Social Networks and Farmer Exposure to Improved Cereal Varieties in Central Tanzania

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Abstract

This study uses probit and Poisson models to analyse the determinants of social network links for the exchange of information among 345 cereal farmers and the effects of social networks on farmer exposure to improved varieties in Central Tanzania. Results show that network links are determined by education, wealth, association membership, geographical proximity, kinship ties, community leadership role, and links to extension officers. Further, farmer networks positively affect the intensity of exposure to seed technologies with mostly missing or malfunctioning markets. Moreover, it is information networks outside a farmer's village, rather those inside the village, that determine intensity of exposure.

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

1. Introduction

Food insecurity remains a major development challenge for many agrarian economies and the use of improved varieties is key to increasing food production and hence food security (FAO, 2002). However, adoption of these varieties remains incomplete (CGIAR, 2011), with Sub-Saharan Africa (SSA) recording the lowest adoption rates (Smale, Byerlee & Jayne, 2011). Lack of exposure (awareness) to improved varieties has been identified as a major constraint to their diffusion in many parts of SSA (Doss et al., 2003; Kabunga, Dubois & Qaim, 2012). The argument in such studies is that farmers cannot adopt improved varieties whose existence or attributes they are unaware of. Pervasive lack of exposure to improved varieties may surprise, given that the development of varieties often involves considerable degree of farmer participation along the research and development chain (Heinrich & Mgonja, 2002). The philosophy underlying involvement of farmers in variety testing and dissemination is that participating farmers would adopt, and, through their social networks, disseminate both information and seeds to other farmers, leading to widespread exposure and diffusion. Social networks are seen as powerful informal institutions through which information diffuses in farming communities (Udry & Conley, 2004). However, many studies on diffusion of improved varieties in SSA (Shiferaw et al., 2008; Kassie et al., 2012) rarely investigate explicitly the role and effectiveness of social networks, particularly in exposing farmers to the varieties. Thus, it remains largely unknown whether and which characteristics of social networks determine the extent of farmer exposure to agricultural technologies.

In the recent past, there has been growing interest in the use of social network theory to assess adoption and diffusion of technological innovations (Bandiera & Rasul, 2006; Kremer & Miguel, 2007 Kimura, 2011). The studies show that, although social networks affect technology diffusion, there is no general consensus on the magnitude of these effects and on the factors that drive such mechanisms. Effects of social networks on technology diffusion therefore seem to be technology and context specific. Previous studies investigating the role of social networks in diffusion of agricultural technologies have focused mainly on cash crops such as pineapples (Udry & Conley, 2004), sunflower (Bandiera & Rasul, 2006) and cotton (Maertens & Barret, 2013), while those investigating cereals have focused mainly on hybrid technologies such as wheat and millet (Matuschke & Qaim, 2009) for which seed markets exist in the study areas. Moreover, although social networks have been known to cross geographical boundaries (De Weerdt, 2004; Fafchamps & Gubert, 2007), past studies on social networks tend to assess mainly relationships within villages, ignoring inter-village networks that might play an important role in technology diffusion.

The purpose of this study is to assess the role of social networks in exposing farmers to improved cereal varieties in Central Tanzania. Specifically, we address two questions. The first is what factors determine farmer network links for exchange of cereal farming information; and the second, what effects social networks have on farmer exposure to improved varieties. In doing so, we build on and broaden the focus of the above mentioned studies by first, explicitly addressing the effect of intra- versus inter-village networks; second, assessing sorghum and maize, which represent different seed technology sets; and, third, modeling the intensity of exposure. Sorghum varieties in our study area are purely OPV (open pollinated variety) technologies, while those of maize are largely hybrid technologies (but also with some OPVs). Due to low replacement rate of OPVs, their seed market is less developed than that of maize hybrids. Past studies that assess the determinants of exposure define farmers as exposed to improved varieties if they are aware of at least one variety. We depart from this binary variable definition of exposure because it has a major drawback of treating farmers who are aware of only one variety as having the same level of exposure as those aware of several varieties. Yet by virtue of their dissimilar agronomic and organoleptic characteristics, improved varieties of each crop are actually different technologies, which present farmers with options for adopting varieties that suit their preferred attributes (Mafuru et al., 2007; Lunduka, Fisher & Snapp, 2012). We argue for intensity of exposure (number of improved varieties a farmer is aware of), following emerging evidence that farmers exposed to more improved varieties tend to have a higher adoption rates (Diagne & Demont, 2007; Asfaw et al., 2011). Furthermore in our dataset, adoption of improved varieties is highly correlated with the intensity of exposure.

The rest of the paper is structured as follows. Section 2 discusses the methodology of our study, including conceptual framework, econometric models, data and study area. We present our results in Section 3, while Section 4 concludes.

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 & Riddle, 2005). Social networks evolve due to *ties* between actors, which may arise because of kinship, affection or familiarity between them (Easley & 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 & Christakis, 2008). A fundamental question for this study is, what factors would place farmers in each other's information exchange network. We illustrate our conceptual framework for addressing this question using two farmers *A* (not exposed to an improved variety) and *B* (exposed). By invoking elements of *social contagion* theories that 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 getting exposed to an improved variety. We can summarize these characteristics into two categories, following Borgatti et al. (2009), 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 are social relationships, which include kinship ties, other roles such as friendships, 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. One popular measure of the size of a farmer's network is the number of links in the network that connect directly to the farmer, technically known as *degree* (Newman, 2010). We hypothesize that farmers with higher network degree occupy *positions* that predispose them to more learning opportunities about improved varieties (House et al., 2007; Borgatti et al., 2009), making them more likely to have a higher intensity of exposure than those with a lower degree.

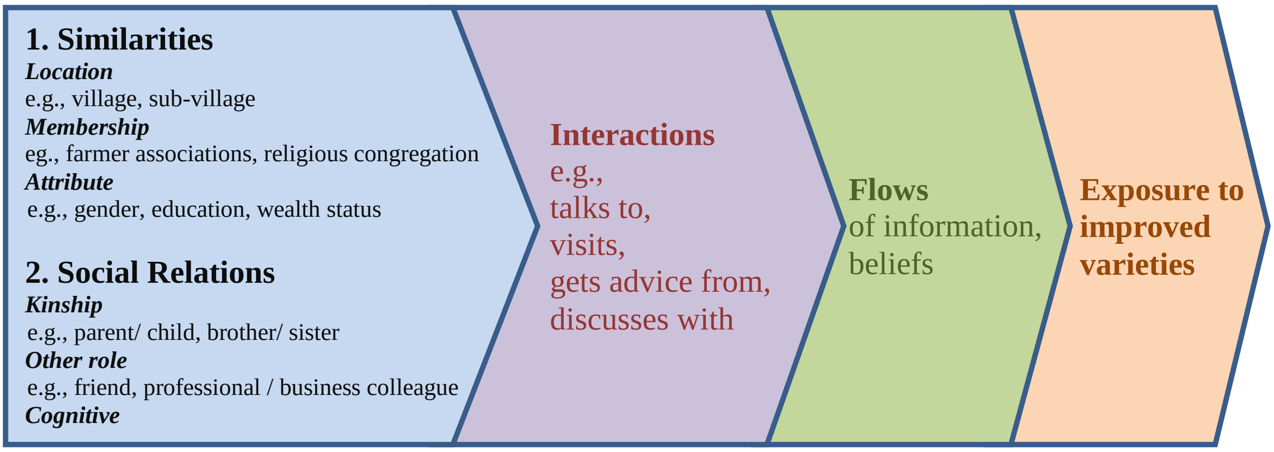

Figure 1: A framework for understanding drivers of learning a link for modern varieties
Source: Adapted from Borgatti et al. (2009).

2.2. Econometric Approach

To empirically assess the factors that determine information exchange networks, we use an econometric framework similar to Conley and Udry (2010) and Maertens and Barrett (2013). Each farmer in our sample (denoted *i*) is paired with six others (denoted *j*)[1]. 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 the crops, as reported by the *ego*. Two main approaches can be used to elicit this kind of data (Santos & Barrett, 2008). Using the first, referred to as *potential network* approach, we could enquire from the *ego* whether they could approach the *alter* for information regarding a cereal crop of interest. Alternatively, we could use the *real network approach* and ask the *ego* whether they have ever sought such information from the *alter*. Since our aim is to assess current exposure, which is itself a function of past behavior, we consider the latter approach more plausible, and define *j* to be in *i*'s sorghum/maize information network if *i* reports that they discuss farming issues related to these crops with *j*.

For each crop, *c*, we estimated the following probit model to assess the determinants of 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 for crop *c* between *i* and *j*, conditional on a set of observable characteristics $\boldsymbol{x}$, defined

[1] When using the random matching approach, there is no explicit rule regarding the number of matches per respondent, which rarely exceeds seven in most studies. We chose six to minimize tiring respondents and also due to time and other resource constraints.

for each dyad, d, and subject to i knowing j[2]. Key among these characteristics are similarities in personal attributes of *ego* and *alter* (such as age, sex, education level, wealth status and religion), membership in the same community associations, kinship ties between *ego* and *alter* as well as geographical proximity. Φ is a standard normal cumulative distribution function that forces predicted probabilities to be between zero and one; $\boldsymbol{\beta_k}$ are parameters to be estimated by the model. Since each respondent is paired with several others, stochastic error terms for all dyads involving the respondent are not independent, but rather correlated in two dimensions (Fafchamps & Gubert, 2007; Cameron et al., 2011). We therefore cluster the probit standard errors in the two dimensions, following Petersen (2009). This was executed using the probit2 Stata code written by Guan and Petersen (2008).

To determine the effect of social networks on exposure, we define exposure in terms of intensity, i.e. the number of improved varieties to which a farmer is exposed. This intensity can be modeled as a discrete variable, V, with a Poisson distribution (Cameron & Trivedi, 1998; Greene, 2012) given by

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

where for each farmer, i, $\boldsymbol{v}$ is the number of improved varieties the farmer is exposed to; $\boldsymbol{z}$ is a set of personal and household attributes hypothesized to influence exposure to improved varieties, such as age, education level, sex, and wealth; $\boldsymbol{w}$ is a set of variables that indirectly capture the quantity of information available to the farmer through social networks with other farmers, village administrators, and government agricultural extension officers and μ is a loglinear function that can be expressed as:

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

where $\boldsymbol{\beta}\ and\ \boldsymbol{\partial}$ are vectors of parameters to be estimated by the model. Based on this specification, a farmer's intensity of exposure is given by

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

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), leading to imprecise estimators (Cameron & 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.

2.3. Data and Study Area

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

[2] Since matching is random, not all of a farmer's matches are necessarily known to the respondent. Logically, we do not expect a network link between matches who do not know each other; hence we restrict regression analysis to subsample of pairs whereby respondent knows the match.

still popular. 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 developed a number of 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 & Mgonja, 2002; Erenstein et al., 2011). 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[3] baseline survey in Tanzania, in 2010. In each district, 3 village clusters (2-5 villages each) were purposively selected from 2-3 Wards, for the purposes of project implementation. The logic followed in this clustering was to group villages that are geographically close to each other and sharing the same local agricultural extension officer. Respondents were then randomly selected from each village. Face-to-face interviews with heads of selected households were conducted using a pre-tested structured questionnaire administered by enumerators, under the supervision of the first author and a representative of the Agriculture Ministry's Department for Research and Development (DRD), Central Zone.

3. Results

3.1. Determinants of Information Network Links

As stated earlier, each farmer was matched to six randomly selected farmers. 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 (because the *alter* was also asked about the *ego*), while for 82 other dyads, some information about the *alters* was missing, primarily because the *alters* could not be traced for interviews[4], or *ego* could not tell some key details about the *alter*. We therefore excluded these dyads from regression analysis and used 1,879 dyads. Our data shows that respondents knew only 50% of their 6 random matches. This familiarity is, however, much higher if farmers are geographically proximate to each other. The respondents know 77 % of their alters if they live in the same village (85% if they live in same sub-village) compared to just 26.4% if they are from neighboring villages. We used the probit model specified in Equation 1 to assess the influence of each dyadic characteristic on the probability of detecting a network link for exchanging information on sorghum and maize farming. We included village cluster dummies to control for unobserved cluster fixed effects, but these are not reported. Subject to knowing each other, we find that just about one third of the random dyads discuss cereal farming issues, with about 17% of these discussions occurring across villages. Santos and Barrett (2010) use a similar approach, and report exchange of farming information in 30% of dyads, which is comparable to our result. Other characteristics of these dyads are presented in Table 2.

Table 3 reports the results of the econometric analysis. Among the personal characteristics, only difference in education level between actors shows significant results. Farmers are less likely to exchange information on the two crops if they belong to the different education levels. Difference in the size of land owned by a household (which is commonly used as a wealth indicator) has a positive and significant influence for both crops. We hypothesize that farmers with comparable land holdings have similar farming knowledge,

[3] Detailed information about the project is available at http://hope.icrisat.org

[4] Matching was done before the interviews using the list of respondents interviewed in 2010. If any ego's alter was not interviewed, the data for that dyad was rendered incomplete hence the dyad discarded from analysis.

making information exchange redundant and less attractive (Borgatti et al., 2009; Dufhues et al., 2010).

Table 2: Dyadic variable definitions and descriptive statistics

Variable	Definition	Mean (D=948)	Standard Deviation
Sorghum network	Presence of sorghum network ties between ego and alter (1=Yes; 0=Otherwise)	0.34	0.47
Maize network	Presence of maize network ties between ego and alter (1=Yes; 0=Otherwise)	0.32	0.47
Age	Ego and alter age difference (years)	11.9	8.98
Education	Ego and alter belong to different education levels (1=Yes; 0=Otherwise)	0.74	0.44
Gender	Ego and alter belong to different gender 1=Yes; 0=Otherwise)	0.75	0.43
Religion	Ego and alter belong to different religions (1=Yes; 0=Otherwise)	0.68	0.47
Land	Difference in ego's and alter's own land (hectares)	3.82	6.19
Livestock	Difference in ego's and alter's livestock value (millions of Shillings)	2.73	3.86
Association	Ego and alter belong to a common association or group (1=Yes; 0=Otherwise)	0.09	0.28
Village	Ego and alter belong to same village (1=Yes; 0=Otherwise)	0.73	0.44
Sub-village	Ego and alter belong to same sub-village (1=Yes; 0=Otherwise)	0.24	0.43
Kinship	Ego and alter have kinship ties (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 is a leader (1=Yes; 0=Otherwise)	0.67	0.47
Extension1	Only ego/alter has links with extension officer (1=Yes; 0=Otherwise)	0.36	0.48
Extension2	Ego and alter have links with extension officer (1=Yes; 0=Otherwise)	0.55	0.50

Source: Computed from survey data 2012

Membership in a common association has a strong effect on the formation of an information network link. This is plausible, because farmers who belong to same association meet more frequently, and hence have a higher probability of exchanging information. Geographical proximity between ego and alter, as expected, returned positive results, which were highly significant for both crops. The probability that farmers in a dyad have an information network link increases by 12 and 9 percentage points for sorghum and maize respectively, if both reside in the same village, compared to dyads comprising farmers from different villages. The effect of kinship ties on the probability of a network link is positive and significant for both crops. The likelihood of farmers exchanging sorghum and maize information increases by 11-13 percentage points if the farmers have kinship ties. The duration over which ego and alter have known each other also has a positive and significant effect for both crops, indicating that time plays an important role in building farmer-to-farmer relationships that can be relied on to convey farming information. Having a leadership role in the community is associated with a higher and significant probability of a network link. The likelihood of a network link increases by about 8 and 7 percentage points for sorghum and maize respectively, if at least one farmer is a leader. This is plausible since community leaders are likely to know (or be known by), and hence exchange information with more farmers. Closely related results also show that farmers with links to government extension officers discuss farming matters more than those without such links, most likely because the officers are a key source of new farming information that farmers can discuss. Overall, we find that information exchange networks for both sorghum and maize are determined by the same variables. This is plausible, as egos and alters may not limit their farming discussions to only certain crops, unless they cultivate entirely different crops. Udry and Conley (2004) make similar conclusions by finding that network links for information, credit, land and labor, among the same set of farmers, were determined by same factors.

Table 3: Estimates of the determinants of information network links

Variables	**Sorghum**			**Maize**		
	Coefficient	Robust standard errors	Marginal effects	Coefficient	Robust standard errors	Marginal effects
Constant	-2.029***	0.299		-1.967***	0.306	
Age	0.002	0.001	0.001	-0.001	0.006	-0.000
Education	-0.202*	0.117	-0.063	-0.232**	0.112	-0.073
Gender	-0.229	0.144	-0.072	-0.215	0.147	-0.067
Religion	-0.039	0.096	-0.012	-0.107	0.104	-0.034
Land	0.022*	0.012	0.007	0.030***	0.011	0.009
Livestock	0.018	0.015	0.006	0.004	0.013	0.001
Association	0.808***	0.218	0.254	0.678***	0.195	0.213
Village	0.395***	0.129	0.124	0.284**	0.119	0.089
Sub-village	0.378***	0.124	0.119	0.309***	0.120	0.097
Kinship	0.413***	0.142	0.130	0.356**	0.151	0.112
Duration	0.012**	0.005	0.004	0.015***	0.005	0.005
Leader	0.250**	0.114	0.079	0.206*	0.121	0.065
Extension1	0.379*	0.199	0.119	0.450**	0.208	0.141
Extension2	0.403*	0.208	0.127	0.489**	0.225	0.153

Note: *** p<0.01, ** p<0.05, * p<0.1; *D* (dyads used) =948

3.2. Status of Exposure to Improved Varieties

Farmer exposure to improved varieties is summarized in Table 4. 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 OPVs.

Table 4: Farmer exposure to improved varieties (N=345)

Exposure	**Sorghum**	**Maize**	**Maize OPVs**	**Maize Hybrids**
No 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	3.2	9.9
4	7.8	11.0	0.0	3.2
5 and above	2.3	7.0	0.0	0.3
Mean intensity of exposure	*1.7*	*1.8*	*0.6*	*1.2*

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 mean intensity of exposure is 1.7 for sorghum and 1.8 for maize. In the case of maize, exposure to hybrids is higher than to OPVs; and this is probably due to the role of seed markets (see Section 3.1). 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.

3.3. Determinants of Exposure

To assess the individual determinants of exposure to improved varieties, we estimate Poisson regression models following Equations (3) and (4). The definition of the explanatory variables used and some descriptive statistics are presented in Table 5. Among the key social network variables are total degree, which we expect to have a positive effect on intensity of exposure. We further split the network degree into intra- and inter-village degrees, hypothesizing that since more interactions happen within the village, intra-village network links may lead to higher intensity of exposure than inter-village links. Other social network variables are strength of links with village administrators and links with extension officers. Village administrators are the key sources of information regarding extension events such as meetings, trainings and field days, whereas extension officers are the main source of information on new varieties. We expect farmers with links to these individuals to have higher exposure than those without such (or only weak) links. We finally control for personal and household characteristics which may also have an effect on exposure intensity, including age, sex, education level, religion, land size, and ownership of radio and mobile phone.

Table 5: Variable definitions and descriptive statistics for the exposure model

Variable	Definition	Mean	Standard Deviation
Social network attributes of respondent			
Crop network degree			
Sorgnetw	Total sorghum network degree	1.11	1.40
Sorgnetw1	Intra-village sorghum network degree	0.93	1.08
Sorgnetw0	Inter-village sorghum network degree	0.19	0.57
Maiznetw	Total maize network degree	1.03	1.38
Maiznetw1	Intra-village maize network degree	0.83	1.06
Maiznetw0	Inter-village maize network degree	0.20	0.55
Networks with institutional information channels			
Adminlink	Strength of links with village administration (contacts per month with a member of the village administration)	13.8	9.57
Extlink	Talks with extension officer (not necessarily to consult, but more social interaction) 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

Regression results are presented in Table 6, but village cluster dummies that are also included in the regressions to control for heterogeneity across the clusters are not shown. In models 1-4, the total size of the crop information network is used, while in models 5-8, the network is broken into a network within and a network outside the village. Results show that the size and strength of farmers' social networks matter for intensity of exposure to improved cereal varieties. As shown in models (1) and (2), network degree positively influences intensity of exposure to sorghum varieties. In case of maize, however, an extra member in the network has no significant effect on intensity of exposure. Surprisingly, 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 implies that farmer networks facilitate more exposure to seed technologies with mostly missing or malfunctioning markets, than those with better markets.

Table 6: Estimates of the determinants of exposure to improved varieties

Explanatory Variable	**(1) *Sorghum***	**(2) *Maize***	**(3) *OPVs***	**(4) *Hybrids***	**(5) *sorghum***	**(6) *maize***	**(7) *OPVs***	**(8) *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: Figures are marginal values, with robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. N=345.

The results in the models (5) and (7) indicate that the size of the farmer network outside the village positively and significantly affects intensity of exposure to sorghum varieties and OPVs of maize, while the network 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 extra network members within the village redundant. Networking outside the village therefore 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 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. 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.

4. Conclusions

This study assesses factors that determine cereal information exchange among farmers and the role of social networks in farmer exposure to improved varieties of two cereals in central Tanzania. We apply probit models to assess the determinants of social network links for the exchange of information on cereal farming among farmers, and Poisson models to identify the role of social networks on exposure to the improved varieties, using household survey data from 345 farmers. Our results show farmers are less likely to exchange cereal farming information if they have different levels of formal education, but are more likely to exchange information if they are of different wealth status, members in the same association, live in the same village or sub-village, have kinship ties, have known each other for a longer time, at least one is a leader in the community, and if at least one has links with government agricultural extension officers. We conclude that social network links for information exchange for both sorghum and maize are determined by the same variables and the level of information exchange among farmers does not differ by crop. Results for determinants of farmer exposure to improved varieties show that the size of a farmer's sorghum network influences their intensity of exposure to sorghum varieties. The size of maize network influences exposure to OPVs positively, but we do not find a significant effect on exposure to hybrids. This finding demonstrates that *ceteris paribus*, farmer networks facilitate higher exposure to seed technologies with mostly missing or malfunctioning markets (sorghum varieties and OPVs of maize). Moreover, we 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. Other results show that the strength of network connections with village administrators is associated with a higher intensity of exposure to sorghum varieties. Similarly, network connections with public extension officers influence intensity of exposure positively for sorghum varieties and maize hybrids.

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