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Agriculture-nutrition linkages in farmers' communication networks

Lisa Jäckering [a,*], Theda Gödecke [a], Meike Wollni [a]

Abstract. In the recent development discourse, much emphasis has been placed on making agriculture more nutrition-sensitive as an important component in combating hunger and malnutrition among rural households in developing countries. In order to achieve this at scale, nutrition information could be diffused to farm households organized in community-based organizations (CBOs) through the existing agricultural extension systems. However, to date little is known about how information flows within CBOs and how extension interventions could be designed to deliver combined information on agriculture and nutrition. This study uses unique network data from 815 farm households in Kenya to investigate the structure and characteristics of agricultural and nutrition information networks within CBOs. Dyadic regressions are used to analyze the factors influencing link formation for the exchange of agricultural and nutrition information. In addition, we apply fixed-effects models to identify the characteristics of central persons driving information exchange in the two networks, as well as potentially isolated persons, who are excluded from information networks within their CBOs. Our results show that nutrition information is exchanged within CBOs, although to a limited extent, and mostly flows through the existing agricultural information links. Thus, diffusing nutrition information through agricultural extension systems may indeed be a viable approach. Our findings further suggest that group leaders and persons living in central locations are important drivers in the diffusion of information in both networks and may thus serve as suitable entry points for nutrition-sensitive extension programs. However, we also identify important heterogeneities in network characteristics. In particular, nutrition information is less often exchanged between men and women, and some group members are completely isolated from nutrition information exchange within their CBOs. We derive recommendations on taking these differences in network structure and characteristics into account when designing nutrition-sensitive extension programs.

Keywords: Communication networks; community-based organizations; nutrition-sensitive agriculture; dyadic regressions; Africa; Kenya

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1. Introduction

Globally, about 800 million people are undernourished and about two billion people suffer from micronutrient deficiencies (IFPRI 2017). Most of these people live in rural areas of developing countries and depend on agriculture for food and income generation (IFPRI 2011; FAO 2015). Thus, agriculture can play a central role in improving nutrition (Hawkes & Ruel 2008; Fan & Pandya-Lorch 2012; Ruel et al. 2013). A growing body of literature tries to understand agriculture-nutrition linkages and in particular the pathways through which agriculture can influence nutrition (Malapit et al. 2015; Sibhatu et al. 2015; Carletto et al. 2015; Pandey et al. 2016; Ruel et al. 2018). Linking nutrition and agriculture is especially important since obesity, besides undernutrition and micronutrient deficiencies, is becoming prevalent in rural African communities, affecting both men and women (Popkin et al. 2012; Gómez et al. 2013). One way of making agriculture more nutrition-sensitive, is to deliver nutrition information that particularly targets farmers. A possible platform to channel nutrition information to farmers might be the existing agricultural extension systems.

In the extension systems of developing countries, community-based organizations (CBOs) and individuals within CBOs are important target units (Anderson & Feder 2007). Group-based extension is considered pro-poor, as it can reach women and low educated farmers of East Africa, which are especially vulnerable to poverty (Davis et al. 2012). Besides that, the rationale of targeting CBOs or key individuals within CBOs it to reduce transaction costs. This is based on the assumption that new information will flow among CBO members, or key individuals will pass on the new information to other group members. Yet, relatively little is known about how exactly information flows within CBOs and between CBO members.

To date, there is little evidence on how agricultural extension services should be designed to combine information on agriculture and nutrition. Women's empowerment can be seen as an important pathway through which development interventions can improve child nutrition (Carletto et al. 2015; Darrouzet-Nardi et al. 2016). Therefore, nutrition-sensitive programs usually target mothers, households with children, or women groups (De Brauw et al. 2015; Ruel et al. 2018). Although women play an important role for agriculture in Sub-Saharan Africa, conventional extension sessions are still predominantly attended by men (Ragasa et al. 2013). CBOs are often mixed-gender groups and thus could be a useful platform to sensitize both, men and women, on nutrition-related topics. In order to design effective interventions for nutrition-sensitive agriculture, it is however important to understand whether and how nutrition information is exchanged within agricultural information networks.

Previous studies have documented the important role of key persons within networks. Evidence suggests that farmers mostly learn about new technologies from a few progressive farmers, who consequently have a strong impact on project outcomes (Maertens 2017). In line with this, Kim et al. (2015) find that targeting influential individuals and their friends can help to increase project outreach. Aubel (2012) argued that exclusively training mothers might not be sufficient for better child nutrition outcomes, and instead culturally accepted key persons such as grandmothers should also be targeted. Indeed, very selective targeting of key persons may not be the most effective strategy. Experimental evidence has shown that efficiency in the diffusion of information is lost when farmers focus too much on a few popular individuals (Caria & Fafchamps 2015). It is thus critical to identify central persons driving information exchange within networks as well as isolated persons who are excluded from such information exchange. Based on such insights, targeting strategies can be developed that maximize the outreach of nutrition-sensitive information distributed through agricultural extension programs.

To be able to assess how information diffuses, it is crucial to have data on the networks' structure, preferably in form of a census. Due to the high costs of census data, such studies are rare, even though they would be especially suited to depict the quality of networks (Smith & Christakis 2008).

Instead, individual measures are predominantly used to determine social networks in the context of agricultural technology adoption; for example, the number of contacts a farmer reports (Maertens 2017; Murendo et al. 2017; Matuschke & Qaim 2009). To the best of our knowledge, our study is the first using a combination of directed census data and individual network measures to analyze the structure of nutrition and agricultural communication networks and to characterize key persons within these networks. The results could help to develop network targeting strategies to effectively incorporate nutrition information in agricultural extension programs and thus making agriculture more nutrition-sensitive.

We contribute to the literature by addressing the following questions: First, how are agricultural and nutrition information networks within CBOs structured and to what extent do they overlap? Second, what are the characteristics of persons forming links to exchange agricultural and nutrition information? Third, what are the characteristics of particularly central persons that are important for agriculture and nutrition information networks, as well as of isolated persons that are excluded from these networks? The rest of the paper is structured as follows. Section two presents the study area and data collection. In section three, we introduce the network measures and estimation strategies employed on CBO, dyadic and individual levels. Section four presents the results, and the final section concludes and derives policy implications.

2. Context and data

The study was conducted in Kisii and Nyamira County in Kenya. These counties are densely populated, and more than half of the population is mainly employed in the agricultural sector. Farmers grow maize, beans, bananas, sugar cane, tea, and horticultural crops (KNBS & SID 2013). The farming system is characterized as intensive, subsistence, and almost all of the land is under cultivation (Mbuvi et al. 2013). The majority of the population depends on the produce from small and fragmented pieces of land. Regarding the nutritional status, people in Kisii and Nyamira Counties are close to the national average, with one-quarter of the children being stunted, which means that they are too short for their age. At the same time, a third of the women of reproductive age are overweight or obese (KNBS 2015). Against this background, agronomic and nutrition trainings could contribute to an improvement of livelihoods, and Kisii and Nyamira can be considered suitable settings for nutrition-sensitive interventions.

This article builds on data collected on CBO, dyadic, and individual levels in late 2015. CBOs refer to all sorts of membership organizations at the community level, such as credit groups or agricultural groups. CBOs can be divided into groups that have already existed for a long time (customary) or groups that were formed due to a development intervention (World Bank & IFPRI 2010). In the context of Kenya, the latter play an important role.[1] In the early millennium years, more than 7000 CBOs were founded in the context of the "National Livestock and Extension Program" (NALEP), which was rolled out in Kisii County among others. The CBOs were formed with the aim to channel extension services through them and were seen as cost-efficient entry points (Cuellar et al. 2006). In more recent years, the government with support of the World Bank launched the "Kenya Agricultural Productivity Program" (KAPAP) that also builds on CBOs.

CBOs and households were randomly selected in a two-stage procedure. To construct the sampling frame for the selection of CBOs, a non-governmental organization active in the area helped us to compile the list of current groups in Kisii and Nyamira. From this list, 48 CBOs (N_G) were randomly sampled with a probability proportionate to the total number of CBOs in each County. Accordingly, 32 CBOs were selected in Kisii and 16 in Nyamira County. The sampling frame of households was based on the list of group members updated for each of the selected CBOs shortly

[1] CBOs are also referred to as common-interest groups (CIGS) in Kenya. CIGs are "organization of some members of the community that get together to achieve a common purpose" (Manssouri & Sparacino 2009, p.16).

before the interviews with the help of group leaders. As the sampling frame centers on households, spouses and other household members were removed from the lists resulting in an average group size of 21 members (see Table 3). Based on the adjusted group member lists, about 17 households were randomly sampled and interviewed in each of the selected CBOs. We were able to collect full network information from 4 groups and close to full information from two thirds of our groups. Taking all groups together, more than 80% of group members were interviewed. As a result, our data is nearly equivalent to a census providing the most accurate information for understanding the structure of networks (Hanneman & Riddle 2005).

On CBO level, we collected data with the help of a semi-structured group level questionnaire. It captured information about the CBOs' purpose and history among others. The questions were answered by one of the CBO's officials. Data on dyadic and individual levels were collected through a household survey using a structured questionnaire that included detailed crop and livestock, nutrition and social network modules. Before data collection, both the CBO level and the household level questionnaires were carefully pretested in the field and adjusted.

The network module was answered by the CBO member and the questions were asked in a dyadic fashion: we asked the respondents to indicate for all members of their CBO whether they talked to each other and whether they shared information on nutrition and agriculture. The respondents were also asked about their relationship towards each other (such as being relatives or friends), whether their plots are located next to each other, as well as questions related to asset sharing and agricultural activities. For all questions, the past 12 months were used as the reference period. Overall, 815 out of 824 respondents answered the network module. We take our data as directional given that a stated link between member *i* to member *j* is not automatically reciprocated. In other words, it is possible that member *i* states to share information with member *j*, but *j* states not to share with *i* (Wasserman & Faust 1994). In contrast to most studies that rely on self-reported data and hence undirected network data[2], directional data allows us to differentiate between prominent group members (being named often) and influential members (persons naming many people) (Hanneman & Riddle 2005).

Overall, our analyses are performed on three levels: First, on the group level with all 48 CBOs (N_G). Second, our analysis on the dyadic level will be based on 13318 dyads (N_D). Third, analyses will be performed on the level of the CBO member. This individual level data set consists of 815 observations (N_I).

3. Network measures and estimation strategy

3.1. CBO level analysis: Network structure and overlaps

On group level, we analyze to what extent agricultural and nutrition information is exchanged in CBOs. For that purpose, we explore the structure of agricultural and nutrition information networks in terms of their densities as well as their overlaps. The concept of *network density D* is associated with the speed with which information is transmitted within groups and can be used as an indicator of the groups' connectedness (Hanneman & Riddle 2005). Based on Wasserman & Faust (1994) we calculated densities for directed graphs as

$$D_g(m) = \frac{L_g(m)}{n_{ig}(n_i - 1)}, \qquad (1)$$

where i refers to the group member (node). All nodes i are embedded in their CBOs g, that vary with respect to their number of members n_i. Within CBOs, each node can potentially engage in conversation with n_i-1 members. A link l_{ij} is defined as a binary variable, being one if information exchange about a certain topic m exists. L_g is the sum of actual links l_{ij} within a CBO g. Our information networks m of interest are *AGRICULTURE* and *NUTRITION*. CBO structure is analyzed descriptively and with the help of mapping techniques.

[2] Undirected network data does not allow inference on the prominence of the respondents.

This also allows us to identify isolates for *AGRICULTURE* and *NUTRITION.* Isolates are nodes without any links, and hence these nodes are at risk that new information bypasses them. Therefore, the identification of isolates can be important for network-based interventions (Carrington et al. 2005). For the analysis of overlaps, we introduce the network *MULTIPLEX*[3], which is a binary variable that turns one if a link is at the same time an agricultural and a nutrition link. To further investigate the overlap, we correlate the underlying adjacency matrices for both networks, *NUTRITION* and *AGRICULTURE*, for each CBO[4]. The adjacency matrix is a square and binary matrix. The cells record whether a link between two actors exists (Izquierdo & Hanneman 2006). The correlation coefficient equals 1 if both networks match completely, and -1 if they are inverse to each other (Grund 2015).

3.2. Dyadic level analysis: Link formation

On dyadic level, we study the link formation of individuals within CBOs. The dyadic analysis gives insights on the characteristics of individuals who are likely to exchange information on *NUTRITION* and *AGRICULTURE.* In a dyadic model, the regressors need to enter the regression in a symmetric fashion. At the same time, standard errors need to be corrected for cross-observation correlation involving similar individuals (Fafchamps & Gubert 2007). Accounting for these two issues, we apply the grouped dyadic regression model as proposed by Fafchamps & Gubert (2007). The approach has more recently been applied by De Weerdt & Fafchamps (2011), Van den Broeck & Dercon (2011), and Barr et al. (2015). The model preserves symmetry and is specified as:

$$l_{ij}(m) = \alpha_1\, s_{ij} + \alpha_2\,(x_i - x_j) + \alpha_3\,(x_i + x_j) + \varepsilon_{ijg.} \qquad (2)$$

[3] The overlap can also be interpreted as a measure of a link's "multiplexity", referring to the number of topics a link covers.
[4] This is done using the nwcommands in STATA developed by Grund (2015).

where l_{ij} is a binary variable that equals one if a link between group member *i* and *j* exists for network *m*. The vector s_{ij} captures proximity variables such as both members are female, kinship (social proximity), or members sharing the same plot borders (geographical proximity). The α_1 is a vector of parameters measuring the effects of the proximity variables on link formation for information exchange. The vectors x_i and x_j refer to characteristics of *i* and *j*, respectively, such as age, education, and land size. Parameter vector α_2 measures the effects of differences in characteristics, whereas parameter vector α_3 measures the effects of the sum of characteristics on the dependent variable. ε_{ijg} is the dyadic error term. Due to the complexity of the models, we model the binary dependent variables using linear probability models (LPM)[5]. Summary statistics of variables used in the dyadic regression are presented in Table A1 in the Appendix.

3.3. Individual level analysis: Characteristics of central persons and isolates

Network measures

On individual level, we are interested in characterizing central persons and potentially isolated individuals within information networks for agriculture and nutrition. Degrees are common-used measures of network centrality (Wasserman & Faust 1994). They can be divided into prominent (high in-degrees) and influential persons (high out-degrees) (Hanneman & Riddle 2005). Based on the data collected about the *AGRICULTURE* and *NUTRITION* networks explained above, we construct frequencies of being named (in-degrees) or naming others (out-degree). Following Jaimovich (2015), we define in-degrees of group member *i* in CBO *g* for the information network *m* as

$$d_i^{in}(m)=\sum_j l_{ji}\,(m), \qquad (3)$$

[5] For comparison, logit estimates are shown in Table A3 in the Appendix.

as our proxy for the prominence of a person. The underlying assumption is that high-in-degree persons will be good entry points for development projects since they are the ones others claim to communicate with most often about the topics of interest. It was recently applied by Kim et al. (2015), who use the in-degree as a measurement of centrality in public health interventions. Calculating in-degrees is rarely done, since it requires directed network data. Most commonly out-degrees are used as a measure for centrality, since they can also be derived from self-reported data.

Out-degrees represent the number of persons within CBO g that group member i indicates to exchange information with about *m*. Out-degrees can therefore be used as a proxy for the influence of a person (Hanneman & Riddle 2005) and are defined as

$$d_i^{out}(m) = \sum_j l_{ij}(m). \qquad (4)$$

Finally, isolates can be defined based on in-degrees, out-degrees or a combination of both. We apply the most comprehensive definition where $ISO_i(m) = 1$ if $d_i^{in}(m)=0$ and $d_i^{out}(m)=0$, and $ISO_i(m) = 0$ otherwise. Thus, a person is referred to as isolate, if he or she is never named by others and at the same time claims not to share information with any group member on topic *m*.

Estimation strategy

We expect that the centrality of a group member i in network m is influenced by vectors of individual (*I*) and household (*H*) characteristics. The econometric model is specified as

$$d_i(m) = \beta_0 + \beta_1 I + \beta_2 H + v + \varepsilon, \qquad (5)$$

where d measures the in-degree $d_i^{in}(m)$ or out-degree $d_i^{out}(m)$ for network m of individual i, embedded in household h and CBO g. I is a vector of individual characteristics such as gender, age as a proxy for experience, education, as well as holding a leadership position and the number of external links, among others. H represents a vector of household related control variables such as land size and economic dependency ratio. To control for unobserved heterogeneity within CBOs, we introduce group level fixed effects v. Further, clustered standard errors are introduced to control for heteroscedasticity. The error term is represented by ε. Given that the regressands are count variables, we estimate equation (5) using fixed-effects Poisson regressions (Wooldridge 2002).

Finally, we model isolation as a function of individual (I) and household (H) related variables as well as group level fixed effects (v):

$$ISO_i(m) = \partial_0 + \partial_1 I + \partial_2 H + v + \mu \qquad (7)$$

where $ISO_i(m) = 1\ if\ \ d_i^{in}(m)$=0 and $d_i^{out}(m)$=0, and $ISO_i(m) = 0$ otherwise, and μ is an i.i.d. error term following a normal distribution. Given the binary nature of the dependent variable, equation (7) is estimated using a linear probability model with group-level fixed effects. In an alternative specification, we replace the group-level fixed effects with a vector G of CBO-level variables in order to understand which underlying factors are captured by the fixed effects.[6] G consists of CBO related variables such as whether the group's main activity is agriculture or whether the group received external support. Table A2 gives an overview of the individual and household level variables included in the Poisson and linear probability models. Information on group-level variables is provided in Table 1.

Based on previous literature, we derive several hypotheses regarding the expected effects of included covariates. First, persons holding leadership positions are usually well connected, and thus are expected to have higher in-degrees and out-degrees as well as a lower probability of being

[6] Results with group-related variables for in-degrees and out-degrees are shown in Table A4 in the Appendix.

isolated with respect to a certain topic. Nonetheless, it should be kept in mind that in cases where chairpersons are externally appointed (e.g. by donor organizations) leadership may not necessarily represent the most central person within a network (BenYishay & Mobarak 2013). Second, we expect differentiated gender effects depending on the information topic. In agricultural information networks, we expect men to be more central. In the African setting, the role of women in agriculture remains underestimated and men are commonly perceived as the main decision-makers (World Bank & IFPRI 2010). Also, agricultural extension services are still predominantly attended by male household heads (e.g. Ragasa et al. 2013). We therefore expect that men are less likely to be excluded from agricultural information networks. In contrast, in nutrition information networks, we expect women to be more central. In the African context, women are responsible for food preparation and for the nutritional status of their family and in particular children. Previous research has found that women spend on average a larger share of their expenditures on food related items (Hoddinott & Haddad 1995), and that in particular older female family members play an important role in influencing social norms and beliefs within the family, and thus nutrition behavior (Aubel 2012). Based on these findings, nutrition-specific programs mostly target women. We therefore expect that women are less likely to be excluded from nutrition information networks.

4. Results

4.1. Results on CBO level: Network structure and overlaps

On CBO level, we are interested in exploring the structure of agricultural and nutrition information networks. Specifically, we want to explore how dense these networks are and to what extent they overlap. Agriculture is an important function of all CBOs in our sample, and they have received agricultural extension at some point in the past. Overall, 52% of the CBOs in our sample indicated that agriculture is their main focus (Table 1). Other functions of the selected CBOs include savings and credit activities as well as accessing funds or extension services from the government. Almost one-third of the sampled groups (Table 1) were initially formed for the KAPAP program that aimed at increasing agricultural productivity through the delivery of trainings to CBOs.

Table 1: Group related summary statistics

	Mean	s.d.	Minimum	Maximum
Group characteristics				
External Support (1=yes)	0.47	0.50	0	1
Group's age in years	7.07	4.6	2	23
Share of men within CBO	0.39	0.25	0	1
Female only (1=yes)	0.08	0.28	0	1
Female dominated (>50%) (1=yes)	0.38	0.49	0	1
Balanced (40-59%) (1=yes)	0.33	0.05	0	1
Male dominated (>50%) (1=yes)	0.21	0.21	0	1
Mean age of members	46.50	5.83	32.53	58.90
Mean years of education	8.69	1.34	5.25	11.44
Share of kinship relations	0.54	0.19	0.12	1
Main function agriculture (1=yes)	0.52	0.50	0	1
KAPAP group (1=yes)	0.27	0.44	0	1
Actual group size	21	3.43	15	30
Potential links (n_g-1)	16.34	2.35	10	19
Network measures on CBO level				
TALK density: $D_g(TALK)$	0.90	0.09	0.60	0.99
Density: $D_g(AGRICULTURE)$	0.50	0.13	0.28	0.75
Density: $D_g(NUTRITION)$	0.09	0.05	0.01	0.24
Isolates: $ISO_{ig}(NUTRITION)$	0.16	0.37	0	1
N_G=48				

Note: s.d.=Standard Deviation.

The network densities presented in Table 1 and Figures 1 and 2 provide us with information about the structure of networks. Densities can be interpreted as the share of links formed of all links that could potentially be formed. The high *TALK* density of 90% on average indicates that most of the interviewed group members talk to each other (Table 1). This reflects the fact that our sample consists of relatively small CBOs, whose members know each other and frequently interact. In line with the CBOs' focus on agriculture, we find that agricultural information flows very well within groups: the agricultural information network has an average density of 50% (Table 1), and everyone is connected (Figure 1). In contrast, nutrition information networks are sparse: average density indicates that only 9% of all potential links are formed to exchange nutrition information (Table 1), and in total 16% of group members are completely isolated from nutrition information exchange within their groups (Figure 2).

Furthermore, the analysis of overlaps between the two networks shows that the nutrition information that is exchanged within the CBOs – even though limited in quantity – mostly flows through agricultural links. Of all links created in the CBOs, the majority are agricultural links (82%), 15% are multiplex links covering both agricultural and nutrition information exchange, and only 3% are pure nutrition links (Figure 3). The underlying adjacency matrices of *AGRICULTURE* and *NUTRITION* for each CBO are positively correlated (average correlation coefficient: 0.18; range from -0.13 to 0.46), indicating some overlap between the networks. Yet, the relatively small correlation coefficients are likely driven by the fact that network densities are in general much higher for *AGRICULTURE* than for *NUTRITION*. Overall, of the existing nutrition connections 81% are at the same time agricultural links, and thus, only 19% of the nutrition links are exclusively *NUTRITION*. Thus, our results suggest that nutrition information is mostly transmitted through existing channels of agricultural information exchange.

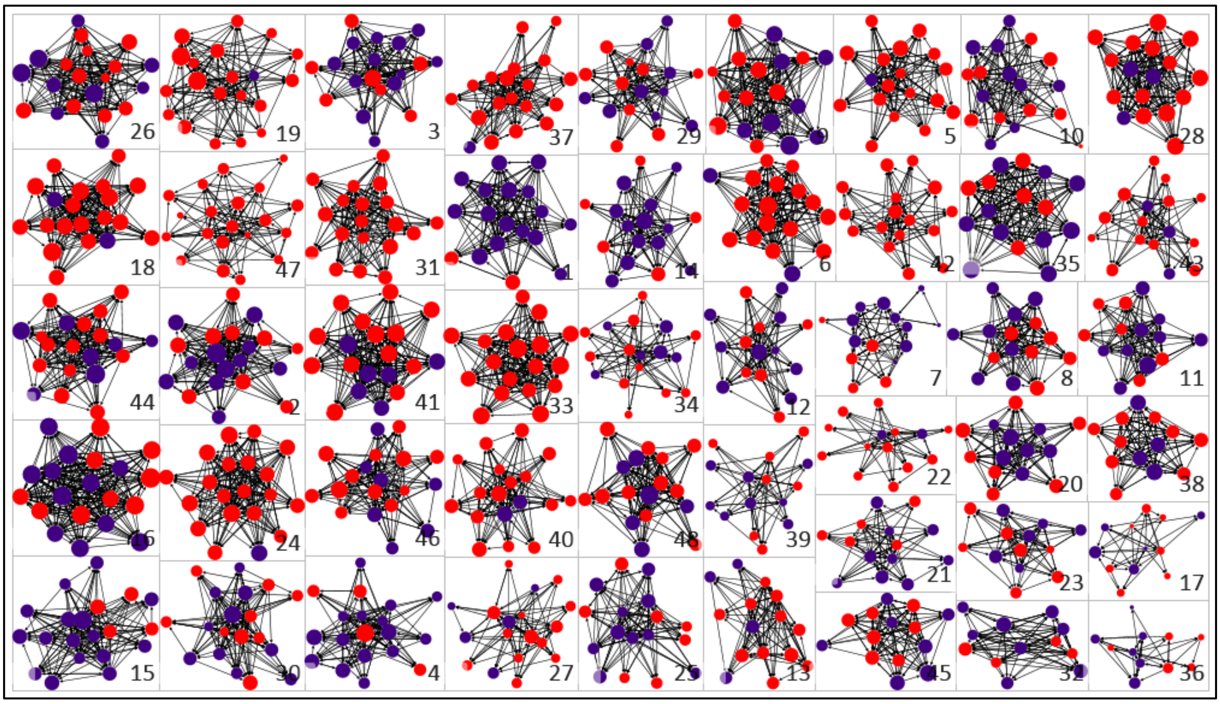

Figure 1. *AGRICULTURE: Color of nodes: Gender (red=female, blue=male); Size of nodes: In-degrees; Numbers indicate the CBOs' IDs.*

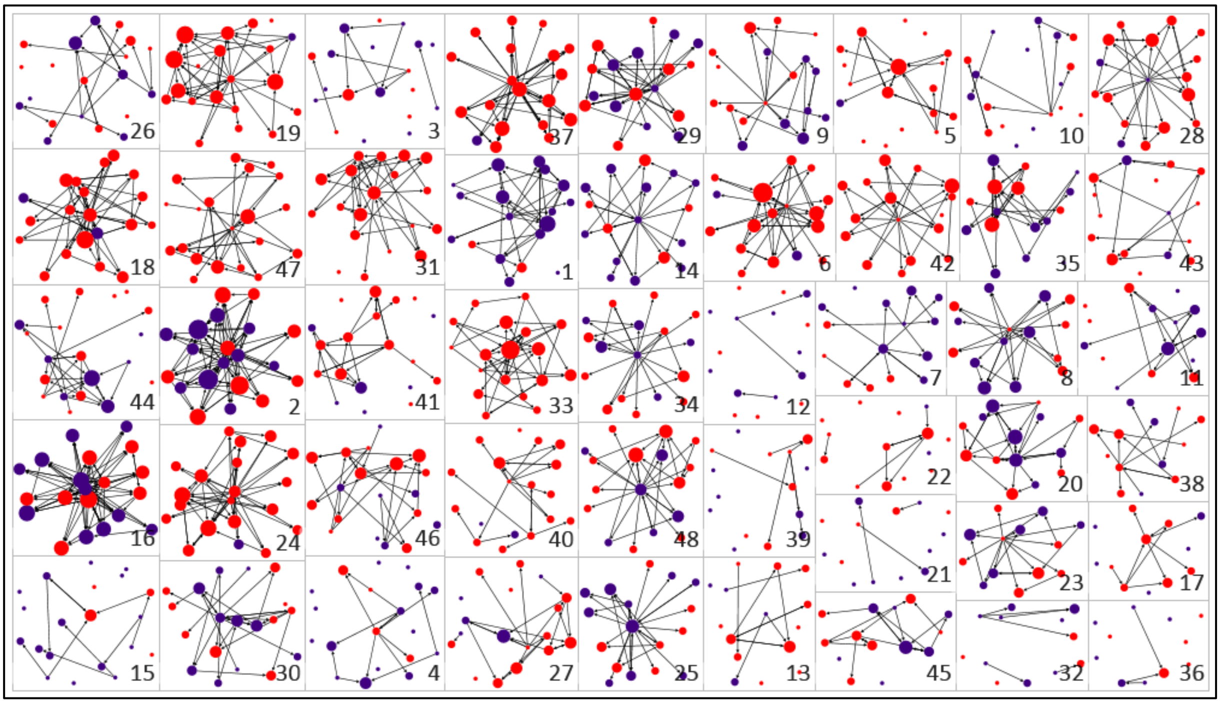

Figure 2. *NUTRITION: Color of nodes: Gender (red=female, blue=male); Size of nodes: In-degrees; Numbers indicate the CBOs' IDs.*

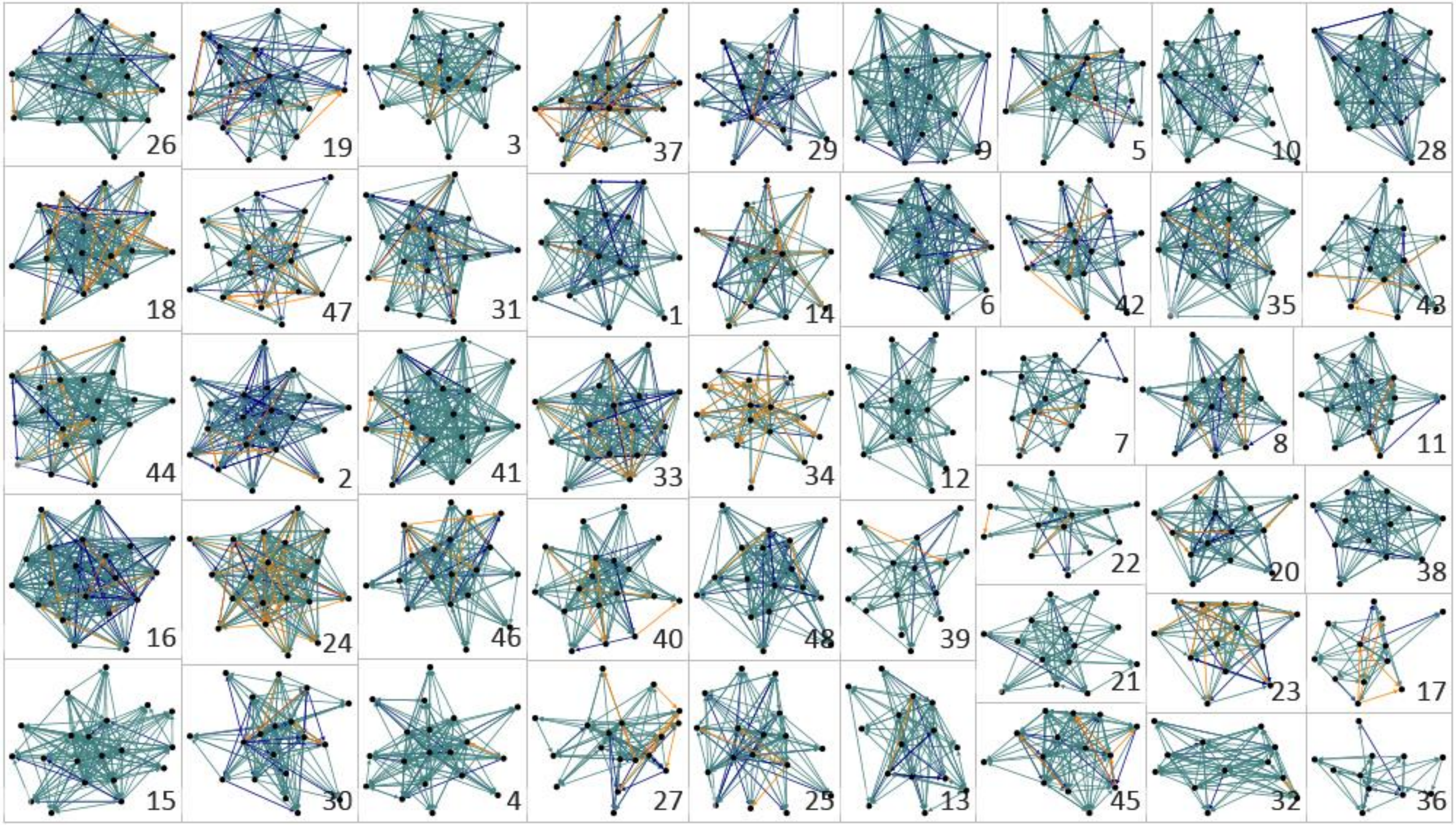

Figure 3.*Multiplexity of AGRICULTURE and NUTRITION: Color of links: orange= Nutrition only (233 links), turquoise= Agriculture only (5624links), dark blue=multiplex links (both nutrition and agriculture (1014 links).*

4.2. Results on dyadic level: Link formation

On CBO level, we observed that 50% of all potential links are formed to exchange agricultural information and 9% to exchange nutrition information. Using dyadic regressions, we analyze who is likely to form such links with each other (Table 2). First, we find that centrality in terms of spatial and social position matters for link formation in both communication networks: i is more likely to form a link with j, if their agricultural plots are next to each other or if j is a leader. Other proximity variables are relevant in particular for the exchange of nutrition information: nutrition links are more likely to be formed between kin and group members of the same gender, and in particular between women. These results confirm that the transfer of nutrition information between men and women cannot be taken for granted, which is an important insight for the design of nutrition-sensitive extension programs.

Our results further confirm that trust and social capital in general are conducive to link formation. Group members who connect with a larger external network and who trust others are more likely to form a link within their farmer group to exchange agricultural and nutrition information. Moreover, nutrition links are more likely to be formed between more educated persons. These findings may cause concern about the inclusiveness of information networks within farmer groups, which may exclude the least connected and least educated members from information exchange. However, our results show that differences in external links and, in the case of nutrition, differences in education have significantly positive effects on link formation, indicating that information does also reach group members with lower education and less external connections.

In sum, we have seen that agricultural information flows widely and relatively unrestricted in the studied farmer groups, even though spatial proximity and social position do play a role for link formation. Nutrition information, which is exchanged to a much smaller extent and mostly flows through existing agricultural information links, relies on somewhat more exclusive channels. In particular, nutrition links are formed between kin, same gender (especially women), and more educated persons. When relying on the existing agricultural extension system to design nutrition-sensitive programs, these differences in network structure and characteristics need to be taken into account.

Table 2: Dyadic regression results: Forming links for *AGRICULTURE* and *NUTRITION*

	(1) *AGRICULTURE*	(2) *NUTRITION*
Proximity		
Both female (1=yes)	0.0196	0.0458***
	(0.0233)	(0.0114)
Both male (1=yes)	0.0405*	0.0209*
	(0.0212)	(0.0116)
Kinship (1=yes)	-0.0352	0.0188*
	(0.0240)	(0.0108)
J is group leader (1=yes)	0.0686***	0.0354***
	(0.0134)	(0.00791)
Plots sharing same border (1=yes)	0.128***	0.109***
	(0.0225)	(0.0156)
Sum of:		
Land size	0.00291	0.00192
	(0.00733)	(0.00294)
Years of education	0.00111	0.00256**
	(0.00252)	(0.00125)
Years of age	0.000866	-0.000202
	(0.000714)	(0.000307)
Trust towards others	0.0530***	0.0174*
	(0.0167)	(0.00912)
External links	0.0184***	0.00720***
	(0.00285)	(0.00151)
Difference in:		
Land size	-0.00401	0.00305
	(0.00672)	(0.00287)
Years of education	0.00163	0.00257**
	(0.00228)	(0.00108)
Years of age	0.000834	0.000266
	(0.000713)	(0.000331)
Trust towards others	0.0404***	0.0110
	(0.0152)	(0.00853)
External links	0.0129***	0.00507***
	(0.00262)	(0.00128)
Constant	0.166*	-0.0608
	(0.0929)	(0.0436)
l_{ij} *(m)=1*	6656	1247
N_D	13,318	13,318

Notes: Coefficients and standard errors from grouped dyadic regression (LPM); data grouped on CBO level; standard errors (in brackets) clustered by dyads. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.3. Results on individual level

Characteristics of central persons

At the individual level we aim to identify particularly central persons that influence the diffusion of information, and thus represent promising entry points for targeting. We therefore analyze the characteristics of prominent persons with high in-degrees (those who are named often), as well as the characteristics of influential persons with high out-degrees (those who name many others). Figure 4 shows the distributions of in-degrees (*prominence*) and out-degrees (*influence*) for both communication networks.

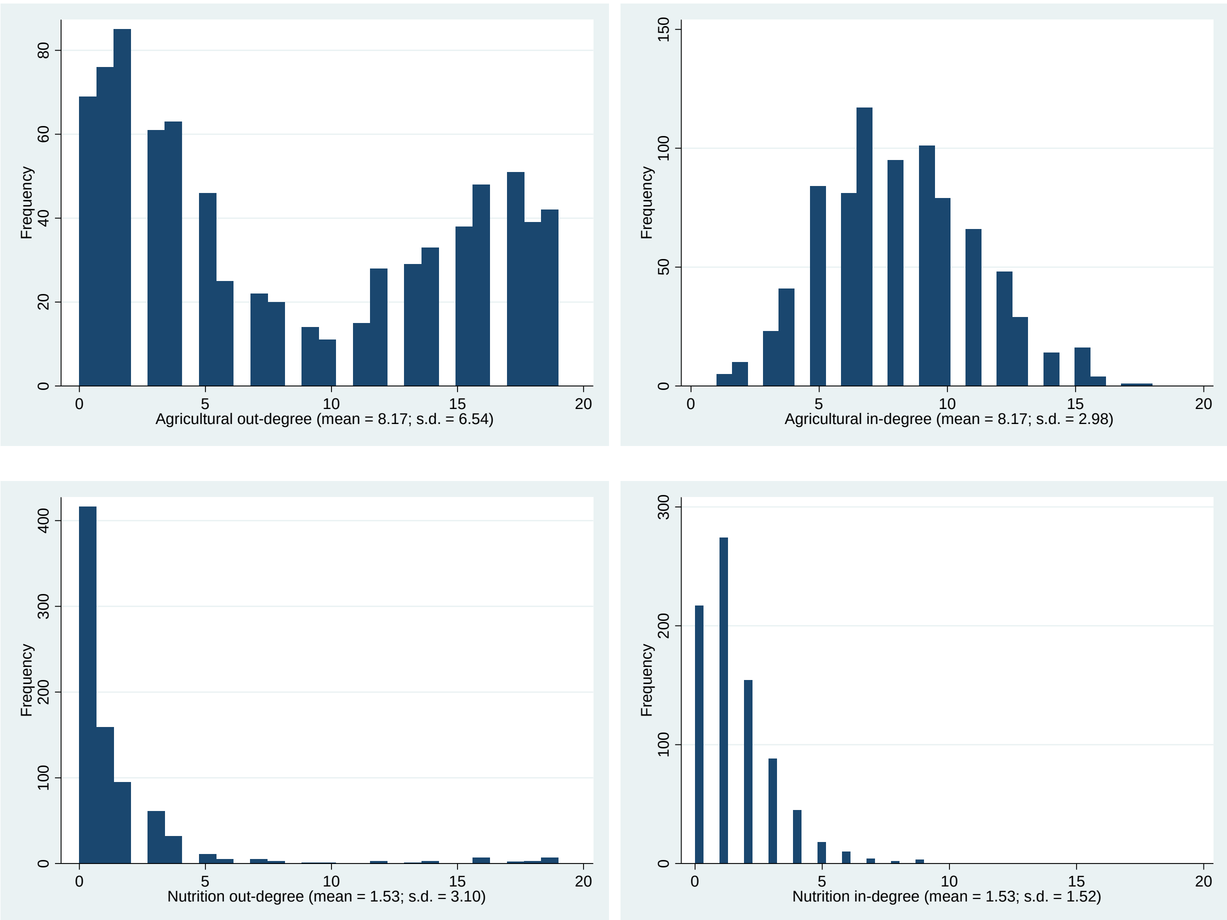

Figure 4: *Distributions of out-degrees and in-degrees for AGRICULTURE and NUTRITION.*

Poisson regression results show that across centrality measures and in both networks, group leadership is positively associated with being identified as a central person (Table 3). In the agricultural network, older members tend to be more central in terms of both prominence and influence, whereas members in spatially central locations tend to be more prominent, *i.e.*, more often named by others. Accordingly, central persons are usually the ones in important social and spatial positions, which is in line with our earlier findings at the dyadic level. Regarding gender, we find that men are more often named in the agricultural network. In the nutrition network, the gender dummy has a negative sign indicating that women tend to be named more often, but it is not statistically significant. Finally, in both networks the number of external links is positively associated with the out-degree suggesting that the overall network size is an important determinant of being influential within the CBO.

Table 3: Fixed-effects Poisson regression analysis of centrality measures for *AGRICULTURE*, *NUTRITION*

	(1)	(2)	(3)	(4)
	d_i^{in}*(prominence)*		d_i^{out}*(influence)*	
	AGRICULTURE	*NUTRITION*	*AGRICULTURE*	*NUTRITION*
Individual level variables				
Gender (1=male)	0.0636***	-0.111	0.0217	0.0809
	(0.0203)	(0.0751)	(0.0684)	(0.113)
Years of education	0.000928	0.00736	0.00776	0.0470*
	(0.00261)	(0.0120)	(0.00821)	(0.0241)
Age in years	0.00233***	0.00216	0.00559**	0.00441
	(0.000828)	(0.00272)	(0.00232)	(0.00770)
External links named	0.00184	0.0122	0.0540***	0.124***
	(0.00287)	(0.0110)	(0.00999)	(0.0210)
Spatial centrality proxy	0.0585***	0.0379	-0.0352	0.284
	(0.0207)	(0.0591)	(0.0886)	(0.178)
Group leadership position (1=yes)	0.113***	0.273***	0.139***	0.370**
	(0.0180)	(0.0652)	(0.0450)	(0.146)
Household level variables				
Land size (acres)	0.00597	-0.00229	-0.0122	0.0832
	(0.00788)	(0.0283)	(0.0190)	(0.0533)
Economic dependency ratio	0.00872	0.0192	0.0183	0.0542
	(0.00561)	(0.0219)	(0.0259)	(0.0482)
Small business activities (1=yes)	0.00520	0.0342	-0.0635	0.0191
	(0.0187)	(0.0653)	(0.0558)	(0.151)

N_H=815

Notes: Clustered standard errors at CBO level in parentheses. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Characteristics of isolated persons for NUTRITION

Finally, we focus on isolated persons that have no links in the nutrition network and are therefore at risk of being excluded from the diffusion of nutrition information within the CBO. As identified in the CBO-level analysis, these represent 16% of respondents. Results in Table 4 show that group leaders and members with a larger external network are less likely to be isolates. Also, larger farmers are less likely to be excluded from nutrition information within the CBO. Several group characteristics also contribute to explaining the prevalence of isolated persons within the nutrition communication networks of the CBOs. Isolates are less likely found in older groups (who most likely have built stronger social capital over time), smaller groups, female-dominated groups and groups with a main focus on agriculture.

Table 4: Regression analysis of isolates for *NUTRITION*

	(1) $ISO_i(NUTRITION)$ $d_i^{in}(m)$=0 and $d_i^{out}(m)$=0	(2) $ISO_i(NUTRITION)$ $d_i^{in}(m)$=0 and $d_i^{out}(m)$=0
	Fixed-effects LPM	LPM with group controls
Individual level variables		
Gender (1=male)	0.0184	0.0104
	(0.0329)	(0.0324)
Years of education	-0.000142	0.00459
	(0.00442)	(0.00410)
Age in years	-0.00105	0.000250
	(0.000962)	(0.00115)
External links named	-0.0124**	-0.0147***
	(0.00482)	(0.00473)
Spatial centrality proxy	-0.00400	-0.0322
	(0.0290)	(0.0271)
Group leadership position (1=yes)	-0.0433*	-0.0675**
	(0.0232)	(0.0262)
Household level variables		
Land size (acres)	-0.0229**	-0.0186**
	(0.00931)	(0.00920)
Economic dependency ratio	-0.00428	-0.00474
	(0.00852)	(0.0102)
Small business activities (1=yes)	-0.0261	-0.0327
	(0.0304)	(0.0264)
Group level variables		
External support (1=yes)		0.00748
		(0.0258)
Group's age in years		-0.0119***
		(0.00245)
Main function agriculture (1=yes)		-0.123***
		(0.0263)
KAPAP group (1=yes)		-0.00414
		(0.0343)
Actual group size		0.0162***
		(0.00455)
Share of male within CBO		0.132*
		(0.0718)
Potential links (n_g-1)		-0.0304***
		(0.00738)
Constant	0.324***	0.493***
	(0.0824)	(0.136)
N_H=815		

Notes: Clustered standard errors at CBO level in parentheses. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

5. Conclusions

In the recent development discourse, much emphasis has been placed on making agriculture more nutrition-sensitive as an important component in combating hunger and malnutrition among rural households in developing countries. In order to achieve this at scale, nutrition information could be diffused to farm households organized in CBOs through the existing agricultural extension systems. However, to date little is known about the structure and characteristics of agricultural and nutrition information networks within CBOs and whether nutritional information is exchanged between CBO members at all. Based on unique network data from Kenya we analyze the structures and overlaps of agricultural and nutrition information networks within CBOs as well as the factors influencing link formation. In addition, we identify the characteristics of central persons that drive information exchange in the two networks, as well as potentially isolated persons who are excluded from information exchange within CBOs.

Our results show that compared to agricultural information networks, nutrition information networks are sparse. Nutrition-related information is exchanged within CBOs, but only to a very limited extent. This implies that there is ample room for nutrition training to sensitize group members, nudge information exchange on nutrition-related topics, and thereby make agriculture more nutrition-sensitive. It is noteworthy that nutrition information is exchanged mostly through the existing agricultural information links. Hence, channeling nutrition information through agricultural extension systems may indeed be a viable approach. Our findings further suggest that group leaders and persons living in central locations are important drivers in the diffusion of information in both networks and may thus serve as suitable entry points for nutrition-sensitive extension programs.

While these results are promising, heterogeneity in network structure and characteristics must not be ignored when relying on the existing agricultural extension system to design nutrition-sensitive programs. While agricultural information flows widely and relatively unrestricted in CBOs, nutrition information relies on somewhat more exclusive channels. In particular, nutrition links are formed between kin, same gender (especially women), and more educated persons. Based on our results it cannot be taken for granted that nutrition information is exchanged frequently between women and men. Therefore, targeting women and men alike with nutrition training is critical for making agriculture more nutrition-sensitive. Providing a combination of agricultural and nutrition trainings to mixed-gender groups through the extension system could be a suitable way to achieve this.

Furthermore, nutrition information networks are characterized by isolates, implying that some group members are completely excluded from nutrition information exchange within their CBO. This is particularly worrisome, as it affects mostly smaller farmers and individuals who are also less well connected outside their group. In line with Caria & Fafchamps (2015), we therefore suggest encouraging the formation of links with less popular people in order to enhance network efficiency. Nutrition information networks seem to be more inclusive in older and smaller groups (who are likely to have stronger and more cohesive social capital), as well as in groups with a larger share of women and a main focus on agriculture. In such groups, nutrition information channeled through agricultural extension may diffuse naturally without requiring extra efforts. On the other hand, in larger, recently founded, and mixed-gender groups particular efforts may be needed to ensure the inclusiveness of nutrition information and thus maximize the outreach of nutrition-sensitive extension programs.

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Appendix

Table A1: Summary statistics of dependent variables and covariates entering the dyadic regression

	Mean	s.d.	Minimum	Maximum
Dependent Variables				
$l_{ij}(AGRICULTURE)$	0.50	0.50	0	1
$l_{ij}(NUTRITION)$	0.09	0.29	0	1
Explanatory variables				
Proximity				
Both female (1=yes)	0.44	0.50	0	1
Both male (1=yes)	0.19	0.40	0	1
Kinship (1=yes)	0.35	0.48	0	1
J is group leader (1=yes)	0.28	0.45	0	1
Plots sharing same border (1=yes)	0.09	0.28	0	1
Difference in:				
Land size	0.00	1.60	-9.43	9.43
Years of education	0.00	5.00	-18	18
Years of age	0.00	16.11	-57	57
Trust towards others	0.00	0.62	-1	1
External links	0.00	3.81	-10	10
Sum of:				
Land size	2.80	1.78	0	15.65
Years of education	17.34	5.42	0	33
Years of age	93.10	19.32	40	154
Trust towards others	0.52	0.62	0	2
External links	8.93	3.94	0	20
$N_{D=}$13318				

Note: s.d.=Standard Deviation.

Table A2: Summary statistics of individual and household level covariates used in Poisson and Probit regressions

	Description	Mean	s.d.
Dependent variables			
d_i^{in}*(AGRICULTURE)*	Number of times the respondent has been cited as agricultural information exchange agent	8.17	2.98
d_i^{out}*(AGRICULTURE)*	Number of persons respondent has cited as agricultural information exchange agent	8.17	6.54
d_i^{in}*(NUTRITION)*	Number of times the respondent has been cited as nutrition information exchange agent	1.53	1.51
d_i^{out}*(NUTRITION)*	Number of persons respondent has cited as nutrition information exchange agent	1.53	3.10
Explanatory variables			
Individual level variables			
Gender	1=male, 0=female	0.38	0.49
Education	In years of completed education	8.68	3.67
Age	In years	46.50	12.51
External links named	Number of persons the respondents talks about nutrition/agriculture outside of his CBO	4.46	2.74
Spatial centrality proxy	=1 if respondent shares the same plot border with at least 2 of his/her fellow CBO members, 0=otherwise	0.22	0.41
Group leadership position	=1 if yes, 0=otherwise	0.33	0.47
Household level variables			
Land size	Land owned in acres	1.40	1.19
Economic dependency ratio	Non-working household members divided by working household members	1.73	1.23
Small business activities	=1 if respondent is engaged in small business activities, 0=otherwise	0.34	0.48
CBO level variables			
External support	=1 if CBO received external support during the last 5years, 0=otherwise	0.47	0.50
Group's age	Number of years the CBO exists	7.07	4.6
Main function agriculture	= 1 if yes, 0=otherwise	0.52	0.50
KAPAP group	=1 if group was founded to receive KAPAP support, 0=otherwise	0.27	0.44
Actual group size	Number of CBO members	21.32	3.58
Share of men in CBO	Number of male members divided by group size	0.38	0.25
Potential links (n_g-1)	Number of potential links the respondent can cite based on the number we interviewed	16.34	2.25
N_I= 815; N_G= 48			

Note: s.d.= Standard Deviation.

Table A3: Dyadic logit regression results: Forming links for *AGRICULTURE* and *NUTRITION*

	(1) *AGRICULTURE*	(2) *NUTRITION*
Proximity		
Both female (1=yes)	0.0832	0.567***
	(0.0981)	(0.146)
Both male (1=yes)	0.171*	0.283**
	(0.0892)	(0.136)
Kinship (1=yes)	-0.149	0.220*
	(0.102)	(0.126)
J is group leader (1=yes)	0.289***	0.412***
	(0.0570)	(0.0835)
Plots sharing same border (1=yes)	0.545***	0.990***
	(0.0987)	(0.117)
Sum of:		
Land size	0.0120	0.0230
	(0.0312)	(0.0359)
Years of education	0.00485	0.0337**
	(0.0106)	(0.0163)
Years of age	0.00368	-0.00296
	(0.00302)	(0.00391)
Trust towards others	0.222***	0.200**
	(0.0709)	(0.0997)
External links	0.0768***	0.0854***
	(0.0125)	(0.0174)
Difference in:		
Land size	-0.0174	0.0408
	(0.0286)	(0.0348)
Years of education	0.00697	0.0355**
	(0.00963)	(0.0144)
Years of age	0.00354	0.00294
	(0.00302)	(0.00418)
Trust towards others	0.169***	0.129
	(0.0643)	(0.0968)
External links	0.0540***	0.0592***
	(0.0113)	(0.0145)
Constant	-1.406***	-4.279***
	(0.397)	(0.565)
$l_{ij}(m)=1$	6656	1247
N_D	13,318	13,318

Notes: Coefficients and standard errors from grouped dyadic logit regression; data grouped on CBO level; standard errors (in brackets) clustered by dyads. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A4: Poisson regression analysis of centrality measures for *AGRICULTURE, NUTRITION* (including group-level controls)

	(1)	(2)	(3)	(4)
	AGRICULTURE		*NUTRITION*	
	d_i^{in}	d_i^{out}	d_i^{in}	d_i^{out}
Individual level variables				
Gender (1=male)	0.0684***	0.0281	-0.0978	0.0870
	(0.0218)	(0.0707)	(0.0802)	(0.114)
Years of education	7.49e-05	0.00572	0.00152	0.0380
	(0.00452)	(0.00905)	(0.0119)	(0.0232)
Age in years	0.000899	0.00347	-0.00309	-4.31e-05
	(0.00190)	(0.00253)	(0.00372)	(0.00704)
	0.0117***	0.0602***	0.0204	0.124***
External links named				
	(0.00381)	(0.0101)	(0.0129)	(0.0209)
Spatial centrality proxy	0.0200	-0.0553	0.0795	0.322*
	(0.0261)	(0.0794)	(0.0700)	(0.173)
Group leadership position (1=yes)	0.129***	0.150***	0.348***	0.448***
	(0.0201)	(0.0458)	(0.0661)	(0.146)
Household level variables				
Land size (acres)	0.0155	-0.00238	-0.00429	0.0501
	(0.0122)	(0.0178)	(0.0277)	(0.0542)
Economic dependency ratio	0.0107	0.0170	0.0184	0.0562
	(0.00795)	(0.0259)	(0.0207)	(0.0470)
Small business activities (1=yes)	-0.0414	-0.0994*	0.0789	0.0664
	(0.0265)	(0.0522)	(0.0725)	(0.147)
Group level variables				
External support (1=yes)	0.0141	0.0143	0.230	0.218
	(0.0736)	(0.0685)	(0.157)	(0.149)
Group's age in years	0.00491	0.00693	0.0126	0.00922
	(0.00674)	(0.00608)	(0.0137)	(0.0118)
Main function agriculture (1=yes)	0.150**	0.150**	0.363**	0.333**
	(0.0694)	(0.0633)	(0.145)	(0.134)
KAPAP group (1=yes)	-0.0369	-0.0590	-0.0861	-0.126
	(0.0799)	(0.0733)	(0.211)	(0.206)

Continued

Table A4 *continued*

	(1)	(2)	(3)	(4)
	AGRICULTURE		*NUTRITION*	
	d_i^{in}	d_i^{out}	d_i^{in}	d_i^{out}
Actual group size	-0.0156	-0.0172*	-0.0226	-0.0307
	(0.0102)	(0.00921)	(0.0238)	(0.0247)
Share of men in CBO	0.0449	0.0309	-0.180	-0.561*
	(0.118)	(0.126)	(0.336)	(0.339)
Potential links (n_g-1)	0.0831***	0.0827***	0.157***	0.143***
	(0.0150)	(0.0151)	(0.0430)	(0.0436)
Constant	0.738**	0.434	-2.141***	-2.859***
	(0.303)	(0.307)	(0.743)	(0.881)
N_H=815				

Notes: Clustered standard errors at CBO level in parentheses. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.