Received: 27 August 2018 | Revised: 20 March 2019 | Accepted: 10 July 2019

DOI: 10.1111/agec.12516

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE
WILEY

ORIGINAL ARTICLE

Agriculture–nutrition linkages in farmers' communication networks

Lisa Jäckering | **Theda Gödecke** | **Meike Wollni**

Department of Agricultural Economics and Rural Development, University of Goettingen, Goettingen, Germany

Correspondence
Lisa Jäckering, University of Goettingen, Platz der Goettinger Sieben 5, 37073 Goettingen, Germany.
Email: ljaeckering@gmail.com

Funding information
German Federal Ministry of Food and Agriculture, Grant/Award Number: 2813FSNu01

Abstract

To date, little is known about how information flows within farmer groups 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 farmer groups. 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 farmer groups. Our results show that nutrition information is exchanged within farmer groups, although to a limited extent, and mostly flows through the existing agricultural information links. Thus, diffusing nutrition information through agricultural extension systems may 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 farmer groups. We derive recommendations on taking these differences in network structure and characteristics into account when designing nutrition-sensitive extension programs.

KEYWORDS

Africa, communication networks, dyadic regressions, farmer groups, Kenya, nutrition-sensitive agriculture

JEL CLASSIFICATION

Q16, Q01, D02, D83, D85

1 | INTRODUCTION

Globally, about 800 million people are undernourished and about 2 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 (FAO, 2015; IFPRI, 2011). Thus, agriculture can play a central role in improving nutrition (Fan &

Pandya-Lorch, 2012; Hawkes & Ruel, 2008; Ruel, Alderman, & Maternal and Child Nutrition Study Group, 2013). A growing body of literature tries to understand agriculture–nutrition linkages and in particular the pathways through which agriculture can influence nutrition (Carletto, Ruel, Winters, & Zezza, 2015; Hirvonen & Hoddinott, 2017; Malapit, Kadiyala, Quisumbing, Cunningham, & Tyagi, 2015; Pandey, Dev, & Jayachandran, 2016; Ruel, Quisumbing, & Balagamwala, 2018; Sibhatu, Krishna, & Qaim, 2015; Zeng et al., 2017). Linking nutrition and agriculture is especially important because obesity, besides undernutrition and micronutrient deficiencies, is becoming prevalent in rural African communities, affecting both men and women (Gómez et al., 2013; Popkin, Adair, & Ng, 2012). 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. Channeling nutrition information to farmers through the infrastructure of existing extension systems could be a cost-effective solution, because synergy effects between nutrition and agricultural programs could be used.

In the extension systems of developing countries, farmer groups and individuals within farmer groups 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 farmer groups or key individuals within farmer groups it to reduce transaction costs. This is based on the assumption that new information will flow among farmer group members, or key individuals will pass on the new information to other group members. Yet, relatively little is known about how exactly agricultural and nutrition information flows within farmer groups and among farmer group 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, Eozenou, & Moursi, 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 and the quality of the extension services is often not tailored towards women (Buehren, Goldstein, Molina, & Vaillant, 2019; Ragasa, Berhane, Tadesse, & Taffesse, 2013). Extension groups are often mixed-gender groups and thus could be a useful platform to sensitize both, men and women, on nutrition-related topics. This is particularly crucial because recent studies have found that training men and women of the same household jointly on nutrition can increase food security more effectively compared to only targeting women, because women often have little power to implement the new knowledge (Ragasa, Aberman, & Mingote, 2019). Hence, in order to design effective interventions for nutrition-sensitive agriculture, it is 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; Matuschke & Qaim, 2009; Murendo, Wollni, De Brauw, & Mugabi, 2017). 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 farmer groups 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 2 presents the study area and data collection. In Section 3 we introduce the network measures and estimation strategies employed on farmer group, dyadic, and individual levels. Section 4 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 and SID, 2013). The farming system is characterized as intensive, subsistence, and almost all of the land is under cultivation (Mbuvi, Kenyanya, & Muthengia, 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, one-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 as suitable settings for nutrition-sensitive interventions.

This article builds on data collected on farmer group, dyadic, and individual levels in late 2015. Our study builds on farmer groups that were formed with the aim to channel extension services through them. At some point in the past, all our groups received agricultural extension. Farmer groups are seen as cost-efficient entry points for extension and are hence commonly used in Kenya (Cuellar, Hedlund, Mbai, & Mwangi, 2006). In more recent years, the government with support of the World Bank launched the "Kenya Agricultural Productivity Program" (KAPAP) that also builds on farmer groups. Farmer groups 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 and IFPRI, 2010). In the context of Kenya, the latter play an important role. In the early millennium years, more than 7,000 farmer groups were founded in the context of the "National Livestock and Extension Program" (NALEP), which was rolled out in Kisii County among others. Further, besides being extension groups, some farmer groups may engage in other activities such as joint saving activities or charity (for an overview, see Table A1 in the Online Appendix). Yet, all groups have in common that they are active agricultural groups consisting of farmers, with an interest in receiving new information through the extension system. So far, the sampled groups did not receive any form of nutrition training in the past. However, it is well possible that individual farmers received nutrition information from other sources than their farmer groups.

Farmer groups and households were randomly selected in a two-stage procedure. To construct the sampling frame for the selection of farmer groups, a nongovernmental organization active in the area helped us to compile the list of all current groups in Kisii and Nyamira. From this list of in total 107 active farmer groups, almost half of the existing groups (48 farmer groups (N_G) were randomly sampled with a probability proportionate to the total number of farmer groups in each county. Accordingly, 32 farmer groups 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 farmer groups shortly before the interviews with the help of group leaders. In a few cases, household head and spouse were both member of the farmer group. In these cases, only the most active group member—household head or spouse—remained on the list, while less active household members were removed from the lists resulting in an average group size of 21 members (see Table 1). Based on the adjusted group member lists, about 17 households were randomly sampled and interviewed in each of the selected farmer groups.

On farmer group level, we collected data with the help of a semi-structured group-level questionnaire. It captured information about the farmer groups' purpose and history among others. The questions were answered by one of the farmer group'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 farmer group-level and the household-level questionnaires were carefully pretested in the field and adjusted.

The network module was answered by the farmer group member—which was sometimes the household head and sometimes the spouse—and the questions were asked in a census fashion: we asked the respondents to indicate for all members of their farmer group—irrespective of group size—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 the sampled 824 respondents answered the network module. Because we sampled a high number of group members (on average 17 out of 21), we were able to collect full network information from four 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 are nearly equivalent to a census providing the most accurate information for understanding the structure of networks (Hanneman & Riddle, 2005). We aimed at collecting census data rather than sampling a few farmers

TABLE 1 Group-related summary statistics

	Mean	*SD*	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 farmer group	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 (40–49%; 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
Primary 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 farmer group 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. The variable external support indicates whether a group received external support during the last 5 years. Group's age refers to the number of years the farmer group exists. KAPAP group refers to a group that was created to benefit from the KAPAP development intervention.
Number of potential links refers to the links the respondent can cite based on the number of group members we interviewed. The first network measure "density" is calculated by dividing the existing links through the number of potential links. The *TALK* network refers to links based on general information exchange, *AGRICULTURE* refers to agricultural information exchange, and *NUTRITION* refers to nutrition information exchange. Isolates refers to persons that are not part of the nutrition network because they do not name anyone as a nutrition link and were not named by anyone.

from a larger number of groups, because we are interested in getting a detailed picture on how information is exchanged within groups, how nutrition and agricultural information networks overlap, and the identification of central persons.[1]

Although we asked each respondent about their links to all members of their group, we dropped the links to non-interviewed members from the analysis, so that we include only those links in the regressions for which we have information from both i and j. This allows us to treat our data as directional, given that a stated link between member i and 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 exclusively on self-reported data and hence undirected network data,[2] directional data allow 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 farmer groups (N_G). Second, our analysis on the dyadic level will be based on 13,318 dyads (N_D). Third, analyses will be performed on the level of the farmer group member. This individual level dataset consists of 815 observations (N_I).

[1] Even though we have randomly chosen our respondents and we interviewed a large share of group members on the average, we are aware that potentially valuable network information might be missing and we therefore cannot be sure that our sampled network is representative for the whole network of a farmer group (Chandrasekhar and Lewis, 2011).

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

3 | NETWORK MEASURES AND ESTIMATION STRATEGY

3.1 | Farmer group-level analysis: Network structure and overlaps

On group level, we analyze to what extent agricultural and nutrition information is exchanged in farmer groups. 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" can be used as an indicator of the groups' connectedness (Hanneman & Riddle, 2005). Based on Wasserman and Faust (1994), we calculated densities as

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

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

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, Scott, & Wasserman, 2005). For the analysis of overlaps, we introduce the network *MULTIPLEX*,[3] which is a binary variable that turns 1 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 farmer group.[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 farmer groups. 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 (Fafchamps & Gubert, 2007). Dyadic regressions have more recently been applied by De Weerdt and Fafchamps (2011), Van den Broeck and Dercon (2011), and Barr, Dekker, and Fafchamps (2015). The model preserves symmetry and is specified as

$$l_{ij}\ (m) = \boldsymbol{\alpha}_1\ \mathbf{s}_{ij} + \boldsymbol{\alpha}_2\left(\mathbf{x}_i - \mathbf{x}_j\right) + \boldsymbol{\alpha}_3\left(\mathbf{x}_i + \mathbf{x}_j\right) + \upsilon + \varepsilon_{ijg}, \tag{2}$$

where l_{ij} is a binary variable that equals 1 if a link between group member i and j exists for network m. The vector $\mathbf{s}_{ij}$ captures proximity variables such as both members are female, kinship (social proximity), or members sharing the same plot borders (geographical proximity). The $\boldsymbol{\alpha}_1$ is a vector of parameters measuring the effects of the proximity variables on link formation for information exchange. The vectors $\mathbf{x}_i$ and $\mathbf{x}_j$ refer to characteristics of i and j, respectively, such as age, education, and land size. ε_{ijg} is the dyadic error term. Parameter vector $\boldsymbol{\alpha}_2$ measures the effects of differences in characteristics, whereas parameter vector $\boldsymbol{\alpha}_3$ measures the effects of the sum of characteristics on the dependent variable. A positive coefficient of a sum regressor signals positive assortative matching—people with the same characteristics are more likely to form communication links (McPherson, Smith-Lovin, & Cook, 2001)—while a positive coefficient of a difference regressor indicates that there is negative assortative matching taking place, meaning links are created among people with differences in their characteristics such as age or education (Arcand & Fafchamps, 2012). We add group-level fixed effects υ. Further, the standard errors are clustered at a group level to correct for within-cluster correlation. Due to the complexity of the models, we model the binary dependent variables using linear probability models (LPM).[5] As described above, links to non-interviewed members were dropped. As a robustness check, we re-estimated the dyadic regressions including the links to non-interviewed members and adding a binary control variable turning 1 if both ends of the dyad were interviewed. Results remain robust and are reported in Table A3 in the Online Appendix.[6] Summary statistics of variables used in the dyadic regressions are presented in Table A5 in the Online Appendix.

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

3.3.1 | 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

[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).

[5] For comparison, logit estimates are shown in Table A2 in the Online Appendix.

[6] We performed two additional robustness checks: First, we estimated the dyadic regressions without sums and differences of individual level characteristics. Second, we estimated dyadic regressions and weighted the observations by the inverse of the group size. The results remain robust and are shown in Table A4 in the Online Appendix.

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 farmer group g for the information network m as

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

as our proxy for the prominence of a person. The underlying assumption is that high-in-degree persons could be good entry points for development projects, because they are the ones others claim to communicate with most often about the topics of interest. We find further support for this network measure in our data: the in-degree of a person is significantly correlated with the number of times he or she was named by other group members to be the most informed person with respect to agricultural or nutrition topics in the group (see Table A6 in the Online Appendix). Calculating in-degrees is rarely done, because it requires directed network data. A recent application can be found in Kim et al. (2015), who use the in-degree as a measurement of centrality in public health interventions. Most commonly out-degrees are used as a measure for centrality, because they can also be derived from self-reported data.

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

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

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.

3.3.2 | 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

$$d_i\ (m)\ = \beta_0\ + \beta_1 \mathbf{I} + \beta_2 \mathbf{H} + v +\ \varepsilon, \tag{5}$$

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 farmer group 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 farmer groups, we introduce group-level fixed effects v.[7] Further, clustered standard errors are introduced to control for heteroscedasticity. The error term is represented by ε. We estimate Equation (5) using fixed-effects ordinary least square (OLS) regressions. Given that the regressands are count variables, we also estimate Equation (5) using fixed-effects Poisson regressions (Wooldridge, 2002). The OLS and Poisson results are similar. For the ease of interpretation, we display the OLS results in Table 3, while the Poisson results can be found in Table A8 in the Online Appendix.

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

$$ISO_i\ (m)\ \ = \partial_0\ + \partial_1 \mathbf{I} + \partial_2 \mathbf{H} + v + \mu, \tag{6}$$

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 (6) is estimated using a LPM with group-level fixed effects. In an alternative specification, we replace the group-level fixed effects with a vector **G** of farmer group-level variables in order to understand which underlying factors are captured by the fixed effects. **G** consists of farmer group-related variables such as whether the group's primary focus is agriculture or whether the group received external support. Table A9 in the Online Appendix gives an overview of the individual- and household-level variables included in the OLS/Poisson and LPM. 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 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 and Mobarak, 2013). Second, we expect differentiated gender patterns 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).

[7] In an alternative specification, we replace the group-level fixed effects with selected farmer group-level variables. Results are shown in Table A7 in the Online Appendix.

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 farmer group level: Network structure and overlaps

On farmer group 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 farmer groups in our sample, and they have received agricultural extension at some point in the past. Overall, 52% of the farmer groups in our sample indicated that agriculture is their primary focus (Table 1). Other functions of the selected farmer groups 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 farmer groups. None of the farmer groups had received nutrition information in the past. However, unrelated to the group activities, almost half of our respondents stated to have noticed or received nutrition information on healthy eating or healthy diets during the last 12 months. The most mentioned sources of information were the radio (34%), church (21%), and relatives or friends (12%).

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 farmer groups, whose members know each other and frequently interact. In line with the farmer groups' 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 farmer groups (Figure 2).

Furthermore, the analysis of overlaps between the two networks shows that the nutrition information that is exchanged within the farmer groups—even though limited in quantity—mostly flows through agricultural links. Of all links created in the farmer groups, 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 farmer group are positively correlated (average correlation coefficient: 0.18; range from –0.13 to 0.46), indicating some overlap among 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.

4.2 | Results on dyadic level: Link formation

On farmer group level, we observed that 50% of all potential links are formed to exchange agricultural information and 9% to exchange nutrition information. In total, our data report 1,247 nutrition links. The majority of links is created among women only (614), followed by mixed-gender information sharing (366), and finally between two men (267). Using dyadic regressions, we analyze who is likely to form such links with each other (Table 2). The presented results describe the likelihood of link formation and do not refer to causal relationships. First, we find that centrality in terms of spatial and social position is associated with 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. These social proximity variables are also largest in magnitude. For instance, farmers who have plots next to each other are 12 percentage points more likely to share information on agriculture and 10 percentage points more likely to form a nutrition link. Other proximity variables seem to be relevant in particular for the exchange of nutrition information: kins and group members of the same gender tend to be more likely to form nutrition links. These results suggest 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.

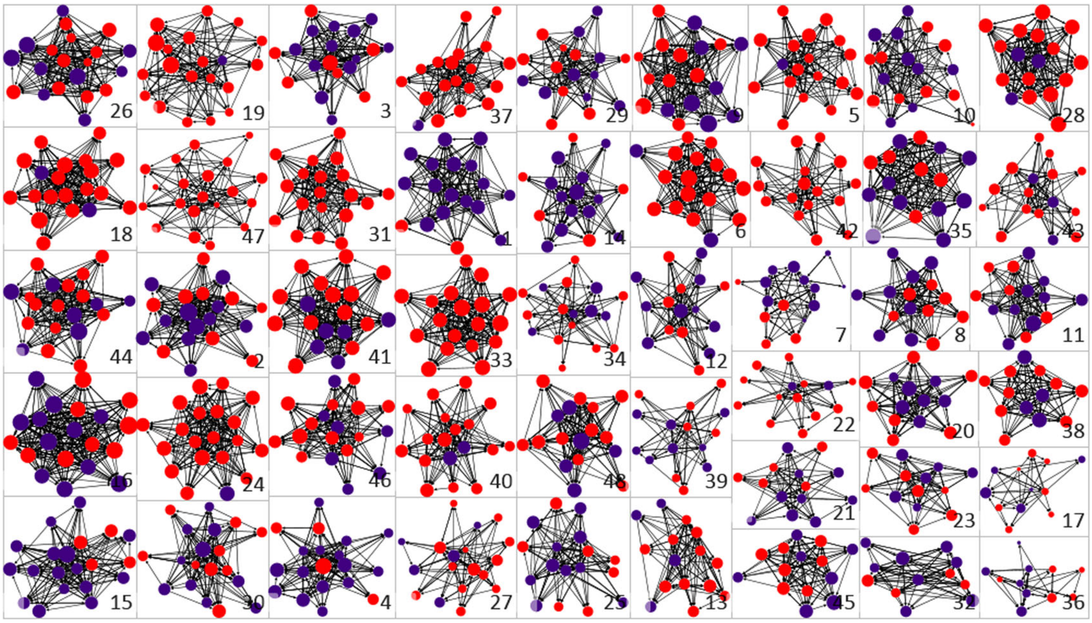

FIGURE 1 *AGRICULTURE* networks: Color of nodes—gender (red, female; blue, male). Size of nodes, in-degrees. Numbers indicate the farmer groups' IDs [Color figure can be viewed at wileyonlinelibrary.com]

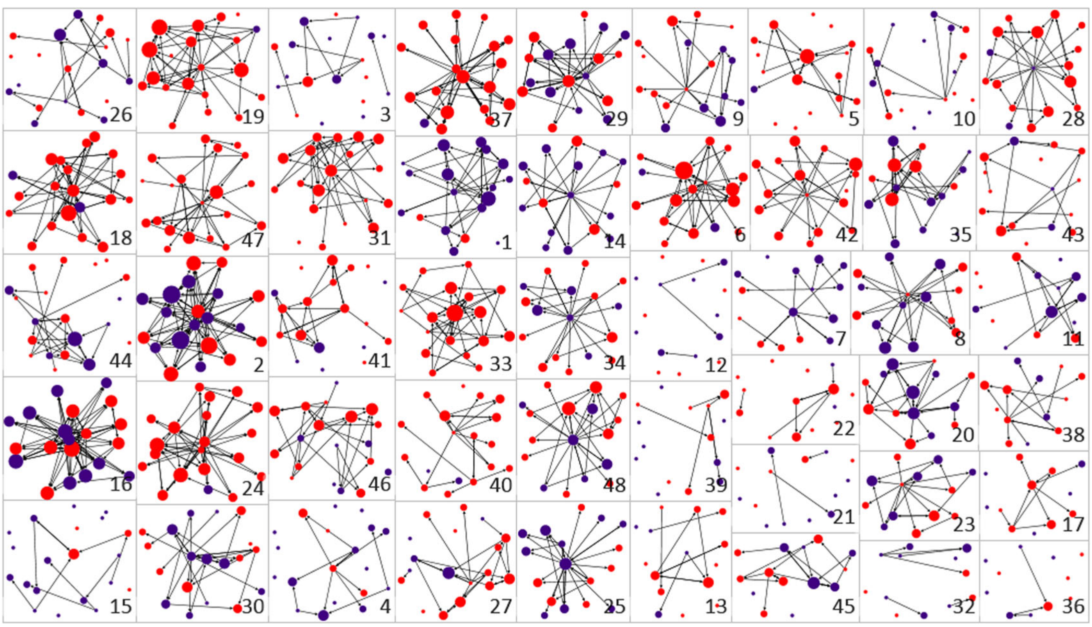

FIGURE 2 *NUTRITION* networks: Color of nodes—Gender (red, female; blue, male). Size of nodes, in-degrees. Numbers indicate the farmer groups' IDs [Color figure can be viewed at wileyonlinelibrary.com]

Our results further confirm that there is evidence of positive assortative matching: group members who both connect with a larger external network and who both trust others are more likely to form a link with each other to exchange agricultural and nutrition information. Moreover, more educated persons are more likely to form nutrition links. At first sight, 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, this concern is not further supported because our difference estimates signal negative assortative matching along the same dimensions: differences in external links and, in the case of nutrition, differences in education are positively associated with link formation, indicating that group members with lower education and less external connections are included in the communication network.

In the previous section, our results on a group level suggested that nutrition information is mostly transmitted through

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
WILEY

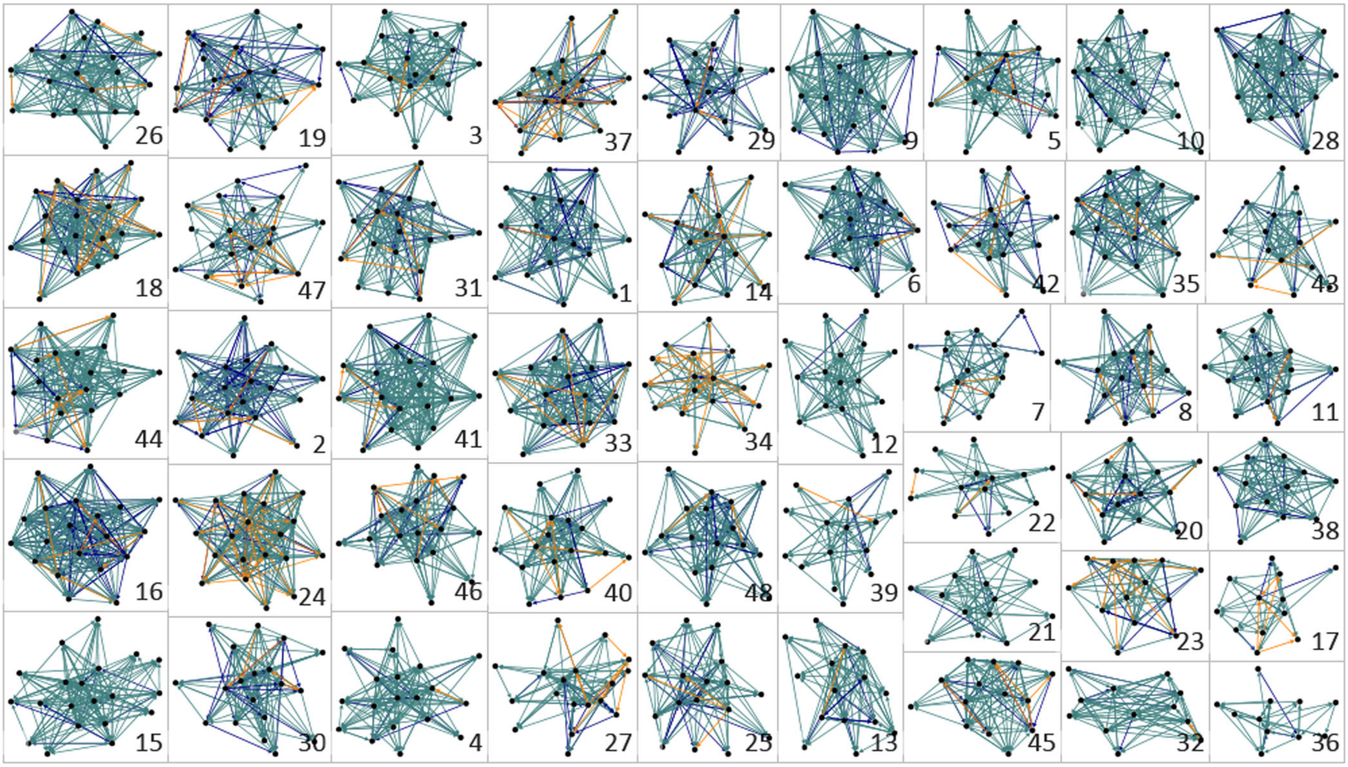

FIGURE 3 Multiplexity of *AGRICULTURE* and *NUTRITION*: Color of links: orange, nutrition only (233 links); turquoise, agriculture only (5,624 links); dark blue, multiplex links (both nutrition and agriculture (1,014 links) [Color figure can be viewed at wileyonlinelibrary.com]

existing channels of agricultural information exchange. To empirically explore whether agricultural link formation is associated with forming nutrition links, we estimate another dyadic regression specification, in which we include the agricultural network variable as a potential explanatory factor for nutrition link formation (Table 2, column 3). We acknowledge that the agricultural network variable is likely endogenous in the nutrition network regression and including it may yield biased estimates. We therefore treat results as tentative evidence that needs to be interpreted with caution. The results show that there is a positive and significant association between link formation for the exchange of agricultural and nutrition information, respectively. Hence, these results provide tentative support for our group-level finding that the agricultural network can be a predictor for the nutrition network.[8]

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 with respect to the proximity variables. In particular, kins and farmers of the same gender are associated with forming nutrition links.

At the same time, we find evidence for negative and positive assortative matching along the same dimensions, namely, education and external links. In this respect, communication networks within farmer groups seem to be inclusive, because also people who are not alike are likely to share information with each other (McPherson et al., 2001). When relying on the existing agricultural extension system to design nutrition-sensitive programs, these potential benefits of farmer groups and the differences in network structure and characteristics need to be taken into account.

4.3 | Results on individual level

4.3.1 | Characteristics of central persons

At the individual level, we aim to identify particularly central persons that could influence the diffusion of information, and thus represent promising entry points for targeting.[9] We therefore analyze the characteristics of prominent persons with high in-degrees on (those who are named often), as well as

[8] Further evidence that nutrition information is more frequently exchanged in farmer groups with a primary focus on agriculture is provided by our subgroup analysis presented in Table A10 in the Online Appendix. In the subgroup analysis, we estimate dyadic regressions separately for groups that primarily engage in agricultural activities and for groups that primarily engage in saving and credit or other activities.

[9] Despite our focus on central persons, it should be noted that noncentral persons can also be very relevant for passing information (Banerjee, Chandrasekhar, Duflo, & Jackson, 2013).

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

	(1) *AGRICULTURE*	(2) *NUTRITION*	(3) *NUTRITION*
Proximity			
Both female (1 = yes)	0.00523	0.0311***	0.0309***
	(0.0238)	(0.0105)	(0.0102)
Both male (1 = yes)	0.0537**	0.0257***	0.0204**
	(0.0216)	(0.00863)	(0.00902)
Kinship (1 = yes)	−0.0275	0.0270***	0.0295***
	(0.0321)	(0.0101)	(0.0102)
j is group leader (1 = yes)	0.0624***	0.0275***	0.0215***
	(0.00913)	(0.00619)	(0.00597)
Plots sharing same border (1 = yes)	0.124***	0.107***	0.0944***
	(0.0222)	(0.0156)	(0.0145)
Both main occupation is farming (1 = yes)	0.0253	0.0120	0.00907
	(0.0280)	(0.0115)	(0.0111)
Sum of:			
Land size	−0.00149	0.00295	0.00302
	(0.00488)	(0.00241)	(0.00253)
Years of education	0.00293	0.00349**	0.00320**
	(0.00199)	(0.00147)	(0.00142)
Years of age	0.00203***	0.000157	0
	(0.000543)	(0.000364)	(0.000344)
Trust towards others	0.0533***	0.0173**	0.0121
	(0.0158)	(0.00856)	(0.00819)
External links	0.0150***	0.00736***	0.00588***
	(0.00282)	(0.00144)	(0.00134)
Household size	0.00702*	−0.000306	−0.000989
	(0.00368)	(0.00174)	(0.00159)
Difference in:			
Land size	−0.00434	0.00300	0.00342
	(0.00563)	(0.00280)	(0.00296)
Years of education	0.00160	0.00248**	0.00233**
	(0.00202)	(0.000984)	(0.000965)
Years of age	0.000886	0.000226	0.000141
	(0.000668)	(0.000349)	(0.000336)
Trust towards others	0.0392**	0.0112	0.00736
	(0.0155)	(0.00775)	(0.00783)
External links	0.0122***	0.00514***	0.00395***
	(0.00247)	(0.00123)	(0.00122)
Household size	0.00641*	−0.000972	−0.00159
	(0.00363)	(0.00145)	(0.00134)
AGRICULTURE			0.0967***
			(0.0130)

(Continues)

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
IAAE
WILEY

TABLE 2 (Continued)

	(1) AGRICULTURE	(2) NUTRITION	(3) NUTRITION
Constant	−0.0282	−0.118**	−0.115**
	(0.0698)	(0.0581)	(0.0562)
l_{ij} $(m) = 1$	6656	1247	1247
N_{D}	13,318	13,318	13,318

Note. The dependent variable in column 1 refers to a binary variable turning one if a link between group member *i* and *j* exists for agricultural information exchange. The dependent variable in column 2 and 3 refers to a binary variable turning one if a link between group member *i* and *j* exists for nutrition information exchange. Although column 1 and 2 depict our main specification, we added the endogenous agricultural network as potential explanatory variable to the specification shown in column 3. External links refer to the number of persons *i* and *j* named as contacts outside of the farmer group. Coefficients and standard errors are based on dyadic regressions (LPM) including farmer group-level fixed effects and standard errors (in brackets) clustered at a group level.
Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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.

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). A group leader is associated with a 1.2 degrees higher agricultural in-degree and a 0.69 degree higher nutrition in-degree than a person who is not in a leadership position. In the agricultural network, older members tend to be more central in terms of both prominence and influence, whereas members in spatially

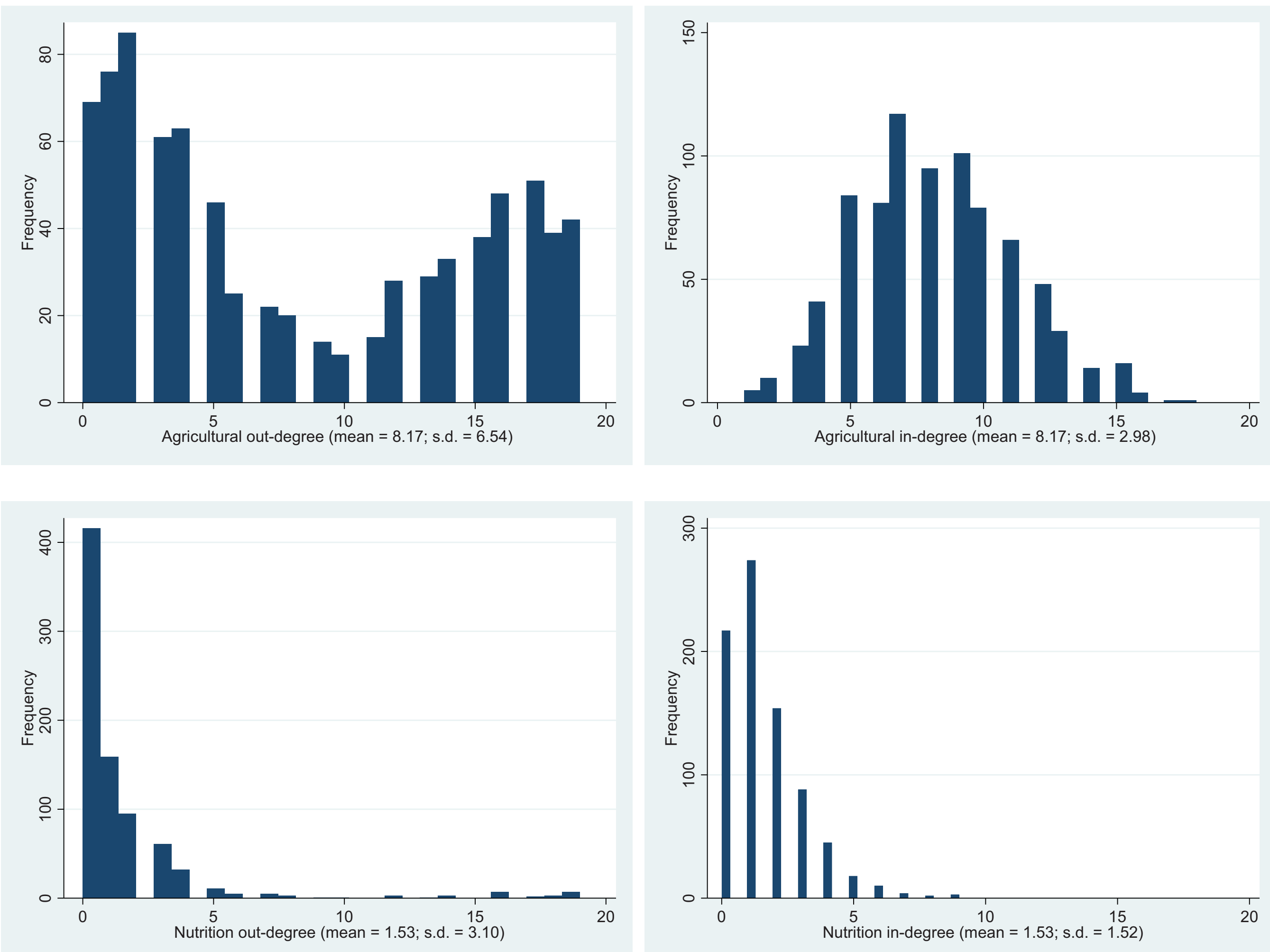

FIGURE 4 Distributions of out-degrees and in-degrees for *AGRICULTURE* and *NUTRITION* [Color figure can be viewed at wileyonlinelibrary.com]

TABLE 3 Fixed-effects ordinary least square (OLS) regression analysis of centrality measures for *AGRICULTURE* and *NUTRITION*

	(1)	(2)	(3)	(4)
	d_i^{in} (prominence)		d_i^{out} (influence)	
	AGRICULTURE	*NUTRITION*	*AGRICULTURE*	*NUTRITION*
Individual level variables				
Gender (1 = male)	0.513***	−0.169	0.188	0.0536
	(0.165)	(0.107)	(0.569)	(0.168)
Years of education	0.00994	0.0118	0.0633	0.0674*
	(0.0213)	(0.0182)	(0.0676)	(0.0344)
Age in years	0.0192***	0.00299	0.0456**	0.00748
	(0.00686)	(0.00414)	(0.0183)	(0.0111)
External links named	0.0126	0.0220	0.450***	0.195***
	(0.0241)	(0.0174)	(0.0793)	(0.0376)
Spatial centrality proxy	0.452**	0.0673	−0.327	0.556
	(0.177)	(0.0991)	(0.745)	(0.372)
Group leadership position (1 = yes)	0.956***	0.455***	1.206***	0.680**
	(0.147)	(0.105)	(0.391)	(0.296)
Household level variables				
Land size (acres)	0.0589	−0.00195	−0.115	0.101
	(0.0679)	(0.0413)	(0.165)	(0.0778)
Economic dependency ratio	0.0770	0.0366	0.158	0.101
	(0.0471)	(0.0360)	(0.229)	(0.0819)
Small business activities (1 = yes)	0.0207	0.0526	−0.569	−0.0518
	(0.149)	(0.102)	(0.453)	(0.245)
Constant	6.324***	1.024***	3.211***	−0.918
	(0.430)	(0.324)	−1.168	(0.783)
N_H	815	815	815	815

Note. The dependent variables of column 1 and 2 are in-degrees that were calculated for the agricultural network (column 1) and the nutrition network (column 2). In-degrees refer to frequencies of being named as a contact for the respective network. The dependent variables of column 3 and 4 are out-degrees that were calculated for the agricultural network (column 3) and the nutrition network (column 4). Out-degrees refer to frequencies of naming fellow group members as a contact for the respective network. The spatial centrality proxy is a binary variable turning one if respondent shares the same plot border with at least two of his/her fellow group members. Coefficients and standard errors are based on OLS regressions including farmer group-level fixed effects. Standard errors are clustered at a farmer group level and are shown in parentheses.
Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

central locations tend to be more prominent, that is, 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 the expected in-degree for a man is 0.51 degree higher compared to a woman, reflecting that men are 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 farmer group. However, if we compare the prominent and influential persons for agriculture and nutrition, we need to acknowledge that the profile of persons that might be key for nutrition is less detailed because we only find strong positive associations with external links and group leadership. Again, this is likely driven by the fact that the nutrition network is too sparse to allow for a more detailed characterization.[10]

4.3.2 | 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 farmer group. As identified in the farmer group-level analysis, these

[10] In addition, potentially omitted variables, such as the reliability or extraversion of a person, may confound our results. Unfortunately, this individual-level information is not available to us. However, many potentially omitted variables would also be difficult to observe in practice and therefore do not necessarily represent appropriate targeting criteria.

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists
WILEY

TABLE 4 Regression analysis of isolates for *NUTRITION*

	(1) $ISO_i(NUTRITION)$ $d_i^{in}(m)=0$ and $d_i^{out}(m)=0$ Fixed-effects LPM	(2) $ISO_i(NUTRITION)$ $d_i^{in}(m)=0$ and $d_i^{out}(m)=0$ 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)
Primary focus 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 farmer group		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	815

Note. The dependent variable of column 1 and 2 refer to isolates. Isolates are binary variables, turning one if a farmer is excluded from the nutrition network because he/she does not name anyone as a nutrition link and was not named by anyone as a link. Column 1 shows the main specification that includes group-level fixed effects. Column 2 shows an alternative specification in which we replace the group-level fixed effects with selected farmer group-level variables. The spatial centrality proxy is a binary variable turning one if respondent shares the same plot border with at least two of his/her fellow farmer group members. In both specifications, clustered standard errors at farmer group level are shown in parentheses.

Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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 farmer group. Several group characteristics also contribute to explaining the prevalence of isolated persons within the nutrition communication networks of the farmer groups. 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 primary focus on agriculture.

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 farmer groups through the existing agricultural extension systems. However, to date little is known about the structure and characteristics of agricultural and nutrition information networks within farmer groups and whether nutritional information is exchanged between farmer group members at all. Based on unique network data from Kenya, we analyze the structures and overlaps of agricultural and nutrition information networks within farmer groups as well as the factors associated with 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 farmer groups.

Our results show that compared to agricultural information networks, nutrition information networks are sparse. This is not surprising, as the farmer groups in our sample were organized for agricultural extension purposes and have not been targeted for nutritional training yet. Nonetheless, nutrition-related information is exchanged within farmer groups, 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. As half of the respondents in our sample received nutrition information outside the farmer group, the reporting on nutrition linkages can be considered the lower bound of what is to be expected when nutritional messages are deliberately targeting farmer groups.[11] It is noteworthy that nutrition information is exchanged mostly through the existing agricultural information links. Further, we find some tentative indication that the agricultural network can be a predictor for the nutrition network. 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 potentially important drivers in the diffusion of information in both networks and may thus serve as suitable entry points for nutrition-sensitive extension programs.

Although 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. Although agricultural information flows widely and relatively unrestricted in farmer groups, nutrition information relies on somewhat more exclusive channels. In particular, nutrition links are formed between kins and persons of the same gender. 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 sampled group members are completely excluded from nutrition information exchange within their farmer group. 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 and Fafchamps (2015), we therefore suggest encouraging the formation of links with less popular people in order to enhance network efficiency.

At the same time, we find that nutrition communication within farmer groups can also be inclusive: farmers with different characteristics engage in information exchange. For instance, farmers with different education levels exchange information, which suggests that the less educated farmers potentially learn from the more educated and vice versa. This signals that farmer groups could provide a good platform for learning and the diffusion of nutrition information. However, the characteristics of the farmer groups matter in this case: 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 primary 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. Although our study gives new descriptive insights on how farmer groups communicate about agriculture and

[11] Thank you to an anonymous reviewer for pointing this out.

nutrition, future research could test how nutrition knowledge diffuses into the networks and how these respective networks react to nutrition-sensitive interventions.

ACKNOWLEDGMENTS

This research was financially supported by the German Federal Ministry of Food and Agriculture (BMEL) based on the decision of the Parliament of the Federal Republic of Germany (grant number 2813FSNu01). The authors thank the University of Nairobi and Africa Harvest (Kenya) for their research cooperation. We would like to express our special gratitude to all respondents and enumerators who were part of this survey.

REFERENCES

Anderson, J. R., & Feder, G. (2007). Agricultural extension. *Handbook of Agricultural Economics*, *3*, 2343–2378.

Arcand, J. L., & Fafchamps, M. (2012). Matching in community-based organizations. *Journal of Development Economics*, *98*(2), 203–219.

Aubel, J. (2012). The role and influence of grandmothers on child nutrition: Culturally designated advisors and caregivers. *Maternal and Child Nutrition*, *8*(1), 19–35.

Banerjee, A., Chandrasekhar, A. G., Duflo, E., & Jackson, M. O. (2013). The diffusion of microfinance. *Science*, *341*(6144), 1236498.

Barr, A., Dekker, M., & Fafchamps, M. (2015). The formation of community-based organizations: An analysis of a quasi-experiment in Zimbabwe. *World Development*, *66*, 131–153.

Buehren, N., Goldstein, M., Molina, E., & Vaillant, J. (2019). The impact of strengthening agricultural extension services on women farmers: Evidence from Ethiopia. *Agricultural Economics*, *50*, 407–419.

BenYishay, A., & Mobarak, A. M. (2013). *Communicating with farmers through social networks*. Yale University Economic Growth Center Discussion Paper No. 1030; Yale Economics Department Working Paper No. 121.

Caria, A. S., & Fafchamps, M. (2015). *Can farmers create efficient information networks? Experimental evidence from rural India (No. 2015-07)*. Oxford, U.K.: Centre for the Study of African Economies, University of Oxford.

Carletto, G., Ruel, M., Winters, P., & Zezza, A. (2015). Farm-level pathways to improved nutritional status: Introduction to the special issue. *Journal of Development Studies*, *51*(8), 945–957.

Carrington, P. J., Scott, J., & Wasserman, S. (Eds.). (2005). *Models and methods in social network analysis* (Vol. 28). Cambridge, U.K.: Cambridge University Press.

Chandrasekhar, A., & Lewis, R. (2011). Econometrics of sampled networks. Unpublished manuscript, MIT. [422].

Davis, K., Nkonya, E., Kato, E., Mekonnen, D. A., Odendo, M., Miiro, R., & Nkuba, J. (2012). Impact of farmer field schools on agricultural productivity and poverty in East Africa. *World Development*, *40*(2), 402–413.

Cuellar, M., Hedlund, H., Mbai, J., & Mwangi, J. (2006). *The National Agriculture and Livestock Extension Programme (NALEP) Phase I: Impact assessment*. Stockholm, Sweden: Sida.

Darrouzet-Nardi, A. F., Miller, L. C., Joshi, N., Mahato, S., Lohani, M., & Rogers, B. L. (2016). Child dietary quality in rural Nepal: Effectiveness of a community-level development intervention. *Food Policy*, *61*, 185–197.

De Brauw, A., Eozenou, P., & Moursi, M. (2015). Programme participation intensity and children's nutritional status: Evidence from a randomised control trial in Mozambique. *The Journal of Development Studies*, *51*(8), 996–1015.

De Weerdt, J., & Fafchamps, M. (2011). Social identity and the formation of health insurance networks. *Journal of Development Studies*, *47*(8), 1152–1177.

Fafchamps, M., & Gubert, F. (2007). The formation of risk sharing networks. *Journal of development Economics*, *83*(2), 326–350.

Fan, S., & Pandya-Lorch, R. (Eds.). (2012). *Reshaping agriculture for nutrition and health*. Washington, DC: International Food Policy Research Institute.

FAO. (2015). *The state of food insecurity in the world*. Rome, Italy: Author.

Gómez, M. I., Barrett, C. B., Raney, T., Pinstrup-Andersen, P., Meerman, J., Croppenstedt, A., … Thompson, B. (2013). Post-green revolution food systems and the triple burden of malnutrition. *Food Policy*, *42*, 129–138.

Grund, T. U. (2015). *nwcommands. Network Analysis in Stata*. Retrieved from http://nwcommands.org

Hanneman, R. A., & Riddle, M. (2005). *Introduction to social network methods*. Riverside, CA: University of California, Riverside.

Hawkes, C., & Ruel, M. T. (2008). *From agriculture to nutrition: Pathways, synergies and outcomes. Agricultural and Rural Development Notes; No. 40*. Washington, DC: World Bank.

Hirvonen, K., & Hoddinott, J. (2017). Agricultural production and children's diets: Evidence from rural Ethiopia. *Agricultural Economics*, *48*, 469–480.

Hoddinott, J., & Haddad, L. (1995). Does female income share influence household expenditures? Evidence from Côte d'Ivoire. *Oxford Bulletin of Economics and Statistics*, *57*(1), 77–96.

IFPRI. (2011). *Global food policy report*. Washington, DC: Author.

IFPRI. (2017). *Global nutrition report 2017. Nourishing the SDGs*. Washington, DC: Author.

Izquierdo, L. R., & Hanneman, R. A. (2006). *Introduction to the formal analysis of social networks using mathematica*. Riverside, CA: University of California, Riverside.

Jaimovich, D. (2015). Missing links, missing markets: Evidence of the transformation process in the economic networks of Gambian villages. *World Development*, *66*, 645–664.

Kim, D. A., Hwong, A. R., Stafford, D., Hughes, D. A., O'Malley, A. J., Fowler, J. H., & Christakis, N. A. (2015). Social network targeting to maximise population behaviour change: A cluster randomised controlled trial. *Lancet*, *386*(9989), 145–153.

KNBS. (2015). *Kenya Demographic and Health Survey 2014. Kenya National Bureau of Statistics (KNBS)*. Retrieved from https://dhsprogram.com/pubs/pdf/FR308/FR308.pdf

KNBS & SID. (2013). *Exploring Kenya's inequality: Pulling apart or pooling together? Kisii County*. Nairobi, Kenya: Kenya National Bureau of Statistics (KNBS) and Society for International Development (SID).

Maertens, A. (2017). Who cares what others think (or do)? Social learning and social pressures in cotton farming in India. *American Journal of Agricultural Economics*, *99*(4), 988–1007.

Malapit, H. J. L., Kadiyala, S., Quisumbing, A. R., Cunningham, K., & Tyagi, P. (2015). Women's empowerment mitigates the negative effects of low production diversity on maternal and child nutrition in Nepal. *The Journal of Development Studies*, *51*(8), 1097–1123.

Matuschke, I., & Qaim, M. (2009). The impact of social networks on hybrid seed adoption in India. *Agricultural Economics*, *40*(5), 493–505.

Mbuvi, H. M., Kenyanya, O., & Muthengia, J. W. (2013). Determination of potassium levels in intensive subsistence agricultural soils in Nyamira County, *Kenya. International Journal of Agriculture and Forestry*, *3*(7), 294–302.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual review of sociology*, *27*(1), 415–444.

Murendo, C., Wollni, M., De Brauw, A., & Mugabi, N. (2017). Social network effects on mobile money adoption in Uganda. *The Journal of Development Studies*, *54*(2), 327–342.

Pandey, V. L., Dev, S. M., & Jayachandran, U. (2016). Impact of agricultural interventions on the nutritional status in South Asia: A review. *Food policy*, *62*, 28–40.

Popkin, B. M., Adair, L. S., & Ng, S. W. (2012). Global nutrition transition and the pandemic of obesity in developing countries. *Nutrition reviews*, *70*(1), 3–21.

Ragasa, C., Aberman, N. L., & Mingote, C. A. (2019). Does providing agricultural and nutrition information to both men and women improve household food security? Evidence from Malawi. *Global Food Security*, *20*, 45–59.

Ragasa, C., Berhane, G., Tadesse, F., & Taffesse, A. S. (2013). Gender differences in access to extension services and agricultural productivity. *The Journal of Agricultural Education and Extension*, *19*(5), 437–468.

Ruel, M. T., Alderman, H., & Maternal and Child Nutrition Study Group. (2013). Nutrition-sensitive interventions and programmes: How can they help to accelerate progress in improving maternal and child nutrition? *Lancet*, *382*(9891), 536–551.

Ruel, M. T., Quisumbing, A. R., & Balagamwala, M. (2018). Nutrition-sensitive agriculture: What have we learned so far? *Global Food Security*, *17*, 128–153

Sibhatu, K. T., Krishna, V. V., & Qaim, M. (2015). Farm production diversity and dietary diversity in developing countries. *Proceedings of the National Academy of Sciences (PNAS)*, *112*, 10657–10662.

Smith, K. P., & Christakis, N. A. (2008). Social networks and health. *Annual Review of Sociology*, *34*, 405–429.

Van den Broeck, K., & Dercon, S. (2011). Information flows and social externalities in a Tanzanian banana growing village. *The Journal of Development Studies*, *47*(2), 231–252.

Wasserman, S., & Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 8). Cambridge, U.K.: Cambridge University Press.

Wooldridge, J. M. (2002). *Econometric analysis of cross section and panel data*. Cambridge, U.K.: The MIT Press.

World Bank & IFPRI. (2010). *Gender and governance in rural services: Insights from India, Ghana, and Ethiopia*. Washington, DC: The World Bank and International Food Policy Research Institute.

Zeng, D., Alwang, J., Norton, G. W., Shiferaw, B., Jaleta, M., & Yirga, C. (2017). Agricultural technology adoption and child nutrition enhancement: Improved maize varieties in rural Ethiopia. *Agricultural Economics*, *48*, 573–586.

SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

How to cite this article: Jäckering L, Gödecke T, Wollni M. Agriculture–nutrition linkages in farmers' communication networks. *Agricultural Economics*. 2019;50:657–672. https://doi.org/10.1111/agec.12516