.

To better understand the flow of information between farmers, respondents who named other farmers as the source of first information were also asked about the type of relationship they have with the informant and the occasion at which they got exposed to the variety. This information is shown in the lower part of Table 2.1. For all varieties, neighbors and friends were the main source of first information, followed by parents and other relatives. Most respondents stated that they first saw the improved variety in the other farmer’s field and then approached that other farmer for more information. These results suggest that the experience individual farmers make with new varieties is a very important source of information for other farmers to learn about the new varieties.

Table 2.1: Farmers' sources of first information about improved varieties

	Sorghum varieties	Maize varieties	Maize OPVs	Maize hybrids
<i>Source of information (% of responses)</i>	<i>(N=578)</i>	<i>(N=658)</i>	<i>(N=216)</i>	<i>(N=405)</i>
Other farmer	27.7	49.7***	52.8	48.6
Government extension officer	67.3	23.9***	25.9	22.2
Trader	0.9	8.7**	9.3	8.2
Mass media	0.5	12.2***	5.6	16.5***
Other	3.6	5.6**	6.5	4.4
<i>Relationship if source is other farmer (% of responses)</i>	<i>(N=159)</i>	<i>(N=326)</i>	<i>(N=114)</i>	<i>(N=196)</i>
Neighbor/friend	68.9	67.1	63.2	68.5
Parent	16.2	16.8	18.4	16.2
Other relative	14.9	16.2	18.4	15.2
<i>How learned about variety if source is other farmer (% of responses)</i>				
Saw it in farmer's field and enquired	69.8	71.2	66.7	74.0*
Information came from the other farmer first	11.3	9.8	9.6	9.7
Not specified	18.9	19.0	23.7	16.3*

*, **, *** differences between sorghum and maize varieties (first two columns), and between maize OPVs and hybrids (last two columns), significant at 10%, 5%, and 1% level, respectively.

2.4 Determinants of network links

As explained, each farmer was matched to six randomly selected other farmers in the sample. For the 345 farmers interviewed, this would make a total of 2,070 dyads. However, because matching was random, 109 dyads were discovered to be duplicates (the alter was also asked about the ego). For 82 other dyads, some information about the alters was missing. These dyads were excluded from the analysis. In about 50% of the remaining cases, respondents did not know their random match. These cases were also excluded. We use 948 dyads in the regression analysis.

The probit model specified in equation (2.1) is employed to assess the influence of dyadic characteristics on the probability of detecting an information network link for sorghum and maize. We include village cluster dummies to control for unobserved cluster fixed effects, but these are not reported. Two-way cluster robust standard errors discussed earlier are estimated to correct for heteroscedasticity. Subject to knowing each other, about one third of the random dyads discuss sorghum or maize farming issues, with about 17% of these discussions occurring across village boundaries. The explanatory variables used in the regressions are defined in Table 2.2 together with descriptive statistics.

Table 2.2: Definitions and descriptive statistics for variables used in the dyadic regressions

Variable	Definition	Mean
Sorghum network	Presence of sorghum network link between ego and alter (1=yes; 0=otherwise)	0.34 (0.47)
Maize network	Presence of maize network link between ego and alter (1=yes; 0=otherwise)	0.32 (0.47)
Age difference	Ego and alter absolute age difference (years)	11.9 (8.98)
Education difference	Ego and alter belong to different education levels (1=yes; 0=otherwise)	0.26 (0.44)
Gender difference	Ego and alter belong to different gender (1=yes; 0=otherwise)	0.25 (0.43)
Religion difference	Ego and alter belong to different religions (1=yes; 0=otherwise)	0.32 (0.47)
Land difference	Absolute difference in ego's and alter's size of own land (ha)	3.82 (6.19)
Livestock difference	Absolute difference in ego's and alter's livestock value [millions of shillings (1,560 Shillings=1USD during survey)]	2.73 (3.86)
Same association	Ego and alter belong to a common association or group (1=yes; 0=otherwise)	0.09 (0.28)
Same village	Ego and alter live in same village (1=yes; 0=otherwise)	0.73 (0.44)
Same subvillage	Ego and alter live in same subvillage (1=yes; 0=otherwise)	0.24 (0.43)
Kinship	Ego and alter have kinship tie (1=yes; 0=otherwise)	0.14 (0.35)
Duration	Duration since ego and alter knew each other (years)	26.2 (12.8)
Leader	Ego or alter has a leadership role in the community (1=yes; 0=otherwise)	0.67 (0.47)
Extension1	Only ego or alter has links with public extension officer (1=yes; 0=otherwise)	0.36 (0.48)
Extension2	Both ego and alter have links with public extension officer (1=yes; 0=otherwise)	0.55 (0.50)

Notes: Figures in parentheses are standard deviations. D (total dyads used) = 948.

The probit estimation results are shown in Table 2.3. The effects of all variables are very similar for the sorghum and maize models. This is expected, because farmers who grow the same crops and communicate with each other are unlikely to discuss only one crop and not the other. Differences in education levels between ego and alter reduce the probability of an information network link. Larger differences in the size of land owned by the households (which is commonly used as a wealth indicator) increase the likelihood of a network link. For this variable, an a priori expectation is difficult to form. In their analysis for cotton technology, Maertens and Barrett (2013) found the opposite effect, namely that farmers with

similar farm sizes are more likely to exchange information. We interpret our result such that farmers with similar landholdings may also have similar technological experiences, so that an information exchange could be less fruitful (Borgatti *et al.*, 2009; Dufhues *et al.*, 2010).

Table 2.3: Determinants of information network links

Variable	Sorghum		Maize	
	Coefficient	ME	Coefficient	ME
Constant	-2.029*** (0.299)		-1.967*** (0.306)	
Age difference	0.002 (0.001)	0.001	-0.001 (0.006)	-0.000
Education difference	-0.202* (0.117)	-0.063	-0.232** (0.112)	-0.073
Gender difference	-0.229 (0.144)	-0.072	-0.215 (0.147)	-0.067
Religion difference	-0.039 (0.096)	-0.012	-0.107 (0.104)	-0.034
Land difference	0.022* (0.012)	0.007	0.030*** (0.011)	0.009
Livestock difference	0.018 (0.015)	0.006	0.004 (0.013)	0.001
Same association	0.808*** (0.218)	0.254	0.6783*** (0.195)	0.213
Same village	0.395*** (129)	0.124	0.84** (0.119)	0.089
Same subvillage	0.378*** (0.124)	0.119	0.309*** (0.120)	0.097
Kinship	0.413*** (0.142)	0.130	0.356** (0.151)	0.112
Duration	0.012** (0.005)	0.004	0.015*** (0.005)	0.005
Leader	0.250** (0.114)	0.079	0.206* (0.121)	0.065
Extension1	0.379* (0.199)	0.119	0.450** (0.208)	0.141
Extension2	0.403* (0.208)	0.127	0.489** (0.255)	0.153

Notes: Dependent variables are sorghum network and maize network. In parentheses are cluster robust standard errors; ME, marginal effects. D (dyads used) =948. *, **, *** significant at 10%, 5%, and 1% level, respectively.

Being member in the same group or association increases the probability of an information network link by more than 20 percentage points, for both crops. This is plausible, because farmers who belong to the same association meet more frequently and hence have a higher propensity to exchange information. Similarly, geographical proximity between ego and alter has a positive influence: living in the same village increases the probability of a

network link by 12 and 9 percentage points for sorghum and maize, respectively. Living in the same subvillage further increases the likelihood of information exchange. Moreover, family ties between farmers and the duration of knowing each other have positive effects on the exchange of farming information. This is expected and is likely related to trust. Similar results for the role of kinship for information networks were reported by Conley and Udry (2010).

If either ego or alter have a community leadership role, the likelihood of an active information link is higher. Community leaders do not only know more people, but they are also likely to have more and better information, so they are attractive contact points for other farmers to seek advice. Similarly, the likelihood of information exchange is higher if either one or both of the farmers have a direct link with a public extension officer. Extension officers are an important source of information about agricultural technologies – information which is then further discussed among farmers themselves. However, the relatively high marginal effect of the extension variables suggest that farmers rely on first and second-hand information and that the farmer-to-farmer exchange may be less effective across multiple network nodes. Hence, informal social networks can support the flow of information among farmers, but they do not reduce the need for widespread outreach of agricultural extension services.

2.5 Determinants of exposure to improved varieties

2.5.1 Status of exposure

Farmers' exposure to improved varieties is summarized in Table 2.4. For sorghum, a total of six improved varieties are available in the study area. About 79% of the respondents know at least one of these varieties. For maize, 11 improved varieties are available, of which six are hybrids and five OPVs. About 74% of the respondents know at least one of these improved maize varieties. If we would define exposure to improved varieties as a binary variable, as often done in the literature, exposure would be somewhat lower for maize than for sorghum. However, as explained above, we define exposure in terms of the number of improved varieties known, where the picture is reversed. On average, farmers know more improved maize than sorghum varieties. Nevertheless, for both crops the number of improved varieties known by farmers is quite small. This indicates that farmers are constrained in their access to information, so that better understanding the factors that influence exposure is important.

Table 2.4: Farmer exposure to improved varieties

Exposure	Sorghum	Maize	Maize OPVs	Maize hybrids
Total number of varieties known in the study area	6	11	5	6
Exposed to at least one (% of sample)	78.8	73.6	42.3	66.1
Intensity of exposure (% of sample)				
0	21.2	26.4	58.0	33.9
1	30.4	25.2	24.9	32.2
2	21.5	18.0	13.9	20.6
3	16.8	12.5	3.19	9.86
4	7.83	11.0	0.0	3.19
5 and above	2.32	6.96	0.0	0.29
Mean intensity of exposure	1.67	1.79	0.62	1.17
	(1.32)	(1.62)	(0.84)	(1.12)

Notes: Figures in parenthesis are standard deviations. N=345.

2.5.2 Regression results

To analyze the determinants of exposure to improved varieties, we estimate Poisson regression models, as described in equations (2.3) and (2.4). The explanatory variables used in these models are defined in Table 2.5. In addition to these variables, we include village cluster dummies; these dummies are not shown for brevity. Regression results are presented in Table 2.6. In models (1) to (4), we use network variables that capture the network degree relative to all six random matches for each farmer. In models (5) to (8), we differentiate between intra-village and inter-village network degrees by referring to the three random matches within and outside the ego's village, respectively.

The results of model (1) show that the network degree positively influences the intensity of exposure to improved sorghum varieties. Each additional network link increases the number of sorghum varieties known by almost 0.09. For maize, this effect is not statistically significant (model 2). However, once we disaggregate between maize OPVs and hybrids (models 3 and 4), the effect for OPVs turns significant. Remember that the sorghum varieties available in the study area are also all OPVs. This is an interesting result, as it suggests that social networks are more important for the spread of information about technologies for which formal markets fail. Unlike maize hybrids, improved sorghum and maize OPVs are not promoted by the private seed sector, so informal sources of information play a larger role.

Table 2.5: Definitions and descriptive statistics for variables used in the exposure models

Variable	Definition	Mean
Sorghum network degree	Number of sorghum information links out of six random matches	1.11 (1.40)
Sorghum network degree1	Intra-village sorghum network degree (number of links out of three random matches within the village)	0.93 (1.08)
Sorghum network degree2	Inter-village sorghum network degree (number of links out of three random links outside the village)	0.19 (0.57)
Maize network degree	Number of maize information links out of six random matches	1.03 (1.38)
Maize network degree1	Intra-village maize network degree (number of links out of three random matches within the village)	0.83 (1.06)
Maize network degree2	Inter-village maize network degree (number of links out of three random links outside the village)	0.20 (0.55)
Admin link	Strength of links with village administration (number of contacts per month with village administrators)	13.8 (9.57)
Extension link	Talks with public extension officer at least once per month (1=yes, 0=otherwise)	0.64 (0.48)
Age	Age of respondent (years)	46.0 (11.4)
Female	Respondent is a female (1=yes; 0=otherwise)	0.27 (0.44)
Education	Respondent has more than four years of formal education (1=yes; 0=otherwise)	0.83 (0.37)
Muslim	Respondent is Muslim (1=yes; 0=otherwise – mostly Christian)	0.57 (0.50)
Land owned	Land owned by the respondent's household (ha)	4.41 (5.71)
Mobile phone	Household owns a mobile phone (1=yes; 0=otherwise)	0.70 (0.46)
Radio	Household owns a radio (1=yes; 0=otherwise)	0.75 (0.43)

Notes: Figures in parentheses are standard deviations. N=345.

The results of models (5) and (7) in Table 2.6 indicate that inter-village networks matter more than intra-village networks for gaining awareness of improved sorghum and maize OPVs. This does not imply that networks outside the own village are stronger, but they seem to be more relevant for the influx of new information than networks within the farmer's own village. This is consistent with Schaefer (2010) who argues that strong ties within an established network (for instance, those in intra-village networks) can make such networks conservative and less exposed to new ideas. In a similar vein, Rauch (2010) posits that bridging network clusters produces synergies that lead to higher outcomes. As mentioned, previous studies that investigated the role of social networks for technology diffusion

primarily focused on intra-village networks, thus missing the potentially important role of inter-village networks.

Table 2.6: Determinants of exposure to improved varieties

Variable	(1) Sorghum	(2) Maize	(3) Maize OPVs	(4) Maize hybrids	(5) Sorghum	(6) Maize	(7) Maize OPVs	(8) Maize hybrids
Sorghum network degree	0.087** (0.042)							
Sorghum network degree1					0.022 (0.065)			
Sorghum network degree2					0.223** (0.106)			
Maize network degree		0.047 (0.056)	0.048* (0.028)	-0.006 (0.040)				
Maize network degree1						-0.018 (0.082)	-0.003 (0.044)	-0.020 (0.058)
Maize network degree2						0.194 (0.140)	0.148** (0.072)	0.029 (0.101)
Admin link	0.014** (0.007)	0.013 (0.008)	0.005 (0.005)	0.008 (0.006)	0.014** (0.007)	0.014 (0.008)	0.0051 (0.005)	0.008 (0.006)
Extension link	0.365** (0.147)	0.410** (0.179)	0.156 (0.096)	0.254** (0.129)	0.379*** (0.146)	0.423** (0.182)	0.168* (0.098)	0.256** (0.130)
Age	0.018** (0.007)	0.017* (0.007)	0.013*** (0.005)	0.004 (0.007)	0.019*** (0.007)	0.018* (0.010)	0.014*** (0.005)	0.004 (0.007)
Female	-0.298 (0.201)	-0.576** (0.248)	-0.147 (0.128)	-0.437** (0.172)	-0.320 (0.201)	-0.584** (0.246)	-0.149 (0.128)	-0.439** (0.172)
Education	0.348 (0.213)	0.495* (0.268)	0.286** (0.141)	0.208 (0.192)	0.359* (0.213)	0.496* (0.268)	0.291** (0.140)	0.207 (0.192)
Land owned	-0.005 (0.011)	-0.009 (0.017)	-0.003 (0.010)	-0.008 (0.010)	-0.008 (0.012)	-0.011 (0.017)	-0.005 (0.010)	-0.008 (0.010)
Mobile phone	0.221 (0.154)	0.306 (0.206)	0.280** (0.120)	0.032 (0.145)	0.219 (0.153)	0.298 (0.205)	0.272** (0.118)	0.030 (0.145)
Radio	0.123 (0.185)	0.421* (0.241)	0.156 (0.135)	0.267* (0.160)	0.128 (0.185)	0.432* (0.241)	0.170 (0.134)	0.269* (0.161)

Notes: Dependent variables are the number of improved varieties known by the respondent. Marginal effects of Poisson regressions are shown with robust standard errors in parentheses. N=345. *, **, *** significant at 10%, 5%, and 1% level, respectively.

Having frequent interactions with village administrators significantly increases exposure to improved sorghum varieties. The same effect is not observed for maize, neither for hybrids nor for OPVs. This difference is probably due to the fact that the government has recently promoted sorghum cultivation in the study area. Village administrators are involved in this campaign as local government representatives. Furthermore, frequent interactions with public extension officers have positive and significant effects in almost all models in Table 2.6. It is worth noting that for both crops the marginal effects of these extension variables are several times larger than those of the network links with other farmers. This reinforces our

earlier statement that informal social networks can support but not replace the flow of information through the extension service and other formal channels.

In terms of farmers' personal characteristics, age increases exposure to improved varieties, which we attribute to the longer experience of older farmers. The only exception are the models for hybrid maize, where the effect of age is very small and not statistically significant. It is likely that older farmers are less receptive for technologies that require more profound changes in traditional cultivation practices, such as purchasing fresh seeds every year, which is required with hybrids in order to prevent productivity decline. Education increases exposure to improved varieties in most models, which is expected. Farmers with more education tend to have better access to new information. Furthermore, owning a mobile phone and/or a radio has positive impacts on exposure to improved maize varieties. Radio seems to play a significant role especially for maize hybrids. As hybrids are promoted by private seed companies, commercial media advertisements are commonplace.

Land ownership does not have significant effects on exposure, indicating that there is no scale bias in the flow of information about improved varieties. Yet, being a female farmer has a negative effect on exposure. There seems to be a gender bias in the flow of information about improved seed technologies, which holds for both OPVs and hybrids. This is consistent with Kabunga *et al.* (2012) who showed that women tend to be less aware of new banana technologies in Kenya.

2.6 Conclusions and policy implications

In this study, we have analyzed the role of social networks for farmers' exposure to improved crop varieties in Tanzania. Unlike previous social network studies, which mostly focused on crops for which formal seed markets exist, we have looked at sorghum and maize varieties for which seed market imperfections are commonplace. While maize hybrids are sold by private seed companies in Tanzania, improved OPVs of sorghum and maize are primarily promoted by public sector institutions. And, while previous studies concentrated primarily on intra-village social networks, we have extended the approach and have also considered inter-village networks.

In explaining the existence of informal networks, we found that farmers are more likely to exchange relevant agricultural information if they have similar levels of education, different farm sizes, are members of the same association, live in the same village, and have kinship ties. At the same time, the probability of exchanging farming information increases if

a community leader is involved and if at least one of the farmers has a direct link to a public extension officer. These patterns are the same for both crops, sorghum and maize.

However, in terms of the role of social networks for farmers' exposure to improved varieties, we found more pronounced differences between the two crops. The degree of social network interactions increases farmers' awareness of improved sorghum varieties, but not of improved maize varieties. Further disaggregation showed that for maize the effect differs between improved OPVs and hybrids: while social networks play a positive and significant role for farmers' exposure to maize OPVs, the result remains insignificant for hybrids. Obviously, the flow of information through informal networks is more important for seed technologies for which formal markets fail. Strikingly, inter-village networks play a larger role for generating awareness about new varieties than intra-village networks.

In addition to social networks, personal characteristics of farmers matter for their awareness of improved varieties. Unsurprisingly, farmer education has a positive effect on exposure to improved varieties of both crops. Age has a positive effect for sorghum and maize OPVs, but not for maize hybrids. On the other hand, ownership of a radio increases farmers' awareness of improved maize hybrids, as these tend to be promoted by private companies through commercial media advertisements. The gender of the farmers also matters. Being a female farmer is associated with reduced exposure to improved sorghum and maize varieties, which points at a significant gender bias in information flows. Finally, the results show that regular contacts of farmers to public extension officers and village administrators increase exposure considerably. The marginal effects of extension are much larger than those of the social network variables, suggesting that informal information channels are not a substitute for awareness creation through formal channels.

These results have a number of policy and research implications. First, social networks matter for the spread of new agricultural technologies. Hence, technology dissemination programs should try to make use of such networks. Second, the role that social networks play for the spread of information differs by type of crop and technology. They seem to be more important for technologies that are not promoted by the private sector and for which formal markets fail. Third, social networks can support but not replace formal extension programs. Fourth, new extension models should be developed that explicitly build on the synergies between formal and informal information channels. Much more research is needed to establish what type of extension model is cost-effective in a particular situation. An intensive training of lead farmers, who then pass on their knowledge to other farmers, may be more effective than assuming that snowball effects across multiple network nodes would occur

automatically. Farmer associations and well managed demonstration plots may play important roles in this respect. Fifth, gender biases in access to information about agricultural technologies should be addressed. This will require gender mainstreaming of extension programs, among other things. Sixth, the finding that inter-village networks matter for farmers' exposure to improved varieties points to the potential that facilitation of exchange across village boundaries may have for the spread of information and technology. Follow-up studies should explicitly analyze the formation and functioning of inter-village social networks.

3 Social networks and the adoption of agricultural innovations: The case of improved cereal varieties in Central Tanzania⁵

Abstract

Literature on the adoption of agricultural innovations highlights the importance exposure to these technologies for the adoption decision of small scale farmers. This study assesses the relevance of exposure and other constraints in the adoption of improved sorghum and maize varieties in Central Tanzania. Specifically, we analyze the determinants of exposure to improved varieties; and of adoption itself, focusing more on the role of social networks. We use survey data collected from 345 farmers between September and November 2012. We apply Poisson models to assess exposure, and average treatment effect procedures to analyze adoption. Our results show that about 79% and 74% of the respondents are exposed to at least one improved variety of sorghum and maize respectively. The average intensity of exposure (number of improved varieties a farmer is exposed to) was 1.7 for sorghum and 1.8 for maize. Farmer networks are found to be a key source of variety information, and exchange of this information among farmers is triggered when a farmer sights a variety grown in a network member's field. Most farmers consider improved varieties of both crops generally better than traditional ones. However, while 83% of farmers think improved varieties of maize are better than traditional ones, only 54% of farmers think so for sorghum. The size of a farmer's network is found to positively influence their intensity of exposure to improved sorghum and open-pollinated maize varieties, but not to maize hybrids. This demonstrates that farmer networks facilitate higher exposure to seed technologies with mostly missing or malfunctioning markets. We find that farmers have substantial information networks outside their own villages, and it is these often understudied networks that determine the intensity of exposure. The strength of network connections with village administrators positively affects intensity of exposure to sorghum varieties, while network connections with agricultural

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As already pointed out in Chapter 1, the methodological framework we use to model adoption of improved varieties controls for biases in exposure to the varieties. Hence, some sections on exposure overlap with those discussed in the previous chapter, and this was intended to maintain consistency and make the paper more understandable as an independent article.

extension officers influence intensity of exposure positively for sorghum varieties and maize hybrids. Other determinants of exposure are age and education of household head, and household ownership of information and communication assets. Female farmers have less exposure to maize hybrids than their male counterparts. On adoption, we find that adoption rates are pretty low – just about 42% in the case of sorghum and 60% for maize. After accounting for non-exposure and selection biases, the estimated population adoption rate is 52% for sorghum and 71% for maize, implying adoption gaps of 9.3 and 10.9 percentage points, respectively. Sorghum networks positively influence adoption even after accounting for their role in exposure. However, it is the intra-village and not inter-village networks that produce this effect. Intensity of exposure influences adoption positively for both crops. Households with more female adults are more likely to adopt improved sorghum, while those with more male adults are more likely to adopt improved maize. Poor soil fertility negatively affects adoption of improved sorghum, while non-farm income activities and size of maize farm positively influence adoption of maize varieties. Farmers mentioned seed availability followed by perceived susceptibility to pests as the most limiting factors to adoption. The importance of these reasons changes if we compare farmers without past adoption experience to those who have ever adopted. These results raise a number of implications for policy design and further research, which are discussed in the last chapter of this paper.

Keywords: social networks, exposure, adoption, improved varieties, maize, sorghum

3.1 Introduction

Food insecurity remains a major development challenge for many agrarian economies (World Bank, 2007) and the use of improved crop varieties (ICVs) is seen as a key to increasing food production and hence food security (FAO, 2002). However, adoption of improved varieties remains incomplete. Estimates by the Consultative Group on International Agricultural Research (CGIAR, 2011) show that for the world's 10 key crops, improved varieties have been adopted in only 65% of the cultivated area, with Sub-Saharan Africa (SSA) recording the lowest adoption rates (Gollin *et al.*, 2005; Smale *et al.*, 2011).

Adoption of improved varieties has been widely studied (Doss, 2006), but the incomplete and heterogeneous diffusion of these technologies across regions calls for more research into the drivers of this process. A major strand in the adoption literature focused on the identification of constraints. Several recent studies (Ransom *et al.*, 2003; Kijima *et al.*, 2011; Uiaene, 2011; Mal *et al.*, 2012) show that adoption is influenced by farm and farmer characteristics (such as age, experience, education) as well as institutional factors such as access to input markets, credit and extension services. Other have studies identified lack of exposure to improved varieties as a major constraint to adoption in many parts of SSA (Doss *et al.*, 2003; Diagne 2006; Simtowe *et al.*, 2011; Dibba *et al.*, 2012; Kabunga *et al.*, 2012). The argument in such studies is that farmers cannot adopt improved varieties whose existence or attributes they are unaware of. Building on the information constraint paradigm, a growing number of technology adoption studies (Bandiera and Rasul, 2006; Matuschke and Qaim, 2009; Conley and Udry, 2010) assessed the role of social ties and interactions, also known as social structures or social networks (Borgatti *et al.*, 2009). This is based on the understanding that flows of information, ideas, beliefs and attitudes within social networks can influence the perception about the benefits of new varieties and hence farmers' decisions to adopt (Baerenklau, 2005).

In this study we analyze the determinants of exposure, which is a precondition for adoption, and of adoption itself. We focus on the role of social networks on exposure and adoption of improved cereal technologies. Our study deviates from Bandiera and Rasul (2006) and Conley and Udry (2010) by focusing on sorghum and maize, which are grown primarily for home consumption and are critical for food security in Central Tanzania. In a departure from Matuschke and Qaim (2009), who also investigate the role of social networks on technology adoption for key cereals, we explicitly address the role of different types of

social networks (i.e. networks to other farmers as well as links to the village administration and the extension officer) on exposure and adoption.

3.2 Research questions

The above mentioned adoption literature highlights the importance of exposure constraints as well as farm and farmer characteristics for the adoption decision of small scale farmers in developing countries. This study aims to assess the relevance of these factors for the adoption of improved cereal varieties in Central Tanzania. The findings are important for designing policies to foster innovation adoption and productivity growth. Specifically, we address the following research questions:

1. With respect to knowledge about ICVs:
 - 1.1. How many farmers know about ICVs of maize and sorghum?
 - 1.2. What factors determine exposure? What role do social networks play?
 - 1.3. What are the perceived characteristics of ICVs compared to local varieties?
2. With respect to adoption of ICVs:
 - 2.1. What is the status of adoption of ICVs and how does this differ across crops?
 - 2.2. What are determinants of adoption? What role do social networks play?
 - 2.3. What are the stated key constraints to adoption of ICVs?

3.3 Analytical framework

3.3.1 Definition and measurement of social networks

We define a social network as a set of actors or nodes (individuals, agents, or groups) that have relationships with one another (Hanneman and Riddle, 2005; Marin and Wellman, 2011). Social networks evolve due to ties between actors, which may arise because of kinship, affection or familiarity between them (Easley and Kleinberg, 2010). The simplest social network is a dyad (pair of linked actors), in which one actor (whose network is being studied), is referred to as the ego, and the other as the alter (Smith and Christakis, 2008). This raises the question for our study, whether the number of connections an actor has determines their exposure to ICVs. To address this question, we apply the concept of node-level properties of social networks, particularly centrality measures (Borgatti, 2005). These measures determine positions and power of network actors, which predispose them to opportunities and constraints that determine outcomes (House *et al.*, 2007; Borgatti *et al.*, 2009). Key among centrality measures is degree, which refers to the number of other actors

to which an actor is directly connected (Newman, 2010). We hypothesize that respondents with a higher network degree occupy positions that predispose them to more learning opportunities about improved varieties; hence they are more likely to have a higher intensity of exposure than those with a lower degree.

Empirical measurement of social networks is a highly debated and evolving topic. In this study, we address two major challenges commonly faced in measuring social networks, which informed our choice of data collection methods. The first involves selection of actors to be studied. Some researchers use a complete network approach, which involves a census of the population being studied (Barroga-Jamias and Brien, 1996; Goswami and Basu, 2010; van den Broeck and Dercon, 2011). This approach, while theoretically appealing, is of limited practical use in studying large populations. Besides, even with a complete census, it is impossible to capture all of an individual's social links, because some are often unreported, while others span out of geographical boundaries set by empirical studies (Udry and Conley, 2004; Fafchamps and Gubert, 2007; Handcock and Gile, 2010). Researchers therefore often use samples to study social networks in large populations. However, Santos and Barrett (2010) and Chandrasekhar and Lewis (2011) argue that little can be learned about the real networks if individuals in the network are sampled, and recommend the sampling of paired actors (dyads) and graphical reconstruction respectively. We use the sampling of dyads approach due to its simplicity, and because our interest is not in the characteristics of the actual networks per se.

The second challenge is how to establish which actors constitute an individual's network. Three main approaches have been used in past studies. In one approach, each individual being studied is asked to name a certain number of individuals with whom they interact (Barroga-Jamias and Brien, 1996; Bandiera and Rasul, 2006; Tatlonghari *et al.*, 2012). The weakness of this approach is that individuals are likely to name only persons, to whom they are strongly linked, leading to estimates of network properties that are biased towards strong links. The second method, called matches within sample, asks each individual about their ties and interactions with every other individual in the sample while the third approach, called random matching within sample, pairs each individual in the sample with only a specified number of individuals randomly selected from the sample (Santos and Barrett, 2008). The matches-within-sample approach suffers the same limitations as the census method if the sample is large (Fafchamps and Gubert, 2007). Furthermore, Santos and

Barrett (2008) demonstrate using Monte Carlo simulations that the latter approach produces network parameters that represent the real network more efficiently.

Based on these considerations, we formed hypothetical social networks by randomly pairing each farmer with six others in the sample: three from the respondent's village and three from neighboring villages which make up the respondent's village cluster (see Chapter 3.4 for a detailed description). Although single villages have been the geographical focus of most social network studies, we preferred a village clusters approach for two reasons. First, many technology awareness and dissemination activities carried out by research and extension agencies have been held at administrative units higher than the village (comprising several villages). Second, literature reviewed suggested that farmers' networks may extend outside their villages of residence, yet this information often disregarded in most social network studies. It was therefore interesting to assess the presence of inter-village social networks and their effect on information exchange across villages. The respondents were then asked whether they know their random matches and for how long they have known them, whether and how often they talk on general and crop specific (sorghum and maize) issues, and whether they have any kinship ties or common membership in community groups or associations. In addition to farmer-to-farmer networks, each respondent was asked about their ties with village administrators and public extension officers. This was aimed at assessing how strongly farmers are connected to official information channels and whether network connections to these channels influence exposure to improved varieties. We present a detailed description of data collection methods for social networks in Chapter 3.4.

3.3.2 Determinants of exposure

To identify the determinants of exposure, we define exposure in terms of intensity, i.e. the number of improved varieties to which a farmer is exposed. We model the farmer's intensity of exposure to improved varieties (number of varieties the farmer knows) as a discrete variable, V , with a Poisson distribution (Cameron and Trivedi, 1998; Greene, 2012) given by

$$(3.1) \quad Pr(V = v_i | z_i, w_i) = \frac{e^{-\mu_i} \mu_i^{v_i}}{v_i!} \quad v_i = 0, 1, 2 \dots$$

where μ is a loglinear function that can be expressed as:

$$(3.2) \quad \ln \mu_i = z_i' \beta + w_i' \delta$$

Based on this specification, intensity of exposure is given by

$$(3.3) \quad E[v_i | z_i, w_i] = Var[v_i | z_i, w_i] = \mu_i = e^{z_i' \beta + w_i' \delta} \quad v_i = 0, 1, 2 \dots$$

Where for each farmer i , v is the intensity of exposure to improved varieties; z is a set of personal and household attributes hypothesized to influence exposure, such as age, education level, sex, and wealth; w is a set of variables that indirectly capture the quantity of information on improved varieties available to the farmer through social networks with other farmers, village administrators, and government agricultural extension officers; and β and δ are vectors of parameters to be estimated by the model, denoting the partial effects of personal and household characteristics, and social networks, respectively. We hypothesize that controlling for z , social networks influence a farmer's exposure directly through discussions about improved varieties between the farmer and network members, or indirectly when the farmer is invited or persuaded in some other way by network members to attend forums where improved varieties are discussed, such as extension meetings and field days.

One critical assumption of the Poisson distribution in Equation 3.3 is that the expected value of the dependent variable is equal to its expected variance (equidispersion), a condition that is violated if the latter exceeds the former (overdispersion), leading to imprecise estimators (Cameron and Trivedi, 1998). A likelihood ratio test did not reject the null hypothesis of no overdispersion in our data. Furthermore, results of a negative binomial regression model (not presented here), which accounts for overdispersion, produced almost identical estimates. We therefore maintained the results of the Poisson regression models.

3.3.3 Determinants of adoption

To determine the drivers of adoption of improved varieties, we apply the methodology proposed by Diagne and Demont (2007). The basic logic of this framework is that farmer exposure to improved varieties, which is a precondition for adoption of the varieties, is not necessarily random in the population. For instance, farmers may self-select themselves into exposure, or be targeted by technology promoters for exposure into these varieties. Furthermore, adoption may be influenced by unobserved factors that influence exposure. Thus, if exposure to improved varieties among farmers is incomplete (as it is the case for ICVs of sorghum and maize in Central Tanzania), modeling adoption without taking into account the potential non-exposure bias yields inconsistent estimates. That also means that the interpretation of the coefficients of standard adoption models is difficult if there is a lack of exposure (Besley and Case, 1993; Saha *et al.*, 1994; Dimara and Skuras, 2003).

Diagne and Demont's (2007) method is based on the modern treatment effect estimation literature, which goes back to the seminal work of Rubin (1973). They use a counterfactual outcome framework, which assumes that every farmer in the population has

two potential adoption outcomes: with and without exposure. Following the notation of Diagne and Demont (2007) we denote the observed exposure status as the binary variable w that takes on the value one if the farmer is exposed to the new technology and zero otherwise. The binary outcome variable y_1 indicates the potential adoption status of a farmer, who is exposed to the technology and y_0 if he is not exposed. The treatment effect for farmer i is then measured by the difference $(y_{i1} - y_{i0})$. The corresponding population level effect is given by $E(y_1 - y_0)$, which is by definition the average treatment effect (ATE). We cannot measure this effect directly because it is not possible to observe both the outcome and its counterfactual for an individual farmer. However, since exposure to a new technology is a necessary condition, y_{i0} is always equal to zero and hence the effect for an exposed farmer i is given by y_{i1} . The corresponding population level reduces to $E(y_1)$, which is called the average treatment effect on the treated (ATE_1). The adoption impact y_{i1} for non-exposed farmers, which is called the average treatment effect on the untreated (ATE_0), is not observed and has to be estimated. The identification and estimation of ATE_0 and ATE is based on the conditional independence (CI) assumption, which states that the treatment status w is independent of the potential outcomes y_1 and y_0 conditional on an observed set of covariates z : $P(y_j = 1|w, z) = P(y_j = 1|z); j = 0, 1$. Based on this assumption the ATE estimators can be obtained using parametric or non-parametric methods. Following Diagne *et al.* (2009), we apply a parametric estimation approach for the following model, which involves the observed covariates x , y and w :

$$(3.4) \quad E(y|x, w = 1) = g(x, \beta),$$

where g is a function of the vector of covariates x and the unknown parameter vector β . The parameter vector β can be estimated by standard Least Squares (LS) or Maximum Likelihood Estimation (MLE) using the observations from the subsample of exposed farmers with y as the dependent variable and x as the independent variables. The estimated parameters of β , $\hat{\beta}$, are used to calculate the predicted values for all the observations in the sample including the observations in the non-exposed subsample. ATE, ATE_1 and ATE_0 are estimated by taking the average of the predicted values across the full sample in the case of ATE and respective subsamples in the case of ATE_1 and ATE_0 :

$$(3.5) \quad \widehat{ATE} = \frac{1}{n} \sum_{i=1}^n g(x_i, \hat{\beta})$$

$$(3.6) \quad \widehat{ATE}_1 = \frac{1}{n_e} \sum_{i=1}^n w_i g(x_i, \hat{\beta})$$

$$(3.7) \quad \widehat{ATE}_0 = \frac{1}{n-n_g} \sum_{i=1}^n (1 - w_i) g(x_i, \hat{\beta})$$

As mentioned earlier, exposure to a technology is not random and hence we need to control for it. This is done before estimating the adoption model by estimating the determinants of exposure (Diagne and Demont, 2007).

3.4 Study area and data

This study uses primary data collected in Singida Rural and Kondoa Districts in Central Tanzania between September and November 2012. Central Tanzania is mainly semi-arid, and farmers in this region cultivate mainly cereals (sorghum and maize), but also grow some pulses, oil, root and tuber crops, and keep livestock. There has been a deliberate effort by the government to promote cultivation of sorghum over maize in the study region, but maize is still popular. Among the cereals cultivated in the season preceding the survey, maize was the most widely grown (88% of surveyed households), followed by sorghum (71%). Pearl millet and finger millet are less important and grown by 37% and 33% of the sample, respectively. Most sorghum growers also grow maize – 89% of maize growers cultivated sorghum while 72% of sorghum growers also cultivated maize. Until late 1960s, sorghum and maize varieties grown in the study area were mainly landraces. However, over the last four decades, the agricultural research system in Tanzania (which includes national and international agricultural research organizations and private seed companies) has been developing improved sorghum and maize varieties, which are introduced to farmers through approaches such as on-farm trials, participatory variety selection (PVS), field days, direct seed distributions by government and non-governmental organizations' extension staff, and farmer field schools (Heinrich and Mgonja, 2002; Mgonja and Monyo, 2002; Erenstein *et al.*, 2011; Lyimo *et al.*, 2014).

The data were collected through a household survey involving 345 farmers from 21 villages. The farmers were part of the 360 respondents interviewed by the International Crops Research Institute for Semi-Arid Tropics (ICRISAT), Nairobi, during their HOPE project baseline survey in Tanzania, in 2010. Fifteen of the 360 households were not re-interviewed because either the entire household had migrated, or the household head was temporarily out of the study area doing off-farm jobs. In each district, 3 village clusters (2-5 villages each) were purposively selected from 2-3 administrative Wards, for the purposes of the HOPE Project implementation. The logic followed in this clustering was to group villages that are geographically close to each other and sharing the same local agricultural extension officer.

Respondents were then randomly selected from each village. Face-to-face interviews with heads of selected households were conducted using a pre-tested structured questionnaire administered by enumerators, under the supervision of the first author and a representative of the Agriculture Ministry's Department of Research and Development (DRD), Central Zone. To elicit data on presence (absence) of social network links, the respondents were asked questions about their random matches in this sequence: "Do you know j (the match)?" if the answer was "no", then no further network questions about the match were asked. If the answer was yes, then the respondent was asked "Do you discuss sorghum (maize) farming issues with j?" We interpret a "yes" response as presence of a network link for sorghum (maize), and a "no" answer as absence of a network link between ego and alter. Similar information about the respondent was not sought from his/her alters, implying that we assess undirected networks. We also collected data on household characteristics, knowledge and adoption of cereal varieties, farmers' perception of characteristics of ICVs, and input and output data for crop production.

3.5 Results

3.5.1 Knowledge of improved varieties

We begin our analysis by looking at the exposure of farmers to improved varieties (Table 3.1); i.e. how many farmers know about the existence of ICVs. For sorghum, six improved varieties are known in the study area, and about 79% of respondents are aware of at least one. On the other hand, maize has 11 improved varieties, of which six are hybrids and five are open pollinated varieties (OPVs). About 74% of respondents know at least one maize variety, meaning that when exposure is defined as a binary variable, the average level of exposure to maize varieties is slightly lower than that of sorghum varieties, although more varieties of maize than sorghum are known in the area. The proportion of farmers exposed to a certain number of improved varieties does not differ much too. About 30% of the farmers are aware of only one variety of sorghum and a slightly lower proportion is aware of only one maize variety. For sorghum, the proportion of farmers aware of two and three varieties respectively was 22% and 17%. Similar values were also reported for maize varieties. Only about 10% and 18% of farmers are aware of more than three varieties of sorghum and maize, respectively. On average each farmer knows 1.7 varieties of sorghum and 1.8 of maize. For maize, exposure to hybrids is higher than to OPVs; and this is probably due to the role of seed markets (see Chapter 3.5.2). It is surprising that farmers are aware of just two improved

varieties on average. This may be attributed to constraints in information flows about the varieties, or it may be the case that some varieties do not perform to the satisfaction of many farmers, such that the farmers are not persuaded to seek information about the varieties from social network members who try them out.

Table 3.1: Farmer's exposure to improved varieties

Exposure	Sorghum	Maize	Maize OPVs	Maize Hybrids
Total number of varieties known in the study area	6	11	5	6
Exposed to at least one (% sample)	78.8	73.6	42.3	66.1
Intensity of exposure (% sample)				
0	21.2	26.4	58.0	33.9
1	30.4	25.2	24.9	32.2
2	21.5	18.0	13.9	20.6
3	16.8	12.5	3.19	9.86
4	7.83	11.0	0.0	3.19
5 and above	2.32	6.96	0.0	0.29
Mean intensity of exposure	1.67	1.79	0.62	1.17
	(1.32)	(1.62)	(0.84)	(1.12)

Note: N=345; Figures in parenthesis are standard deviations.

3.5.2 Main sources of information on improved varieties

We continue our analysis by looking at the source of first information that exposes respondents to improved varieties. Since many respondents are exposed to more than one improved variety, and sources of first information are not necessarily the same for all the varieties, we report percentage of 'responses' rather than of 'respondents', to account for multiple responses (Table 3.2). Our results indicate that for sorghum, government extension officers are the main source of first information (67% of responses). Other farmers also play a key, but far less important role, with 28% of responses from exposed farmers reporting other farmers as their source of first information. A similar pattern is also reported by Hossain *et al.* (2012) in their study on adoption of rice varieties in Bangladesh and India. For maize, however, other farmers are the main source of information, accounting for 50% of responses. Contrary to the case of sorghum, government extension officers play a much less important role, as they account for only 24% of responses. Another striking contrast is that, while media and grain/seed traders jointly account for 21% of responses in maize, their role in the case of sorghum is almost negligible (less than 2% of responses). Differentiating between maize OPVs and hybrids shows that media as a source of information is particularly important for maize hybrids. Contrary to the case of sorghum varieties and to a large extent, maize OPVs,

the demand for maize hybrid seeds has attracted seed companies to invest in the maize seed market, leading to the development of a seed industry which disseminates information about the technologies through private and commercial channels such as radio and print media (AGRA, 2010).

Table 3.2: Sources of first information on improved sorghum and maize varieties

	Sorghum varieties	Maize varieties	Maize OPVs	Maize hybrids
<i>Source of information (% of responses)</i>	<i>(N=578)</i>	<i>(N=658)</i>	<i>(N=216)</i>	<i>(N=405)</i>
Other farmer	27.7	49.7***	52.8	48.6
Government extension officer	67.3	23.9***	25.9	22.2
Trader	0.9	8.7**	9.3	8.2
Mass media	0.5	12.2***	5.6	16.5***
Other	3.6	5.6**	6.5	4.4
<i>Relationship if source is other farmer (% of responses)</i>	<i>(N=159)</i>	<i>(N=326)</i>	<i>(N=114)</i>	<i>(N=196)</i>
Neighbor/friend	68.9	67.1	63.2	68.5
Parent	16.2	16.8	18.4	16.2
Other relative	14.9	16.2	18.4	15.2
<i>How learned about variety if source is other farmer (% of responses)</i>				
Saw it in farmer's field and enquired	69.8	71.2	66.7	74.0*
Information came from the other farmer first	11.3	9.8	9.6	9.7
Not specified	18.9	19.0	23.7	16.3*

*, **, *** differences between sorghum and maize varieties (first two columns) or maize OPVs and Hybrids (last two columns) significant at 10%, 5% and 1% respectively.

To better understand how information that leads to farmer exposure to improved varieties is transmitted from exposed farmers to non-exposed colleagues, we asked farmers who reported their fellows as the source of first information on improved varieties to state their relationship with the information source, and how they learnt about the improved variety of these farmers. Results in Table 3.2 show that neighbors and friends were the main source of first information (69% and 67% of the sorghum and maize responses respectively), followed by other relatives and parents in almost equal proportions of 15% to 17% of the responses for both crops. The main mechanism through which respondents become exposed to the source farmer's improved variety is by seeing it in the farmer's field and then enquiring more about it from the farmer (70% and 71% of responses for sorghum and maize respectively). These results have two implications. One, farmer networks facilitate exposure to improved varieties by first 'displaying' them, which stimulates demand for more information, and thereafter provide information about them to network members. Two,

farmers are more likely to exchange information on improved varieties if their residences or fields are more geographically close.

3.5.3 Farmers' perceptions of characteristics of ICVs

We asked the respondents during the survey to compare the best improved and the best traditional variety known to them with respect to some specific characteristics. The farmers who were aware of improved varieties but unable to name a particular variety compared the best local variety known to improved varieties in general. A number of key agronomic, utilization- and market-related traits identified from variety descriptors and focus group discussions with farmers prior to the household survey, were used in this comparisons module. For each trait, farmers were asked to state whether the ICVs, the local varieties, or none of them was superior. Susceptibility to bird damage is a problem related to sorghum cultivation, while maize is not commonly used for traditional brewing. These traits are therefore only analyzed for sorghum. Table 3.3 summarizes the results of these comparisons for improved varieties which were mentioned by at least 20 respondents (n). In addition, the last two rows for each crop show the responses for improved and traditional varieties in general.

As shown in the last column, improved varieties of both crops are generally considered better than traditional ones by most farmers. However, while 83% of farmers think improved varieties of maize are better than traditional ones, only 54% of farmers think so for sorghum, a factor that may, *ceteris paribus*, result in improved varieties of maize being adopted more than those of sorghum. Results of specific traits show that improved varieties of sorghum are perceived to be better in terms of grain yield and size, drought tolerance and threshabililty, but were more susceptible to bird damage, compared to traditional ones. On the other hand, traditional varieties were rated better than improved varieties in tolerance to excess rain (especially if planted early), market demand and prices, storability, taste, and suitability for traditional brewing. However, the varieties were perceived to be more susceptible to lodging. For maize, improved varieties were perceived to have better grain yield and size, drought tolerance, threshabililty and market demand and prices. On the other hand, traditional varieties were perceived to be better only in storability, but were rated more susceptible to lodging. For other traits, neither traditional nor improved varieties were perceived to be better by more than half of the respondents. Specific variety results show that

Macia and *Pato* varieties were overall ranked better than traditional sorghum varieties. For maize, all improved varieties shown were perceived to be better than traditional ones.

Table 3.3: Farmers' perception about improved varieties compared to traditional ones.

Crop/Variety	Better grain yield	Better grain size	Better tolerance to drought	Less susceptible to pests/disease	More susceptible to bird damage	More susceptible to lodging	More tolerant to excess rain	Better threshability	Less labor demand	Better market/demand	Better price	Better storability	Easier to process	Better flour quality	Better taste/aroma	More suitable for traditional brewing	Better overall
Sorghum (N=277)																	
<i>Macia</i> (n=91)	79	70	63	30	65	18	32	51	34	24	23	25	45	56	46	10	63
<i>Pato</i> (n=66)	79	76	61	45	68	21	21	59	41	21	23	12	45	41	26	12	61
<i>Tegemeo</i> (n=51)	65	65	43	29	55	20	22	49	41	25	24	24	27	33	37	14	43
<i>Serena</i> (n=39)	49	74	46	36	44	15	28	44	18	15	13	10	28	23	28	13	41
<i>Improved</i> (n=21)	71	71	29	33	33	24	14	48	33	29	19	10	38	19	14	5	52
<i>Improved</i>	71	71	54	34	58	19	25	51	34	23	21	18	39	39	33	12	54
<i>Traditional</i>	18	15	26	44	27	71	60	24	26	61	55	67	17	30	51	74	42
Maize (N=268)																	
<i>Pannar</i> (n=57)	91	77	60	32		37	26	45	40	79	68	16	37	47	46		89
<i>Seedco</i> (n=51)	92	63	61	27		45	33	75	33	53	47	20	35	39	39		86
<i>Kilima</i> (n=31)	90	68	77	45		23	32	74	35	58	45	35	48	28	65		80
<i>Cargil</i> (n=53)	77	58	49	33		28	34	70	36	53	55	25	38	48	47		75
<i>Improved</i> (n=33)	88	76	61	30		21	39	67	39	48	48	33	42	55	33		82
<i>Improved</i>	86	65	60	34		32	32	72	39	59	55	24	39	47	45		83
<i>Traditional</i>	10	30	29	34		52	45	11	26	15	13	54	15	18	29		14

3.5.4 Determinants of exposure

To assess the individual determinants of exposure to improved varieties, we estimate Poisson regression models following Equations (3.2) and (3.3). The definition of the explanatory variables used and some descriptive statistics are presented in Table 3.4. Also included in the regressions are village cluster dummies that control for heterogeneity across the clusters in some physical and economic characteristics not captured in the models, such as soil types and distances to market centers. Regression results are presented in Table 3.5, but village cluster dummies are not shown. In models 1-4, the total degree of the specific crop information network (number of dyads in which there is a link for exchange of crop information) is used, while in models 5-8, the crop network is broken into a network within and a network outside the village. The reported estimates in Table 3.5 are marginal values, which for each explanatory variable show the partial change in expected intensity of exposure due to a unit change in the variable, holding other variables at their means.

The results show that the size of farmers' social networks matter for intensity of exposure to improved cereal varieties. Models (1) and (2) show that the network degree

positively influences intensity of exposure to sorghum varieties. In case of maize, however, an extra link in the network has no significant effect on intensity of exposure. This implies that *ceteris paribus*, sorghum information networks may be more effective in exposing farmers to improved varieties than maize networks. However, by disaggregating maize varieties into OPVs and hybrids (Models 3 and 4); we find that the degree of maize networks is positively and significantly associated with the intensity of exposure to OPVs but not hybrids. This finding is consistent with that for sorghum, whose improved varieties are purely OPVs, and implies that farmer networks facilitate more exposure to seed technologies with mostly missing or malfunctioning markets, than to those with better markets.

Table 3.4: Definitions and descriptive statistics for the variables used in the exposure model

Variable	Definition	Mean
Social network attributes of respondent		
<i>Crop network size</i>		
Sorghum network degree	Number of sorghum information links out of six random matches	1.11 (1.40)
Sorghum network degree1	Intra-village sorghum network degree (number of links out of three random matches within the village)	0.93 (1.08)
Sorghum network degree2	Inter-village sorghum network degree (number of links out of three random links outside the village)	0.19 (0.57)
Maize network degree	Number of maize information links out of six random matches	1.03 (1.38)
Maize network degree1	Intra-village maize network degree (number of links out of three random matches within the village)	0.83 (1.06)
Maize network degree2	Inter-village maize network degree (number of links out of three random links outside the village)	0.20 (0.55)
<i>Links with institutional information channels</i>		
Admin link	Strength of links with village administration (number of contacts per month with village administrators)	13.8 (9.57)
Extension link	Talks with public extension officer at least once per month (1=yes, 0=otherwise)	0.64 (0.48)
Personal and household attributes of respondent		
Age	Age of respondent (years)	46.0 (11.4)
Female	Respondent is a female (1=yes; 0=otherwise)	0.27 (0.44)
Education	Respondent has more than four years of formal education (1=yes; 0=otherwise)	0.83 (0.37)
Muslim	Respondent is Muslim (1=yes; 0=otherwise – mostly Christian)	0.57 (0.50)
Land owned	Land owned by the respondent's household (ha)	4.41 (5.71)
Mobile phone	Household owns a mobile phone (1=yes; 0=otherwise)	0.70 (0.46)
Radio	Household owns a radio (1=yes; 0=otherwise)	0.75 (0.43)

Note: Figures in brackets are standard deviations. N=345

The results in models (5) and (7) indicate that the degree of the farmer network outside the village positively and significantly affects intensity of exposure to sorghum varieties and OPVs of maize, while the network degree within the village has no significant effect. We hypothesize that information about sorghum varieties and maize OPVs is not uniformly distributed across villages, such that varieties known in one village are not necessarily the same as those known in the neighboring villages. Farmers within a village are likely to be exposed to the same varieties, rendering variety information from additional network links within the village redundant. Schaefer (2010) argues that strong ties within a network (for instance, those in intra-village networks), can make such networks less exposed to new ideas or just conservative, while Rauch (2010) posits that bridging network clusters produces synergies that lead to higher outcomes. We thus hypothesize that networking across the village increases a farmer's chances of gaining higher intensity of exposure. Most studies that investigate the role of social networks in technology diffusion focus on intra-village networks, which are considered stronger and perhaps more relevant, but this result demonstrates that for some technologies, the apparently weak inter-village networks (when present) may matter even more, consistent with Granovetter's (1973) "strength of weak ties" notion.

Having network connections with institutions that facilitate information dissemination influences intensity of exposure to some technologies. Results show that an extra contact per month with a member of the village administration increases the intensity of exposure to improved sorghum varieties, but the result is insignificant for the maize models. Our explanation for this effect is that the government has been promoting sorghum farming in the study area, and these administrators, being part of the government, are involved in that campaign. Further results indicate that farmers with network links to extension officers have a higher intensity of exposure to improved varieties in all models. It is worth noting that for both crops, the marginal effect of network connections with an extension officer on intensity of exposure is several times larger than that of network links with another farmer. Being the information brokers between researchers and farmers, extension officers are naturally more informed about improved varieties and hence, more effective in exposing farmers to new seed technologies, than other actors in the farmers' information network.

Table 3.5: Estimates of the determinants of exposure to improved varieties

Explanatory Variable	(1) Sorghum	(2) Maize	(3) Maize OPVs	(4) Maize Hybrids	(5) Sorghum	(6) Maize	(7) Maize OPVs	(8) Maize Hybrids
Sorghum network degree	0.087** (0.042)							
Sorghum network degree1					0.022 (0.065)			
Sorghum network degree2					0.223** (0.106)			
Maize network degree		0.047 (0.056)	0.048* (0.028)	-0.006 (0.040)				
Maize network degree1						-0.018 (0.082)	-0.003 (0.044)	-0.020 (0.058)
Maize network degree2						0.194 (0.140)	0.148** (0.072)	0.029 (0.101)
Admin link	0.014** (0.007)	0.013 (0.008)	0.005 (0.005)	0.008 (0.006)	0.014** (0.007)	0.014 (0.008)	0.0051 (0.005)	0.008 (0.006)
Extension link	0.365** (0.147)	0.410** (0.179)	0.156 (0.096)	0.254** (0.129)	0.379*** (0.146)	0.423** (0.182)	0.168* (0.098)	0.256** (0.130)
Age	0.018** (0.007)	0.017* (0.007)	0.013*** (0.005)	0.004 (0.007)	0.019*** (0.007)	0.018* (0.010)	0.014*** (0.005)	0.004 (0.007)
Female	-0.298 (0.201)	-0.576** (0.248)	-0.147 (0.128)	-0.437** (0.172)	-0.320 (0.201)	-0.584** (0.246)	-0.149 (0.128)	-0.439** (0.172)
Education	0.348 (0.213)	0.495* (0.268)	0.286** (0.141)	0.208 (0.192)	0.359* (0.213)	0.496* (0.268)	0.291** (0.140)	0.207 (0.192)
Land owned	-0.005 (0.011)	-0.009 (0.017)	-0.003 (0.010)	-0.008 (0.010)	-0.008 (0.012)	-0.011 (0.017)	-0.005 (0.010)	-0.008 (0.010)
Mobile phone	0.221 (0.154)	0.306 (0.206)	0.280** (0.120)	0.032 (0.145)	0.219 (0.153)	0.298 (0.205)	0.272** (0.118)	0.030 (0.145)
Radio	0.123 (0.185)	0.421* (0.241)	0.156 (0.135)	0.267* (0.160)	0.128 (0.185)	0.432* (0.241)	0.170 (0.134)	0.269* (0.161)

Notes: N=345. Column numbers represent different models for each technology under different specifications of farmer social networks. Figures inside the table are marginal values, with robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Results for personal characteristics show that farmer's age is a positive and significant determinant of intensity of exposure to improved varieties, with exception of maize hybrids. This result is generally unsurprising since we expect older farmers to know more varieties, by virtue of their experience. Gender of farmers affects exposure intensity for maize varieties in general and hybrids in particular. Being a female farmer is the most limiting constraint to exposure to maize varieties. Women farmers are exposed to about 0.6 maize varieties less than their men counterparts. Another result shows that education generally influences intensity of exposure positively, but this effect is significant only for maize varieties, particularly OPVs. We hypothesize that with less information on maize OPVs reaching farmers through extension officers and seed market channels, higher cognitive ability gives farmers a higher propensity to seek information on OPVs, thereby getting more exposed to

them. Interesting results emerge with respect to the effect of information and communication technologies on exposure. Ownership of cell-phones positively influences intensity of exposure to OPVs of maize, while radio ownership is associated with higher intensity of exposure to maize hybrids. The positive effect of radio could be explained by the fact that hybrids have a much more developed seed market than OPVs; hence more information about hybrids than OPVs may be passed to farmers through radio advertisements. A reason for positive effect of mobile phone ownership on exposure to OPVs might be that cell-phones enable farmers to search for information from other farmers and actors, since flow of information about OPVs through commercial channels is limited, and contrary to the case of sorghum, public sector interest in maize in the study area is much less.

3.5.5 Adoption rates of ICVs

We continue our analysis by investigating the relationship between exposure and adoption. The incidence of exposure is about 79% in the case of sorghum and 74% for maize (Table 3.6), a difference that is only weakly significant. The adoption rates in the full sample are pretty low and just about 42% for sorghum and 60% for maize. These findings, however, have to be interpreted with caution, because the estimated figures suffer from non-exposure bias (Diagne and Demont, 2007). This bias occurs when not all farmers, as it is the case in our study, are exposed to a new technology. Farmers who have not been exposed cannot adopt it even if they might have done so if they had known about it. In such a case, the observed sample adoption rate always underestimates the true population adoption rate.

Table 3.6: Observed exposure and adoption rates of improved varieties

Exposure/Adoption rates	Sorghum	Maize
Exposure (% sample)	0.788 (0.022)	0.736* (0.024)
Ever adopted (% sample)	0.652 (0.026)	0.646 (0.026)
Ever adopted (% of exposed)	0.827 (0.023)	0.878* (0.021)
Adopted in 2011/12 season (% sample growers)	0.424 (0.0316)	0.600*** (0.028)
Adopted in 2011/12 season (% of exposed growers)	0.531 (0.036)	0.769*** (0.027)

Note: Differences between sorghum and maize varieties significant at *** $p < 0.01$, * $p < 0.1$.

Conditional on exposure, the adoption rate increases in our case to about 53% for sorghum and 77% for maize (table 3.6). Strikingly, not all exposed farmers adopt ICVs, suggesting that further constraints exist or that the expected net benefits are low or uncertain,

as demonstrated in Table 3.3. Moreover, the proportion of respondents that has ever adopted ICVs is statistically higher for maize than for sorghum (at 10% level). In case of maize almost 88% of the exposed have ever adopted an ICV, while it is 83% for sorghum. Comparing these figures to adoption rate in the last season suggests that a substantial share of farmers decided to cease using ICVs. The share of dis-adopters is higher in the case of sorghum. These descriptive results suggest that the lack of adoption cannot be explained by exposure alone, and that the adoption of sorghum ICVs is more constrained than that of maize ICVs. The findings, however, have to be interpreted cautiously, because even the estimated adoption rates conditional on exposure might still suffer from selection bias (Diagne and Demont, 2007). They are likely to overestimate the true population adoption rate, because farmers, who are most likely to adopt, get exposed first. Sources of such a positive selection bias are, for example, the targeting of progressive farmers by researchers and extension workers (Diagne, 2006). We use the framework developed by Diagne and Demont (2007) to calculate unbiased estimates of the population adoption rates.

After accounting for exposure, the predicted population adoption rate is 51.4% for sorghum and 71.0% for maize (Table 3.7). Comparing these findings to the adoption rate in the full sample shows that accounting for non-exposure bias increases population adoption rates by 9.3 and 10.9 percentage points for sorghum and maize, respectively. This is the so-called *adoption gap*. Furthermore, there is also a significant *positive population selection bias* of 6.1 percentage points for maize, meaning that farmers currently exposed to improved maize varieties are those with higher propensity to adopt than a randomly selected farmer in the population.

Table 3.7: Estimated adoption rates of improved varieties

Predicted exposure/adoption rates (treatment effects)	Sorghum (N=245)	Maize (N=305)
Population adoption rate (ATE)	0.514*** (0.034)	0.710*** (0.031)
Adoption rate among exposed subsample (ATE1)	0.526*** (0.031)	0.771*** (0.025)
Adoption rate among non-exposed subsample (ATE0)	0.465*** (0.073)	0.495*** (0.075)
Classic adoption rate - joint exposure and adoption (JEA)	0.421*** (0.025)	0.601*** (0.019)
Non-exposure bias (Adoption gap)	-0.093*** (0.015)	-0.109*** (0.016)
Population selection bias (PSB)	0.012 (0.013)	0.061*** (0.014)

Notes: Figures in brackets are standard errors. *** p<0.01.

3.5.6 Determinants of adoption

To estimate the drivers of adoption of improved varieties, we apply the average treatment effects (ATE) framework proposed by Diagne and Demont (2007). The basic logic of this framework is that farmer exposure to improved varieties, which is a precondition for adoption of the varieties, is not necessarily random in the population. For instance, farmers may self-select themselves into exposure, or be targeted by technology promoters for exposure into these varieties. Furthermore, adoption may be influenced by unobserved factors that influence exposure. Thus, if exposure to improved varieties among farmers is incomplete, modeling adoption without taking into account the potential non-exposure bias yields inconsistent estimates. We employ Probit models to estimate determinants of exposure and of adoption after correcting for non-exposure bias. Table 3.8 presents the definitions and descriptive statistics of the variables used in the exposure-adoption model.

Estimates for determinants of adoption are shown in Table 3.9. The results of the exposure model are not discussed in detail here, because we have already discussed the determinants of exposure in Chapter 3.5.4. However, since the results discussed are from count models (Poisson regressions), we provide the results of the binary exposure models (Probit regressions) that were estimated together with the adoption models, for comparison and robustness check. The results show that inter-village social network size positively influences the probability of exposure improved varieties of sorghum. For maize, social network size has no effect on probability of exposure. These findings are qualitatively similar to those of the Poisson regressions, implying that the conclusions for the effects of social network size on exposure are robust to model specification. However, a number of variables that are significant in most of the Poisson regressions, including farmer links to village administrators and extension officers, and education and gender of the respondent, become insignificant in the Probit regression models, implying that the effects of these variables on exposure depend on how the exposure variable is specified. Moreover, modeling exposure as a discrete rather than binary variable gives results with richer policy implications.

Results for determinants of adoption are presented in two columns, for each crop. The *parametric* models shows results of the Probit regressions estimated for the sub-sample of exposed growers only, while the *classic* models show results for the full sample of growers, including those who are not exposed to ICVs. We discuss the results of the parametric models only, because the non-exposure bias for both crops was significant. However, we also show results for the *classic* models that do not control for non-exposure bias, for comparison.

Table 3.8: Description and mean values of variables used in adoption models

Variable	Definition and measurement	Sorghum (N=245)	Maize (N=305)
Knwsorg	Dependent variable1 (1=Yes if sorghum grower is aware of at least one improved variety, 0=Otherwise)	0.80 (0.40)	
Knwmaiz	Dependent variable1 (1=Yes if maize grower is aware of at least one improved variety, 0=Otherwise)		0.78 (0.41)
Adopso	Dependent variable2 (1=Yes if sorghum grower cultivated at least one improved variety in 2011/12 season, 0=Otherwise)	0.42 (0.50)	
Adopma	Dependent variable2 (1=Yes if maize grower cultivated at least one improved variety in 2011/12 season, 0=Otherwise)		0.60 (0.49)
Sorghum network degree1	Intra-village sorghum network degree (number of links out of three random matches within the village)	1.09 (1.10)	
Sorghum network degree2	Inter-village sorghum network degree (number of links out of three random links outside the village)	0.23 (0.63)	
Maize network degree1	Intra-village maize network degree (number of links out of three random matches within the village)		0.89 (1.09)
Maize network degree2	Inter-village maize network degree (number of links out of three random links outside the village)		0.20 (0.57)
Admin link	Strength of links with village administration (number of contacts per month with village administrators)	13.6 (9.62)	13.8 (9.68)
Extension link	Talks with public extension officer at least once per month (1=yes, 0=otherwise)	0.67 (0.47)	0.64 (0.48)
Intesorg	Intensity of exposure to sorghum varieties (number of improved varieties known)	1.76 (1.32)	
Intemaiz	Intensity of exposure to maize varieties (number of improved varieties known)		1.97 (1.57)
Mobile phone	Household owns a mobile phone (1=yes; 0=otherwise)	0.69 (0.46)	0.69 (0.46)
Radio	Household owns a radio (1=yes; 0=otherwise)	0.74 (0.44)	0.76 (0.43)
Leader	Respondent is a community leader (Yes, 0=Otherwise)	0.41 (0.49)	0.37 (0.48)
Female	Gender of respondent is female (1=Yes; 0=Otherwise)	0.24 (0.43)	0.26 (0.44)
Age	Age of respondent (years)	45.9 (10.7)	46.6 (11.7)
Education	Respondent has more than four years of formal education (1=yes; 0=otherwise)	0.86 (0.35)	0.82 (0.39)
Hhsize	Household size (no. of members)	6.67 (2.45)	6.35 (2.42)
Fem1564	No. of female household members aged 15-64 years	1.54 (0.93)	1.43 (0.87)
Mal1564	No. of male household members aged 15-64 years	1.80 (1.11)	1.66 (1.07)
Nonfarm	Respondent has nonfarm income (1=Yes, 0=Otherwise)	0.42 (0.49)	0.39 (0.49)
Land owned	Land owned by the respondent's household (ha)	4.64 (6.30)	4.67 (5.98)
Poorsoil	Proportion (%) of cultivated land area classified as having 'poor' soil fertility by farmer	22.3 (36.3)	19.4 (34.7)
Sorgarea	Size of land allocated to sorghum in 2011/12 (Ha)	1.02 (1.03)	
Maizarea	Size of land allocated maize in 2011/12 (Ha)		1.01 (0.94)

Notes: Figures in sorghum and maize columns are mean values, with standard deviations in brackets.

Interestingly, we find that after accounting for the role of social networks in exposure, and controlling for the intensity of exposure, social networks have a further positive influence on variety adoption, especially for sorghum varieties. However, it is particularly the intra-village and not inter-village networks that produce this effect. This result implies that other than the learning effects of social networks, social influence could play a role in adoption of improved sorghum (Hogset and Barrett, 2010). Hedström *et al.*, (2000) and Easley and Kleinberg (2010) hypothesize that such influence can result from imitation or mimicry, which means that farmers could adjust their adoption behavior just to conform to observed behavior of their peers and not because of any factual information that they learn about the varieties from the social network. This could happen because they admire the adopting peers or they just want to ‘flow’ with the rest. Another argument proposed by An (2010) may be that farmers are encouraged or persuaded by their social network members to adopt improved varieties. Given that (the stronger) intra-village networks are the more important drivers of adoption than inter-village networks, these arguments seem plausible.

The intensity of exposure to improved varieties positively influences adoption decision for both crops. This is plausible because different varieties present farmers with a much wider range of crop attributes from which they can choose, thereby increasing a farmer’s chance of finding a variety with interesting attributes that compels him/her to adopt it. This is consistent with results in Table 3.3, where farmer perceptions of trait superiority between improved and traditional varieties differ for each improved variety. Households with higher number of female members in working age (15-64 years) are more likely to adopt improved sorghum varieties, while for maize, adoption of improved varieties is influenced by the number of male household members in working age. This implies that female labor is a key input in the cultivation of improved sorghum varieties, while for maize male, labor is more important. These results may be indicative of different gender responsibilities for different crops in Africa (Crehan, 1997). Interestingly, even after netting out the effect of non-farm income activities on exposure, we find that having these activities also increases the probability of adopting improved maize varieties. This is plausible since seeds of improved maize varieties are more commercialized than those of improved sorghum. Additional income sources increase a farmer’s purchasing power for improved maize seeds, thereby increasing farmers’ probability of adopting them.

Table 3.9: Determinants of adoption of improved varieties

Variable	Sorghum			Maize		
	Exposure	Adoption		Exposure	Adoption	
		Parametric	Classic		Parametric	Classic
Sorghum network degree1	-0.027 (0.106)	0.432*** (0.122)	0.336*** (0.184)			
Sorghum network degree2	0.880*** (0.303)	-0.219 (0.192)	-0.108 (0.184)			
Maize network degree1				0.031 (0.100)	0.209 (0.129)	0.200** (0.094)
Maize network degree2				0.101 (0.194)	-0.005 (0.214)	-0.068 (0.194)
Admin link	0.017 (0.011)	0.003 (0.010)	0.002 (0.009)	0.010 (0.009)	-0.004 (0.010)	-0.004 (0.010)
Extension link	-0.057 (0.224)	0.045 (0.229)	0.065 (0.203)	0.301 (0.189)	-0.247 (0.252)	-0.103 (0.205)
Intesorg		0.223** (0.094)	0.480*** (0.082)			
Intemaiz					0.283*** (0.089)	0.646*** (0.087)
Mobile phone	0.517** (0.233)	-0.144 (0.236)	-0.094 (0.214)	0.280 (0.201)	-0.005 (0.248)	-0.067 (0.205)
Radio	-0.369 (0.248)	0.272 (0.244)	0.140 (0.218)	0.258 (0.208)	0.265 (0.276)	0.180 (0.227)
Leader	0.330 (0.214)	-0.176 (0.214)	-0.040 (0.197)	0.100 (0.188)	-0.050 (0.216)	-0.072 (0.198)
Age	0.034*** (0.012)	-0.005 (0.013)	0.000 (0.011)	0.016* (0.009)	-0.012 (0.011)	-0.004 (0.010)
Female	-0.190 (0.267)	0.345 (0.298)	0.351 (0.248)	-0.396* (0.205)	-0.116 (0.267)	-0.074 (0.220)
Education	0.533 (0.381)	0.217 (0.382)	0.255 (0.315)	0.308 (0.255)	0.034 (0.321)	0.027 (0.307)
Hhsize		-0.001 (0.055)	-0.014 (0.049)		-0.055 (0.059)	-0.043 (0.050)
Fem1564		0.249* (0.143)	0.230* (0.118)		0.105 (0.139)	0.050 (0.124)
Mal1564		-0.096 (0.109)	-0.074 (0.097)		0.256** (0.109)	0.208** (0.099)
Nonfarm	0.057 (0.206)	-0.246 (0.208)	-0.199 (0.193)	0.464** (0.181)	0.402* (0.213)	0.480** (0.192)
Land owned	0.005 (0.021)	0.009 (0.020)	0.002 (0.019)	-0.009 (0.017)	0.010 (0.029)	-0.002 (0.017)
Poorsoil		-0.006** (0.003)	-0.005* (0.003)		-0.003 (0.003)	-0.003 (0.003)
Sorgarea		-0.028 (0.110)	-0.014 (0.094)			
Maizarea					0.634*** (0.190)	0.602*** (0.159)
Constant	-1.422 (0.878)	-0.774 (0.864)	-1.726** (0.726)	-0.588 (0.597)	-0.103 (0.826)	-1.363* (0.744)
N	245	196	245	305	238	305
Pseudo R ²	0.170	0.194	0.229	0.127	0.181	0.357

Notes: Figures are Probit coefficients, with robust standard errors in parenthesis. * P<10%, ** P<5%, *** P<1%.

Soil characteristics also seem to matter for adoption of improved sorghum but not of improved maize varieties. Farmers with a high proportion of cultivated land that they perceive to have poor soil fertility have a lower probability of adopting improved sorghum varieties. This may be related to the fact that most improved varieties tend to be responsive to soil fertility status. The scale of production also affects adoption of improved maize varieties. We find that the probability of adoption increases with the size of land area allocated to maize. This may be so because the larger scale farmers tend to be wealthier and may therefore afford seeds, or they are more commercially oriented and hence exploiting the profitability advantage of improved varieties. It may also be the case that larger scale farmers can spare some land to ‘experiment’ with new varieties, or they are better able to cope with risks that may be associated with adopting new technologies. While the underlying reasons for the association between the cultivated area and adoption are ambiguous, it has been widely reported that farmers with a larger cropping area tend to adopt earlier than those with smaller ones (see reviews by Feder *et al.*, 1985 and Geroski, 2000).

3.5.7 Constraints to the adoption of ICVs

After identifying the determinants of adoption of ICVs, we present the reasons stated by the farmers for the non-adoption of ICVs in this section. For farmers, who have never adopted sorghum and maize ICVs (never-adopters), the most limiting factor is seed availability, followed by perceived susceptibility to pests, both of which make close to three quarters of responses (Table 3.10). There are, however, significant differences between the two crops. About 56% of never-adopters of maize mentioned seed availability as a constraint, but just 44% of the sorghum never-adopters cited this as reason for non-adoption. Susceptibility to pests was mentioned by 30% of the sorghum never-adopters, while it was mentioned by only 16% of the maize never-adopters. The importance of reasons changes, if we only consider farmers who have adopted ICVs in the past but not in the last growing season. For sorghum ICVs, the most important constraint to adoption is pest susceptibility, followed by seed access problems. However, for maize ICVs, the most important constraint is low adaptation to local conditions; followed by again seed access problems. An important implication of this result is that adoption constraints may be different for those without previous adoption experience compared to those who have ever adopted them.

Table 3.10: Stated reasons for non-adoption of known varieties (% responses)

Reason	Never adopted		Ever adopted but did not adopt in 2011/12	
	Sorghum	Maize	Sorghum	Maize
Seed constraints	44.4	56.4**	27.6	28.6
Pests, including birds	30.7	15.7***	33.6	15.5***
Adaptation (low yields, takes long to mature)	3.9	7.4*	6.0	29.1***
Post-harvest (markets, utilization)	3.9	0.0**	11.3	0.5***
Land constraints (small land, infertile soil)	6.5	8.3	5.0	1.9**
Other (weather, lack of interest, not specified)	10.5	12.3	16.6	24.3**
<i>N</i>	153	204	301	206

Notes: Figures are based on responses for each variety known. *, **, *** indicates differences between the two crops are significant at 10%, 5% and 1%, respectively.

3.6 Conclusions

This study analyzes the determinants of exposure, which is a precondition for adoption, and of adoption itself. We focus on the role of social networks on exposure and adoption of improved cereal technologies. In a departure from previous studies on the determinants of exposure to improved varieties, we assess the intensity of exposure, which is modeled as a discrete variable. Moreover, we compare technologies with largely missing seed markets (sorghum varieties and OPVs of maize) and those with considerably functional markets (maize hybrids). We also explicitly address the effect of intra- versus inter-village networks on exposure and adoption, which has, at least to our knowledge, not been done in previous studies. Using household survey data from 345 farmers living in Central Tanzania, we apply Poisson models to identify the role of social networks on exposure to improved varieties. The analysis of adoption is based on a methodology proposed by Diagne and Demont (2007), which is able to account for non-exposure bias.

Our results show that about 79% of the respondents are aware of at least one improved sorghum variety, while 74% of respondents know at least one maize variety. Farmer networks are found to be key sources of information on improved varieties. Exchange of information that exposes farmers to improved varieties within these networks is triggered mainly when a farmer sights a variety in a network member's field. Improved varieties of both crops are generally considered better than traditional ones by most farmers. Results for determinants of farmer exposure to improved varieties show that the size of a farmer's sorghum network positively influences their intensity of exposure to improved varieties of the crop. The size of maize network influences exposure to OPVs positively, but we do not find a

significant effect on exposure to hybrids. We also find that farmers have substantial information networks outside their villages of residence, and it is these often understudied networks rather than those inside the village, that determine the intensity of exposure to improved varieties. Important are also linkages to the village administrators in the case of sorghum and to the public extension officers in case of both crops.

After accounting for exposure, the estimated population adoption rate is 52% for sorghum and 71% for maize. Social networks for sorghum have a positive influence on variety adoption even after accounting for the role of social networks in exposure, and controlling for the number of improved varieties known by a farmer, indicating endogenous social effects. However, it is particularly the intra-village and not inter-village networks that produce this effect. This result implies that other than the social learning effects of social networks, social influence could also play a role in sorghum adoption. Households with more female adults are more likely to adopt improved sorghum, while those with more male adults are more likely to adopt improved maize. Poor soil fertility negatively affects adoption of improved sorghum, while non-farm income activities and size of maize farm positively influence adoption of maize varieties. Farmers mentioned seed availability followed by perceived susceptibility to pests as the most limiting factors to adoption. However, the importance of these reasons changes if we compare farmers without past adoption experience to those who have ever adopted.

These results raise a number of implications for policy and further research. First, there is still a substantial share of farmers, who are not aware of any improved varieties. To increase adoption, efforts directed towards improving the knowledge about ICVs need to be stepped up. Second, our results suggest that an important starting point of variety information flows in social networks is visibility of the varieties in other farmers' fields. Yet, focus group discussions held during the survey revealed that farmers were critical of the very small demo plots that are often used, arguing that it is difficult to judge the potential of the technologies from such small plots. This result underscores the need for well managed demo farms, positioned strategically for many farmers to see the technology being promoted. Third, farmer networks with extension officers need to be strengthened, for instance by improving the facilitation of extension officers' mobility. Fourth, the power of farmer networks with community leaders and village administrators can be exploited, which calls for research into the possibility of targeting the farms of these leaders for demonstration plots, and increasing their exposure to improved varieties through facilitated forums such as seminars, agricultural shows and meetings with seed traders. Fifth, the finding that inter-village networks matter for

exposure to improved varieties points to the need for facilitated forums that enable farmers to exchange technological information across villages, such as tours to other villages. From a theoretical perspective, this result implies that inter-village networks cannot be generally ignored in studies on social networks. Studies on inter-village networks in the context of technology diffusion are rare and more studies are needed to enrich the debate on our findings. Sixth, the result shows that adoption increases with the number of improved varieties a farmer knows of. It is hence important to develop a set of ICVs, which are characterized by a range of crop attributes. This increases the chance that a farmer finds a variety that suits his/her requirements. Seventh, in the development of future sorghum varieties more emphasis should be placed on the performance on less fertile soils and reducing susceptibility to pests. Eighth, for the adoption of sorghum varieties it is crucial to target female farmers in extension activities because their level of exposure to improved varieties is generally lower than that of men although they are responsible for sorghum cultivation. Finally, the availability of improved varieties needs to be enhanced. The strategies, however, need to be adapted according to the source of seeds. Seeds of sorghum and non-hybrid maize ICVs, which are open pollinated, are usually obtained from fellow farmers. Distributing the seeds directly to farmers during field days and farmer field schools is hence a promising strategy. Another strategy would be to strengthen the initiative of producing quality declared seeds (QDS) by fellow farmers, which would bring the producer of seeds closer to the actual users. Moreover, popularizing the QDS farmers would be critical as the current ones are still unknown to many farmers, as was revealed during focus group discussions. For hybrid maize varieties, a different strategy needs to be applied, because they are usually obtained through local input dealers. It is hence important to improve the availability throughout the planting season in the local shops. This can only be achieved in collaboration with seed producers and retailers.

4 Effects of social networks on technical efficiency in smallholder agriculture: The case of cereal producers Tanzania⁴

Abstract

The use of improved crop varieties is key to increasing food production, but in Sub-Saharan Africa traditional varieties still dominate smallholder farming. Lack of information is a major constraint to the adoption of improved varieties and the role of social networks in their diffusion is increasingly being studied. Social networks can, however, also affect the efficiency with which farmers use these technologies. In this paper we investigate the influence of social networks on technical efficiency of smallholder cereal producers. Using the case of Tanzania, we apply stochastic frontier analysis on plot-level data of sorghum and maize producers. Results show that the effects of social networks on efficiency differ by crop. Inter-village farmer-to-farmer networks positively influence technical efficiency of improved varieties of sorghum, but they have no effect in case of maize. We further find that links to public extension officers increase efficiency of improved maize varieties. Some wider research and policy implications are discussed.

Keywords: Improved varieties, social networks, information, technical efficiency, stochastic frontier.

⁴ This chapter is co-authored with Dr. Theda Gödecke and Dr. Stefan Schwarze (Assistant Professors, Department of Agricultural Economics and Rural Development, Georg-August-University Göttingen). The authors acknowledge the contribution of Prof. Dr. Bernhard Brümmer, Department of Agricultural Economics and Rural Development, Georg-August-University Göttingen.

4.1 Introduction

Global demand for food and agricultural products is on the rise and there is need to increase production to meet this growing demand. Smallholders, who form the majority of farmers around the world, will play a significant role in this regard (FAO, 2014). The use of improved crop varieties (ICVs) has been identified as an important strategy by which smallholders can increase productivity and food production (World Bank, 2007). However, in most of Sub-Saharan Africa, traditional varieties still dominate smallholder production systems (Walker et al., 2014), limiting the envisaged output and productivity gains. Lack of agricultural information has been identified as a key constraint to ICV diffusion, and its role is increasingly being studied (Diagne and Demont, 2007; Simtowe et al., 2011; Kabunga, Dubois and Qaim, 2012). Based on this information constraint paradigm, a number of ICV diffusion studies (Matuschke and Qaim, 2009; Maertens and Barrett, 2013) have assessed the role of social ties and interactions, also known as social structures or social networks (Borgatti et al., 2009). This is anchored on the understanding that social networks are powerful informal institutions for information diffusion in farming communities, and that flows of information, beliefs and attitudes within social networks can influence farmers' technology adoption decisions (Baerenklau, 2005).

Social networks, however, can affect not only the adoption by farmers, but also the efficiency with which farmers use these technologies. Based on information obtained from network members, individual farmers adjust the type and timing of crop husbandry methods used (such as seedbed preparation, sowing, and management of soil fertility, pests and diseases), which then influences their technical efficiency. While there have been a number of studies assessing the impact of ICVs on efficiency and productivity (Huang and Bagi, 1984; Adesina and Djato, 1996; Sherlund, Barrett and Adesina, 2002; Aye and Mungatana, 2010), we are not aware of any study that has investigated explicitly the effect of farmer-to-farmer social networks. We hence add to the literature by investigating the role of these social networks for technical efficiency. We use data from 231 plots of sorghum and 287 of maize, collected from 345 cereal producers in Central Tanzania. Another interesting aspect of our study refers to the characteristics of social networks themselves. Past studies report that social networks cross geographical boundaries (De Weerd, 2004; Fafchamps and Gubert, 2007), but previous studies of network effects primarily focus on intra-village links, ignoring inter-

village networks that may play an important role in information dissemination. Hence, an attempt is made to assess the effects of social networks both within and across villages.

The rest of the paper is structured as follows. Section 2 discusses the methodology of our study. After describing the data and empirical models in Section 3, we present our results in Section 4. In Section 5, we conclude and discuss implications of the study for policy and future research.

4.2 Methodology

4.2.1 Technical efficiency and its measurement

Efficiency in resource allocation is the central concept in neoclassical theory of production, in which firms are assumed to be profit maximizing. According to Kumbhakar and Lovell (2000), we define technical efficiency (TE) of a farm as the ratio of its observed output to the maximum feasible output. Following Kumbhakar and Lovell (2000) and Greene (2008), we use stochastic frontier analysis to estimate the production frontier and to obtain measures of technical efficiency. The stochastic frontier model is specified as

$$\ln Y_i = f(\mathbf{X}_i, \boldsymbol{\beta}) + v_i - u_i \quad (4.1)$$

where Y_i is the quantity of output produced by farm i ($i=1,2,\dots,N$), \mathbf{X}_i is a vector of inputs into the production process, and $\boldsymbol{\beta}$ is a vector of parameters to be estimated, $(v_i - u_i)$ is the composed error term, ε_i , with v_i being the stochastic component that accounts for measurement errors, omitted variables, model (mis)specification and random variation across farms. This stochastic error is assumed to be normally distributed and can take negative, zero, or positive values. It is further assumed that $E(v_i) = 0$; $E(v_i^2) = \sigma_v^2$ and $E(v_i v_j) = 0$ for all $i \neq j$ (Coelli *et al.*, 2005). The term $u_i \geq 0$ represents the technical inefficiency, and captures the extent to which observed yield deviates from potential output, given inputs and production technology. This term is assumed to follow a half-normal, truncated-normal, exponential or gamma distribution. It is also assumed that $E(u_i^2) = \sigma_u^2$ and $E(u_i u_j) = 0$ for all $i \neq j$ (Coelli *et al.*, 2005). From this term, a farm's level of technical efficiency (TE) is calculated using equation 4.2. Jondrow *et al.* (1982) and Greene (2008) discuss the derivation of these terms in detail.

$$TE_i = \exp(-u_i) \quad (4.2)$$

Letting technical inefficiency to be influenced by farm and management characteristics, then the inefficiency model can be specified as

$$u_i = \alpha_0 + s_i \alpha + z_i \delta + w_i \quad (4.3)$$

where α and δ are vectors of parameters to be estimated, s represents a vector of *social network* characteristics of farmer i , z_i is a vector of farm and farmer characteristics, and w_i represents unobserved normally distributed random factors that influence inefficiency. Equations (4.1) and (4.3) are then estimated simultaneously by maximum likelihood methods (Kumbhakar and Lovell, 2000). We assume half-normal distribution and test for the presence of inefficiency (i.e., null hypothesis that $\lambda = 0$, against the alternative that $\lambda > 0$) using a special likelihood ratio test for on-boundary values described by Gutierrez, Carter and Drukker (2001).

4.2.2 Information, social networks and technical efficiency

The key sources of new agricultural information in our study area are seed and agro-chemical companies/dealers; government agricultural extension officers; non-governmental organizations; and public agricultural research and development organizations (Figure 4.1). Farmers obtain this information through two main channels. One, they may directly access the information by participating in the activities offered by these institutions such as farmer field days, on-farm trials and demo plots. The second pathway is informal, i.e., farmers obtain the information from other farmers, through their social networks. We define a *social network* as a set of actors or nodes (individuals or households) that have relationships or ties with one another (Marin and Wellman, 2011).

Social networks affect an individual farmer's behavior through *social learning* or *social influence* (Young, 2009; Hogset and Barrett, 2010). In the case of social learning, the farmer actively searches for information within his/her networks. The information obtained may in turn influence the farmers' decision to adopt a more efficient farming method. By contrast, social influence results from *imitation* or *mimicry*, which means that a farmer adjusts their farming practice mainly to *conform* to observed behavior of other farmers, and not necessarily based on any factual information about the motivation for their peers' adoption of the given farming method (Hedström, Sandell and Stern, 2000; Easley and Kleinberg, 2010). According to these pathways, we hypothesize that the information obtained from formal sources and from farmer-to-farmer networks influences individual farmers to adjust the type and timing of crop husbandry methods used (such as seedbed

preparation, sowing, and management of soil fertility, pests and diseases), resulting to changes in technical efficiency.

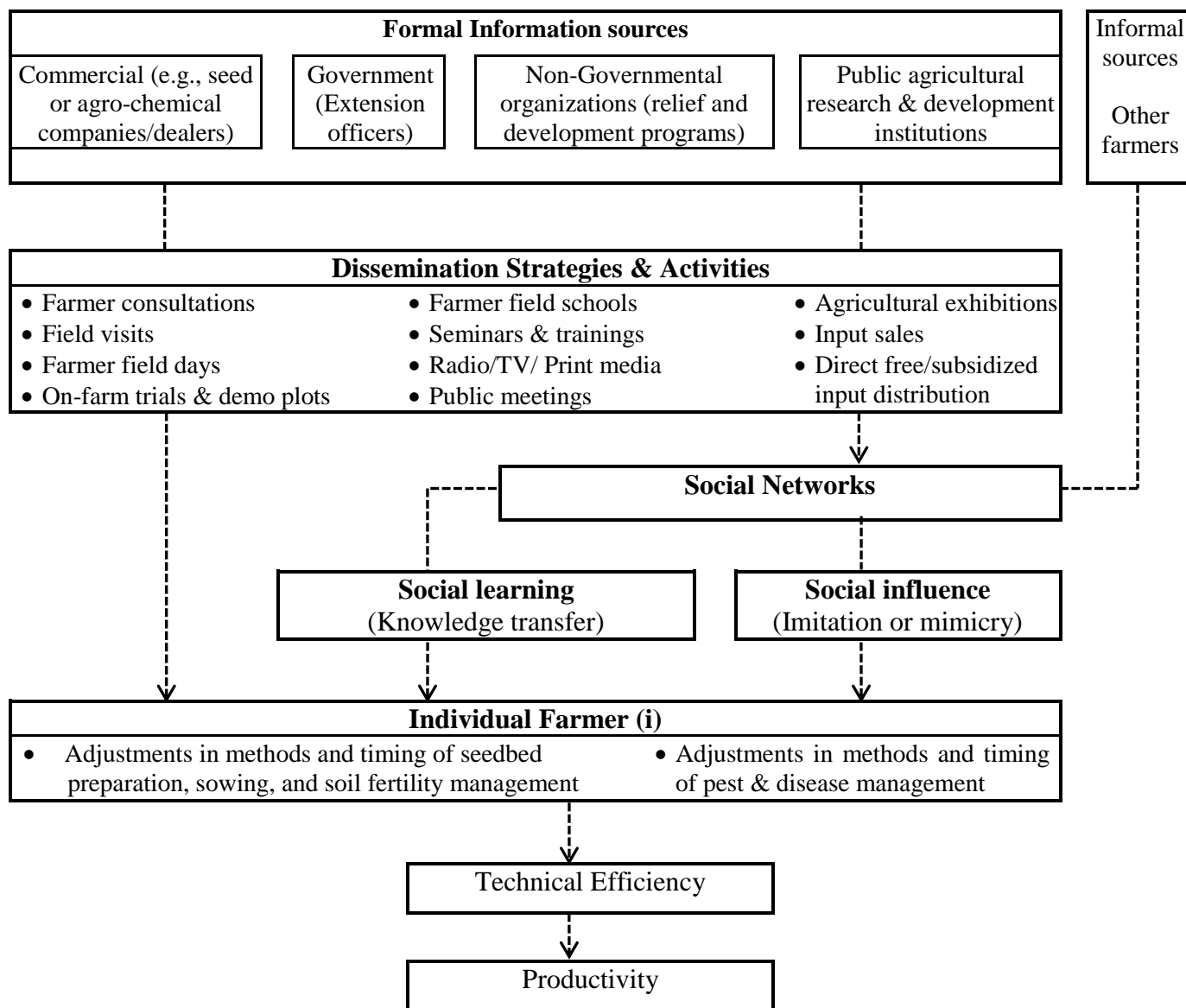


Figure 4.1: Information sources and pathways, and the role of social networks for technical efficiency.
Source: Authors' impressions.

4.2.3 Potential endogeneity in adoption of improved varieties

The type of seed technology (improved or traditional varieties) used is an important factor influencing productivity. The adoption of improved varieties is, however, potentially endogenous. Mutter *et al.* (2013) argue that efficiency estimation procedures that do not account for endogeneity introduce bias in the results due to correlation between the endogenous variable and the composed error of the stochastic frontier. In our study, it is

likely that endogeneity is present due to farmers self-selecting or being selected non-randomly into adoption. Information on and seeds of improved varieties are often passed to farmers in a selective manner. For instance, agricultural research and extension staff often target particular geographic locations, individual farmers or groups of farmers (Diagne and Demont, 2007) for ICV research, extension and development activities. In the case of Tanzania, Monyo *et al.* (2004) and Lyimo *et al.* (2014) document heavy involvement of the public agricultural extension service and development organizations in disseminating improved varieties of sorghum and maize. Moreover, in our data, the seeds used in 26.3% of the improved sorghum plots were sourced from agricultural extension officers. It is therefore very likely that the adoption of improved varieties is non-random and that an endogeneity problem is present due to sample selection.

4.2.4 Addressing endogeneity in variety adoption

Recently, studies employing SFA have begun to address the problem of endogeneity in technology adoption (Solís, Bravo-Ureta and Quiroga, 2007; Rao, Brümmer and Qaim, 2012; Wollni and Brümmer, 2012). In this study, we use a matching method known as propensity score matching (PSM) (Rosenbaum and Rubin, 1983) to correct for potential endogeneity. This non-parametric method enables us to construct a group of plots sown with traditional varieties (control or counterfactual group) which is comparable to those plots sown with improved varieties (treatment or treated group). An advantage of this grouping is that it gives us the flexibility to analyze technical efficiency of the two groups separately. Technological differences between the improved and traditional varieties imply that production constraints and information needs are different, hence separate analyses are interesting. We implement PSM by first computing a propensity score, which is the probability to adopt an ICV, using a Logit model. Next we use kernel matching (for sorghum) and nearest neighbor matching (for maize) algorithms to construct the treatment and control groups within the region of common support (Caliendo and Kopeinig, 2008). One shortcoming of PSM is its reliance on observables to address confoundedness, but self-selection can also be influenced by unobserved variables, resulting in hidden bias (DiPrete and Gangl, 2004). The Rosenbaum bounding procedure (RBP) has been commonly used to assess the sensitivity of the results to unobservables (Rosenbaum, 2005). In this study, we follow DiPrete and Gangl (2004) to perform the RBP. For brevity, since we do not use the results of the matching directly, we do not show the matching models, but refer the reader to the cited references.

4.3 Data and empirical model

4.3.1 Data sources

The data we use were collected in Singida Rural and Kondoa Districts in Central Tanzania between September and November 2012. Central Tanzania is mainly semi-arid, and farmers in the region cultivate mainly cereals (sorghum and maize are the staples), but also grow some pulses, oil, root and tuber crops, and keep livestock (United Republic of Tanzania, 2012). The data were collected through a household survey involving 345 farmers from 21 villages. In each district, 3 village clusters (2-5 villages each) were purposively selected. Each cluster consists of villages that are geographically close to each other and that share the same local agricultural extension officer. This approach was chosen because it enables us to investigate the effect of inter-village networks. In each village, households were then selected by simple random sampling, and their heads interviewed by enumerators using a pre-tested structured questionnaire. We collected information on respondent, household and farm characteristics, and plot-level data on crops cultivated in the 2011/12 season. Plot-level data was preferred to data for total area allocated to these crops because it is easier to remember for the respondent, given that the farmers do not keep formal records. To improve accuracy and reliability of labor data, respondents were asked to select only one plot of sorghum and maize, respectively, and recall the labor use by production activity for this plot.

To elicit data on social networks, we sampled pairs of the selected farmers using the random matching within sample approach (Conley and Udry, 2010; Maertens and Barrett, 2013). Each farmer (i) was randomly paired with six other respondents (j) from our sample: three from his/her village and three from neighboring villages⁵. The respondents were asked questions about their six random matches in this sequence: “Do you know j (the match)?” If the answer was “no”, no further network questions about the particular match were asked. If the answer was “yes”, the respondent was asked: “Do you discuss sorghum (maize) farming issues with j ?” Based on these answers, we interpret a “yes” response as presence of a network link for sorghum (maize), between the respondent and his/her match, and a “no” response as absence of such a link. Similar information about the respondent was not sought from his/her matches, implying that we use undirected network links. In addition to the farmer-to-farmer networks, respondents were asked about their frequency of interactions with

⁵ When using the random matching approach, there is no explicit rule regarding the number of matches per respondent, which rarely exceeds seven in most studies.

village administrators (chair or other executives at village or sub-village level) and public extension officers.

4.3.2 Model specification

The models used in this study are shown in equations (4.3) and (4.4). Different functional forms have been used for $f(.)$ in equation (4.1), but the most common are Cobb-Douglas (CD) and Translog (TL). Although TL is usually preferred in empirical work due to its flexibility, we use the CD function in this paper, because it best fits our data. The dataset showed high multicollinearity between input variables and their cross-products, which rendered estimation of the frontier impossible, or to produce coefficients that were unstable or with counterintuitive signs. Such challenges have been reported in studies by Dawson, Lingard, and Woodford (1991) and Wilson, Hadley and Asby (2001).

Thus, our empirical production frontier takes the following form:

$$\ln Production_{ic} = \beta_{0c} + \sum_{x=1}^X \beta_{xc} Input_{xic} + \beta_{vc} Variety_{vic} + \sum_{e=1}^E \beta_{ec} Environment_{eic} + v_{ic} - u_{ic} \quad i=1,2,\dots,N; \quad c=1,2 \quad (4.3)$$

where the subscripts i and c represent individual farmers and crops, respectively, and β are the parameters to be estimated. **Input** is a vector of discretionary inputs: *land*, *labor* and *seeds*. None of the farmers reported using fertilizers or irrigation in production of either crop, while the use of pesticides was negligible. This is consistent with minimal use of these inputs reported in recent national surveys (World Food Programme, 2010; United Republic of Tanzania 2012). *Variety* is a dummy variable representing the type of seed technology used (traditional or improved⁶), and we hypothesize that improved varieties would have a positive effect on grain output. **Environment** is a vector of dummy variables controlling for the effect of physical production environment on crop output. Sherlund *et al.* (2002) show that omitting such environmental factors can bias efficiency estimates. Hence, we use *soil types* to control for differences in soil fertility (Sommer *at al.*, 2013), *distance* from the homestead to the plots, to control for differences in other soil and environmental characteristics (Rowe *et al.*, 2006) and crop management challenges associated with plots located away from the

⁶ In this study, we categorize recycled seeds of improved varieties as improved, because from the perspective of the farmer, the varieties are still distinct from the traditional ones and failure to acquire fresh seeds may due to farmer or market constraints rather than their unwillingness to do so. Since recycled hybrid seeds tend to lose vigor over time, we acknowledge that this categorization could potentially underestimate their productivity.

homestead (Tan, Kruseman and Heerink, 2007). A district dummy is also included to control for unobserved heterogeneity due to agro-climatic factors.

We estimate the determinants of inefficiency simultaneously with the production frontier, using the following model

$$u_{ic} = \alpha_{0c} + \sum_{k=1}^K \alpha_{kc} \mathbf{Network}_{kic} + \sum_{m=1}^M \delta_{mc} \mathbf{z}_{mic}$$
$$i=1,2,\dots,N; \quad c=1,2 \quad (4.4)$$

where subscripts i and c are as previously defined, and α and δ are coefficients to be estimated. $\mathbf{Network}$ is a vector of variables capturing the effect of different types of network links on efficiency. We use the total *network degree* (number of network links out of the six random matches) as a proxy for total farmer-to-farmer network size and further split it into intra-village and inter-village network degrees. The vector also includes variables measuring the link of farmers with village administrators and public agricultural extension officers. Our hypothesis is that farmers with a higher network degree or stronger ties with formal institutional actors are better placed to obtain more or higher quality production information, which may enhance technical efficiency. Finally, \mathbf{z} is a vector of control variables hypothesized to affect efficiency, such as farming experience, wealth-related variables, ownership of information asset such as radio, and membership to community associations that engage in agricultural activities.

4.3.3 Descriptive statistics of model variables

In this section we present descriptive statistics for the variables used in the frontier and inefficiency models. Additional variables that we use only for the estimation of the propensity scores are presented in Table A1 in the Appendix. Table 1 shows summary statistics of the plot-level variables disaggregated by crop and seed technology (traditional vs. improved). About 27% of sorghum plots are sown with improved varieties, while for maize, improved varieties occupy 63% of the plots. On average, plots of traditional sorghum varieties are significantly larger (0.78 ha) than those of improved varieties (0.57 ha), but for maize, it is the plots of improved varieties that are larger (0.85 ha) than those of traditional varieties (0.69 ha). Input use shows some significant differences only for sorghum, with farmers using more seeds and labor in plots sown with traditional varieties than in plots sown with improved varieties. Plots on sandy soil are the most common, followed by those on clay

and loam soils, respectively. Most of the plots are located within the homestead or can be reached within 30 walking minutes. However, for a sizeable proportion of plots, farmers have to walk for a longer time to reach them and in this study we refer to them as “far plots”. For maize, the proportion of far plots is significantly higher for improved than traditional varieties.

Table 4.1: Descriptive statistics for variables used in the production frontier models

Variable	Description	Sorghum		Maize	
		Traditional (N=169)	Improved (N=62)	Traditional (N=106)	Improved (N=181)
Variables used in the frontier model					
<i>Output</i>					
Output	Grain output per plot (tons)	0.47 (0.57)	0.31** (0.41)	0.40 (0.70)	0.58** (0.68)
<i>Inputs</i>					
Land	Plot size (ha)	0.78 (0.80)	0.57** (0.63)	0.69 (0.48)	0.85** (0.76)
Labor	Total labor used (Days)	113.9 (95.4)	87.8** (72.3)	82.0 (57.0)	79.9 (76.8)
Seed	Total seed used (kg)	8.95 (10.3)	4.60*** (5.67)	10.0 (10.4)	10.6 (12.4)
<i>Production environment</i>					
Sand soil	Soil type is mostly sandy (1=Yes, 0=otherwise)	0.56 (0.50)	0.55 (0.50)	0.44 (0.50)	0.41 (0.49)
Clay soil	Soil type is mostly clay (1=Yes, 0=otherwise)	0.23 (0.42)	0.24 (0.06)	0.34 (0.48)	0.37 (0.48)
Loam soil	Soil type is mostly loam (1=Yes, 0=otherwise)	0.21 (0.41)	0.19 (0.40)	0.22 (0.41)	0.22 (0.41)
Far plot	Plot is located far from the homestead (1=Yes, 0=otherwise)	0.12 (0.32)	0.13 (0.34)	0.12 (0.33)	0.22** (0.42)
Kondoia	Plot is in Kondoia district (1=Yes, 0=Otherwise)	0.43 (0.50)	0.45 (0.50)	0.52 (0.50)	0.58 (0.50)

Note: Figures are mean values, with their standard deviations in parenthesis. *, **, *** differences in means between traditional and improved varieties are significant at 10, 5 and 1% respectively.

Table 4.2 presents a summary of the social network, respondent, and household characteristics of our sample, disaggregated by crop and type of seed technology used. Social network data shows that the measures of crop network degree for sorghum are significantly different between growers of improved and traditional varieties. The total sorghum network degree is 1.9 for adopters of improved varieties and 1.1 for non-adopters. Similarly, both intra-village and inter-village network degrees are higher for adopters than for non-adopters. For maize, only the inter-village network degree differs significantly between adopters and non-adopters. The proportion of farmers with ties to extension officers is higher for growers of improved varieties than for growers of traditional varieties for both crops. For maize, adopters of improved varieties have more frequent communication with members of the

village administration compared to non-adopters. Finally, the proportion of farmers with membership in a community group or association that engages in some agricultural activities is significantly higher for adopters of improved varieties of both crops.

Table 4.2: Descriptive statistics for variables used in the technical inefficiency models

Variable	Description	Sorghum		Maize	
		Traditional (N=169)	Improved (N=62)	Traditional (N=106)	Improved (N=181)
<i>Informal Networks</i>					
Sorghum network degree	Total sorghum network degree (no. of links out of all six random matches)	1.09 (1.36)	1.86*** (1.62)		
Sorghum network degree1	Intra-village sorghum network degree (no. of links out of three random matches within the village)	0.92 (1.07)	1.47*** (1.10)		
Sorghum network degree2	Inter-village sorghum network degree (no. of links out of three random matches outside the village)	0.17 (0.52)	0.39*** (0.84)		
Maize network degree	Total maize network degree (no. of links out of all six random matches)			0.95 (1.30)	1.14 (1.49)
Maize network degree1	Intra-village maize network degree (no. of links out of three random matches within the village)			0.81 (1.09)	0.91 (1.09)
Maize network degree2	Inter-village maize network degree (no. of links out of three random matches outside the village)			0.14 (0.45)	0.24* (0.63)
Association membership	Household head is a member of a community association that engages in agricultural activities	0.10 (0.29)	0.21*** (0.41)	0.08 (0.27)	0.13* (0.34)
<i>Formal Networks</i>					
Extension link	Talks with public extension officer at least once per month (1=Yes; 0=otherwise)	0.65 (0.48)	0.74* (0.44)	0.56 (0.50)	0.68** (0.47)
Admin link	Strength of links with village administration (no. of contact days per month with a village administrator)	13.7 (9.97)	14.3 (8.96)	12.4 (8.91)	14.7** (10.1)
<i>Other farmer/farm characteristics</i>					
Farming experience	Experience in own farming activities (years)	25.6 (11.5)	24.6 (9.86)	25.3 (12.5)	26.1 (10.8)
Maize farming experience	Maize farming experience (years)			21.9 (12.1)	22.7 (11.5)
Land owned	Total land owned (Ha)	4.16 (4.82)	6.04** (9.31)	3.81 (5.65)	5.13 (6.17)
Plots	Number of sorghum (maize) plots cultivated	1.54 (0.76)	1.66 (0.70)	1.14 (0.51)	1.50*** (0.69)
Radio	Household owns a radio (1=yes; 0=otherwise)	0.75 (0.43)	0.69 (0.47)	0.68 (0.47)	0.79** (0.41)
Nonfarm income	Household head earns a non-farm income	0.43 (0.50)	0.39 (0.49)	0.37 (0.49)	0.40 (0.49)
Livestock wealth	Total value of livestock owned (Millions of Shillings. 1,560 Shillings=1USD during survey)	2.15 (3.45)	2.32 (3.43)	2.45 (4.31)	2.16 (3.10)
Tech2011	Attended a technology/information dissemination event in 2011	0.45 (0.50)	0.68*** (0.47)	0.39 (0.49)	0.50** (0.50)

Note: Figures are mean values, with their standard deviations in parenthesis. *, **, *** differences in means between traditional and improved varieties are significant at 10, 5 and 1% respectively.

Turning to respondent and household characteristics, we find that farming experience of respondents is about 25 years and crop-specific farming experience does not differ much from overall experience. Furthermore, adopters of improved sorghum tend to be wealthier –

they own more land (6.0 ha) than growers of traditional varieties (4.2 ha). Adopters of improved maize have significantly more maize plots than non-adopters, but the difference in number of sorghum plots does not differ significantly between adopters and non-adopters of improved sorghum. Ownership of radios is higher among adopters for the case of maize, but does not differ between adopters and non-adopters of improved sorghum.

4.4 Results

4.4.1 Results for the propensity score matching

Results for the logit models are shown in Table A2 in the appendix. We summarize the matching quality in Table 4.3. The test for the balancing of covariates shows that the bias drops well below 10% after matching. The mean bias reduced by 83.5% for sorghum and 61% for maize. In addition, the Pseudo R-squared values of the Logit models were reduced to less than 5%, while the LR Chi-squared values dropped to statistically insignificant levels, implying that matched improved and traditional variety plots do not differ systematically with respect to observable physical and management characteristics. The critical values of gamma at 10% level of significance are about 2.3 for sorghum and 2.0 for maize. This means, if there is an unobserved variable that is significantly influencing adoption of ICVs, then its value must at least double, to invalidate our results. We hence conclude that PSM substantially reduced covariate biases and is quite robust to hidden bias. The distribution of the propensity scores is shown in Figure 2 indicating sufficient common support. Detailed results on covariate balancing are reported in the Appendix (Table A3).

Table 4.3: Matching quality

Variable	Sorghum			Maize		
	Before matching	After matching	Bias reduction	Before matching	After matching	Bias reduction
Biases						
Median bias (%)	21.3	5.9	72.3%	17.7	8.0	53.2%
Mean bias (%)	26.0	4.3	83.5%	20.5	8.0	61.0%
Pseudo R ²	0.20	0.02		0.23	0.04	
LR Chi squared	54.5	3.20		85.9	18.5	
p> Chi squared	0.00	0.99		0.00	0.49	
Bounding						
Critical Gamma (Γ) at 5%		1.9 – 2.0			1.7 – 1.8	
Critical Gamma (Γ) at 10%		2.2 – 2.3			1.9 – 2.0	

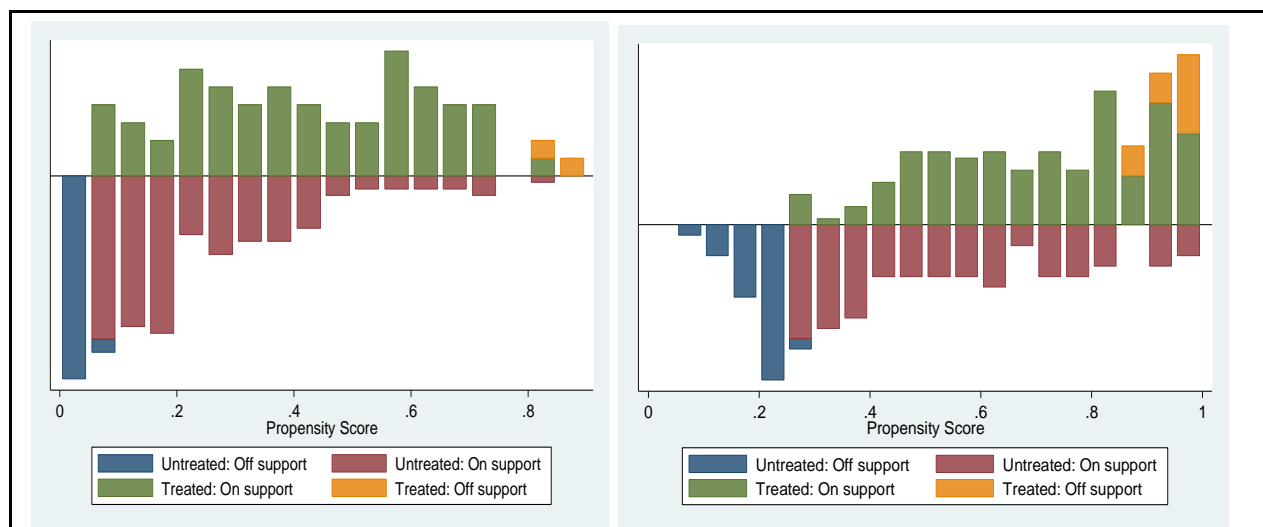


Figure 4.2: Distribution of propensity scores for sorghum (left) and maize (right), showing common support.

4.4.2 Results for technical efficiency analysis

For each crop, we estimated a pooled model and separate models for traditional and improved varieties using the matched samples. To test the effect of social networks, we included different proxies into the model. We begin our discussion with results of the frontier models presented in Table 4.4. The first three models of each crop (models 1-3 and 6-8) use the total crop (sorghum/maize) network degree, while in the last two models (4-5 and 9-10) we split the network into intra- and inter-village network degrees. Variance estimators provided at the bottom of the table show that λ is greater than one, implying that variation of output is more due to inefficiency than random errors. Based on the likelihood ratio (LR) test statistics (chibar2) we reject the null hypotheses that $\sigma_u=0$ in all models, implying that the component of inefficiency in the composed error is significant. The estimated coefficients for all discretionary inputs (land, labor and seeds) have the expected positive signs in all models. The pooled models reveal that improved sorghum varieties have no significant effect on the yield, contrary to our hypothesis. Maredia, Byerlee and Pee (2000) demonstrate that in Sub-Saharan Africa, yield gains from use of improved sorghum varieties are likely to be marginal in drier regions, if, like in our study, other inputs especially inorganic fertilizers are not used. However, for maize, improved varieties produced about 43% more grain than traditional varieties, which is comparable to a nationally representative figure of 38% (Lyimo, et al., 2014). Turning to the seed technology-specific models, results show that grain yields of improved varieties of both crops are more sensitive to environmental factors than traditional ones, suggesting that yields of traditional varieties are stable over a wider range of growing conditions than those of improved varieties.

Table 4.4: Results of the production frontier models

Variable	Sorghum					Maize				
	Total sorghum network degree			Intra- vs. inter- village sorghum network degree		Total maize network degree			Intra- vs. inter- village maize network degree	
	Pooled (1)	Traditional (2)	Improved (3)	Traditional (4)	Improved (5)	Pooled (6)	Traditional (7)	Improved (8)	Traditional (9)	Improved (10)
Land	0.46*** (0.12)	0.28** (0.12)	0.60** (0.26)	0.27** (0.12)	0.63** (0.26)	0.47*** (0.09)	0.52*** (0.11)	0.47*** (0.12)	0.52*** (0.11)	0.44*** (0.13)
Labor	0.20*** (0.07)	0.35*** (0.07)	0.01 (0.10)	0.34*** (0.07)	0.06 (0.11)	0.09 (0.08)	0.01 (0.13)	0.07 (0.12)	0.01 (0.13)	0.10 (0.12)
Seed	0.24*** (0.09)	0.23** (0.10)	0.10 (0.22)	0.24** (0.10)	0.08 (0.23)	0.32*** (0.07)	0.36*** (0.12)	0.30*** (0.10)	0.36*** (0.12)	0.31*** (0.10)
Improved	-0.14 (0.14)					0.43*** (0.11)				
Clay soil	0.24 (0.15)	0.15 (0.17)	0.58** (0.25)	0.13 (0.17)	0.64** (0.25)	-0.02 (0.12)	0.02 (0.21)	0.14 (0.16)	0.02 (0.21)	0.11 (0.16)
Loam soil	-0.09 (0.17)	0.14 (0.17)	-0.03 (0.46)	0.12 (0.17)	-0.06 (0.47)	0.12 (0.14)	0.23 (0.25)	0.28* (0.16)	0.21 (0.25)	0.27* (0.16)
Far plot	-0.30 (0.19)	0.14 (0.21)	-1.21*** (0.45)	0.14 (0.21)	-1.12*** (0.42)	0.17 (0.15)	0.48 (0.30)	0.15 (0.17)	0.48 (0.30)	0.16 (0.18)
Kondoa	0.19 (0.16)	-0.03 (0.21)	0.44 (0.34)	-0.04 (0.21)	0.44 (0.34)	-0.04 (0.18)	0.07 (0.28)	-0.27 (0.23)	0.07 (0.28)	-0.26 (0.23)
Constant	-1.39*** (0.42)	-2.52*** (0.39)	-0.51 (0.68)	-2.49*** (0.39)	-0.72 (0.73)	-1.24*** (0.43)	-1.14** (0.51)	-0.76 (0.63)	-1.14** (0.51)	-0.90 (0.66)
N	196	136	60	136	60	237	79	158	79	158
σ_u	1.49	0.98	2.03	0.98	2.03	1.38	1.60	1.33	1.60	1.33
σ_v	0.42	0.49	0.00	0.49	0.00	0.48	0.24	0.50	0.24	0.50
λ	3.58	2.01	1.88e+07	2.01	1.88e+07	2.90	6.64	2.65	6.64	2.65
Chibar2	21.27***	3.40**	19.89***	3.40**	19.89***	22.74***	16.80***	9.18***	16.80***	9.18***

Note: In brackets are robust standard errors. *p<0.1, ** p<0.05, *** p<0.01.

Table 4.5 shows the results of the technical inefficiency models including the determinants and levels of technical efficiency. The model numbers correspond to those in Table 4.4. Since it is our aim to compare the effects of model covariates between improved and traditional varieties, we discuss the results for the seed technology-specific models only. The results show that for sorghum, the total social network degree does not have any significant effect on technical efficiency. However, by splitting the social network degree (models 4-5) we find that the inter-village network degree has a significant positive effect on technical efficiency for improved varieties, while the intra-village network degree has no significant effect. This implies that a bigger sorghum network with other farmers outside the village may be a more important source of information on productivity-enhancing farming practices than intra-village links. These results agree with Schaefer (2010) who argues that strong ties within an established network (for instance, those in intra-village networks) can make such networks conservative and less exposed to new ideas. In a similar vein, Rauch (2010) posits that bridging network clusters (for example, establishing network links to other

villages) produces synergies that lead to higher outcomes. Moreover, Van den Broeck and Dercon (2011) report using data from a Tanzanian village that farming techniques that farmers learnt from others outside the village were more likely to be applied than those learnt from other farmers inside the village. As mentioned earlier, previous studies that investigated the effects of social networks on technology diffusion primarily focused on intra-village networks, thus the potentially important role of inter-village networks may have been missed.

The strength of links with village administrators had a small and insignificant effect. Having links to agricultural extension officers and attending technology and information dissemination events had a positive effect on technical efficiency of improved varieties and a negative effect on efficiency of traditional varieties, but these effects were statistically insignificant. Lack of evidence of positive effects of extension services on technical efficiency is often reported in developing countries (Coelli, Rahman and Thirtle, 2002; Theriault and Serra, 2014). Possible explanations for this is that due to some infrastructural, institutional or cultural challenges, extension messages are not disseminated effectively, or a number of farmers may find it difficult to apply recommendations from extension workers (Davis, 2008). We hypothesized that farmers linked to agricultural officers or attending their events would receive more information and hence achieve higher technical efficiency. However, since improved varieties of sorghum are OPVs, and many farmers obtain seeds from their networks, it seems that information from these networks is more important for technical efficiency than that from formal sources such as extension officers and events.

Results for maize show that, when controlling for other information sources and producer characteristics, the maize network degree has a negative and significant effect on technical efficiency of traditional varieties, but no effect on technical efficiency of improved varieties (models 7-8). By disaggregating the network degree into intra- and inter-village degree (models 9-10), we show that the effect for traditional varieties is driven by information received from farmers inside the village. This is rather surprising, but we hypothesize that since adoption of improved maize in our sample is quite high, discussions about maize farming mostly entail new farming methods associated with improved varieties. Some of the methods may be unsuitable for traditional varieties leading to lower technical efficiency. The strength of farmer links with members of the village administration did not have any significant effect on technical efficiency. We find, however, that links to public extension officers and attending information and technology dissemination events had significant positive effects on technical efficiency for improved but not traditional varieties.

This finding is consistent with our hypothesis in section 4.2.2. It highlights that the information disseminated through formal sources is specific to improved varieties and underscores the complementarity between ties with extension officers and other formal information dissemination approaches such as extension meetings or farmer field days.

Table 4.5: Determinants of technical inefficiency and estimated technical efficiency scores

Variable	Sorghum			Maize						
	Total sorghum network degree			Intra- vs. inter- village sorghum network degree		Total maize network degree			Intra- vs. inter- village maize network degree	
	Pooled (1)	Traditional (2)	Improved (3)	Traditional (4)	Improved (5)	Pooled (6)	Traditional (7)	Improved (8)	Traditional (9)	Improved (10)
Sorghum network degree	-0.01 (0.08)	-0.02 (0.13)	-0.11 (0.11)							
Sorghum network degree1				-0.17 (0.26)	0.26 (0.30)					
Sorghum network degree2				0.39 (0.45)	-0.58** (0.29)					
Maize network degree						0.02 (0.08)	0.43** (0.22)	-0.09 (0.10)		
Maize network degree1									0.47* (0.25)	0.01 (0.17)
Maize network degree2									0.24 (0.48)	-0.33 (0.29)
Association membership	0.08 (0.37)	-0.88 (0.58)	0.93* (0.49)	-1.00 (0.62)	0.63 (0.53)	-0.07 (0.38)	-1.28 (0.91)	-0.27 (0.46)	-1.22 (0.88)	-0.23 (0.46)
Admin link	0.01 (0.01)	-0.01 (0.01)	0.02 (0.02)	-0.01 (0.02)	0.03 (0.03)	0.01 (0.01)	0.00 (0.02)	0.01 (0.01)	-0.00 (0.02)	0.02 (0.01)
Extension link	0.17 (0.26)	0.29 (0.45)	-0.58 (0.45)	0.36 (0.49)	-0.46 (0.46)	-0.63** (0.26)	-0.35 (0.38)	-0.58** (0.28)	-0.34 (0.39)	-0.63** (0.29)
Tech2011	0.10 (0.22)	0.34 (0.37)	-0.04 (0.38)	0.38 (0.41)	-0.13 (0.43)	-0.49** (0.25)	0.68 (0.52)	-0.88*** (0.31)	0.70 (0.51)	-0.97*** (0.33)
Radio	-0.21 (0.25)	-0.26 (0.41)	-0.27 (0.45)	-0.28 (0.42)	-0.41 (0.42)	-0.08 (0.22)	0.01 (0.42)	-0.15 (0.33)	0.03 (0.45)	-0.14 (0.32)
Farming experience	0.02* (0.01)	0.00 (0.01)	0.07** (0.03)	0.00 (0.01)	0.08*** (0.03)					
Maize farming experience						0.01* (0.01)	-0.02 (0.02)	0.02* (0.01)	-0.02 (0.02)	0.02* (0.01)
Non-farm income	0.08 (0.24)	0.94** (0.42)	-0.70* (0.39)	1.01** (0.48)	-0.69** (0.34)	0.12 (0.22)	0.33 (0.41)	0.10 (0.32)	0.35 (0.42)	0.11 (0.31)
Land owned	-0.09*** (0.03)	-0.28*** (0.10)	-0.09** (0.04)	-0.33*** (0.13)	-0.07* (0.04)					
No of plots	0.39** (0.17)	0.14 (0.21)	0.73*** (0.24)	0.14 (0.23)	0.82*** (0.21)	-0.33* (0.18)	-1.74** (0.74)	-0.24 (0.20)	-1.72** (0.74)	-0.24 (0.20)
Livestock wealth	0.01 (0.05)	-0.16** (0.07)	0.05 (0.06)	-0.15** (0.07)	-0.01 (0.08)	-0.01 (0.04)	-0.37** (0.15)	0.00 (0.05)	-0.36** (0.16)	-0.00 (0.05)
Kondo	1.31*** (0.32)	2.15*** (0.57)	1.65*** (0.47)	2.23*** (0.60)	1.46*** (0.47)	0.39 (0.30)	1.30** (0.63)	-0.16 (0.39)	1.26** (0.62)	-0.17 (0.39)
Constant	-0.94* (0.54)	-1.08 (1.20)	-1.87* (1.00)	-1.18 (1.21)	-2.88** (1.41)	0.92** (0.41)	1.92* (1.06)	1.10** (0.52)	1.88* (1.06)	1.09** (0.51)
Mean Technical Efficiency	0.45 (0.24)	0.63 (0.22)	0.42*** (0.28)	0.65 (0.22)	0.43*** (0.28)	0.46 (0.22)	0.50 (0.26)	0.48 (0.22)	0.50 (0.25)	0.48 (0.22)
N	196	136	60	136	60	237	79	158	79	158

Note: In brackets are robust standard errors (standard deviations for technical efficiency). *p<0.1, **, p<0.05, *** p<0.01. For mean technical efficiency, comparisons are made between Traditional and Improved varieties.

Predicted technical efficiency (TE) scores are shown at the bottom of Table 4.5. Assuming common production technology for each crop, the pooled models show almost equal mean TE scores of about 45% for sorghum and 46% for maize. When making comparisons between the seed technology-specific models, we find that the mean TE for sorghum is significantly higher for traditional varieties (63% and 65%) than for improved ones (42% and 43%). For maize, the TE scores are higher for traditional varieties, but this difference is not significant. These overall low TE scores imply that opportunities exist for farmers to increase their technical efficiency and hence productivity.

4.5 Conclusions and policy implications

This paper has investigated the role of social networks for technical efficiency of smallholder farmers, using the case of cereal producers in Tanzania. Unlike previous social network studies, which mostly focused on cash crops, we have looked at sorghum and maize, which are grown mainly for home consumption. While previous studies concentrated primarily on intra-village social networks, we have extended the approach and have also considered inter-village networks. We applied stochastic frontier analysis to simultaneously estimate the production frontiers and the determinants of technical efficiency after correcting for potential self-selection in adoption of improved varieties using propensity score matching.

Our results show that for sorghum, while the total and intra-village network degrees (proxies for farmer-to-farmer network size) do not significantly influence technical efficiency, the inter-village sorghum network degree has a positive effect on technical efficiency of improved but not of traditional varieties. For the case of maize, we find no significant effect of maize network degree on technical efficiency of improved varieties. However, for traditional varieties, the intra-village network degree has a significant negative effect on technical efficiency. This demonstrates that social network effects on technical efficiency vary by crop and seed technology. The strength of ties with village administrators does not have any significant effect on technical efficiency of either crop. Consistent with our hypothesis, we find that having links to public extension officers and attending information and technology dissemination events organized through the officers has a positive effect on technical efficiency for improved varieties, which is significant only for maize. This result shows that efficiency-enhancing production information for the largely commercialized seed technologies may be much more technical, hence requiring more specialized dissemination, than for the less commercialized technologies. Further results show that the average technical

efficiency scores are below 50% for both crops, meaning there is potential for farmers to more than double their productivity. The mean technical efficiency score of traditional varieties exceeds that of improved varieties, although this is significant for sorghum only. This implies that information or other production constraints that limit efficient utilization of production inputs are more severe for growers of improved than of traditional varieties.

These findings raise a number of implications for policy and further research. First, the finding that social networks are a key determinant of technical efficiency of improved sorghum varieties calls for further research into how these networks can be best used to raise technical efficiency and consequently crop productivity. Special emphasis should be given to inter-village networks, whose role for agricultural outcomes is rarely assessed. In addition, since this study assessed the effect of only one farmer network characteristic (degree) due to data limitations, future studies could consider the effects of other network characteristics as well. Secondly, from the findings on the positive effect of extension links and attendance of technology and information transfer events on technical efficiency, it is imperative that interactions between farmers and extension officers are increased, perhaps by facilitating their mobility into the villages and having more officers and extension activities at the lower administrative levels. However, more research may be necessary to identify the most cost-effective ways of doing this. Thirdly, since technical efficiency scores of both crops and seed technologies are generally low, there is need to train farmers on farming practices that can raise their technical efficiency and hence productivity. One strategy would be to investigate the extent to which recommended crop management practices are currently being applied by farmers and focus farmer advisory services on practices that need more attention.

5 Conclusions and policy implications

5.1 Main findings

Global demand for food and agricultural products is on the rise and there is need to increase production to meet this growing demand. Smallholders, who form the majority of farmers around the world, will play a significant role in this regard. The use of modern technologies such as improved crop varieties is seen as key to increasing agricultural productivity and production, but in Sub-Saharan Africa traditional varieties still dominate smallholder farming, limiting the envisaged output and productivity gains. Lack of agricultural information is a major constraint to adoption of improved varieties, and the role of social networks in information diffusion and variety adoption is increasingly being studied. However, several gaps still exist in the literature. First, while existing studies shows that social networks influence technology diffusion, the effects seem to be technology and context specific. For instance, most studies assessing the role of social networks in technology adoption focus on cash crops, and the few that have looked at staple cereals investigate hybrids that have functional private seed markets. Hence, it remains largely unknown what role social networks would play in situations where seed markets are weak or non-existent. Secondly, the concrete role of social networks in exposing farmers to improved technologies has not been investigated, yet exposure is a pre-condition for technology adoption. Thirdly, social networks have been shown to disseminate information that can potentially effect agricultural production, but no studies have investigated the role of social networks in productive efficiency of farms. Finally, although there is documented evidence that social networks cross geographical boundaries such as villages, most social network studies in agriculture focus on intra-village networks, ignoring inter-village networks that could play a significant role.

Thus, this study has contributed to the available literature by making an attempt to fill the above mentioned gaps, using data collected from 345 cereal growers Central Tanzania between September and November 2012, as an example. We focus on sorghum and maize, the staple cereals in the central region of the country. Sorghum ICVs available in Tanzania are purely open pollinated variety (OPV) technologies characterized by underdeveloped private seed markets, while those of maize are largely hybrids, for which functional private seed markets exist.

The main results are graphically summarized in Figure 5.1, where the arrows indicate evidence of social network effects on various outcomes for sorghum and maize. Our first objective was to assess the factors that determine the existence of network links for the exchange of agricultural information between farmers. Using 948 pairs of farmers (dyads) randomly drawn from our sample, we found that even at the lowest administrative unit, the sub-village, not all farmers know each other. Yet, even in the cases where both farmers in a random dyad are familiar with each other, exchange of agricultural information occurs in only about one third of such dyads. Most of this exchange occurs if the farmers are from the same village, but 17% of these discussions occur across village boundaries. Dyadic regression results show that farmers are more likely to exchange relevant agricultural information if they have similar levels of education, different farm sizes, are members of the same community association, live in the same village, have known each other for a longer time, or have kinship ties. Moreover, the probability of exchanging farming information increases if a community leader is involved or if one of the farmers has a direct link to a public extension officer. These patterns are almost the same for sorghum and maize, meaning that if farmers exchange information about farming, they are unlikely to limit this information exchange to certain crops.

The second objective was to examine the role of social networks in exposing farmers to improved sorghum and maize varieties and hybrids. We found more pronounced differences between the two crops. While farmers gain first knowledge of sorghum varieties through their networks with other farmers in only 28% of the cases, they get exposed to maize varieties through such networks in 50% of the cases. However, controlling for personal characteristics of farmers such as education, age, gender, and ownership of information and communication assets, we find that increasing the social network degree (proxy for size of a farmer's social network) increases farmers' intensity of exposure (number of varieties known) to improved sorghum varieties, but not of improved maize varieties. Further disaggregation showed that for maize, the effect differs between OPVs and hybrids: while social networks play a positive and significant role in farmers' exposure to maize OPVs, the result remains insignificant for hybrids. Given that sorghum varieties are also OPVs, we conclude that the flow of information through informal networks is more important for seed technologies for which formal markets fail. Ownership of radio through which private seed markets commonly advertise their products increases exposure to maize hybrids, suggesting that for the more commercialized technologies, seed markets play a greater role than social networks in creating awareness. Strikingly, inter-village networks play a larger role in

generating awareness about new varieties than intra-village networks. This confirms our proposition that a potential role of inter-village social networks may have been missed in past studies. By networking with public extension officers and village administrators, farmers increase their exposure considerably. The marginal effects of extension officers are much larger than those of the farmer network variables, suggesting that informal information channels complement, but do not substitute awareness creation through formal channels.

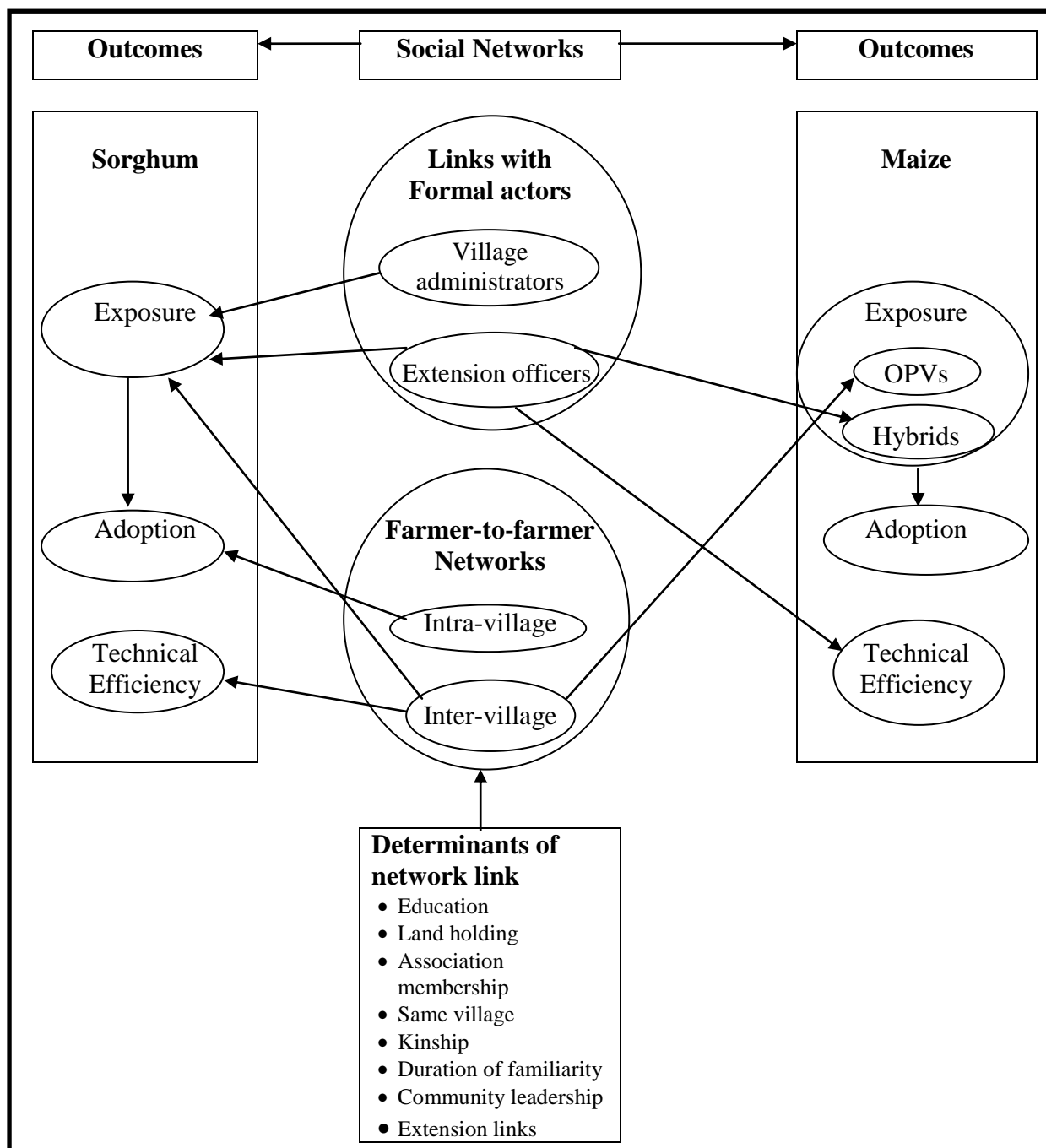


Figure 5.1: Effects of social networks on agricultural outcomes.
 Source: Author's impression from key results of the study.

Having analyzed how farmers gain knowledge about improved varieties, and their level of exposure to them, our third objective was to analyze the determinants of adoption, focusing on the role of social networks. This was done based on the Diagne and Demont (2007) estimation framework that controls for non-exposure bias. We additionally control for household and farm characteristics such as demographic, wealth, and soil quality indicators. Results show that consistent with expectation, intensity of exposure positively influences adoption of improved varieties of both crops. Significant non-exposure biases confirm lack of exposure to be an important constraint to adoption. Results predict that adoption rates would increase by 9% -11%, if all farmers were aware of the technologies. Interestingly, even after accounting for the role of social networks in exposure, and controlling for the intensity of exposure, we find that social networks for sorghum have a positive effect on variety adoption. This result implies that other than the learning effects of social networks (by which farmers expose each other to improved varieties), social influence could also play a role in sorghum adoption. Moreover, since improved sorghum varieties are not normally sold in formal seed markets, farmer networks could influence adoption by acting as seed sources for some farmers. We do not find significant social network effects on adoption of improved maize varieties, implying that influence of social networks on adoption is greater for improved varieties whose markets often fail. This is further supported by a positive influence of non-farm income on adoption of improved maize, which implies that additional income from non-farm activities could have been used to purchase seeds from formal markets as opposed to sourcing them from other farmers. Surprisingly, we find that contrary to the influence of social networks on exposure, it is the intra-village and not inter-village networks that produce this effect for sorghum. It means that while inter-village networks are more important for learning about new varieties as shown above, intra-village networks play a more important role in adoption, perhaps because it is easier to see and judge varieties grown inside than outside the village. Network links with village administrators or extension officers do not influence adoption once their role in exposure is controlled for, meaning that these communication channels are more relevant for raising awareness about the technologies.

The fourth objective of this study was to investigate the role of social networks in technical efficiency, which we compare between improved and traditional varieties. Using data from 231 plots of sorghum and 287 of maize, we applied stochastic frontier analysis after correcting for potential self-selection in adoption of improved varieties using propensity score matching. Our results show that for sorghum, while the total and intra-village network degrees (proxies for network size) do not significantly influence technical efficiency, the

inter-village sorghum network degree has a positive effect on technical efficiency of improved but not of traditional varieties. For the case of maize, we find no significant effect of network degree on technical efficiency of improved varieties. However, for traditional varieties, the intra-village network degree has a significant negative effect on technical efficiency. This demonstrates social network effects on technical efficiency are dependent on crop and seed technology type. When comparing social network effects between improved varieties of the two crops, we conclude that the effects are more relevant for the varieties that do not have functioning private seed markets, consistent with the findings we discuss for exposure and adoption. Moreover, it shows that information from other villages may be much more novel for the respondent, than that coming from his/her village. Strength of ties with village administrators does not have any significant effect on technical efficiency of either crop. But consistent with our hypothesis, we find that having links to public extension officers and attending events organized through the officers has a positive effect on technical efficiency for improved varieties, which is significant only for maize. This shows that efficiency-enhancing production information for the largely commercialized seed technologies may be much more technical, hence requiring more specialized dissemination.

5.2 Implications of the study

This study has established that the levels of exposure, adoption and technical efficiency of improved varieties are still low and need to be addressed if full benefits of the technologies are to be realized. The findings raise a number of implications for policy and future research. First, social networks matter for the spread and efficient utilization of new agricultural technologies. Further, the role that social networks play for the spread and efficient utilization of new technologies differs by type of crop and technology: they seem to be more important for technologies that are not promoted by the private sector and for which formal markets fail. Technology dissemination programs should hence try to make use of such networks.

Second, the finding that inter-village networks matter for farmers' exposure to and technical efficiency of improved varieties points to the potential that facilitation of information exchange across village boundaries may have for awareness creation and the spread of new technologies. Follow-up studies should explicitly analyze the formation and functioning of inter-village social networks.

Third, farmers seem to discuss agricultural farming more with community leaders, while their links to village administrators in particular, play a role in creating awareness to improved varieties. Hence, the power of farmer networks with community leaders and village

administrators can be exploited, which calls for research into the possibility of targeting the farms of these leaders for demonstration plots, and increasing their exposure to improved varieties through facilitated forums such as seminars, agricultural shows and meetings with seed traders.

Fourth, we find a positive effect of extension officers in facilitating discussions about crop farming, creating awareness and technical efficiency of improved technologies. This implies that formal extension programs can be complemented, but not replaced by social networks. Therefore, new extension models could be developed that explicitly build on the synergies between formal and informal information channels. Much more research is needed to establish what type of extension model is cost-effective in a particular situation. Our results suggest that an intensive training of lead farmers, who then pass on their knowledge to other farmers, may be more effective than assuming that snowball effects across multiple network nodes would occur automatically. Modeling this around farmer associations and well managed demonstration plots may be one promising approach.

5.3 Limitations of the study and further research

The results of this study have enabled us to draw important general implications as stated above. Nevertheless, we acknowledge some key limitations and suggest how they could be addressed in future. First, our results are from a case study which is not representative of the entire country or sorghum and maize growing areas. Rural Tanzania is ethnically and culturally diverse, meaning that formation and functioning of social networks may not follow the patterns discussed in this study, everywhere. More studies in other parts of the country can help to enrich our findings and in designing national agricultural extension policies that incorporate social networks. Second, our study is based on cross-sectional data and some of the results may have been influenced by prevailing weather conditions in the season studied. Panel studies could help to capture longer-term effects of social networks and further reduce unobserved heterogeneity caused by time invariant factors. Third, the farmer-to-farmer networks used here are only sampled and obviously do not reflect exactly what happens in the real networks themselves. It may be the case that some farmers rely on very specific networks which cannot be adequately captured by a sampled network. The methodology for sampling networks is still developing and future studies should pay attention on how to collect more data on these specific networks. Finally, this study did not assess the specific kind of farming information that farmers exchange, beyond the names of improved varieties. Studies in the future could investigate information exchange on key farming practices and

perhaps the extent to which such information is applied. This may shed light on which information farmers can easily and effectively exchange, and which information requires specialized dissemination, perhaps by extension officers or other players in the pluralistic provision of farmer advisory services.

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Appendices

Appendix A: Additional tables

Table A1: Additional variables used in the logit models

Variable	Description	Sorghum		Maize	
		Traditional (N=169)	Improved (N=62)	Traditional (N=106)	Improved (N=181)
Striga plot	Plot gets infested with <i>striga</i> weeds (1=Yes, 0=Otherwise)	0.28 (0.45)	0.11*** (0.32)	0.20 (0.40)	0.16 (0.36)
Female	Respondent is a female (1=yes; 0=otherwise)	0.27 (0.44)	0.19 (0.40)	0.32 (0.47)	0.23** (0.42)
Education	Respondent has more than four years of formal education (1=yes; 0=otherwise)	0.84 (0.37)	0.90 (0.30)	0.79 (0.41)	0.83 (0.38)
Sorghum farming experience	Sorghum farming experience (years)	23.6 (12.4)	21.1 * (12.1)		
Exposure	Level of exposure to improved varieties (number of sorghum/maize varieties known)	1.44 (1.30)	2.34*** (1.23)	0.94 (1.29)	2.51*** (1.53)
Ever adopted	Ever adopted an improved sorghum (maize) variety (1=Yes, 0=otherwise)	0.54 (0.50)	0.82 (0.39)	0.26 (0.44)	0.91*** (0.29)
Extension strength	Strength of links with public extension officer (no. of contact days per month)	3.36 (5.98)	4.11 (5.79)	3.05 (5.84)	4.12* (6.25)
Muslim	Respondent is Muslim (1=yes; 0=otherwise – mostly Christian)	0.49 (0.50)	0.50 (0.50)	0.53 (0.50)	0.62* (0.49)
Mobile phone	Household owns a mobile phone (1=yes; 0=otherwise)	0.68 (0.47)	0.71 (0.46)	0.61 (0.49)	0.74** (0.44)

Note: Figures are mean values, with their standard deviations in parenthesis. *, **, *** differences in means between traditional and improved varieties are significant at 10, 5 and 1% respectively.

Table A2: Logit results for the estimation of propensity scores

Variable	Coefficient		Variable	Coefficient		Variable	Coefficient	
	sorghum	Maize		sorghum	Maize		sorghum	Maize
Constant	-2.15*** (0.83)	-0.67 (0.71)	Ever adopted	1.19*** (0.45)		Striga plot	-1.40*** (0.51)	-0.41 (0.36)
Sorghum network degree1	0.39** (0.18)		Exposure		0.81*** (0.16)	Village cluster2	-0.30 (0.63)	-0.37 (0.52)
Sorghum network degree2	0.11 (0.33)		Radio	-0.48 (0.41)	0.07 (0.37)	Village cluster3	-1.73** (0.72)	-0.35 (0.49)
Maize network degree1		0.02 (0.14)	Mobile phone		0.09 (0.32)	Village cluster4	-0.56 (0.65)	-0.02 (0.49)
Maize network degree2		0.26 (0.33)	Education	0.88* (0.54)		Village cluster5	-0.43 (0.72)	0.02 (0.63)
Admin link		-0.08 (0.06)	Female	-0.36 (0.41)		Village cluster6	-1.39* (0.78)	-0.47 (0.50)
Admin link squared		0.00 (0.00)	Muslim	-0.22 (0.40)	-0.20 (0.34)	Mean propensity score	0.27 (0.21)	0.63 (0.25)
Extension strength		-0.00 (0.03)	Land owned	0.01 (0.03)	0.23*** (0.08)	Pseudo R-squared	0.20	0.24
Tech2011	0.84** (0.36)		Land owned squared		-0.01** (0.00)	N	231	287
Farming experience		-0.01 (0.01)	Livestock wealth		-0.09* (0.05)	Robust standard errors in brackets. * p<0.1, ** p<0.05, *** p<0.01		

Table A3: Covariate balancing before and after matching

Variable	Sample	Sorghum				Maize			
		Mean		% reduction	t-test	Mean		% reduction	t-test
		<i>Treated</i>	<i>Control</i>	in bias	p> t	<i>Treated</i>	<i>Control</i>	in bias	p> t
Village cluster1	Unmatched	0.18	0.10		0.11	0.33	0.19		0.01
	Matched	0.17	0.12	33.6	0.43	0.30	0.23	55.9	0.20
Village cluster2	Unmatched	0.19	0.13		0.23	0.14	0.17		0.55
	Matched	0.18	0.18	99.4	1.00	0.15	0.23	-215	0.06
Village cluster3	Unmatched	0.08	0.20		0.04	0.10	0.16		0.13
	Matched	0.08	0.09	99.0	0.98	0.10	0.08	58.4	0.43
Village cluster4	Unmatched	0.29	0.26		0.65	0.20	0.25		0.36
	Matched	0.30	0.33	11.6	0.76	0.22	0.27	-9.20	0.29
Village cluster5	Unmatched	0.16	0.15		0.80	0.12	0.10		0.75
	Matched	0.17	0.19	-45.8	0.78	0.12	0.07	-313	0.13
Village cluster6	Unmatched	0.10	0.17		0.19	0.11	0.13		0.59
	Matched	0.10	0.10	95.0	0.95	0.12	0.13	70.7	0.87
Striga plot	Unmatched	0.11	0.28		0.01	0.16	0.20		0.35
	Matched	0.12	0.12	99.1	0.98	0.17	0.22	-16.6	0.25
Sorghum network degree1	Unmatched	1.47	0.92		0.00				
	Matched	1.42	1.43	97.0	0.94				
Sorghum network degree2	Unmatched	0.39	0.17		0.02				
	Matched	0.32	0.46	35.5	0.34				
Maize network degree1	Unmatched	1.47	0.92		0.00	0.91	0.81		0.48
	Matched	1.42	1.43	97.0	0.94	0.91	1.00	-0.20	0.45
Maize network degree2	Unmatched	0.39	0.17		0.02	0.24	0.14		0.17
	Matched	0.32	0.46	35.5	0.34	0.18	0.22	67.1	0.64
Radio	Unmatched	0.69	0.75		0.38	0.79	0.68		0.05
	Matched	0.70	0.67	49.0	0.73	0.79	0.77	82.0	0.69
Muslim	Unmatched	0.50	0.49		0.84	0.62	0.53		0.13
	Matched	0.48	0.48	62.7	0.95	0.59	0.65	30.1	0.25
Tech2011	Unmatched	0.68	0.45		0.00				
	Matched	0.68	0.69	99.0	0.98				
Ever adopted	Unmatched	0.82	0.54		0.00				
	Matched	0.82	0.76	79.9	0.46				
Education	Unmatched	0.90	0.84		0.23				
	Matched	0.90	0.91	82.8	0.84				
Female	Unmatched	0.20	0.27		0.26				
	Matched	0.20	0.17	56.9	0.66				
Land owned	Unmatched	6.04	4.16		0.05	5.13	3.81		0.07
	Matched	4.89	5.83	49.8	0.50	4.77	4.79	98.6	0.98
Land owned squared	Unmatched					64.1	46.2		0.50
	Matched					56.2	57.3	94.2	0.97
Livestock wealth	Unmatched					2.16	2.45		0.51
	Matched					2.27	1.86	-39.9	0.32
Admin link	Unmatched					14.7	12.4		0.06
	Matched					14.2	14.2	97.2	0.96
Admin link squared	Unmatched					316	233		0.03
	Matched					303	317	84.2	0.74
Extension strength	Unmatched					4.12	3.05		0.15
	Matched					3.98	3.48	52.9	0.47
Exposure	Unmatched					2.51	0.93		0.00
	Matched					2.24	2.22	98.9	0.91
Mobile phone	Unmatched					0.74	0.61		0.03
	Matched					0.72	0.78	48.0	0.20
Farming experience	Unmatched					26.1	25.34		0.60
	Matched					26.2	26.23	94.9	0.98

Appendix B: Survey Questionnaire

HOPE: Early Adoption Survey Instrument – Tanzania 2012

ICRISAT/DRD/University of Goettingen

0.0 Survey quality control

Date of interview: Day: Month: Year:

Interviewed by:

Starting time: Ending time:

Date entered: Day: Month: Year:

Entered by:

Introductory Statement

We are researchers from the DRD (Ministry of Agriculture), Dodoma, collaborating with a number of organizations to improve productivity and incomes of our farmers in line with the Kilimo Kwanza Policy. As part of this initiative, we interviewed among others your household two years ago, and are now doing a follow up to assess changes as well as challenges that still need to be addressed, especially in sorghum, finger millet and maize farming. We would like to talk to the person responsible for production of sorghum, finger millet and maize.

All the information gathered will be kept strictly confidential and solely used for research purposes.

If you are ready, may we now begin?

1.0 Respondent and site identification

1. Household ID: 2. Name of Household head:
3. Village location: Treatment area..... Diffusion area..... Control area.....
4. District 5. Ward.....
6. Village 7. Sub Village.....
8. GPS readings (i) Eastings **E**..... ii) Southings **S**..... iii) Elevation (m)
9. Respondent name
10. Respondent sex 0 male 1 female
11. Number of years the respondent is living in the village.....
12. Experience (**years**) in own farming activities
13. Experience (**years**) in cultivating: i) Sorghum..... ii) Finger millet..... iii) Maize.....
14. Community responsibility of household head
 [0=None; 1=Cell leader 2=Sub-village leader 3=Village Chairman 4=Village Executive Officer 5=Village government member 6=Ward Executive Officer 7=Councilor 8=Political party leader 9=Youth leader; 10=Women's leader; 11=Religious leader 12=Other, specify.....

2.0 Household information

2.1 Household composition and occupation of members (*Please fill the table for all household members who were in the last 12 month living in your household, fill also for non-permanent members eg. Temporary migrants, children living away at school*)

Name of HH member (start with respondent)	Relation to HH head Code A	Gender (0=male; 1=female)	Age (years)	Marital status Code B	Education level Code C	Religion Code D	Number of month s/he was living in the hh	Farm labour participation Codes E	Main occupation Code F	Yearly net income in TSh if NOT farming	2 nd important occupation Code F	Yearly net income in TSh if NOT farming	Other income sources Code G	Yearly net income from other sources (TSh)
1.														
2.														
3.														
4.														
5.														
6.														
7.														
8.														
9.														
10.														
11.														
12.														
13.														
14.														

Codes A

- 1 Household head
- 2 Spouse
- 3 Son/daughter
- 4 Parent
- 5 Son/daughter in-law
- 6 Grand child
- 7 Other relative
- 9 Other, specify.....

Codes B

- 1 Married living with spouse
- 2 Married but spouse away
- 3 Divorced/separated
- 4 Widow/widower
- 5 Never married
- 6 Other, specify.....

Code C

- 0 None (illiterate)
- 1 Basic (can write and read)
- 2 Lower primary (1-4)
- 3 Upper primary (5-7)
- 4 Secondary (9-12)
- 5 High education (13 -14)
- 6 College
- 7 Vocational training
- 8 Not applicable
- 9 Other, specify ...

Codes D

- 0 No religion
- 1 Moslem
- 2 Christian
- 3 Other, specify

Code E

- 0 None
- 1 Full time
- 2 Part-time
- 3 Weekends and holidays
- 4 Other, please specify
-

Codes F

- 0 No occupation
- 1 Farming (crop and/or livestock)
- 3 Herdsboy/girl
- 4 Housekeeping
- 5 Casual labourer on another farm
- 6 Non-farm business (shops, trade, tailor, etc)

- 7 Salaried employment
- 8 Other, specify.....
9. Student

Codes G

- 1 Rented out land
- 2 Rented out oxen for ploughing
- 3 Sale of dung cake for fuel
- 4 Sale of own trees (firewood, etc)
- 5 Sale of own brewed drinks
- 6 Pension income
- 7 Drought relief
- 8 Remittances (sent from non-resident family and relatives)
- 9 Marriage gifts (e.g., dowry)
- 10 Other, specify

3.0 Knowledge and adoption of sorghum, finger millet and maize varieties

3.1 Please fill the following Table for all varieties of sorghum, finger millet and maize the farmer knows (also those s/he does not plant her/himself)

Crop 1=Sorghum; 2=F/Millet; 3=Maize	Varieties known (Variety Codes)	Type of variety (0=Local; 1=Modern)	When (year) did you first hear about the variety?	From whom did you first hear about it? rank up to three Code A	If Main source of variety information was another farmer, fill in the following details at the time information was first acquired					Ever planted the variety? (0=no; 1=yes)	If NO					
					Name of the farmer from which information was sourced	What was your relationship with the farmer? (Relationship codes)	Had you known the farmer before? (0=No; 1=Yes)	How far did the farmer live (walking minutes)	Which year did the farmer first grow the variety?		If this variety is modern, how did you learn about it? (Codes B)	Give reasons (Code C, rank 3)	Ever seen the variety growing? (0=No; 1=Yes)	Ever tasted any meal or beverage made from the variety? (0=No; 1=Yes)	Will you plant variety in future? (0=no; 1=yes)	If NO, why not? (Code C, rank3)

- | | | | | |
|--------------------------------|------------------------------------|---|------------------------------------|---------------------------------------|
| Variety Codes | Code A | Codes B | Relationship Codes | Code C |
| Sorghum | 1 Government extension | 1. I saw it in the plot and asked the farmer about it | 1= Parent | 1 Cannot get seed at all |
| 1. Langalanga (Local) | 2 Farmer club | 2. The farmer told me about it then I asked for details | 2=Child | 2 Lack of cash to buy seed |
| 2. Pato | 3 NGO | 3. The farmer told me about it and invited me to see it | 3=Brother/sister | 3 Susceptible to field pests/diseases |
| 3. Macia | 4 Research centre | 4. Other. | 4=Grandparent | 4 Susceptible to bird attack |
| 4. Tegemeo | 5. On-farm trials/demos/field days | | 5=Grandchild | 5 Susceptible to storage pests |
| 5. Local variety (unspecified) | 6 Seed/grain stockist | | 6=Nephew/Niece | 6 Poor taste |
| 6. Sila | 7 Another farmer/neighbor | | 7=Uncle/aunt | 7 Cannot get credit |
| 7. Serena | 8 Radio/newspaper/TV | | 8=Cousin | 8 Low yielding variety |
| 8. Udo (Local) | 9 Other, specify..... | | 9=Same family lineage | |
| | | | 10=Mother/father in-law | 9 Poor prices |
| | | | 11=Brother/sister in-law | 10 No market |
| | | | 12=Other relative | 11 Requires high skills |
| | | | 13=Fellow villager/Friend/Neighbor | 12 Seeds are expensive |
| | | | 14=Professional/business colleague | 13 Requires more rainfall |
| | | | 15=Other, specify | 14 Other, specify |

3.3. Farmers' perception of characteristics of known modern sorghum, finger millet and maize variety compared with farmer's best local variety. [Let the farmer mention the best local sorghum, finger millet and maize varieties, and the best known modern varieties for comparison. For those who do not know any specific modern variety, or those who think all modern varieties are the same, get their perception on modern varieties in general only]

3.3.1 Name of best local variety: Sorghum Finger millet..... Maize

3.3.2 Name of best modern variety: Sorghum Finger millet..... Maize

Characteristics	Between modern and local SORGHUM variety which one is better? [0=None/indifferent; 1=Improved; 2= Local]		Between modern and local MAIZE variety, which one is better? [0=None/indifferent; 1=Improved; 2= Local]		Between modern and local FINGER MILLET variety, which one is better? [0=None/indifferent; 1=Improved; 2= Local]	
	Best Known Modern Variety	Modern varieties in general	Best Known Modern Variety	Modern varieties in general	Best Known Modern Variety	Modern varieties in general
Production characteristics						
1. Grain yield per acre						
2. Grain size						
3. Drought tolerance						
4. Field pest/disease tolerance						
5. Susceptible to bird damage						
6. Susceptible to lodging						
7. Tolerant to much rain						
8. Threshability						
9. Less labour demand						
Market and economics						
10. Marketability (demand)						
11. Price (Tsh)						
Post-harvest /Consumption						
12. Storability						
13. Ease of processing (eg milling)						
14. Flour quality (for baking/cooking)						
15. Taste/aroma						
16. Suitability for local brewing						
17. Overall comparison						

3.4 Information on informal sorghum, finger millet & maize seed production and exchanges

3.4.1 Seed saving/sharing practice

Seed saving/sharing	Sorghum varieties		Maize varieties		Local F/Millet
	Local	Modern	Local	modern	
1. How often do you save grain for seed? (0=Never; 1=Sometimes; 2=Always)					
2. How often is this saved seed adequate for your requirements? (0=Never; 1=Sometimes; 2=Always)					
3. How often do you share your own produced seed with relatives? (0=Never; 1=Sometimes; 2=Always)					
4. How often do you share your own produced seed with non-relatives? (0=Never; 1=Sometimes; 2=Always)					
5. What are the seed exchange terms for relatives? (0=Free; 1=Cash; 2= with seed/grain of other crops; 3= with other items; 4= with farm labour)					
6. What are the seed exchange terms for non-relatives? (0=Free; 1=Cash; 2= with seed/grain of other crops; 3= with other items; 4= with labour)					
7. Do you have any formal training on seed production? (0=No; 1=Yes)					

3.4.2 Seed saving/sharing during the 2011/2012 planting season

	Sorghum varieties		Maize varieties		Finger Millet	
	Local	Modern	Local	Modern	Local	Modern
1. How much own saved seed did you have at the start of the season (Kg)?						
2. Was this amount enough for your needs? (0=No; 1=Yes)						
3. If No, did you seek seed from other farmers? (0=No; 1=Yes)						
4. Did you give your own saved seeds to any other farmer? (0=No; 1=Yes)						

5. If Yes, to which farmers did you give your own seeds? (fill details below)

Name of the farmer	Relationship (Codes A)	Residence (Codes B)	Sorghum				Maize				Finger Millet	
			Local		Modern		Local		Modern		Kg	Price (TSh/kg)
			Kg	Price (TSh/kg)	Kg	Price (TSh/kg)	Kg	Price (TSh/kg)	Kg	Price (TSh/kg)		
1.												
2.												
3.												
4.												
5.												
6.												

Codes A

1=Parent; 2=Child; 3=Brother/sister; 4=Grandparent; 5=Grandchild; 6=Nephew/Niece; 7=Uncle/aunt; 8=Cousin; 9=Same family lineage; 10=Mother/father in-law; 11=Brother/sister in-law; 12=Other relative; 13=Fellow villager/Neighbor; 14=Attend same church/mosque; 15=Professional/business colleague; 16=Other, specify.....

Codes B 1=In this village 2=Outside this village

4.0 Social Networks

Now I want to ask you questions about your interactions with a number of farmers, as well as key individuals (officers and organizations) who promote farming activities in this village. [Fill in **1** for all YES responses, **0** for all NO responses and **-99** for DON'T KNOW/NOT SURE]

4.1 Relationships and Interactions

Farmers/External agent (X)	House hold ID	Do you know (X)	Since when (Year) have you known (X)?	How is (X) related to you? (Relationship codes)	Do you belong to same religious congregation as (X)?	Do you belong to the same association with (X)? (fill in all that apply, Codes A)	Have you ever talked to (X)?	If yes, how many times per month on average do you talk to (X)?	Have you ever visited the home of (X)?	If yes, how many times per month on average do you visit the home of (X)?	Is (X)'s field/plot adjacent to yours?	Have you ever passed by the field of (X)?	If Yes, how many times per month do you pass by the field of (X)?	Do you discuss sorghum farming issues with (X)?	Do you discuss finger millet farming issues with (X)?	Do you discuss maize farming issues with (X)?	Does (X) inform you of Agric. meetings?
Farmers from same village																	
1.																	
2.																	
3.																	
Farmers from same cluster																	
4.																	
5.																	
6.																	
Village Administrators (7. Sub-village Chairman, 8. Village Chairman, 9. Village Executive)																	
7.																	
8.																	
9.																	
External Agents																	
Agricultural Ext. Officer																	
Research-																	
NGO-																	
Input dealer--																	
Grain buyer--																	

Relationship Codes 1=Parent; 2=Child; 3=Brother/sister; 4=Grandparent; 5=Grandchild; 6=Nephew/Niece; 7=Uncle/aunt; 8=Cousin; 9=Same family lineage; 10=Mother/father in-law; 11=Brother/sister in-law; 12=Other relative; 13=Fellow villager/Neighbor; 14=Attend same church/ mosque; 15=Professional/business colleague; 16=Other, specify.....

Codes A: 0=No; 1=Farming group; 2=Self-help group; 3=Merry go round; 4=Savings and Credit; 5=Other (Specify)

4.3 Social Learning in Sorghum Farming

Farmers (X) – From Table 4.1	Tell me about the following sorghum farming activities of (X) during the 2011/12 season								
	Did (X) cultivate sorghum (Codes A)	If (X) cultivated sorghum							
		Sorghum varieties cultivated (Variety Codes, Record all reported)	Which of the varieties were of modern type? (Variety Codes)	From where did (X) get seeds of modern varieties? (Codes B)	From where did (X) get seeds of local varieties? (Codes B)	Did (X) use manure/fertilizer on sorghum plot? (Codes A)	How much sorghum did (X) harvest (kg)? -99 for don't know	Did (X) sell part of sorghum harvest? (Codes A)	If yes, at what price (TShs/kg)? -99 = don't know
Farmers in same Village									
1.									
2.									
3.									
Farmers in same Cluster									
4.									
5.									
6.									
Village Administrators (7. Sub-village Chairman, 8. Village Chairman, 9. Village Executive)									
7.									
8.									
9.									

Codes A: 0=No; 1=Yes; -99=Don't know

Codes B: 1=Voucher system; 2=Another farmer; 3=Farmer's Club; 4=Local trader or agro-dealers; 5=NGO; 6=Extension officer; 7=Research PVS; 8=Local seed producers; 9=Own storage; 10=Other, specify.....-99= Don't know

4.4 Social Learning in Finger millet Farming

Farmers (X) – From Table 4.1	Tell me about the following Finger millet farming activities of (X) during the 2011/12 season								
	Did (X) cultivate Finger millet (Codes A)	If (X) cultivated Finger millet							
		Finger millet varieties cultivated (Variety Codes, Record all reported)	Which of the varieties were of modern type? (Variety Codes)	From where did (X) get seeds of modern varieties? (Codes B)	From where did (X) get seeds of local varieties? (Codes B)	Did (X) use manure/fertilizer on Finger millet plot? (Codes A)	How much Finger millet did (X) harvest (kg)? -99 for don't know	Did (X) sell part of Finger millet harvest? (Codes A)	If yes, at what price (TShs/kg)? -99 = don't know
Farmers in same Village									
1.									
2.									
3.									
Farmers in same Cluster									
4.									
5.									
6.									
Village Administrators (7. Sub-village Chairman, 8. Village Chairman, 9. Village Executive)									
7.									
8.									
9.									

Codes A: 0=No; 1=Yes; -99=Don't know

Codes B: 1=Voucher system; 2=Another farmer; 3=Farmer's Club; 4=Local trader or agro-dealers; 5=NGO; 6=Extension officer; 7=Research PVS; 8=Local seed producers; 9=Own storage; 10=Other, specify.....-99= Don't know

4.3 Social Learning in Maize Farming

Farmers (X) – From Table 4.1	Tell me about the following maize farming activities of (X) during the 2011/12 season								
	Did (X) cultivate maize (Codes A)	If (X) cultivated maize							
		Maize varieties cultivated (Variety Codes, Record all reported)	Which of the varieties were of modern type? (Variety Codes)	From where did (X) get seeds of modern varieties? (Codes B)	From where did (X) get seeds of local varieties? (Codes B)	Did (X) use manure/fertilizer on maize plot? (Codes A)	How much maize did (X) harvest (kg)? -99 for don't know	Did (X) sell part of maize harvest? (Codes A)	If yes, at what price (TShs/kg)? -99 = don't know
Farmers in same Village									
1.									
2.									
3.									
Farmers in same Cluster									
4.									
5.									
6.									
Village Administrators (7. Sub-village Chairman, 8. Village Chairman, 9. Village Executive)									
7.									
8.									
9.									

Codes A: 0=No; 1=Yes; -99=Don't know

Codes B: 1=Voucher system; 2=Another farmer; 3=Farmer's Club; 4=Local trader or agro-dealers; 5=NGO; 6=Extension officer; 7=Research PVS; 8=Local seed producers; 9=Own storage; 10=Other, specify.....-99= Don't know

5.0 Agricultural production

5.1. Please fill the following Table about land holdings during the 2011/2012 planting season (in acres)

		Total	Cultivated land	Fallow land	Rented/borrowed out	Other, specify**
Land ownership	Own					
	Rented/borrowed in					

**Specification.....

If no land is rented/borrowed out skip to 5.2.

5.1.1. If land was rented/borrowed /out, please fill out the following details

Plot details	Rented/Borrowed out		
	Plot1	Plot2	Plot3
Who (Name) did you rent it to?			
What is your relationship with the tenant? (Codes A)			
Does tenant reside in this village? (0=No; 1=Yes)			
What was the size of the plot (acres)?			
How much rent was received (TSh)?			

Codes A

1= Parent; 2=Child; 3=Brother/sister; 4= Grandparent; 5=Grandchild; 6=Nephew/Niece; 7=Uncle/aunt 8=Cousin; 9=Same family lineage; 10=Mother/father in-law; 11=Brother/sister in-law; 12=Other relative; 13=Fellow villager/Friend/Neighbor; 14=Professional/business colleague; 15=Other, specify

5.2 Key crops and purpose for cultivation

4.1.3 Over the last 10 years, tell me about the area under sorghum, finger millet and maize on your farm.

Sorghum: 0 constant 1 increasing 2 decreasing

Finger millet : 0 constant 1 increasing 2 decreasing

Maize : 0 constant 1 increasing 2 decreasing

4.1.4 If both sorghum and maize areas increased/decreased, which one increased/decreased more?
(1=Sorghum; 2=Maize)

4.1.5 What are the reasons for this decision?

4.1.6 If both finger millet and maize areas increased, which one increased more?
(1= Finger millet; 2=Maize)

4.1.7 What are the reasons for this decision?

5.3 Characteristics of all plots cultivated in the 2011/2012 planting season

Plot Number (number starting from nearest plot to house)	Plot name	Plot location (Codes A)	If plot is not within homestead, walking time to plot (min)	Plot size (acre)	Plot ownership Code B	If plot is not own			Soil fertility Codes D	Soil type Code E	Slope Code F	Soil water conservation (0=no; 1=yes)	Water logging on plot (0=no; 1=yes)	Striga severity (0=No striga; 1=Low; 2=Average; 3=High)
						what is your relationship with the owner (Codes C)	Does owner reside in this village (0=No; 1=Yes?)	How much rent did you pay (TSh)?						
1.														
2.														
3.														
4.														
5.														
6.														
7.														
8.														
9.														
10.														

Codes A

1. Within the homestead
2. Outside the homestead, same village
3. Outside the homestead, different village

Codes B

- 1 Own
- 2 Borrowed
- 3 Rented in

Codes C

- 1=Parent
- 2=Child
- 3=Brother/sister
- 4=Grandparent
- 5=Grandchild
- 6=Nephew/Niece
- 7=Uncle/aunt
- 8=Cousin

- 9=Same family lineage
- 10=Mother/father in-law
- 11=Brother/sister in-law
- 12=Other relative
- 13=Fellow villager/Neighbor
- 14=Attend same church/mosque
- 15=Professional/business colleague
- 16=Other, specify.....

Codes D

- 1 Poor
- 2 Medium
- 3 Good

Codes E

- 1 Finyanzi (clay)
- 2 Tifutifu (loam)
- 3 Kichanga (sandy)
- 4 Other, specify

Codes F

- 1 Gentle slope (flat)
- 2 Medium slope
- 3 Steep slope

5.4 Characteristics of crop production in the 2011/2012 planting season (*information has to be filled per plot and variety for the previous planting season. Each plot and each variety at the same plot have a separate row*)

Plot name (From Table 5.3)	Crops grown Crop codes	If crop grown is sorghum, finger millet or maize		Area cultivated (acres)	Time of Sowing		Inter cropping (0=no; 1=yes)	If inter cropping: With which crop? Crop codes	Irrigated (0=no; 1=yes)	Onset of rains		Time of Harvest		Total amount harvested			Total amount sold			Revenue		
		Name of Variety (Variety codes)	Type of variety (1=Local; 2=Modern)		Month	Week				Month	Week	Month	Week	Bags (120kg)	Tins (20kg)	kg	Bags (120kg)	Tins (20kg)	kg	Average Price (TShs/Kg)	Gross sales (TSh)	

Crop Codes

1. Sorghum
2. Finger Millet
3. Maize
4. Pearl/bulrush millet
5. Sunflower

6. Pigeonpea

7. Cowpea
8. Groundnut
9. Bambara nut
10. Simsim
11. Other, specify.....

Variety Codes

- Sorghum**
1. Langalanga
 2. Pato
 3. Macia
 4. Tegemeo

5. Local variety (unspecified)
6. Sila
7. Serena
8. Udo
9. KARI Mtama 1

10. Modern variety (unspecified)
11. Other sorghum variety...

Maize

21. America (Local)
22. Kiseku (local)
23. Kitumbiri (local)
24. Hybrid
25. Pannar
26. Pioneer
27. DK
28. Ilonga
29. Staha
30. Kilima,
31. SeedCo

32. Situka
33. Cargil,
34. Katumani
35. Modern variety (unspecified)
36. Local variety (unspecified)
37. Other maize variety

5.5 What were your main sources of seeds for sorghum, finger millet and maize in the 2011/2012 planting season?

Crop (Crop codes)	Variety planted (Variety Codes)	Source 1					Source 2					If modern variety, last time fresh seed was acquired (No. of years)	If source 1 and/or 2 was another farmer:				
		Source Code A	Amount (kg)	Reason for the source Codes B	Quality (Purity+ Viability) Codes C	Was seed Quality Declared (QDS)	Source Codes A	Reason for the source Codes B	Amount (kg)	Quality (Purity+ Viability) Codes C	Was seed Quality Declared (QDS)		Name of the farmer	Relationship with the farmer Relationship Codes	Does the farmer reside in this village (0=No, 1=Yes)	Price charged (TSh/ Kg)	Mode of payment Codes D

Crop Codes	Variety Codes		Maize		Codes A	Codes B	Codes C	Codes D
1. Sorghum	Sorghum	7. Serena	21. America (Local)	29. Staha	1 N/A.	0 No other source available	0 Poor	1. Cash
2. Finger Millet	1. Langalanga	8. Udo	22. Kiseku (local)	30. Kilima,	2 Another farmer	1 Best price	1 Good	2. Credit
3. Maize	2. Pato	9. KARI Mtama 1	23. Kitumbiri (local)	31. SeedCo	3 Local trader or agro-dealers	2 Ran out of own seed	2 Very good	3. Exchange with other seed/grain
	3. Macia	10. Modern variety (unspecified)	24. Hybrid	32. Situka	4 Provided by NGOs	3 Best seed quality		4. Exchange with other item
	4. Tegemeo	11. Other sorghum variety...	25. Pannar	33. Cargil,	5 Extension officer	4 Can buy on credit		5. Exchange with labor
	5. Local variety (unspecified)		26. Pioneer	34. Katumani	6 Research PVS	5 Other, specify		6. Voucher system
	6. Sila		27. DK	35. Modern variety (unspecified)	7 Local seed producers	6. Saves cost/money		
			28. Ilonga	36. Local variety (unspecified)	8 Own storage			
				37. Other maize variety	9 Other, specify.....			

5.6 Labor and machinery costs for crop production

5.6.1 Please let the farmer choose one of the plots on which s/he grew sorghum/finger millet/maize in the 2011/2012 planting season and fill the following table for labour inputs for this plot.

Operations		Sorghum		Finger millet		Maize	
		Plot.....		Plot.....		Plot	
		Variety.....		Variety.....		Variety.....	
		Family Labour Days	Total mandays for hired labour	Family Labour Days	Total mandays for hired labour	Family Labour Days	Total mandays for hired labour
1 Land preparation (Ploughing primary and secondary tillage)	Total						
	Adult						
	Child						
2. FYM/C Compost/Manure application	Total						
	Adult						
	Child						
3. Seed treatment	Total						
	Adult						
	Child						
4. Planting/Sowing and fertilizer application	Total						
	Adult						
	Child						
5. Weeding/Herbicide application	Total						
	Adult						
	Child						
6. Plant protection (Spraying/Dusting/Shaking)	Total						
	Adult						
	Child						
7. Irrigation	Total						
	Adult						
	Child						
8.. Watching (Birds, Pigs etc.,)	Total						
	Adult						
	Child						
10.. Harvesting	Total						
	Adult						
	Child						
11. Threshing	Total						
	Adult						
	Child						
12. Seed cleaning, purification	Total						
	Adult						
	Child						
13. Storage (including transport)	Total						
	Adult						
	Child						
Total paid to hired labour (TSh)							
Total paid to hired oxen (TSh)							
Total paid to hired equipment (TSh)							

5.6.2. If you have filled in Table 5.6.1, fill in this table for the same plots as Table 5.6.1

Plot name sorghum:

Plot name finger millet:

Operations	Practices for sorghum	Tick if used	Practices for finger millet	Tick if used
1A. Land preparation (Ploughing primary and secondary tillage)	Animal traction		Animal traction	
	Tractor plough		Tractor plough	
	Power Tiller		Power Tiller	
	Hand hoe		Hand hoe	
	Zero Tillage		Zero Tillage	
	<i>Other, specify.....</i>		<i>Other, specify.....</i>	
2. Compost/Manure application	Farmyard manure		Farmyard manure	
	Compost		Compost	
	<i>Other, specify.....</i>		<i>Other, specify.....</i>	
3. Seed treatment	Fungicide		Fungicide	
	Ash			
	Neem products			
	<i>Other, specify.....</i>		<i>Other, specify.....</i>	
4. Planting/Sowing	Row planting 60 x 20cm		Row planting 40cm x 10cm	
	90cm X 30 cms (local)		30cm x 15 cms	
	80cm X 30 cms (improved)		<i>Other, specify.....</i>	
	<i>Other, specify.....</i>			
5. Fertilizer application	Microdosing		Microdosing	
	Split application		Split application	
	<i>Other, specify.....</i>		<i>Other, specify.....</i>	
6. Weeding/Herbicide application	Hand weeding 1 times		Hand weeding 1 times	
	Hand weeding 2 times		Hand weeding 2 times	
	Herbicide –pre emergence		Herbicide –pre emergence	
	Herbicide post emergence		Herbicide post emergence	
	<i>Other, specify.....</i>		<i>Other, specify.....</i>	
7. Striga control	Mechanical (weeding/hand pulling)		Mechanical (weeding/hand pulling)	
	Integrated striga management (ISM)		Integrated striga management (ISM)	
	<i>Other, specify.....</i>		<i>Other, specify.....</i>	

Operations	Practices for sorghum	Tick if used	Practices for finger millet	Tick if used
8.Plant protection - Spraying/Dusting/ Shaking /Hand picking)	Insecticide for stalk borer		Insecticide for stalk borer	
	<i>Other, specify.....</i>		<i>Other, specify.....</i>	
9. Irrigation	Water harvesting		In situ water harvesting	
	<i>Other, specify.....</i>		<i>Other, specify.....</i>	
10. Watching (Birds, Pigs etc.,)	Bird scaring, specify how		Bird scaring, specify how	
	<i>Other, specify.....</i>		<i>Other, specify.....</i>	
11. Harvesting	Manual harvesting (Cutting the heads)		Manual harvesting (Cutting the heads)	
	<i>Other, specify.....</i>		<i>Other, specify.....</i>	
12. Threshing	Threshers		Threshers	
	Animal tramping		Animal tramping	
	Manual (beating)		Manual (beating)	
	<i>Other, specify.....</i>		<i>Other, specify.....</i>	
13 Post-harvest activities: Dressing	Insecticide		Insecticide	
	<i>Other, specify.....</i>		<i>Other, specify.....</i>	
13 Post-harvest activities: Milling	Dehulling		Dehulling	
	Milling without dehulling		Milling without dehulling	
	Hand milling		Hand milling	
	Hammer mill		Hammer mill	
	<i>Other, specify</i>		<i>Other, specify</i>	

6.2 Livestock input costs (Please record for the last 12 months).

Description	Total cost (TSh)
1.Crop residue	
2.Green fodder	
3.Dry fodder (hay)	
4.Concentrates	
5.Veterinary/AI services	
6.Herds boy (animal tending)	
Other costs, specify	

6.3 Production and utilization of livestock products (Nov 2011 – OCT 2012)

Livestock products	Quantity produced	Units of production (Codes A)	Frequency of production (Codes B)	Number of productive months	Quantity consumed	Quantity sold	price (TSh)
Milk							
Eggs							
Animal skin							
Honey							

Codes A: 1=Litres; 2=Kg; 3=Pieces; 4=Trays; 5=Other, specify.....

Codes B: 1=Daily; 2=Weekly; 3=Monthly; 4=Every 3 months; 5=Every 4 months; 6=Every 6 months; 7=Annually; 8=Other, specify.....

6.4 Please fill the following Table for household farm assets which you currently own

Asset name	Number	Current value per piece (TSH)	Total Current value (TSH)
1. Ox-ploughing set			
2. Ox-cart			
3. Sickle			
4. Panga knife			
5. Axe			
6. Spade/Shovel			
7. Hoes			

Asset name	Number	Current value per piece (TSH)	Total Current value (TSH)
8. Sprayer			
9. Wheel barrow			
10. Bicycle			
11. Motorized vehicles			
12. Radio/radio cassette			
13. Mobile phone			
14. Television (TV)			

7.0 Membership to farmer organizations/clubs

Is any of your household members a member of an association, Group, or club (0=No; 1=Yes)	If no, give reasons (Codes A, rank 3)	If Yes, what's the name of Association, Coop , Group, or club (List all)	Who is a member (Code B)	Type of membership (Codes C)	Association or club functions (Codes D, rank 2)	Year joined	Current entry fee (TSH)	Subscription fee (TSH)	Frequency of subscriptions (Codes E)	Frequency of meetings (Codes E)	Number of meetings member attended in 2012	Total number of members	Has your group been visited by extension officer in the last 2 years? (0=No; 1=Yes)

- Code A**
1. No need to join one
 2. No such groups exist in the area
 3. Cannot afford subscription fee
 4. Does not have time for group meetings
 5. No faith in leadership of existing groups
 6. Other, specify
 -

- Codes B**
- 1 Household head
 - 2 Spouse
 - 3 Son/daughter
 - 4 Parent
 - 5 Son/daughter in-law
 - 6 Grand child
 - 7 Other relative
 - 9 Other, specify.....

- Codes C**
- 1 Ordinary member
 - 2 Executive committee member
 - 3 Other committee member
 - 4 Patron
 - 5 Other, specify.....

- Code D**
- 1 Crop/livestock marketing
 - 2 Input access/marketing
 - 3 Seed production
 - 4 Farmer research group
 - 5 Savings and credit
 - 6 Welfare/funeral club
 - 7 Tree planting and nurseries
 - 8 Soil & water conservation
 - 9 Input credit
 - 10 Local administration
 - 11 Other, specify.....

- Code E**
1. Weekly
 2. Bi-weekly
 3. Monthly
 4. Every 3 Months
 5. Every 4 Months
 6. Every 6 months
 7. Yearly
 8. Not regular
 9. Other, specify.....
 -

8.0 Participation in HOPE activities in the last 2 years

8.1 Did you participate in any HOPE activity during the last 2 years? 0=no; 1=yes

8.2 If yes, in which activities did you participate? (Fill in the table below)

Activity	How many times did you participate in this activity in 2011	How many times did you participate in this activity in 2012	If farmer participated,			If farmer did not participate what are the reasons (Codes B, rank if more than 1)
			how did s/he get information about the activity (Codes A)	Which crops were covered? (Crop codes)	Did you also get some seeds (0=No, 1=Yes)	
Attended/hosted a HOPE field day						
Visited/attended a HOPE trials/demo farm						
Participated in a HOPE' Participatory Variety Selection (PVS)						

Codes A

1. Extension officer
2. Village Chairman
3. Village Executive
4. Cell Leader
5. Ward Executive Officer
6. Councillor

Codes B

1. Did not require extension services
2. Did not know where to get the extension officer
3. Long distance to extension office
4. Cannot afford the cost of bringing extension officer to the farm
5. Was not aware of such an event
6. Was aware but was not invited
7. Invitation came late
8. Was not aware of the agenda

9. Long distance to event venue
10. Other commitments
11. Was sick/attending to a sick person
12. Farmer had travelled out of the village
13. Activity would not have been beneficial
14. Other, specify.....

8.3 If the household participated in any HOPE activities please fill the following table

Please describe in your own words the topics covered/ what you learnt	Had you learnt about this before? (0=No, 1=Yes)	Do you apply them on your farm? (0=No, 1=Yes)	If NO, will you apply them on your farm? (0=No, 1=Yes)	If no: why not?

8.4 Participation in other activities concerning technology transfer in the last 2 years

Activity	How many times did you participate in this activity in 2011	How many times did you participate in this activity in 2012	If farmer participated,				If farmer did not participate what are the reasons (Codes C, rank if more than 1)
			how did s/he get information about the activity (Codes A)	Which crops were covered? (Crop codes)	Which topics did you learn? (Codes B)	Did you also get some seeds	
Consulted Village/Ward Extension Officer							
Attended agricultural extension meeting							
Attended agricultural seminar/training							
Attended Farmer Field School (FFS)							
Attended/hosted a field day							
Visited/attended a trials/demo farm							
Attended agricultural show							

Codes A

7. Extension officer
8. Village Chairman
9. Village Executive
10. Cell Leader
11. Ward Executive Officer
12. Councillor
13. Another farmer
14. Radio/TV
15. Newspaper
16. Posters
17. Other, specify

Codes B

1. Different modern varieties
2. Land preparation
3. Planting methods
4. Striga management
5. Pest & disease management
6. Post-harvest handling
7. Soil & water management
8. Fertilizer use
9. Manure/compost use
10. Produce marketing

Codes C

15. Did not require extension services
16. Did not know where to get the extension officer
17. Long distance to extension office
18. Cannot afford the cost of bringing extension officer to the farm
19. Was not aware of such an event
20. Was aware but was not invited
21. Invitation came late
22. Was not aware of the agenda
23. Long distance to event venue
24. Other commitments
25. Was sick/attending to a sick person
26. Farmer had travelled out of the village
27. Activity would not have been beneficial
28. Other, specify.....

9.0 Access to Credit

9.1 If you needed money, could you borrow it at present? **0**=No; **1**=Yes

9.2 If Yes, could you borrow from the following sources? (Read to the respondent)

Credit source			Could you borrow? (0=No; 1=Yes)
SACCO (Registered)			
Bank			
Micro Finance Institution			
Credit/Farmer/self-help group			
Shopkeeper/trader in the village			
Shopkeeper/trader outside the village			
Other persons (Let the farmer mention these)			
Name	Relationship (Relationship Codes)	Residence (Codes C)	
1.			
2.			
3.			
4.			

Codes C 1=In this village 2=Outside this village

THE END. THANKYOU FOR YOUR PARTICIPATION IN THIS DISCUSSION