GEORG-AUGUST-UNIVERSITÄT
GÖTTINGEN

GlobalFood
www.uni-goettingen.de/globalfood

RTG 1666 GlobalFood

Transformation of Global Agri-Food Systems:
Trends, Driving Forces, and Implications for Developing Countries

Georg-August-University of Göttingen

GlobalFood Discussion Papers

No. 45

Social networks and farmer exposure to improved crop varieties in Tanzania

Elijah N. Muange
Stefan Schwarze
Matin Qaim

September 2014

RTG 1666 GlobalFood · Heinrich Düker Weg 12 · 37073 Göttingen · Germany
www.uni-goettingen.de/globalfood

ISSN (2192-3248)

Social networks and farmer exposure to improved crop varieties in Tanzania

Elijah N. Muange *, Stefan Schwarze, Matin Qaim

Department of Agricultural Economics and Rural Development; Georg-August-University of Goettingen; 37073 Goettingen; Germany.

* Corresponding author. Tel.:+49 551 39 22114; fax: +49 551 394823. E-mail address: elijah.muange@agr.uni-goettingen.de

Abstract In Sub-Sahara 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

JEL codes: O12, O13, O31, Q12, Q16

Acknowledgements: The authors acknowledge the financial support of the Bill and Melinda Gates Foundation through the HOPE project as well as the Federal Ministry for Economic Cooperation and Development (BMZ), Germany. They also thank Alastair Orr (International Crops Research Institute for the Semi-Arid Tropics, Nairobi) for his support during the research process and the Agricultural Research Institute (ARI) in Makutupora of the Department of Research and Development (DRD), Tanzania, for supporting the survey.

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-Sahara 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. Methodology

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, 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 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 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 1 ABOUT HERE>

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. 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.

2.3. 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*):

$$P(Y_{dc} = 1|\boldsymbol{x_d}) = \Phi(\beta_0 + \textstyle\sum_{k=1}^{K} \boldsymbol{\beta_k x_{kd}}) \qquad d=1, 2,..., D \qquad (1)$$

where, the outcome $P(Y_{dc} = 1|\boldsymbol{x_d})$ is the probability of detecting an information network link, conditional on a set of observable characteristics, $\boldsymbol{x}$, defined for each dyad, d.[1] 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 $\boldsymbol{\beta_k}$ 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 (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 dyads where the respondent is the ego, and the second to dyads where the respondent is the

[1] 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).

alter. We account for such correlation by clustering the probit standard errors in these dimensions, following Petersen (2009).

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:

$$Pr\left(V = v_i \,|\mathbf{z}_i, \mathbf{w}_i \right) = \frac{e^{-\mu_i} {\mu_i}^{v_i}}{v_i!} \qquad v_i = 0, 1, 2 \ldots \tag{2}$$

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

$$ln\, \mu_i = \mathbf{z}_i'\boldsymbol{\beta} + \mathbf{w}_i'\boldsymbol{\delta} \tag{3}$$

Based on this specification, intensity of exposure is given by

$$E[v_i \mid \mathbf{z}_i, \mathbf{w}_i] = Var[v_i \,|\mathbf{z}_i, \mathbf{w}_i] = \mu_i = e^{\mathbf{z}_i'\boldsymbol{\beta} + \mathbf{w}_i'\boldsymbol{\delta}} \qquad v_i = 0, 1, 2 \ldots \tag{4}$$

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 $\boldsymbol{\partial}$ 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 $\boldsymbol{z}$, 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 (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 a likelihood ratio test, which rejected the null hypothesis of overdispersion. 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.

3. Data

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.

3.2. Farmers' sources of information

We are particularly interested in the flow of information about improved sorghum and maize varieties. Table 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 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.

<TABLE 1 ABOUT HERE>

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 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.

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 (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. Cluster robust standard errors 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 together with descriptive statistics.

<TABLE 2 ABOUT HERE>

The probit estimation results are shown in Table 3. Differences in education levels between ego and alter reduce the probability of an information network link, although this effect is only significant for maize. The effects of the other 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. 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 3 ABOUT HERE>

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.

5. Determinants of exposure to improved varieties

5.1. Status of exposure

Farmers' exposure to improved varieties is summarized in Table 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 4 ABOUT HERE>

5.2. Regression results

To analyze the determinants of exposure to improved varieties, we estimate Poisson regression models, as described in equations (3) and (4). The explanatory variables used in these models are defined in Table 5. In addition to these variables, we include village cluster dummies; these dummies are not shown for brevity. Regression results are presented in Table 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.

<TABLE 5 ABOUT HERE>

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.

The results of models (5) and (7) in Table 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 6 ABOUT HERE>

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 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.

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 almost 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. Technology dissemination programs should try to make use of such networks in an intelligent way. 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. 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. 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 removed. Among other things, this will require gender mainstreaming of extension programs. 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.

References

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.

Bellon, M.R., Reeves, J., eds., 2002. Quantitative analysis of data from participatory methods in plant breeding. CIMMYT, Mexico, DF, Mexico. Accessed March 2013, available at http://repository.cimmyt.org/xmlui/handle/10883/909.

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.

Burt, R.S., 1987. Social contagion and innovation: Cohesion versus structural equivalence. American Journal of Sociology 92(6), 1287-1335.

Cameron, A.C., Trivedi, P.K., 1998. *Regression Analysis of Count Data*. Cambridge University Press, New York, USA.

Cameron, A.C., Gelbach, J.B., Miller, D.L., 2011. Robust inference with multiway clustering. Journal of Business & Economic Statistics 29(2), 238-249.

Chandrasekhar, A., Lewis, R., 2011. Econometrics of sampled networks. Unpublished manuscript, MIT. Accessed July 2014, Available at http://stanford.edu/~arungc/CL.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.

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

Dufhues, T., Buchenrieder, G., Euler, D.G., Munkung, N., 2011. Network based social capital and individual loan repayment performance. Journal of Development Studies 47(8), 1199–1215.

Easley, D., Kleinberg, J., 2010. Networks, Crowds, and Markets: Reasoning About a Highly Connected World. Cambridge University Press, New York, USA.

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.

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.

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/.

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.

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. Selected paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Portland, Oregon July 29-31, 2007.

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.

Maertens, A., Barrett, C.B., 2013. Measuring social networks effects on agricultural technology adoption. American Journal of Agricultural Economics 95(2), 353–359.

Marin, A., Wellman, B., 2010. Social network analysis: An introduction, in Carrington, P., Scott, J., eds. The SAGE Handbook of Social Network Analysis. 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.J., 2010. Networks: An Introduction. Oxford University Press Inc., New York, USA.

Petersen, M. A., 2009. Estimating standard errors in finance panel data sets: Comparing approaches. The Review of Financial Studies 22 (1), 435-480.

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.

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.

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.

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.

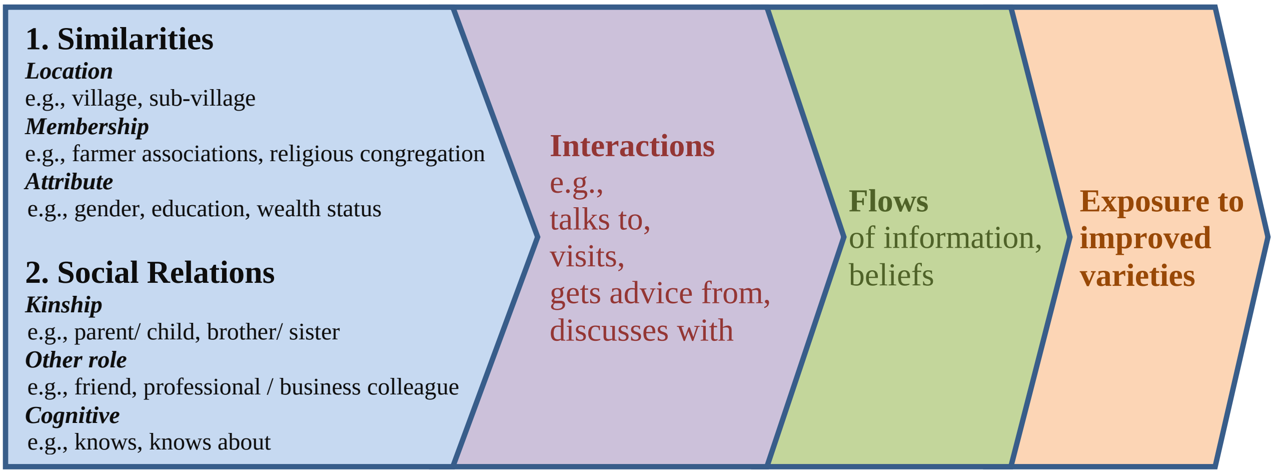

Figure 1: A framework for understanding drivers of learning about improved varieties
Source: Adapted from Borgatti et al. (2009).

Table 1: Farmers' sources of first information about improved varieties

	Sorghum varieties	**Maize varieties**	**Maize OPVs**	**Maize hybrids**
Source of information (% of responses)	*(N=578)*	*(N=658)*	*(N=216)*	*(N=442)*
Other farmer	27.7	49.7***	52.8	48.2
Government extension officer	66.8	23.9***	25.9	22.9
Trader	0.9	8.7**	9.3	8.4
Mass media	0.5	12.2***	5.6	15.4***
Other	4.1	5.6**	6.5	5.2
Relationship if source is other farmer (% of 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 learned about variety if source is other farmer (% of 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), and between maize OPVs and hybrids (last two columns), significant at 10%, 5%, and 1% level, respectively.

Table 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 period)]	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.

Table 3: Determinants of information network links

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

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.

Table 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.

Table 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.

Table 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	0.048*	-0.006				
		(0.056)	(0.028)	(0.040)				
Maize network degree1						-0.018	-0.003	-0.020
						(0.082)	(0.044)	(0.058)
Maize network degree2						0.194	0.148**	0.029
						(0.140)	(0.072)	(0.101)
Admin link	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)
Extension link	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)
Age	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)
Female	-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)
Education	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)
Land owned	-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)
Mobile phone	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)
Radio	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: 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.