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Social networks and the adoption of agricultural innovations: The case of improved cereal cultivars in Central Tanzania

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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 cultivars 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 cultivars 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 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 cultivars, maize, sorghum

JEL classification: O13, Q12

Contents

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1 Introduction

Food insecurity remains a major development challenge for many agrarian economies (World Bank 2007) and the use of improved cultivars (ICs) 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 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.

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 cultivars in Central Tanzania. The findings are important for designing policies to foster innovation adoption and productivity growth. Specifically, we address the following research question:

1. With respect to knowledge about ICs:
   1.1. How many farmers know about ICs of maize and sorghum?
   1.2. What factors determine exposure? What role do social networks play?
   1.3. What are the perceived characteristics of ICs compared to local varieties?

2. With respect to adoption of ICs:
   2.1. What is the status of adoption of ICs 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 ICs?

3 Analytical Framework

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 2010). 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 ICs. 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 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 4.

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

(1) $$Pr\left(V = v_i \,|z_i, w_i \right) = \frac{e^{-\mu_i} \mu_i^{\, v_i}}{v_i!} \qquad v_i = 0,\ 1,\ 2\ \ldots$$

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

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

Based on this specification, intensity of exposure is given by

(3) $$E[v_i \mid z_i, w_i] = Var[v_i \,|z_i, w_i] = \mu_i = e^{z_i'\beta + w_i'\delta} \qquad v_i = 0,\ 1,\ 2\ \ldots$$

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 ∂ 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 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 chi-square test rejected overdispersion in our data. Furthermore, results of a negative binomial regression model (not presented in this paper), which accounts for overdispersion, produced almost identical estimates. We therefore maintained the results of the Poisson regression models.

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 ICs of sorghum and maize in Central Tanzania), modeling adoption without taking into account the potential 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 Skura 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*:

(4) $$\mathrm{E}(y|x, w = 1) = g(x, \beta),$$

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:

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

(6) $$\widehat{ATE_1} = \frac{1}{n_e}\sum_{i=1}^{n} w_i g(x_i, \hat{\beta})$$

(7) $$\widehat{ATE_0} = \frac{1}{n - n_e}\sum_{i=1}^{n} (1 - w_i) g(x_i, \hat{\beta})$$

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).

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 Division 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 ICs, and input and output data for crop and livestock production.

5 Results

5.1 Knowledge of Improved Cultivars

We begin our analysis by looking at the exposure of farmers to improved varieties (Table 1); i.e. how many farmers know about the existence of ICs. 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 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 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.
Source: Survey data 2012

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 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).

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 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.

Table 2: Sources of first information on improved sorghum and maize varieties

Source / Relationship	**Sorghum varieties**	**Maize varieties**	**Maize OPVs**	**Maize Hybrids**
Source of information (% responses)	*(N=578)*	*(N=658)*	*(N=216)*	*(N=442)*
Another farmer	27.7	49.7***	52.8	48.2
Government extension officer	66.8	23.9***	25.9	22.9
Traders	0.9	8.7**	9.3	8.4
Media	0.5	12.2***	5.6	15.4***
Research and development	0.5	-	-	-
Other	3.6	5.6**	6.5	5.2
Relationship with information source if source is another farmer (% responses)	*(N=159)*	*(N=326)*	*(N=114)*	*(N=212)*
Neighbor/friend	68.8	67.0	63.2	69.0
Parent	16.3	16.8	18.4	16.0
Other relative	15.0	16.2	18.4	15.0
How respondent learnt about the variety if source is another farmer (% responses)				
Saw it in farmer's field and enquired	69.8	71.2	66.7	73.6*
Information came from the other farmer first	11.3	9.8	9.6	9.9
Not specified	18.9	19.0	23.7	16.5*

*, **, *** differences between sorghum and maize varieties (first two columns) or maize OPVs and Hybrids (last two columns) significant at 10%, 5% and 1% respectively
Source: Survey data 2012

5.3 Farmers' Perceptions of Characteristics of ICs

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 ICs, 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 summarizes the results of these comparisons for improved varieties, which have been mentioned by at least 20 respondents. 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: Farmers' perception about traditional vs. improved varieties

Crop/Variety	Batter 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)																	
Macia (90)	79	70	62	30	66	17	31	50	33	23	22	26	46	56	46	10	**62**
Pato (66)	79	76	61	45	68	21	21	59	41	21	23	12	45	41	26	12	**61**
Tegemeo (51)	65	65	43	29	55	20	22	49	41	25	24	24	27	33	37	14	**43**
Serena (39)	49	74	46	37	44	15	28	44	18	15	13	10	28	23	28	13	**41**
Improved (22)	73	73	32	36	42	23	14	45	32	27	18	9	36	18	14	5	**50**
Improved	*71*	*71*	*54*	*34*	*58*	*19*	*25*	*51*	*34*	*23*	*21*	*18*	*39*	*39*	*33*	*12*	**54**
Traditional	*18*	*15*	*26*	*44*	*27*	*71*	*60*	*24*	*26*	*61*	*55*	*67*	*17*	*30*	*51*	*74*	**42**
Maize (N=269)																	
Pannar (57)	91	77	60	32		37	26	45	40	79	68	16	37	47	46		**89**
Seedco (52)	92	63	62	27		44	33	75	33	52	46	19	35	40	38		**87**
Kilima (31)	90	68	77	45		23	32	74	35	58	45	35	48	28	65		**80**
Cargil (53)	77	58	49	33		28	34	70	36	53	55	25	38	48	47		**75**
Improved (33)	88	76	61	30		21	39	67	39	48	48	33	42	55	33		**82**
Improved	*86*	*65*	*60*	*34*		*32*	*32*	*72*	*39*	*59*	*55*	*24*	*39*	*47*	*45*		**83**
Traditional	*10*	*30*	*29*	*34*		*52*	*45*	*11*	*26*	*15*	*13*	*54*	*15*	*18*	*29*		**14**

Source: Survey data 2012

5.4 Determinants of exposure

To assess the individual determinants of exposure to improved varieties, we estimate Poisson regression models following Equations (2) and (3). The definition of the explanatory variables used and some descriptive statistics are presented in Table 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.

Table 4: Definitions and descriptive statistics for the variables used in the exposure model

Variable	Definition	Mean
Social network attributes of respondent of		
Crop network size		
Sorgnetw	Number of dyads, in which there is a link for exchange of information about sorghum cultivation	1.11 (1.40)
Sorgnetw1	Number of dyads, in which there is a link for exchange of information about sorghum cultivation to farmers from the same village	0.93 (1.08)
Sorgnetw0	Number of dyads, in which there is a link for exchange of information about sorghum cultivation to farmers from surrounding villages	0.19 (0.57)
Maiznetw	Number of dyads, in which there is a link for exchange of information about maize cultivation	1.03 (1.38)
Maiznetw1	Number of dyads, in which there is a link for exchange of information about maize cultivation to farmers from the same village	0.83 (1.06)
Maiznetw0	Number of dyads, in which there is a link for exchange of information about maize cultivation to farmers from surrounding villages	0.20 (0.55)
Links with institutional information channels		
Adminlink	Contacts per month with the administrator whom respondent talks mostly to	13.8 (9.57)
Extlink	Talks to extension officer at least once per month (1=yes, 0 otherwise)	0.64 (0.48)
Personal and household attributes of respondent		
Agerespo	Age (years)	46.0 (11.4)
Femrespo	Gender of respondent is female (1=Yes; 0=Otherwise)	0.27 (0.44)
Educrespo	Formal education level is >4 years (1=Yes; 0=Otherwise)	0.83 (0.37)
Musirespo	Respondent is Muslim (1=Yes; 0=Otherwise – mostly Christian)	0.57 (0.50)
Ownland	Land owned by household (Ha)	4.41 (5.71)
Ownmobil	Household owns a mobile phone (1=Yes; 0=Otherwise)	0.70 (0.46)
Ownradio	Household owns a radio (1=Yes; 0=Otherwise)	0.75 (0.43)

N=345
Note: Figures in brackets are standard deviations.
Source: Survey data 2012

Regression results are presented in Table 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 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.

Table 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***
Sorgnetw	0.087**							
	(0.042)							
Sorgnetw0					0.223**			
					(0.106)			
Sorgnetw1					0.022			
					(0.065)			
Maiznetw		0.047	0.048*	-0.006				
		(0.056)	(0.028)	(0.040)				
Maiznetw0						0.194	0.148**	0.029
						(0.140)	(0.072)	(0.101)
Maiznetw1						-0.018	-0.003	-0.020
						(0.082)	(0.044)	(0.058)
Adminlink	0.014**	0.013	0.005	0.008	0.014**	0.014	0.0051	0.008
	(0.007)	(0.008)	(0.005)	(0.006)	(0.007)	(0.008)	(0.005)	(0.006)
Extlink	0.365**	0.410**	0.156	0.254**	0.379***	0.423**	0.168*	0.256**
	(0.147)	(0.179)	(0.096)	(0.129)	(0.146)	(0.182)	(0.098)	(0.130)
Agerespo	0.018**	0.017*	0.013***	0.004	0.019***	0.018*	0.014***	0.004
	(0.007)	(0.007)	(0.005)	(0.007)	(0.007)	(0.010)	(0.005)	(0.007)
Femrespo	-0.298	-0.576**	-0.147	-0.437**	-0.320	-0.584**	-0.149	-0.439**
	(0.201)	(0.248)	(0.128)	(0.172)	(0.201)	(0.246)	(0.128)	(0.172)
Educrespo	0.348	0.495*	0.280**	0.208	0.359*	0.496*	0.291**	0.207
	(0.213)	(0.268)	(0.141)	(0.192)	(0.213)	(0.268)	(0.140)	(0.192)
Ownland	-0.005	-0.009	-0.002	-0.008	-0.008	-0.011	-0.005	-0.008
	(0.011)	(0.017)	(0.010)	(0.010)	(0.012)	(0.017)	(0.010)	(0.010)
Ownmobil	0.221	0.306	0.276**	0.032	0.219	0.298	0.272**	0.030
	(0.154)	(0.206)	(0.120)	(0.145)	(0.153)	(0.205)	(0.118)	(0.145)
Ownradio	0.123	0.421*	0.153	0.267*	0.128	0.432*	0.170	0.269*
	(0.185)	(0.241)	(0.136)	(0.160)	(0.185)	(0.241)	(0.134)	(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

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. 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 of sorghum, and maize in general. However, the effect is insignificant for OPVs of maize and larger in the sorghum than maize models. This effect is not surprising, given that it is the responsibility of extension officers to promote new technologies among farmers, and the on-going government campaign in favor of sorghum in the study region. The insignificant effect on exposure to OPVs may be expected since there are more hybrids than OPVs in the market, and most hybrids in the study area are the relatively newer technologies compared to OPVs. Hence, extension officers may be promoting hybrids more than OPVs due to their novelty and higher yield potential. 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.

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.

5.5 Adoption rates of ICs

We continue our analysis by investigating the relationship between exposure and adoption. The incidence of exposure about 79% in the case of sorghum and 74% for maize (Table 6), a difference that is not statistically significant. The adoption rates in the full sample are pretty low and just about 42% in 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

Table 6: Observed exposure and adoption rates of improved cultivars

Exposure/Adoption rates	Sorghum (N=245)	Maize (N=305)
Exposure (% sample)	0.788	0.736*
	(0.022)	(0.024)
Ever adopted (% sample)	0.652	0.646
	(0.026)	(0.026)
Ever adopted (% of exposed)	0.827	0.878*
	(0.023)	(0.021)
Adopted in 2011/12 season (% sample growers)	0.424	0.600***
	(0.0316)	(0.028)
Adopted in 2011/12 season (% of exposed growers)	0.531	0.769
	(0.036)	(0.027)***

Note: Differences between sorghum and maize varieties significant at ***p<0.01, * p<0.1.
Source: Survey data 2012

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. Conditional on exposure, the adoption rate increases in our case to about 53% for sorghum and 77% for maize. Strikingly, not all exposed farmers adopt ICs, suggesting that further constraints exist or that the expected net benefits are low or uncertain. Moreover, the proportion of respondents that has ever adopted ICs is statistically higher for maize than for sorghum (at 10% level). In case of maize almost 88% of the exposed have ever adopted an IC, while it is just 83% for Sorghum. Comparing these figures to adoption rate in the last season suggests that a substantial share of farmers decided to cease using ICs. 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 ICs is more constrained than that of maize ICs. 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 7). Comparing these findings to the adoption rate in the full sample shows that accounting for 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 7: Estimated adoption rates of improved cultivars

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

Notes: Figures in brackets are standard errors. *** p<0.01. Source: Survey data 2012

5.6 Determinants of adoption

To determine 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 exposure bias yields inconsistent estimates.

Table 8: Description and mean values of variables used in adoption models

Variable	Definition and measurement	Mean values	
		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)
Sorgnetw1	Number of dyads in which there is a link for exchange of information about sorghum to farmers from the same village	1.09 (1.10)	
Sorgnetw0	Number of dyads in which there is a link for exchange of information about sorghum to farmers from surrounding villages	0.23 (0.63)	
Maiznetw1	Number of dyads, in which there is a link for exchange of information about maize to farmers from the same village		0.89 (1.09)
Maiznetw0	Number of dyads, in which there is a link for exchange of information about maize to farmers from surrounding villages		0.20 (0.57)
Adminlink	Contacts per month with the administrator whom respondent talks mostly to	13.6 (9.62)	13.8 (9.68)
Extlink	Talks to extension officer at least once per month (1=yes, 0= otherwise)	0.72 (0.45)	0.68 (0.47)
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)
Ownmobil	Household owns a mobile phone (1=Yes; 0=Otherwise)	0.69 (0.46)	0.69 (0.46)
Ownradio	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)
Femrespo	Gender of respondent is female (1=Yes; 0=Otherwise)	0.24 (0.43)	0.26 (0.44)
Agerespo	Age of respondent (years)	45.9 (10.7)	46.6 (11.7)
Educrespo	Formal education level of respondent is >4 years (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)
Ownland	Land owned by 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 brackets are standard deviations. Source: Survey data 2012

We employ Probit models to estimate determinants of exposure and of adoption after correcting for exposure bias. We used the same variables in the exposure model as in the previous analysis of the intensity of exposure. The results of the exposure model are omitted here, because we have already discussed the determinants of exposure in Chapter 5.4. Table 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 9. Results of this analysis are only shown for the parametric model, because the exposure bias for both crops was significant. 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 Barret 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.

Table 9: Determinants of adoption of improved varieties

Variable	***Sorghum***	***Maize***	***Variable***	***Sorghum***	***Maize***
Constant	-0.814	-0.103	Femrespo	0.349	-0.116
	(0.866)	(0.826)		(0.297)	(0.267)
Sorgnetw1	0.429***		Agerespo	-0.005	-0.012
	(0.122)			(0.013)	(0.011)
Sorgnetw0	-0.187		Educrespo	0.245	0.034
	(0.189)			(0.381)	(0.321)
Maiznetw1		0.209	Hhsize	-0.002	-0.055
		(0.129)		(0.055)	(0.059)
Maiznetw0		-0.005	Fem1564	0.242*	0.105
		(0.214)		(0.142)	(0.139)
Adminlink	0.003	-0.004	Mal1564	-0.090	0.256**
	(0.010)	(0.010)		(0.108)	(0.109)
Extlink	0.0112	-0.247	Nonfarm	-0.247	0.402*
	(0.228)	(0.252)		(0.207)	(0.213)
Intesorg	0.208**		Ownland	0.0171	0.010
	(0.091)			(0.019)	(0.029)
Intemaiz		0.283***	Poorsoil	-0.006*	-0.003
		(0.089		(0.003)	(0.003)
Ownmobil	-0.137	-0.005	Sorgarea	-0.048	
	(0.236)	(0.248)		(0.105)	
Ownradio	0.220	0.265	Maizarea		0.634***
	(0.241)	(0.276)			(0.190)
Leader	-0.145	-0.050	N	196	238
	(0.211)	(0.216)	Pseudo R^2	0.1926	0.1807

Notes: Figures are probit coefficients, with robust standard errors in parenthesis
* P<10%, ** P<5%, *** P<1%. Source: survey data 2012

The intensity of exposure to improved varieties positively influences adoption decision for both crops. This is consistent with expectation 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. 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. 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 increases a farmer's purchasing power for improved maize seeds, thereby increasing farmers' probability of adopting them. Soil characteristics also seem to matter for adoption of improved sorghum but not 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).

5.7 Constraints to the adoption of ICs

After identifying the constraints on the adoption of ICs, we present the reasons stated by the farmers for the non-adoption of ICs in this chapter.

For farmers, who have never adopted sorghum and maize ICs (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 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 ICs in the past but not in the last growing seasons. For sorghum ICs, the most important constraint to adoption is pest susceptibility, followed by seed access problems. However, for maize ICs, 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 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**	27.7	28.5
Pests, including birds	30.7	15.7***	34.0	15.5***
Adaptation (low yields, takes long to mature)	3.9	7.4*	6.0	29.0***
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	16.0	24.6**
N	*153*	*204*	*300*	*207*

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

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 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 ICs 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 ICs, 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 ICs, 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.

References

AGRA 2010. Mid-term review of the Program for Africa's Seed Systems – Tanzania. The Alliance for a Green Revolution in Africa, Nairobi, Kenya. Accessed May 2013, available at http://www.agra.org/our-results/independent-evaluations.

An, W. 2011. Models and methods to identify peer effects. Pages 514-532 in The SAGE handbook of social network analysis (Scott, J., and Carrington, P.J., eds.). The SAGE Publications, London, Great Britain.

Baerenklau, K.A. 2005. Toward an understanding of technology adoption: Risk, learning, and neighborhood effects. Land Economics 81(1):1-19

Bandiera, O., Rasul, I. 2006. Social networks and technology adoption in Northern Mozambique. The Economic Journal 116:869–902.

Barroga-Jamias, S., Brien, J.P. 1996. The Adoption of improved mungbean varieties in two rice-based villages in the Philippines: A network analysis. Philippine Journal of Crop Science 21(3):93-104.

Besley, T., Case, A. 1993. Modeling technology adoption in developing countries. The American Economic Review, 83(2):396–402.

Borgatti, S.P. 2005. Centrality and network flow. Social Networks 27:55–71.

Borgatti, S.P., Mehra, A. Brass, D.J., Labianca, G. 2009. Network analysis in the social sciences. Science 323:892-895.

Cameron, A.C., Trivedi, P.K. 1998. Regression analysis of count data. Cambridge University Press, New York, USA. 411 pp.

CGIAR 2011. Forty findings on the impacts of CGIAR research, 1971–2011. Consultative Group on International Agricultural Research (CGIAR) Fund Office, World Bank, Washington, D.C., USA. Accessed April 2013, available at http://www.cgiarfund.org/sites/cgiarfund.org/files/Documents/PDF/Forty-findings-CGIAR_March2011.pdf.

Chandrasekhar, A., Lewis, R. 2011. Econometrics of sampled networks. Unpublished manuscript, MIT. Accessed July 2012, Available at http://ipl.econ.duke.edu/seminars/system/files/seminars/157.pdf.

Conley, T.G., Udry, C.R. 2010. Learning about a new technology: Pineapple in Ghana. American Economic Review 100(1):35–69.

Diagne, A. 2006. Diffusion and adoption of Nerica rice varieties in Côte d'Ivoire. The Developing Economies 44(2):208–31.

Diagne, A., Demont, M. 2007. Taking a new look at empirical models of adoption: Average treatment effect estimation of adoption rate and its determinants. Agricultural Economics 37:201-210.

Diagne, A., Sogbossi, M.-J., Simtowe, F., Diawara, S., Diallo, A. S., Barry, A. B. 2009. Estimation of actual and potential adoption rates and determinants of a new technology not universally known in the population: The case of NERICA rice varieties in Guinea. Contributed Paper prepared for presentation at the International Association of Agricultural Economists' 2009 Conference, Beijing, China, August 16-22 2009. http://purl.umn.edu/51644

Dibba L., Diagne, A., Fialor, S.C., Nimoh, F. 2012. Diffusion and adoption of new rice varieties for Africa (Nerica) in The Gambia. African Crop Science Journal 20(1):141-153.

Dimara, E., Skuras, D. 2003. Adoption of agricultural innovations as a twostage partial observability process. Agricultural Economics 28:187–196.

Doss, C. R., Mwangi, W., Verkuijl, H., de Groote, H. 2003. Adoption of maize and wheat technologies in Eastern Africa: A Synthesis of the findings of 22 case studies. CIMMYT Economics Working Paper 03-06. CIMMYT, Mexico, D.F, Mexico. Accessed April 2013, available at http://repository.cimmyt.org/xmlui/bitstream/handle/10883/1037/76070.pdf

Easley, D., Kleinberg, J. 2010. Networks, crowds, and markets: Reasoning about a highly connected world. Cambridge University Press, New York, USA. 744pp

Erenstein, O., Kassie, G.T., Langyintuo, A., Mwangi, W. 2011. Characterization of maize producing households in drought prone regions of Eastern Africa. CIMMYT. Socioeconomics Working Paper 1. CIMMYT, Mexico, D.F, Mexico. Accessed March 2013, available at http://libcatalog.cimmyt.org/download/cim/95930.pdf.

Fafchamps, M., Gubert, F. 2007. The formation of risk sharing networks. Journal of Development Economics 83:326–350.

FAO 2002. World agriculture towards 2015/30, summary report. Food and Agricultural Organization of the United Nations, Rom Italy. Accessed August 2013, available at ftp://ftp.fao.org/docrep/fao/004/y3557e/y3557e.pdf.

Feder, G., Just, R.E., Zilberman, D. 1985. Adoption of agricultural innovations in developing countries: A Survey. Economic Development and Cultural Change 33(2):255-298.

Geroski, P.A. 2000. Models of technology diffusion. Research Policy 29:603–625.

Gollin, D., Morris, M., Byerlee, D. 2005. Technology adoption in intensive post-green revolution systems. American Journal of Agricultural Economics 87(5):1310–1316.

Goswami, R., Basu, D. 2010. Does information network affect technology diffusion? A study on the spread of banana and guava cultivation among farmers of Nadia District, West Bengal, India. Research Journal of Agriculture and Biological Sciences 6(6):701-707.

Granovetter, M. S. 1973. The strength of weak ties. American Journal of Sociology 78(6):1360-1380.

Greene, W.H. 2012. Econometric analysis. Pearson Education Limited, Essex, Great Britain.

Handcock, M.S., Gile, K.J. 2010. Modeling social networks from sampled data. The Annals of Applied Statistics 4(1):5–25.

Hanneman, R.A., Riddle, M. 2005. Introduction to social network methods. University of California, Riverside, CA. Accessed May 2012, available at http://www.faculty.ucr.edu/~hanneman/nettext/.

Hedström, P., Sandell R., Stern, C. 2000. Mesolevel networks and the diffusion of social movements: The case of the Swedish Social Democratic Party. American Journal of Sociology 106(1):145–72.

Heinrich, G.M., Mgonja, M.A. 2002. Sorghum and Millet Improvement Program (SMIP) midterm review. International Sorghum and Millets Newsletter 43:1–3.

Hogset, H., Barrett, C.B. 2010. Social learning, social influence, and projection bias: A caution on inferences based on proxy reporting of peer behavior. Economic Development and Cultural Change 589(3):563–589.

Hossain M, Jaim, W.M.H., Paris, T.R., Hardy, B. eds. 2012. Adoption and diffusion of modern rice varieties in Bangladesh and eastern India. International Rice Research Institute, Los Baños, Philippines. Accessed July 2013, available at http://books.irri.org/9789712202865_content.pdf.

House, L., Mullady, J., Lobb, A., House, M. 2007. The influence of culture on the impact of recommendations on product adoption: A cross-cultural social network study. Paper presented at tthe American Agricultural Economics Association Annual Meeting, Portland, Oregon, July 29-31 2007. Accessed January 2014, available at http://purl.umn.edu/9984.

Kabunga, N.S, Dubois, T., Qaim, M. 2012. Heterogeneous information exposure and technology adoption: The case of tissue culture bananas in Kenya. Agricultural Economics 43:1–13.

Kijima, Y., Otsuka, K., Sserunkuuma, D. 2011. An inquiry into constraints on a Green Revolution in Sub-Saharan Africa: The case of NERICA rice in Uganda. World Development 39(1): 77–86.

Lyimo, S., Mduruma, Z., De Groote, H. 2014. The use of improved maize varieties in Tanzania. *African Journal of Agricultural Research* 9(7):643–657.

Mal, P., Anik, A.R., Bauer, S., Schmitz, P.M. 2012. Bt cotton adoption: A double-hurdle approach for North Indian farmers. *AgBioForum* 15(3): 294-302.

Marin, A., Wellman, B. 2011. Social network analysis: An introduction. Pages 11-25 in The SAGE handbook of social network analysis (Scott, J., and Carrington, P.J., eds.). The SAGE Publications, London, Great Britain.

Matuschke, I., Qaim, M. 2009. The impact of social networks on hybrid seed adoption in India. Agricultural Economics 40:493–505.

Mgonja, M.A., Monyo, E.S. 2002. Field days in Tanzania enhance regional spillover of models and technology developed in SMIP pilot countries. International Sorghum and Millets Newsletter 43:4-6.

Newman, M.E.J. 2010. Networks: An introduction. Oxford University Press Inc., New York, USA. 784 pp.

Ransom, J.K., Paudyal, K., Adhikari, K. 2003. Adoption of improved maize varieties in the hills of Nepal. Agricultural Economics 29: 299-305.

Rauch, J.E. 2010. Does network theory connect to the rest of us? A review of Matthew O. Jackson's Social and Economic Networks. Journal of Economic Literature 48(4):980–986.

Rubin, D.B. 1973. Matching to remove bias in observational studies. Biometrics 29:159-183.

Saha, L., Alan, L. H., Robert, S. 1994. Adoption of emerging technologies under output uncertainty. American Journal of Agricultural Economics 76:836–846.

Santos, P., Barrett, C.B. 2008**.** What do we learn about social networks when we only sample individuals? Not much. Accessed June 2012, available at http://dx.doi.org/10.2139/ssrn.1141838.

Santos, P., Barrett, C.B. 2010. Interest, identity and information search in a dynamic rural economy. World Development 38(12):1788-1796.

Schaefer, D.R. 2010. A configurational approach to homophily using lattice visualization. Connections 30(2):21-40.

Simtowe, F., Kassie, M., Diagne, A., Asfaw, S., Shiferaw, B., Silim, S., Muange, E. 2011. Determinants of agricultural technology adoption: The case of improved pigeonpea varieties in Tanzania. Quarterly Journal of International Agriculture 50(4):325-345.

Smale, M., Byerlee, D., Jayne, T. 2011. Maize Revolutions in Sub-Saharan Africa. The World Bank Development Research Group, Agriculture and Rural Development Team, Policy Research Working Paper 5659, Washington DC, USA. Accessed August 2013, available at http://documents.worldbank.org/curated/en/2011/05/14180379/maize-revolutions-sub-saharan-africa.

Smith, K.P, Christakis, N.A. 2008. Social networks and health. Annual Review of Sociology 34:405-429.

Tatlonghari, G., Paris, T., Pede, V., Siliphouthone, I. and, Suhaeti, R. 2012. Seed and information exchange through social networks: The case of rice farmers of Indonesia and Lao PDR. Sociology Mind 2(2):169-176.

Udry, C. R., Conley, T.G. 2004. Social networks in Ghana. Economic Growth Center, Yale University, Center Discussion Paper No. 888, New Haven, CT.

Uiaene, R.N. 2011. Determinants of agricultural technology adoption in Mozambique. Pages 375-380 in Proceedings of the 10th African Crop Science Conference, From Soil to Soul: Crop Production for Improved African Livelihoods and a Better Environment for Future Generations, 10-13 October 2011, Maputo, Mozambique. Entebbe, Uganda: African Crop Science Society.

van den Broeck, K., Dercon, S. 2011. Information flows and social externalities in a Tanzanian banana growing village. Journal of Development Studies 47:231–52.

World Bank 2007. World development report 2008: Agriculture for development. The World Bank, Washington DC. 365 pp.