Communication Networks and Nutrition-sensitive Extension in Rural Kenya: Essays on Centrality, Network Effects and Technology Adoption

Dissertation

to obtain the doctoral degree

in the International Ph.D. Program for Agricultural Sciences in Goettingen (IPAG)

at the Faculty of Agricultural Sciences,

Georg-August-University Goettingen, Germany

presented by

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born in Mettingen, Germany

Goettingen, March 2018

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Date of dissertation: 17.05.2018

Summary

Globally, 767 million people live on less than US$ 1.90 a day and two billion people are malnourished. Especially affected by poverty and malnutrition is the rural population of Sub-Saharan Africa (SSA), who depend on the agricultural sector for food and income. Adopting new technologies can help farmers improve their livelihoods through an increase in income, or an improved nutritional and health status. However, adoption rates are comparably low. As agriculture can play a central role for food security, making agriculture more nutrition-sensitive has become one of the hot topics in the recent development discourse. However, also the uptake of pro-nutrition technologies – such as biofortified crops or particularly nutritious pulses – remains below expectations.

While factors influencing the adoption of technologies are manifold (for instance, education, risk preferences or wealth), special attention has recently been paid to the important functions of information access and social networks. In this regards, agricultural extension systems can set in to provide farmers with the missing information on new (pro-nutrition) technologies. A common approach is to channel information regarding the new technologies through farmer groups. However, so far nutrition-sensitive programs mostly focused on mothers only. There is little evidence on how men and women embedded in groups, communicate about topics related to agriculture and nutrition, and which persons can serve as potential target points for nutrition-sensitive extension. Simultaneously, networks play an important role for the diffusion of information. In particular, communication networks are potential pathways that may induce behavioral change and may play a strong role in the setting of group-based extension due to dynamics that trigger peer pressure or competition. However, due to lack of detailed (panel) network data, there is little evidence on how these communication networks are affected by the delivery of agricultural extension, and if communication networks can contribute to finally adopt new technologies.

This dissertation addresses these research gaps by drawing conclusion based on a unique dataset that combines a randomized controlled trial (RCT) with detailed panel data on communication networks of farmer groups. The RCT was implemented in rural Kenya and

consisted of varying combinations of group-based agricultural and nutrition training sessions. The purpose of the extension training was the promotion of the iron-rich black common bean variety KK15. Survey data from 48 farmer groups (824 households) was collected before (October until December 2015) and after (October until December 2016) the intervention (March until September 2016).

Given the background on the importance of a better understanding of communication networks in the context of agricultural extension, this dissertation comprises two essays. The first essay (Chapter 2) of this dissertation deals with nutrition and agricultural communication networks of farmer groups and builds on baseline data of 48 farmer groups (815 individuals), we collected in 2015:

In developing countries, community-based organizations (CBOs) and individuals within CBOs are important target units for agricultural programs. However, little is known about the flow of information within CBOs and between individuals. The objective of this study is to investigate the structure and characteristics of communication networks for nutrition and agriculture. First, we identify the structure of agricultural and nutrition information networks within CBOs, as well as overlaps of the two networks. Dyadic regression techniques are then used to explore the characteristics of persons forming links for agriculture and nutrition. Second, key persons within CBOs that are prominent or influential for agriculture and nutrition information networks are identified, as well as characteristics of persons that are excluded from these networks. Analysis is conducted using descriptive and econometric techniques such as fixed effect Poisson models. Our study finds that nutrition information is exchanged within CBOs but to a moderate extent. Further, agricultural and nutrition information networks overlap and often the same links are used for both topics. At the same time, a large number of people are excluded from nutrition information networks. These persons are more likely to be men, have smaller land sizes and are less connected to persons outside of the group. We conclude that there is room for nutrition training to sensitize group members and nudge communication exchange about nutrition related issues. In particular, we recommend incentivizing communication with isolated persons. Further, our regression results suggest targeting CBO leaders, as well as other group members that live in central locations as an entry point for training. The results can help to increase the outreach of nutrition-sensitive programs.

The second essay (Chapter 3) investigates if interventions, such as agricultural extension, affect agricultural communication networks and if these communication networks can act as pathways leading to the adoption of new technologies. The analysis is based on the mentioned RCT and therefore uses both, baseline, as well as follow-up data:

A growing body of literature focuses on the role of network effects for farmers' adoption decisions. However, little is known on how interventions affect networks. We analyze the effect of group-based trainings on networks and the influence of these networks on the adoption of technologies. Our analysis builds on a unique dataset that combines a randomized controlled trial (RCT) with detailed panel data on communication networks. Results suggest that, first, the intervention had a positive impact on communication among farmers (i.e. the creation of communication links). Second, besides positive direct effects of the intervention, we also find strong positive network effects on adoption, indicating that individual farmers are more likely to adopt, the higher the share of adopters in their communication network. Hence, group-based extension approaches can be efficient in diffusing new technologies, not only because they reduce transaction costs, but also because network effects can stimulate and drive technology adoption.

Acknowledgements

First of all, I would like to express my gratitude to my supervisor Prof. Meike Wollni: Thank you for your support, trust and guidance during the last three years! You gave me the freedom I needed, while at the same time, making sure that I did not lose track. Our meetings were very inspiring and encouraging and you strongly supported me in my own development as a researcher.

Prof. Matin Qaim: Thank you for always joining my Brownbag and Doctoral seminars and for discussing my second paper. Your feedback and thoughts were very valuable to me and certainly shaped my work. Thank you as well for being part of my thesis committee. On the same note, I would like to thank Prof. Stephan von Cramon-Taubadel for being my third supervisor. Last but not least: Thank you Dr. Theda Gödecke for introducing me to the world of networks. I was lost and skeptical in the beginning but ultimately fell in love with the subject!

The research was financially supported by the German Federal Ministry of Food and Agriculture (BMEL) who funded the ADDA project which is gratefully acknowledged. On this note, thank you to all members of the ADDA Team at the University of Nairobi, at Africa Harvest Biotech Foundation International (Kenya office), as well as at the University of Goettingen, to the extension officers who did a great job (Bwema, Joseph, Richard and Hilda) as well as enumerators and student assistants (Ana and Gabriel)! It was great meeting all of you and this work wouldn’t have been possible without you. Thank you Prof. Matin Qaim, for managing the ADDA project – your positive spirit and pragmatism was truly encouraging. A special thanks to Theda Gödecke for putting a lot of energy into the ADDA project to make it become a success! Also many thanks to Ilona Hoepfner for the hard work you put into the project and for having an open ear for all sorts of issues.

To my colleagues: life in Göttingen would not be the same without you! Thanks to my two Chair families (Chair of international food economics and rural development as well as the Chair for environmental and resource economics), and of course to GlobalFood. What an awesome platform for joined learning and networking! It has been a pleasure and a privilege to be part of it.

In this inspiring environment, colleagues become friends: Hanna, Kathrin, Katrin, Denise, Andrea: Our runs up to Bismarkturm energized my life here in Göttingen and filled it with joy! Thanks for your support, jokes and love! The same holds for Eva, Dirk, Luis and Miri! Also, special thanks to Katrin, Sahrah and Jens who supported me in the final phase of my PhD with their comments and patience!

Andrea Fongar, a special thanks to you. I am proud that we went all the way together until we reached the finishing line! Thank you for the countless number of wine bottles we emptied after long days of field work. You are a great colleague and friend. Without you, these journey(s) would have been lonely.

My friends from Lingen and surroundings (Biene, Beesten, Freren): growing up with you was incredibly nice and I am grateful that you are still part of my life today, almost 20 years later.

Finally, thanks to my family: Papa, thanks for visiting me once a year to fix my flat. Thanks Reinhard, for always being there for us. Last but not least: Mama, danke, mein größtes Vorbild bist Du! Danke, für deine bedingungslose Unterstützung und dafür, dass du selbstlos alles dafür gegeben hast, dass es mir und Malte an nichts fehlt und ich studieren konnte!

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1 General introduction

1.1 Background

Worldwide, 767 million people live on less than US$ 1.90 a day and two billion people are malnourished. Especially affected by poverty and malnutrition is the rural population of Sub-Saharan Africa (SSA). Since important parts of the rural population work in agriculture for both income generation and subsistence needs (FAO et al. 2017; IFPRI 2017), the agricultural sector can be identified as key sector in order to fight both poverty and malnutrition simultaneously.

Technology adoption – may it be the rediscovery of old, lost varieties, the adoption of new technologies that improve yields and are resistant to pests, or have nutritional benefits – can help farmers to improve their livelihoods through an increase in income, or an improved nutritional and health status (Minten & Barrett 2008; Headey & Ecker 2013; Qaim 2014). However, in general, adoption rates remain low in SSA (Evenson & Gollin 2003; Emerick et al. 2016). Several factors determine the adoption of technologies, with information being the ones most widely discussed (Aker 2011).

Agricultural extension systems (public or private) are institutional solutions that set in to provide farmers with missing information on, for instance, new technologies. Therefore, agricultural extension services play an important role in the development of the agricultural sector in developing countries (Akroyd & Smith 2007). However, little attention has been paid on rigorous evaluation of agricultural extension approaches regarding their effectiveness in diffusing information and nudging the adoption of technologies (Anderson & Feder 2004; Kondylis et al. 2017).

In addition, because agriculture is not only considered important for income generation, but also as key for influencing the food and nutrition security of the rural population, it is requested to investigate how the agricultural sector can become more nutrition-sensitive. This could be achieved by, for instance, promoting pro-nutrition technologies through the agricultural extension system (Ruel et al. 2013; Ruel et al. 2018).

There is an increasing body of literature that analyzes the impact of nutrition-sensitive programs rigorously by using RCTs or quasi-experimental settings (De Brauw et al. 2015; Olney et al. 2015; Osei et al. 2017; for an extensive overview see Ruel et al. 2018). In most of the literature, the evaluated programs target mothers, households with children or women groups since the objective of the programs is to improve the nutritional status of children. Women are targeted since they are the ones responsible for food preparation and for the nutritional status of their family, and especially children (Hoddinott & Haddad 1995; Ruel et al. 2018). Also, women play an important role for agriculture, but extension sessions are still predominantly attended my men (Ragasa et al. 2013). So far, little evidence exists on how agricultural extension services – that usually targets both men and women – should be designed to combine information on agriculture and nutrition. With regard to group-based extension services, especially when dealing with mixed-gender groups, it is of high importance to understand how farmers communicate about nutrition and agriculture and to identify persons who may serve as suitable target units for nutrition-sensitive programs. Designing agricultural extension systems in a nutrition-sensitive manner could contribute to achieving the United Nations' Sustainable Development Goals one (no poverty), two (zero hunger) and three (good health and well-being).

Besides the fact that little evidence is present on which modes of extension work, also little is known why certain modes may or may not work (Birner et al. 2009). While factors influencing the adoption of technologies are manifold (for instance education, risk preferences or wealth), special attention has recently been paid to the import functions of information access and social networks (Bandiera & Rasul 2006; Conley & Udry 2010; Foster & Rosenzweig 2010; Aker 2011). Networks are especially important in settings that lack formal institutions where they can serve as important substitutes. However, so far networks are most commonly measured by proxies (Breza 2016).

1.2 Problem statement

1.2.1 Nutrition-sensitive agriculture and group-based extension

Agriculture can play a central role in improving nutrition. This is why making agriculture more nutrition-sensitive has become one of the hot topics in the recent development discourse (Hawkes & Ruel 2008; Fan & Pandya-Lorch 2012; IFPRI 2016; Pingali & Sunder 2017). One way of making agriculture more nutrition-sensitive, and thus combating malnutrition, is to disseminate pro-nutrition technologies such as biofortified crops or particular nutritious vegetables or pulses to farmers (De Brauw et al. 2015; Bouis and Saltzman 2017). However, the adoption of these pro-nutrition innovations is particularly low since farmers may be hesitant to adopt if they do not know the taste of the new variety or if the pro-nutrition technology has no other benefits such as being high-yielding (Ogutu et al. 2018). Previous studies have found that the adoption rate of pro-nutrition innovations is higher when farmers have a better knowledge about the attributes of the pro-nutrition innovation (De Brauw et al. 2013; De Groote et al. 2016). A possible platform that can help to channel the required agronomic and nutritional knowledge regarding the pro-nutrition technology to farmers might be the existing agricultural extension service.

Delivering agricultural extension to farmers can take place in different ways (Anderson & Feder 2007). This dissertation focuses on the group-based extension approach. Hereby the entire farmer group receives information directly from an extension officer, in comparison with an individual-based approach, where only individuals are trained and visited by an extensionist, or only model or lead farmers are trained, who then in a second step are supposed to diffuse the new information to their farmer groups. The group-based approach offers several advantages. First, working with groups of farmers reduces transaction costs compared to visiting a large number of dispersed individual farmers (Anderson & Feder 2004). Second, the group-based approach is considered as pro-poor since it is beneficial for women and low-educated farmers of East Africa, both of which are especially vulnerable to poverty (Davis et al. 2012). Third, since group-based approaches are participatory, they are often more effective in spreading information and promoting new technologies (Fischer & Qaim 2012). Because of this, they are widely used by development practitioners (Anderson & Feder 2007) and play an important role in Kenya. For instance, in the early millennium years, more than 7000 farmer groups were founded with the aim to channel agricultural extension through them (Cuellar et al. 2006).

There is a growing body of literature that tries to understand linkages between and the pathways through which agriculture can influence nutrition (Kabunga 2014; Malapit et al. 2015; Sibhatu et al. 2015; Carletto et al. 2015; Ruel et al. 2018), but little evidence exists on how extension services should be designed to combine information on agriculture and nutrition. With regard to group-based extension services, especially the identification of persons who may serve as suitable target groups for nutrition-sensitive programs is of high importance (Ruel et al. 2018). In the context of nutrition-specific interventions, mothers, grandmothers and other accepted key persons are important target groups (Aubel 2012). In contrast, in the setting of nutrition-sensitive extension, it is unclear which persons can be considered as central and may serve as suitable entry points for an effective diffusion of agricultural and nutrition information. Therefore, we collected detailed data on nutrition and agricultural communication networks of farmer groups. These data allow conclusions to be drawn on the structure of communication networks for agriculture and nutrition, and thus on the characteristics of central farmers for the corresponding topics. The results can help to develop network targeting strategies for nutrition-sensitive extension programs. This problem statement will be addressed in the first essay, in Chapter 2 of this dissertation.

1.2.2 Networks and technology adoption

Networks play an important role for the diffusion of information and consequently for the adoption of new technologies (Foster & Rosenzweig 1995; Conley & Udry 2001; Bandiera & Rasul 2006; Conley & Udry 2010; Van den Broeck & Dercon 2011; Beaman et al. 2015; Emerick et al. 2016; overview by De Janvry et al. 2017). Although the importance of social networks for technology adoption is widely acknowledged, several studies still model farmers as independent actors. In addition, some studies use proxies such as group membership or geographical proximity to describe networks, which neglect actual social interactions among farmers (Breza 2016). Recent research has collected more detailed data on social interactions, but relied on network sampling strategies that due to missing information can only reflect certain aspects of the network (Santos & Barrett 2010; Conley & Udry 2010; Maertens & Barrett 2012; Murendo et al. 2017). The collection of detailed census data is rare (exceptions Van den Broeck & Dercon 2011; Jaimovich 2015). In this dissertation, we add to the literature by using data on actual communication networks within farmer groups as potential pathways that may induce behavioral change, and hence the adoption of technologies. Persons we share information with, shape our views, attitudes, and actions explicitly or implicitly. Consequently, communication networks may play a particularly strong role for the adoption of technologies in the setting of group-based extension due to dynamics that may trigger peer pressure or competition (Munshi 2008; Breza 2016). Therefore, we use detailed information on communication networks of 48 farmer groups, combined with a randomized controlled trial (RCTs) in which the treatment groups received group-based extension that focused on a pro-nutrition technology.

In addition, communication networks may easily change over time (Comola & Prina 2017). Due to the lack of actual network data, there is consequently a lack of panel network data, too. These data can give evidence on how interventions such as the provision of group-based agricultural extension can contribute to an increased (or decreased) information exchange, and hence strengthen (or weaken) the social capital of groups (Maertens & Barrett 2012). A recent study by Arcand & Wagner (2016) for instance, suggests that the structure of CBOs become more inclusive when development projects are channeled through them. However, the authors focus on group membership status before and after the intervention and not on actual data on social interactions. To the best of our knowledge, this dissertation is the first that uses panel data on actual communication networks to establish evidence on how group-based extension can influence these networks. To assure a proper identification of our treatment effect, we use the above-mentioned RCT which allows us to compare communication networks of untreated farmer groups with the networks of farmer groups that received grouped-based extension.

In summary, the second essay in Chapter 3 of this dissertation adds to the literature by investigating if interventions, such as agricultural extension, affect agricultural communication networks and if these communication networks can act as pathways leading to the adoption of new technologies.

1.3 Research objectives

This dissertation contains two essays that address the mentioned research gaps by analyzing communication networks within farmer groups from different angles. The first essay in Chapter 2 is set in the context of nutrition-sensitive extension. We study the structure of nutrition and agricultural communication networks within farmer groups and characterize key persons within these networks. In the second essay in Chapter 3, we detect how agricultural communication networks are affected by the offer of group-based agricultural extension, and which role communication networks play for the individual adoption decision. Specifically, we answer the following questions:

1. How does the structure of agricultural and nutrition information networks look like within farmer groups?
2. What are the characteristics of persons forming links to exchange agricultural and nutrition information; and do these networks overlap?

3. Are there certain prominent or influential key persons within farmer groups that are important for agriculture and nutrition information networks and what are their characteristics?
4. Are there isolated persons that are excluded from these information networks and what are their characteristics?
5. How do interventions, such as agricultural extension, affect agricultural communication networks?
6. How are individual adoption decisions influenced by communication and the decision making of others in a farmer group setting?

The results can help to develop network targeting strategies for nutrition-sensitive programs and design policies regarding group-based agricultural extension.

1.3.1 Study background and data

The study is set in Nyamira and Kisii County, in the western part of Kenya. In these densely populated counties, more than half of the population depends on the agricultural sector. Most commonly, farmers grow maize, beans, bananas, sugar cane, tea, and horticultural crops. The farming system is characterized as diverse, and depends on small land sizes, with almost all of the land being under cultivation (Mbuvi et al. 2013). Kisii and Nyamira have two cropping seasons (March-July; September-January). Regarding the nutritional status, one-quarter of the children are stunted in Kisii and Nyamira Counties, defined as being too short for their age. Stunting can be an indication for malnutrition. At the same time, a third of the women of reproductive age are overweight or obese (KNBS 2015). Against this background, the promotion of pro-nutrition technologies – coming along with agronomic and nutrition training – could contribute to an improvement of the farmer's livelihood.

1.3.2 Data

The output of this dissertation is embedded in the interdisciplinary ADDA project, which stands for "Agriculture and Dietary Diversity in Africa". The aim of the project is the impact evaluation of a group-based extension approach that delivered a combination of agricultural, nutrition and marketing information to farmers. The information treatments were tailored to the promotion of a pro-nutrition technology, the black bean variety KK15. Therefore, the author and her team designed and implemented a RCT (for more information on the RCT design see Chapter 3.2.3).

In a first stage, 48 farmers groups in Nyamira and Kisii County in Kenya were randomly sampled from a list of existing farmer groups. In a second stage, 20 members per farmer group were randomly chosen for interviews. Data were collected before (October until December 2015) and after (October until December 2016) the intervention (March until September 2016). During both data collection waves, information on a household level was collected with help of structured questionnaires. Also group level data was elicited with help of a group level questionnaire, answered by one of the group officials. Apart from the collection of detailed agricultural and nutrition-related data, a special focus was put on the collection of network data.

The network module was answered by the group member and the questions were asked in a dyadic fashion: the respondents indicated for all member of their group 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), asset sharing, whom they would borrow money from, whom they visit. Finally, also questions related to agricultural activities were elicited. Overall 824 respondents were interviewed during the baseline survey in 2015 and 746 respondents during the follow-up survey in 2016. The first essay in Chapter 2 of this dissertation builds on the baseline data collected in 2015, while the second essay in Chapter 3 builds on the RCT and uses baseline and follow-up data.

2 Nutrition communication in agricultural information networks[1]

Abstract. Agriculture can play a central role in improving nutrition. One way of making agriculture more nutrition-sensitive and thus combating malnutrition is to deliver nutrition information that particularly target farmers. In developing countries, community-based organizations (CBOs) and individuals within CBOs are important target units for agricultural programs. However, little is known about the flow of information within CBOs and between individuals. The objective of this study is to investigate the structure and characteristics of communication networks for nutrition and agriculture. First, we identify the structure of agricultural and nutrition information networks within CBOs, as well as overlaps of the two networks. Dyadic regression techniques are then used to explore the characteristics of persons forming links for agriculture and nutrition. Second, key persons within CBOs that are prominent or influential for agriculture and nutrition information networks are identified, as well as characteristics of persons that are excluded from these networks. Analysis is conducted using descriptive and econometric techniques such as fixed effect Poisson models. Our study finds that nutrition information is exchanged within CBOs but to a moderate extent. Further, agricultural and nutrition information networks overlap and often the same links are used for both topics. At the same time, a large number of people are excluded from nutrition information networks. These persons are more likely to be men, have smaller land sizes and are less connected to persons outside of the group We conclude that there is room for nutrition training to sensitize group members and nudge communication exchange about nutrition related issues. In particular, we recommend incentivizing communication with isolated persons. Further, our regression results suggest targeting CBO leaders, as well as other group members that live in central locations as an entry point for training. The results can help to increase the outreach of nutrition-sensitive programs.

Keywords: Communication networks, centrality, community-based organizations, nutrition-sensitive agriculture, dyadic regression.

[1] This chapter is co-authored by Theda Gödecke (TG) and Meike Wollni (MW). LJ, TG and MW jointly developed the research idea. I, LJ, collected the survey data in 2015 and 2016, did the data analysis, and wrote the essay. MW and TG commented at the various stages of the research and contributed to writing and revising the essay.

2.1 Introduction

Globally, about 800 million people suffer from hunger. Most of the hungry, especially in rural areas of developing countries, depend on agriculture for food and income (FAO 2015; IFPRI 2011). As agriculture can play a central role in improving nutrition, making agriculture more nutrition-sensitive has become an important topic in the recent development discourse (IFPRI 2016; Fan & Pandya-Lorch 2012; Hawkes & Ruel 2008). One way of making agriculture more nutrition-sensitive, and thus combating malnutrition, is to deliver nutrition information that particularly target farmers. Delivering nutrition knowledge with improved targeting can contribute to better outcomes of nutrition-sensitive programs (Ruel et al. 2013). A possible platform to channel nutrition information might be through existing extension systems. In the extension systems of developing countries, community-based organizations (CBOs) and individuals within CBOs are important target units (Anderson & Feder 2007). The rationale of targeting CBOs or key individuals within CBOs it to reduce transaction costs. It is assumed that costs will be reduced because 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 the flow of information within CBOs and between CBO members.

Furthermore, little evidence exists on how agricultural extension services - that usually target both men and women - should be designed to combine information on agriculture and nutrition. An increasing body of literature analyzes the impact of nutrition-sensitive programs (De Brauw et al. 2015; Olney et al. 2015; Osei et al. 2017; for an extensive overview see Ruel et al. 2018). However, most of the evaluated programs target mothers, households with children or women groups since the objective of the programs is to improve the nutritional status of children. Also, women play an important role for agriculture, but extension sessions are still predominantly attended my men (Ragasa et al. 2013). CBOs, especially when dealing with mixed-gender groups, could be a useful platform to sensitize both, men and women, on nutrition-related topics. Therefore, it is of high importance to understand how farmers communicate about nutrition and agriculture.

Moreover, studies have identified the importance of key persons within networks, particularly in the context of health and nutrition-specific interventions. In addition, individual social networks play a major role in the adoption of new technologies (Conley & Udry 2010; Matuschke & Qaim 2009; Maertens & Barrett 2012; Maertens 2017; Murendo et al. 2017).

Aubel (2012) argued that targeting and training mothers only might not be sufficient for better child nutrition outcomes. Hence, community level communication networks and participation of culturally accepted key persons such as grandmothers should be taken into account. A study by Kim et al. (2015) documented that the targeting of influential individuals plus their friends can help to increase project outreach. Similarly, Moestue et al. (2007) found that mothers with large information networks are associated with better child nutrition. Overall, these studies emphasize the need for further research on the targeting of influential actors besides women for better nutrition outcomes in developing countries.

However, targeting key persons may not always be successful. 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). Therefore, they recommend incentivizing link formation with less popular people. Similarly, Maertens (2017) found that farmers mostly learn from a few progressive farmers who consequently have a (too) powerful role in deciding on the overall success or failure of technologies. To be able to assess how information diffuses, it is crucial to have data on the networks' structure, in the best case in form of a census of all individuals. These studies are rare even though they are 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 cites (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 for nutrition and agricultural communication networks and to characterize key persons within these networks. The results could help to develop network targeting strategies for nutrition-sensitive programs.

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? Forth, what are the characteristics of isolated persons that are excluded from these networks?

The rest of the essay is structured as follows. Chapter 2.2 presents the study area and data collection. In Chapter 2.3, we introduce the network measures and estimation strategies employed on CBO, dyadic and individual levels. Chapter 2.4 presents the results, and Chapter 2.5 concludes and derives policy implications.

2.2 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.[2] 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.

[2] 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).

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 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 2.3). 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 exchanged 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 exchange information with member j but j states not to exchange with i (Wasserman &

Faust 1994). 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).

2.3 Network measures and estimation strategy

2.3.1 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

$$D_g(m)=\frac{L_g(m)}{n_{ig}(n_{ig}-1)}, \tag{2.1}$$

where i refers to the group member (nodes). All nodes i are embedded in their CBOs g, that vary with respect to their number of members n_{ig}. Within CBOs, each node can potentially engage in conversation with $n_{ig}-1$ members. A link l_{ij} is defined as a binary variable, being one if an 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.

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.

2.3.2 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:

$$\mathrm{l_{ij}(m)} = \alpha_1\, \mathrm{s_{ij}} + \alpha_2\, (\mathrm{x_i} - \mathrm{x_j}) + \alpha_3\, (\mathrm{x_i} + \mathrm{x_j}) + \varepsilon_{\mathrm{ijg}}\,, \tag{2.2}$$

where $\mathrm{l_{ij}}$ is a binary variable that equals one if a link between group member *i* and *j* exists for network *m*. The vector $\mathrm{s_{ij}}$ 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 $\mathrm{x_i}$ and $\mathrm{x_j}$ 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. $\varepsilon_{\mathrm{ijg}}$ is the dyadic error term. Due to the complexity of the models, we model the binary dependent variables using linear probability

[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).

models (LPM)[5]. Summary statistics of variables used in the dyadic regression are presented in Table A2.1 in the Appendix.

2.3.3 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 & Faust1994). 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

$$d_{ig}^{in}(m)=\sum_j l_{ji}(m), \qquad (2.3)$$

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.

Yet, being prominent cannot be equated with frequently transmitting information to others. Therefore, it is recommended to also study influential people, measured by their out-degree (Hanneman & Riddle 2005). Out-degrees represent the number of persons within CBO *g* that group member *i* indicates to exchange information with about *m*. Out-degrees, as a proxy for the influence of a person, are defined as

$$d_{ig}^{out}(m)=\sum_j l_{ij}(m). \qquad (2.4)$$

Finally, isolates can be defined based on in-degrees, out-degrees or a combination of both. We apply the most comprehensive definition where $ISO_{ig}(m) = 1$ if $d_{ig}^{in}(m)$=0 and

[5] For comparison, logit estimates are shown in Table A4 in the Appendix.

$d_{ig}^{out}(m)$=0, and $ISO_{ig}(m) = 0$ 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*), household (*H*) and group (*G*) characteristics. The econometric model is specified as

$$d_{ig}(m) = \beta_0 + \beta_1 I + \beta_2 H + v + \varepsilon, \tag{2.5}$$

where d measures the in-degree $d_{ig}^{in}(m)$ or out-degree $d_{ig}^{out}(m)$ 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*. [6] 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 (2.5) using fixed-effects Poisson regressions (Wooldridge 2002).

Finally, we model isolation as a function of individual (*I*), household (*H*) and group (*G*) related variables:

$$ISO_{ig}(m) = \partial_0 + \partial_1 I + \partial_2 H + \partial_3 G + \mu, \tag{2.6}$$

where $ISO_{ig}(m) = 1\ if\ \ d_{ig}^{in}(m)$=0 and $d_{ig}^{out}(m)$=0, and $ISO_{ig}(m) = 0$ otherwise, and μ is an i.i.d. error term following a normal distribution. Given the binary nature of the dependent variable, equation (2.6) is estimated using Probit regressions. Table A2.2 gives an overview of the individual and household level variables included in the Poisson and Probit models. Information on group-level variables is provided in Table 2.1.

[6]). 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. Results are shown in Table A2.5 in the appendix. G consists of CBO related variables such as whether the group's main ativity is agriculture or whether the group received external support.

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 & 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 still 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.

2.4 Results

2.4.1 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 2.1). 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 2.1) were initially formed for the KAPAP program that aimed at increasing agricultural productivity through the delivery of trainings to CBOs.

The network densities presented in Table 2.1 and Figures 2.1 and 2.2 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 2.1). This reflects the fact that our sample consists of relatively small community-based organizations, whose members know each other and frequently interact.

Table 2. 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 male within group	0.39	0.25	0	1
Female only (1=yes)	0.08	0.28	0	1
Female dominated (>=60%) (1=yes)	0.38	0.49	0	1
Balanced (40-59%) (1=yes)	0.33	0.05	0	1
Male dominated (>=60%) (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.

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 2.1), and everyone is connected (Figure 2.1). In contrast, nutrition information networks are sparse: average density indicates that only 9% of all potential links are formed to exchange nutrition information (Table 2.1), and in total 16% of group members are completely isolated from nutrition information exchange within their groups (Figure 2.2).

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* are positively correlated (correlation: 0.18), indicating some overlap between the networks. Yet, the 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 81.5% are at the same time agricultural links, and thus, only 18.5% of the nutrition links are exclusively *NUTRITION*. Thus, our results suggest that nutrition information is mostly transmitted through existing channels of agricultural information exchange.

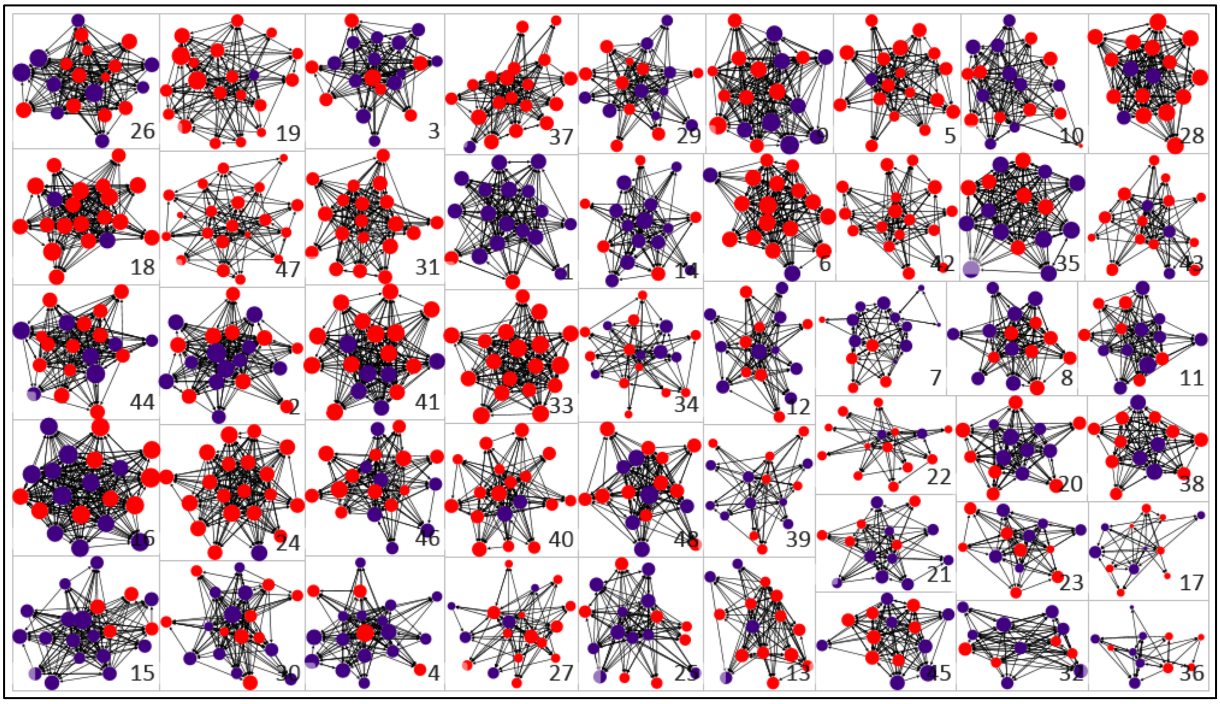

Figure 2. 1 *AGRICULTURE*. Color of nodes: gender (red=female, blue=male); Size of nodes: in-degrees; Numbers indicate the CBOs' IDs.

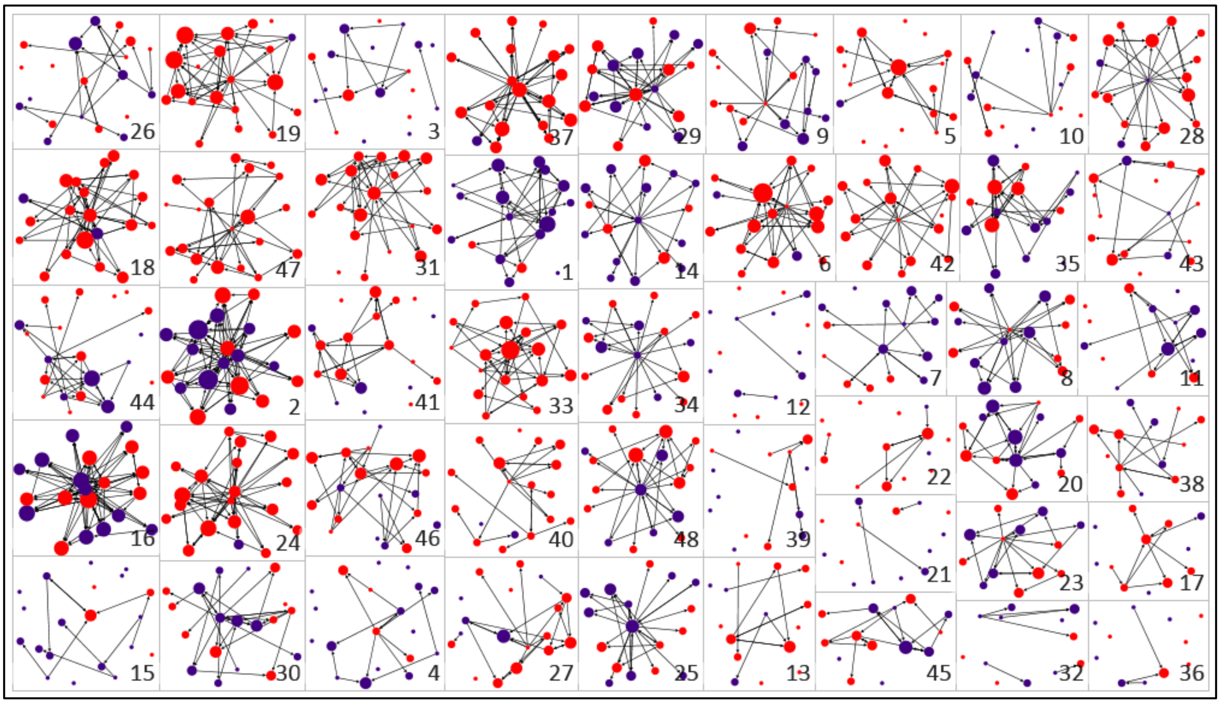

Figure 2. 2 *NUTRITION*. Color of nodes: gender (red=female, blue=male); Size of nodes: in-degrees; Numbers indicate the CBOs' IDs.

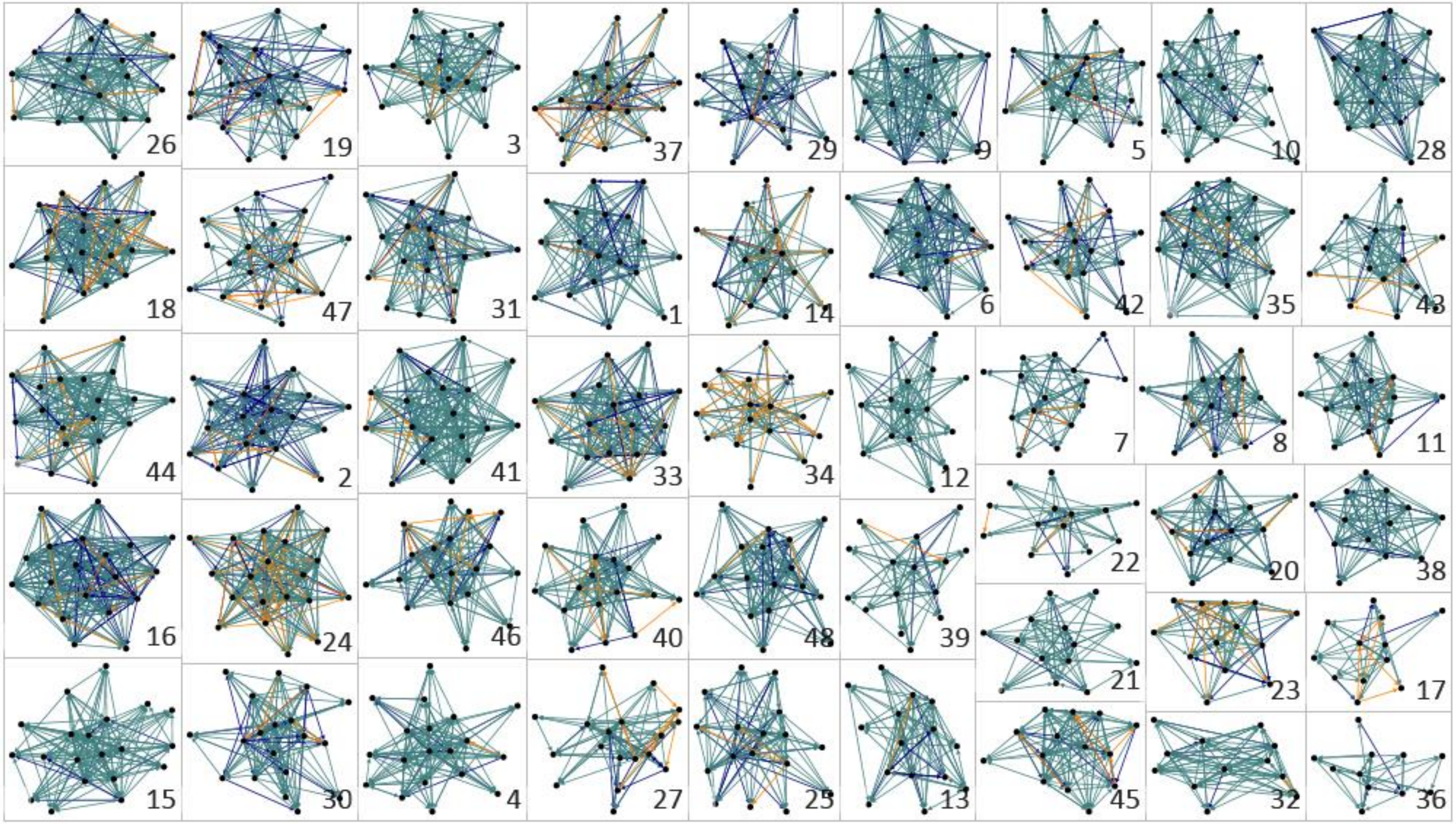

Figure 2. 3 ***Multiplexity*** **of** ***AGRICULTURE*** **and** ***NUTRITION*****: Color of links: orange= nutrition only (233 links), turquoise = agriculture only (5624 links), dark blue = multiplex links (both nutrition and agriculture (1014 links).**

2.4.2 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 2.2). 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. 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

Note: 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.

2.4.3 Results on an 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 2.4 shows the distributions of in-degrees (*prominence*) and out-degrees (*influence*) for both communication networks.

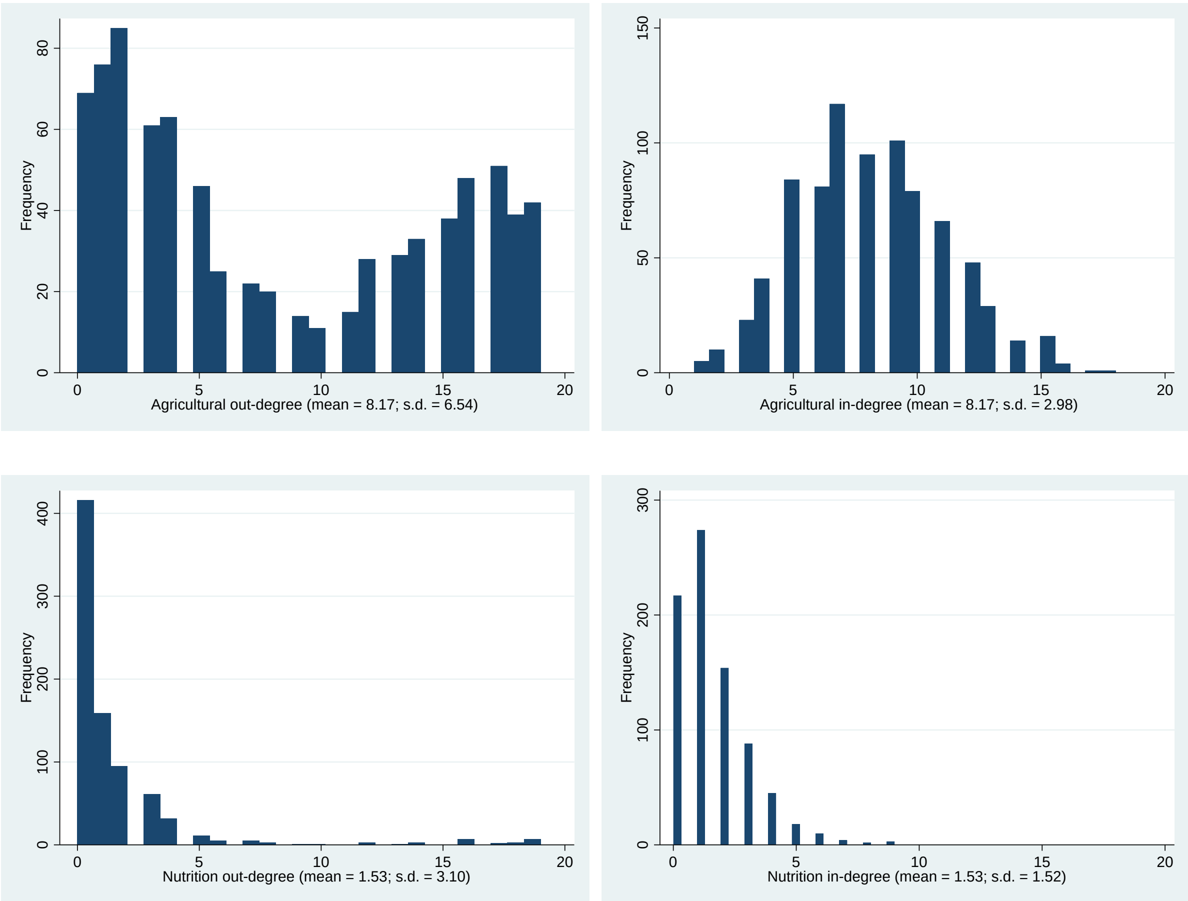

Figure 2. 4 Distributions of out-degrees and in-degrees for *AGRICULTURE* and *NUTRITION*.

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 2.3). 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, confirming the traditional view that agriculture is a male domain. 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 2. 3 Fixed-effect Poisson 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)	0.0636***	-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 (no links) for NUTRITION[7]

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 women are significantly less likely to be isolated from the nutrition network. Furthermore, group leaders and members with a larger external network are less likely to be isolates. Finally, 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 to be found in older groups (who supposedly have built stronger social capital over time), smaller groups, and groups with a main focus on agriculture.

[7] It is possible that the variables do not capture all possible group level heterogeneity. Hence omitted variables bias may be a concern and for that reason, it is suggested interpreting the coefficients as trends.

Table 2. 4 Probit regression analysis of isolates for *NUTRITION*

	$ISO_{ig}(NUTRITION)$
	$d_{ig}^{in}(m)$=0 and $d_{ig}^{out}(m)$=0
Individual level variables	
Gender (1=male)	0.214*
	(0.129)
Years of education	0.0148
	(0.0186)
Age in years	-0.000326
	(0.00496)
External links named	-0.0679***
	(0.0232)
Spatial centrality proxy	-0.222
	(0.146)
Group leadership position (1=yes)	-0.346***
	(0.134)
Household level variables	
Land size (acres)	-0.0940*
	(0.0534)
Economic dependency ratio	-0.0170
	(0.0466)
Small business activities (1=yes)	-0.0859
	(0.122)
Group level variables	
External support (1=yes)	-0.0725
	(0.120)
Group's age in years	-0.0846***
	(0.0175)
Main function agriculture (1=yes)	-0.653***
	(0.138)
KAPAP group (1=yes)	0.0763
	(0.154)
Actual group size	0.0678***
	(0.0157)
Female dominated (>=60%)	-0.156
	(0.135)
Potential links (n_g-1)	-0.139***
	(0.0273)
Constant	1.146**
	(0.561)
N_H=815	

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

2.5 Conclusion

One way of making agriculture more nutrition-sensitive and thus combating malnutrition can be to deliver nutrition information that particularly target farmers within CBOs. However, little is known about the flow of agricultural and nutrition information within CBOs and the prominent and influential key persons embedded in these networks. This knowledge can however be crucial to effectively and efficiently deliver agricultural or nutrition related information to farmers. This study therefore contributes to fill this gap by addressing the following questions; First, how does the structure and density of agricultural and nutrition information networks look like within CBOs and do these networks overlap? Second, what are the characteristics of persons forming links to exchange agricultural and nutrition information? Third, are there certain prominent or influential key persons within CBOs who are important for agriculture and nutrition information networks and what are their characteristics? Forth, are there isolated persons that are excluded from these networks and what are their characteristics?

The analyses conducted in this study have shown that nutrition information is exchanged within CBOs, albeit to a moderate extent. Hence, we conclude that there is room for nutrition training to sensitize group members and nudge communication exchange about nutrition related issues. Due to a large number of isolated persons for *NUTRITION*, we recommend to particularly incentivize the communication with isolates who are more likely to be male, have smaller land sizes and are less connected to persons outside of the group. Our findings support Caria & Fafchamps (2015) who suggest encouraging links with less popular persons to increase the network's efficiency. Having a deeper look at how information is transmitted, we find that agricultural and nutrition information networks overlap and often the same links are used for *NUTRITION* and *AGRICULTURE*. Based on these results we conclude that nutrition information can be transmitted through existing agricultural information links, and thus, incorporating nutrition training into more traditional agricultural trainings may indeed be a promising approach to make agriculture more nutrition-sensitive.

However, when looking at who forms links and who is prominent, we find gender differences: On a dyadic level, men tend to exchange more information with men for both networks, while women tend to stick to women for *NUTRITION*. Hence, traditional perceptions about responsibilities and roles for both topics are confirmed. The formation of homogeneous links is a common behavior, however, not the most effective way for communication networks. Sticking to people that are like oneself may limit ones social world and exposure to new information (McPherson et al. 2001). Therefore, we suggest targeting both men and women complimentarily. Men should get invitations to nutrition training and women should receive special invitations to agricultural extension sessions. This is of special importance in times where diabetes, hypertension and obesity as well as undernutrition are prevalent in rural African communities, affecting both, men and women (Popkin et al. 2012).

Poisson regression results as well as dyadic regression results suggest using group leaders and persons living in central locations as an entry point for training. This is already widely practiced and is reasonable since it may culturally not be acceptable to bypass these informal hierarchies. However, using group leaders as only entry points may lead to elite capture and hence inefficiencies (World Bank & IFPRI 2010).

Further research is needed to deepen the understanding of group heterogeneity and dynamics. In times where farmer groups are still an attractive target unit for development projects, it is crucial to understand how they are functioning and how groups respond to interventions. Our results so far do not show clear differences in terms of the exchange of agricultural and nutrition information between CBOs with a main focus on agriculture compared to CBOs with other foci. However, panel network data and a rigorous impact assessment would be needed to be able to understand if CBOs with different characteristics respond differently to interventions. For further investigation detailed panel network data is required. After understanding the underlying dynamics of CBOs, interventions can contribute to increasing a group’s social capital and ultimately help to turn it into a valuable asset itself.

2.6 Appendix A2

Table A2. 1 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. 2 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
Female dominated (>=60%)	= 1 if yes, 0=otherwise	0.38	0.49
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 A2. 3 Group related summary statistics including missing links

Information flows (N_D=1014)	N_G	Mean	s.d.	Minimum	Maximum
In-degree	48	15.13	2.57	9.41	18.73
Agric. In-degree	48	7.87	2.49	2.91	14.05
Nut. In-degree	48	1.41	0.93	0.12	4.41

Table A2. 4 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 A2. 5 Fixed-effect Poisson regression analysis of centrality measures for *AGRICULTURE* and *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)	0.0986***	0.0530	-0.124	-0.00920
	(0.0325)	(0.0641)	(0.0926)	(0.122)
Years of education	-0.000383	0.00536	0.00117	0.0371
	(0.00461)	(0.00907)	(0.0119)	(0.0229)
Age in years	0.00104	0.00358	-0.00283	0.000529
	(0.00192)	(0.00256)	(0.00364)	(0.00693)
External links named	0.0121***	0.0604***	0.0194	0.121***
	(0.00386)	(0.0103)	(0.0130)	(0.0210)
Spatial centrality proxy	0.0169	-0.0579	0.0854	0.345**
	(0.0267)	(0.0786)	(0.0720)	(0.169)
Group leadership position (1=yes)	0.128***	0.149***	0.353***	0.464***
	(0.0211)	(0.0456)	(0.0692)	(0.144)
Household level variables				
Land size (acres)	0.0197	0.00171	-0.00433	0.0464
	(0.0125)	(0.0181)	(0.0272)	(0.0504)
Economic dependency ratio	0.0107	0.0169	0.0188	0.0575
	(0.00768)	(0.0258)	(0.0203)	(0.0472)
Small business activities (1=yes)	-0.0373	-0.0958*	0.0706	0.0377
	(0.0260)	(0.0517)	(0.0749)	(0.145)
Group level variables				
External support (1=yes)	0.0528	0.0482	0.253	0.244
	(0.0708)	(0.0632)	(0.167)	(0.160)
Group's age in years	0.00558	0.00760	0.0150	0.0158
	(0.00684)	(0.00616)	(0.0132)	(0.0113)
Main function agriculture (1=yes)	0.164**	0.162**	0.379***	0.366***
	(0.0697)	(0.0645)	(0.144)	(0.139)
KAPAP group (1=yes)	-0.0129	-0.0387	-0.0992	-0.177
	(0.0793)	(0.0728)	(0.198)	(0.192)
Actual group size	-0.0134	-0.0154*	-0.0245	-0.0374
	(0.00947)	(0.00886)	(0.0230)	(0.0237)
Female dominated (>=60%)	0.101	0.0900	0.0677	0.119
	(0.0736)	(0.0673)	(0.147)	(0.142)
Potential links (n_g-1)	0.0818***	0.0817***	0.162***	0.159***
	(0.0155)	(0.0162)	(0.0395)	(0.0411)
Constant	0.622**	0.330	-2.322***	-3.278***
	(0.315)	(0.309)	(0.701)	(0.888)
N_H=815				

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

3 The Role of Farmer's Communication Networks for Group-based Extension: Evidence from a Randomized Experiment[8]

Abstract. A growing body of literature focuses on the role of network effects for farmers' adoption decisions. However, little is known on how interventions affect networks. We analyze the effect of group-based trainings on networks and the influence of these networks on the adoption of technologies. Our analysis builds on a unique dataset that combines a RCT with detailed panel data on communication networks. The RCT was implemented in rural Kenya and consisted of varying combinations of group-based agricultural and nutrition training sessions. The purpose of the extension training was the promotion of the iron-rich black bean variety KK15. Survey data from 48 farmer groups (824 households) was collected before (2015) and after (2016) the intervention. Results suggest that, first, the intervention had a positive impact on communication among farmers (i.e. the creation of communication links). Second, besides positive direct effects of the intervention, we also find strong positive network effects on adoption, indicating that individual farmers are more likely to adopt, the higher the share of adopters in their communication network. Hence, group-based extension approaches can be efficient in diffusing new technologies, not only because they reduce transaction costs, but also because network effects can stimulate and drive technology adoption.

Keywords: Network effects, communication networks, RCT, group-based extension

[8] This chapter is co-authored by Andrea Fongar (AF), Theda Gödecke (TG), Mercy Mbugua (MM), Michael Njuguna (MN), Sylvester Ogutu (SO) and Meike Wollni (MW). I (LJ) developed the research idea, collected the survey data in 2015 and 2016, did the data analysis, and wrote the essay. AF, SO, MM provided assistance in data collection and MN took part in the design of the RCT. MW and TG commented at the various stages of the research and contributed to writing and revising the essay.

3.1 Introduction

The adoption of new technologies is key for the economic development of smallholder farmers in Sub-Saharan Africa. Unfortunately, adoption rates remain behind expectations (Evenson & Gollin 2003; Emerick et al. 2016). Several factors determine the adoption of technologies, with information and social networks being the ones most widely discussed (Aker 2011). In settings where formal institutions do not work properly, information gained through informal networks can serve as substitute (Breza 2016). In particular in these settings, networks play an important role for the diffusion of information and consequently for the adoption of new technologies (Foster & Rosenzweig 1995; Bandiera & Rasul 2006; Munshi 2008; Conley & Udry 2010; Van den Broeck & Dercon 2011).

Although the importance of social networks for technology adoption is widely acknowledged, several studies still model farmers as independent actors. Other studies use rough proxies (such as group membership). These proxies neglect actual social interactions among famers (Breza 2016). Recent research has collected more detailed data on social interactions, but relied on network sampling strategies that due to missing information can only reflect certain aspects of the network (Santos & Barrett 2010; Conley & Udry 2010; Maertens & Barrett 2012; Murendo et al. 2017). The collection of detailed census data is rare (exceptions include Van den Broeck & Dercon 2011; Jaimovich 2015). Due to these data constraints, Maertens & Barrett (2012) encouraged the use of detailed network data to be able to, for example, understand how networks change over time and respond to interventions. The underlying question is whether interventions, such as the provision of group-based agricultural extension, can contribute to an increased (or decreased) information exchange, and hence strengthen (or weaken) the social capital of groups. Since then, an emerging body of literature developed on social networks and their impact on technology adoption (Emerick et al. 2016; Beaman et al. 2015; overview by De Janvry et al. 2017). However, we are not aware of any study that uses data on actual communication networks to establish evidence on how group-based extension can influence communication networks and how these networks then influence individual adoption behavior. Therefore, we aim to understand how farmers that are embedded in groups communicate and how communication networks can promote the adoption of new technologies. We contribute to the literature by using a panel data set of detailed information on communication networks within farmer groups, combined with a RCT. The insights generated by our study can help to make agricultural extension more effective.

RCTs have become the gold standard in social science to establish causality. Yet, while RCTs help to rule out selection bias, the pathways that finally lead to behavioral change often remain a black box (Fafchamps 2015). In this article, we combine panel network data with a RCT in order to shed some light on potential drivers of change. Since the persons we share information with shape our views, attitudes and actions explicitly or implicitly (Munshi 2008; Conley & Udry 2010; Breza 2016), communication networks can be considered potential pathways through which behavioral change, and thus technology adoption, occurs. In the context of group-based extension, communication networks potentially play a particularly strong role due to dynamics that trigger peer pressure or competition. Combining the RCT with panel network data allows us to explicitly rule out or control for network changes induced by the intervention. In the case of communication networks this is likely to be especially relevant as they can change easily over time, compared to less flexible networks based e.g. on kinship or neighborhood. So far, according to Comola & Prina (2017), all studies using detailed network data (besides their own study) are cross-sectional and thereby assume that networks are static.

In summary, little is known if interventions, such as agricultural extension, affect agricultural communication networks. Further, the question on how the individual adoption decision is influenced by communication and the decision making of others in a farmer group setting remains unanswered. Based on the presented research gaps we derive our specific research questions: first, can group-based extension approaches help to enhance communication networks, and second, do these networks contribute to fostering technology adoption?

The RCT was implemented in rural Kenya and consists of varying combinations of group-based agricultural and nutrition training sessions. The purpose of the extension training was the promotion of the iron-rich black bean variety KK15. Survey data from 48 farmer groups (824 households) was collected before (2015) and after (2016) the intervention. Our analysis is based on dyadic regressions and linear probability models. This essay is organized as follows: Chapter 3.2 discusses the experimental design and research setting, Chapter 3.3 elaborates on the econometric approach, Chapter 3.4 presents the results and Chapter 3.5 concludes.

3.2 Experimental design and research setting

3.2.1 Background on extension approaches

Delivering agricultural extension to farmers can take place in many different ways (Anderson & Feder 2007). The extension officers can visit individual farmers to advise them, extension service can be provided to groups of farmers, or extension officers can train so called model or contact farmers, who then share the new information with their peers. An increasing body of literature has analyzed the effect of the model farmer approach, with mixed results. Kondylis et al. (2017) for instance found that even if model farmers adopt a technology, their adoption decision has little impact on the adoption decision of other farmers. Maertens (2017) argues that farmers mostly learn from a few progressive farmers. Training exclusively these progressive and powerful farmers consequently bears the risk of project failure in case they eventually decided not to commit to the project.

The group-based extension approach is widely used by development practitioners (Anderson & Feder 2007). Advantages are that, first, working with groups of farmers reduces transaction costs compared to visiting a large number of dispersed individual farmers. Second, the group-based approach is considered as pro-poor since, it is beneficial for women and low-educated farmers in East Africa (Davis et al. 2012). Third, group-based approaches are participatory and said to be efficient in spreading information and hence promoting new technologies (Fischer & Qaim 2012).

3.2.2 Research area

The study is based on a randomized field experiment in which the partnering NGO, Africa Harvest Biotech Foundation International (Africa Harvest), delivered group-based extension training to farmers in Kisii and Nyamira County in Kenya. In these densely populated Counties, more than half of the population depends on the agricultural sector. Most commonly, farmers grow maize, beans, bananas, sugar cane, tea, and horticultural crops. The farming system is characterized as diverse, and depends on small land sizes, with almost all of the land being under cultivation (Mbuvi et al. 2013). Kisii and Nyamira have two agricultural seasons (March-July; September-January). Regarding the nutritional status, one-quarter of the children are stunted in Kisii and Nyamira Counties, which means being 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 training could contribute to an improvement of the farmer's livelihood.

3.2.3 Randomized experiment

The aim of the project was the diffusion of agronomic and nutrition knowledge, as well as the promotion of the black bean variety KK15 which is high in iron and zinc. KK15 was bread conventionally at the Kenyan Agriculture and Livestock Research Organization (KALRO) in Kakamega. Besides its nutritional benefits, KK15 is high-yielding and root-rot resistant. Most of the farmers in our sample grow beans and frequently consume them. However, black beans are not common in our research area and the different color and unknown taste of the new variety may hinder farmers from adopting KK15. Farmers in all groups were able to order the black bean KK15. At any time, farmers had the option to place an order for the bean through the group leader, who then informed the extension officers. In the treatment groups, in addition to the trainings, the bean seeds were subsidized with 30% of the market price.

The training sessions varied in intensity and content (agronomy, nutrition, and marketing) along three treatment arms. Farmers in the first treatment group received seven agronomic training sessions that focused on the attributes and cultivation practices of KK15. The second treatment group received the very same seven agronomic training sessions and additionally three nutrition education sessions. During the nutrition education sessions, farmers were taught on topics related to an adequate human nutrition including modules on balanced diets, food groups and breast feeding practices among others. The overall aim of the nutrition education sessions was to sensitize farmers on the mentioned topics, and to eventually increase their nutritional knowledge. Treatment three received the same as treatment two (seven agricultural training sessions, three nutrition education sessions), plus three marketing sessions. The marketing sessions entailed a theoretical and a practical component. The theoretical part aimed at training farmers on different marketing strategies. The practical component linked farmers with bean traders so that they could jointly discuss the marketing options for KK15. We followed a phase-in design, meaning that also the control group received extension training in 2017 after the follow-up survey was completed.

The extension sessions were harmonized regarding the messages delivered and the way the farmers were mobilized. Information on time and date of the next meetings was agreed at the end of each session. In addition, group leaders and individual members were contacted three days before the sessions took place. Besides the efforts to inform the farmers about the extension sessions, training attendance was not incentivized and entirely voluntary.

3.2.4 Sampling and data collection

The baseline data was collected in 2015 between October and December. The sampling frame was based on existing farmer groups is Kisii and Nyamira County. We selected 48 farmer groups randomly, proportionate to the number of farmer groups per County (16 in Nyamira, 36 in Kisii). The lists of members were carefully checked and cleaned with help of the group leaders before the survey, resulting in an average group size of 21 members. In a second step, based on the adjusted group member lists, about 17 households were randomly sampled and interviewed in each of the selected groups. During baseline, 824 group members were interviewed. After the baseline survey, 36 farmer groups were randomly assigned to treatment and 12 farmer groups to control. The training sessions started in February 2016 and were completed in September 2016. The implementation was closely monitored by the researchers. Afterwards, the follow-up survey took place between October and December 2016. During the follow-up survey, we interviewed the same group members again. Only 78 households could not be interviewed (e.g., respondent passed away, migrated or travelled for longer periods). In addition, the partnering NGO collected detailed information on training attendance as well as information on who ordered the KK15 variety. To ensure uniformity of data collection, standardized participation lists and ordering forms were developed.

3.2.5 Network data

To collect data on social networks within the groups, we asked all randomly selected group members about their links to all (interviewed or not) fellow group members concerning different kind of information networks and measures of proximity (relationship, sharing the same plot borders, sharing inputs). Since the treatment primarily dealt with the delivery of agricultural information, we analyze, whether the training sessions affected the corresponding network, namely the agricultural information network.

A link lij is defined as a binary variable, turning one if information about a certain topic is exchanged. The link questions were framed as: did you share information on agriculture with NAME? The reference period for all questions referred to the last 12 months. On average, around 80% of group members were interviewed, which gives us close to full census data.

Overall, 815 respondents answered the network module during baseline. During the follow-up visit, we were able to collect network data from 719 respondents. We take our network as undirected, meaning we take a link as existing as soon as i or j stated to share information. This assumption is widely applied (Comola & Prina 2017; De Weerdt & Fafchamps 2011; Banerjee et al. 2013). Our dataset consists of 48 block-diagonal matrices since we have only data on information flows within farmer groups, but not across them. Within farmer groups, each respondent can engage in conversation with n_{g-1} members since self-links are excluded where n is the number of members of farmer group *g*.

3.2.6 Attrition

Our attrition rate of 12% shown in Table 3.1 is in general low compared to other RCTs (Ashraf et al. 2014). Normally, statistical techniques are used to control for attrition bias. However, our research design allows us to avoid attrition in a straight-forward way. Our main variables of interest are the communication network variables as well as the variables on KK15 adoption. To avoid the loss of network data, we take the relationship as reciprocal: let us assume to have information from *i* about *j*, but *j* is an attritor: *i* cites to build a communication link with *j*, but we miss information on whether j also cites *i*. We then replace the missing data of *j* with the information given by *i*. Hence, our undirected network dataset consists of 815 group members and 6659 pairs of dyads per year.

Table 3. 1 Attrition per treatment arm on farmer group level

Treatment group	Interviewed 2015	Interviewed 2016	Attrition	Attrition %
Control	207	183	24	0.12
Treatment	608	536	72	0.12
Treatment 1	*203*	*188*	*15*	*0.07*
Treatment 2	*205*	*170*	*35*	*0.17*
Treatment 3	*200*	*178*	*22*	*0.11*
Total Sample	815	719	96	0.12

Further, we avoid attrition by replacing the missing adoption variable (self-reported data on whether the farmer planted KK15) with the administrative data collected by the partnering NGO. We thus implicitly assume that the farmers who ordered the beans have also received and planted them[9]. This strategy allows our estimates to be based on 815 observations on individual level.

3.2.7 Balance and compliance

Table A3.2 and A3.3 (Appendix A3) compare treatment and control group covariates at baseline. Table A3.2 shows the dyadic balance table which is used for our first research question on the impact of group-based extension on network changes, while Table A3.3 shows the balance table on individual level, which is relevant for the second research question addressing network effects on the individual adoption decision. In general, around 60% of our respondents are female, completed primary education (which is the equivalent to eight years of schooling in Kenya), and farm on average a bit more than an acre of land. While all households have received agricultural information at some point in the past, almost half of the respondents indicated in the baseline that they had accessed nutrition information (Table A3.3). The sample means on a dyadic level show that a little less than a third of all potential links are close relatives (kinship) and around ten percent of all links share the same plot border (Table A3.2). While most variables at baseline are balanced between treatment and control group, a few statistically significant differences are found, in particular, regarding age and education. The respondents in the treatment group are on average older and less educated compared to respondents in the control group (Table A3.2 and A3.3). In the econometric analysis, we take the unbalanced variables into account by including them as baseline controls.

The overall compliance rate, including partial compliance, is 70%, indicating that 426 of the 608 interviewed group members, who were assigned to treatment, attended at least one training session. On the average, farmers attended 38% of the training sessions offered to them (for more details, see Table A3.4 in the Appendix A3).

[9] The administrative data slightly underreports the actual adoption recorded in our survey. According to the administrative data 116 farmers in our sample ordered KK15, compared to 146 farmers who reported in the survey to have planted KK15. The discrepancy is due to the fact that a few farmers received seeds from fellow group members or occasionally placed joint orders. By replacing the missing data with administrative data, we thus potentially underestimate the true impact of the intervention.

3.3 Econometric approach

3.3.1 Dyadic intent-to-treat on agricultural information networks

To answer our first research question, i.e. whether group-based extension training has an impact on agricultural communication networks, we estimate intent-to-treat (*ITT*) effects on link formation in a dyadic framework.

$$l_{ij}(t_1)= \alpha_0+ \alpha_1 ITT+ \varepsilon_{ij} \tag{3.1}$$

where $l_{ij}(t_1)$ is a binary variable, turning one if an agricultural communication link between individual i and j exists at time t_1 (follow-up). As noted earlier, we take the network as undirected, assuming that a link exists as long as either i or j stated so. In the intervention, we implemented three different treatment arms that all impart agricultural training, but vary in terms of their intensity and additional contents. Here, we only focus on the overall impact of the group-based extension intervention on agricultural information networks, summarizing the three arms into one treatment.[10] Hence, *ITT* is a dummy taking the value of one, if the respondent was assigned to any of the treatment arms, and zero, if the respondent was assigned to the control group. Our main coefficient of interest is the *ITT* effect measured by parameter α_1. It tells us the effect of being assigned to the treatment group on the likelihood of forming a communication link at follow-up. Standard errors ε_{ij} are clustered at a dyadic level. We are using grouped dyadic OLS regressions, following Fafchamps & Gubert (2007).

In a second specification, we include baseline control variables X_{ij} for those covariates that showed significant differences between control and treatment group at baseline (see Table A3.2). According to Carter et al. (2013), this step can increase the accuracy of our estimates.

$$l_{ij}(t_1)= \beta_0+ \beta_1 ITT+ \beta_2 X_{ij} + \varepsilon_{ij}. \tag{3.2}$$

Any observed increase in communication associated with the intervention can be triggered by two mechanisms: first, it is possible that the contents of the training stimulated sharing of agricultural information. Second, simply the fact that group members spent more time together during the training sessions may have induced more information exchange in general and hence also on agricultural topics. In order to control for a potential increase in the general

[10] We tested whether treatment 2 and treatment 3 had additional effects on the communication network (see Appendix A3, Table A3.1). We did not find significant differences between the treatments, which justifies the choice of treating the three arms as one.

frequency of communication, and thereby isolate the treatment effect of the agricultural extension intervention, we also include in the above specification a binary variable that turns one, if the frequency of general information sharing increased from baseline to follow-up[11].

In principle, observed changes in communication associated with the intervention can be driven by two components: the creation of new links and the decision to maintain or quit old links. To gain further insights into the underlying dynamics of network changes triggered by the intervention, we estimate two additional model specifications exploring the effect on new link formation (n_{ij}) and the maintenance of existing links (d_{ij}).

$$n_{ij}= \delta_0+ \delta_1 ITT+ \varepsilon_{\mathrm{ij}} \tag{3.3}$$

First, n_{ij} is a binary variable that equals one, if $l_{ij}(t_0) = 0$ (at baseline) and $l_{ij}(t_1) = 1$ (at follow-up), i.e., if a link is newly created, and zero otherwise. The parameter of interest, δ_1, indicates whether new communication links are more likely to be formed in treatment groups, compared to control groups.

$$d_{ij}= \lambda_0+ \lambda_1 ITT+ \varepsilon_{\mathrm{ij.}} \tag{3.4}$$

Second, d_{ij} is a binary variable that equals one, if $l_{ij}(t_0) = 1$ and $l_{ij}(t_1) = 0$, i.e., if an existing link was dropped, and zero otherwise. The parameter of interest, λ_1, indicates whether existing communication links are more likely to be dropped in treatment groups, compared to control groups. Following the same procedure as in (3.2), we also estimate equations (3.3) and (3.4) including baseline control variables X_{ij}.

3.3.2 Individual intent-to-treat regressions with network effects

Lastly, we want to detect how communication networks can contribute to promoting the adoption of technologies of individuals. We hypothesize that the intervention can work directly – farmer *i* is offered training, receives information regarding the KK15 bean, which convinces *i* to adopt – or can be channeled through network effects. In the case of group-based extension, fellow group members are also assigned to the treatment, potentially leading to higher adoption rates of the KK15 bean variety within treated groups. Higher adoption rates in farmer *i's* network increase his/her exposure to KK15 and thus his/her likelihood to

[11] The frequency of general information sharing was asked in the following manner: *How often did you talk with NAME between October 2015 and September 2016?*

adopt the bean variety, too. We therefore add a network effect component to the individual *ITT* regressions. Given that treatments are assigned at the group level, the *ITT* effect and the network effects are not separately identified[12], but we consider the network effects as (partial) mechanisms through which the effectiveness of group-based extension may be improved.

The analysis is conducted on an individual – or monadic – level (not on a dyadic level) and the model is specified as follows (modified from Plümper & Neumayer 2010):

$$y_i = \delta_0 + \delta_1 ITT + \rho \sum w_{ij} y_j + \delta_2 X_i + \varepsilon_i \qquad (3.5)$$

Our outcome variable y_i is the adoption decision of individual i at follow-up (t_1). We are interested in ρ, the network effect, which measures the effect of the variable $\sum w_{ij} y_j$ on our dependent variable. The network effect variable indicates the extent to which *i* is connected to other adopters and can be interpreted as an increase or decrease of the likelihood of being an adopter, if all network members *j* were adopters, too. It consists of two parts: a vector of weighing matrices w_{ij}, which indicate the connectivity to other group members (whether a link exists between *i* and *j*) and y_j indicating the adoption decision of *j*. It is important to note, that all weighing matrices are in a second step multiplied with the adoption decision of individual *j*. Hence, for the calculation of network effects, only the adopting links are taken into account, while the non-adopting links turn zero. All network effect variables are normalized by dividing the adopters in *i's* network by the respective network size of w_{ij}.

We estimate the effect of five different networks w_{ij} on the individual adoption decision to be able to identify the networks that are most prominently driving the adoption decision of *i*. To start with, the network effect is based on agricultural links that *i* cited at baseline, i.e., before potential changes could have been induced by the intervention. This will be referred to as "Network effect (baseline)". Then, based on this baseline agricultural network, we derive the following three network effects: first, we look at new agricultural links, referring to links that did not exist at baseline ($l_{ij}(t_0)=0$) but exist at follow-up ($l_{ij}(t_1)=1$) ("Network effect (new links)"). This allows us to investigate whether newly created links influence the individual adoption decision, or whether they are too instable or occasional to really matter for the

[12] Bramoullé et al. (2009) and Comola & Prina (2017) use the characteristics of the friends of friends to instrument the endogenous network effect. We cannot apply this procedure, since in our case both the treatment allocation and the network data collection took place at group level, and consequently the persons farmer *j* cites are frequently also connected to farmer *i*.

decision making process. Second, we consider the role of old, intensified agricultural links: these links existed at baseline, still exist at follow-up, and the frequency of information exchange increased from baseline to follow-up ("Network effect (intensified links)"). We consider these links as strong and stable and therefore expect the intensified network effects to be larger compared to the new network effects. Third, we define w_{ij} as the agricultural leadership network ("Network effect (group leaders)"). This network captures farmer *i*'s agricultural information links with persons in group leadership positions. We hypothesize that leaders act as important role models in farmer groups and their behavior may, therefore, be especially influential in the adoption decisions of fellow group members.

Lastly, we focus on a network based on geographical proximity ("Network effect (geographical)"). In this case, a link exists, if *i's* and *j's* plots share the same border at t_0[13]. As opposed to the previous network definitions, this network is not based on communication links reflecting the actual exchange of agricultural information. Nonetheless, geographical proximity may facilitate observation and learning from the experience of neighboring farmers. Such neighborhood effects are commonly seen as important drivers for the adoption of new technologies (Conley & Udry 2010; Liverpool-Tasie & Winter-Nelson 2012; Krishnan & Patnam 2013).

The network effect, as described above, is composed of two components: the links to other group members and the actual adoption decision of these links. If observed network effects are small, this could be the result of either low network activity of farmer *i*, or low adoption activity within the network. To control for differences in individual network activity, we therefore add the total size of the agricultural information network at t_0 of farmer *i*. Furthermore, vector X_i contains a binary variable that equals one if the farmer holds a leadership position to control for his social role within the group, as well as baseline control variables. Inference is a common problem when dealing with social network effects, because the outcomes of *i* and *j* are likely to be correlated. To control for within-group correlation we cluster the standard errors at farmer group level in specification (5), which is a common procedure (Breza 2016). Due to the complexity of the models (1) to (5), we model the binary

[13] This information was elicited with the following question: *Is NAMES's plot bordering yours?*

dependent variables using linear probability models (LPM).[14] We are aware that simultaneously i may have an effect on j's decision, which implies a reflection problem (Manski 1993; Manski 1999). In our case, we do not consider the simultaneous dynamics as problematic since we are not per se interested in who learns from whom, but rather in tracing the overall role of group dynamics in the adoption process.

Table 3. 2 Definition of different networks w_{ij}

Networks w_{ij}	Description	Number of l_{ij}	Mean (s. d.)
Network (baseline)	Number of agricultural links *i* cited at baseline	9692	0.73 (0.45)
Network (new links)	Number of agricultural links *i* did not cite at baseline, but *i* cited at follow-up	1538	0.12 (0.32)
Network (intensified links)	Number of agricultural links *i* cited at baseline and follow-up, for which the frequency of information sharing increased	2550	0.19 (0.39)
Network (group leaders)	Number of agricultural links *i* cited at baseline that are at the same time group leaders	2861	0.21 (0.41)
Network (geographical)	Number of links *i* cited at baseline to share the same plot border with	1174	0.08 (0.28)
N_D	Number of all potential links	13318	

Note: Since the network variables are undirected, but the adoption decision of j is directed, we have a total number of observations of 13318 (2*6659, because each link is regarded twice: from *i's* and *j's* perspective, respectively).

3.4 Results

3.4.1 How does group-based extension affect agricultural communication networks?

Table 3.3 provides summary statistics of agricultural communication networks. At baseline, 73% of all potential links were formed, with no significant difference between treatment and control groups. In the follow-up survey, overall lower levels of network activity for agricultural information exchange were recorded, however, significantly more links were

[14] We are aware of the problem that LPM estimates can be outside the interval of [0;1]. However, the use of LPM has the advantage of being easily interpreted and estimates are often close to the probit or logit results (Horrace & Oaxaca 2006).

formed in treatment (57%) than in control groups (46%). Furthermore, in treatment groups 13% of potential links were newly formed links, compared to only 7% in control groups (Table 3.3).

Table 3. 3 Descriptive statistics of dyadic dependent variables

	(1)	(2)	(3)	(4)
Dependent variables	Total number of l_{ij}	Control	Treatment	Control-Treatment
		Mean (s.d.)	Mean (s.d.)	Mean difference (t-value)
$l_{ij}(t_0)$	4846	0.73	0.73	0.00805
		(0.44)	(0.45)	(0.64)
$l_{ij}(t_1)$	3617	0.46	0.57	0.11***
		(0.50)	(0.49)	(-8.22)
n_{ij}	769	0.07	0.13	0.06***
		(0.26)	(0.34)	(-6.69)
d_{ij}	1.998	0.35	0.28	-0.06***
		(0.48)	(0.45)	(4.87)
N_D	6659	1705	4954	6659

Note: Coefficients in (2) and (3) indicate a mean share of links that was created*:* l_{ij} refers to agricultural links at baseline (t_0) and follow-up (t_1) respectively; n_{ij} refers to newly created agricultural links if $l_{ij}(t_0)$=0 & $l_{ij}(t_1)$=1; *dij* refers to dropped agricultural links if $l_{ij}(t_0)=1$ & $l_{ij}(t_1)=0$. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The dyadic regression results reveal that being assigned to the intervention (*ITT*) significantly increases the likelihood of link formation. Farmers assigned to the treatment group are 11 percentage points more likely to engage in information exchange on agriculture compared to the control group. Given the fact that on average 54 percent of possible agricultural links are formed at follow-up (Table 3.4), 11 percentage points can be interpreted as a significant contribution to network activities. Hence, we argue that the offer of group-based extension had a significantly positive effect on agricultural information sharing. This result remains robust when we control for changes in the general frequency of communication as well as for covariates that are unbalanced between treatment and control groups at baseline.

The significantly higher network activity observed in the treatment group as compared to the control group could be caused by two different underlying dynamics: first, the intervention may have triggered the formation of new links; second, the intervention may have contributed to the maintenance of existing links in the treatment group to a larger extent than in the control group. Our results show positive *ITT* effects on the creation of new links and no significant impact on dropping existing links (Table 3.5). This implies that the significant increase in network activities compared to the control group mainly stems from the creation of new links. We therefore conclude that the provision of group-based extension service encourages agricultural information sharing not only through the existing but also importantly through newly created links.

Table 3. 4 Effects of treatments on communication networks

	(1) $l_{ij}(t_1)$	(2) $l_{ij}(t_1)$
ITT	0.114**	0.110**
	(0.0464)	(0.0472)
Constant	0.458***	0.238**
	(0.0409)	(0.121)
Controls	No	Yes
Mean dependent variable	0.54	0.54
N_D	6,659	6,659

Note: $l_{ij}(t_1)$ refers to agricultural links at follow-up. *ITT* refers to the intent-to-treat effect and is a dummy turning 1 if *i* and *j* are treated. Coefficients are shown with robust standard errors corrected for dyadic correlation of errors and grouped on a farmer group level. Baseline controls include a dummy variable indicating whether a positive change in communication frequency took place from baseline to follow-up, *i* and *j* being both male (dummy), and sums and differences of land size, age and years of education. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table 3. 5 Effects of treatments on new link creation and canceling old links in communication networks

	(1) n_{ij}	(2) n_{ij}	(3) d_{ij}	(4) d_{ij}
ITT	0.0598***	0.0597***	-0.0626	-0.0655
	(0.0173)	(0.0171)	(0.0394)	(0.0398)
Constant	0.0710***	0.131**	0.347***	0.409***
	(0.0123)	(0.0642)	(0.0355)	(0.0937)
Controls	No	Yes	No	Yes
Mean dependent variable	0.12	0.12	0.30	0.30
N_D	6,659	6,659	6,659	6,659

Note: nij refers to newly created agricultural links if *t0=0* & *t1=1*; *dij* refers to dropped agricultural links if *t0=1* & *t1=0*. *ITT* refers to the intent-to-treat effect and is a dummy turning 1 if *i* and *j* were treated. Coefficients are shown with robust standard errors corrected for dyadic correlation of errors and grouped on a farmer group level. Baseline controls include a dummy variable indicating whether a positive change in communication frequency took place from baseline to follow-up, *i* and *j* being both male (dummy) and sums and differences of land size, age and years of education. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

3.4.2 Can communication networks contribute to promoting technology adoption?

Summary statistics of the different network effects tested in the individual level intent-to-treat regressions are provided in Table 3.6. Given that the network effects are row-standardized, mean values can be interpreted as the share of adopters within the respective network of farmer *i*. On the average, farmer *i's* agricultural baseline network contains 19% adopters. The average share of adopters in the group leader network is comparatively high with 24%, reflecting generally higher adoption rates among leaders.

Table 3. 6 Descriptive statistics of individual-level network effect variables $\sum \boldsymbol{w_{ij} y_j}$

Network effect $\sum w_{ij} y_j$	Description	Mean (s.d.)
Network effect (baseline)	Share of adopters among *i's* agricultural baseline network	0.19
		(0.22)
Network effect (new links)	Share of adopters among *i's* new network	0.11
		(0.25)
Network effect (intensified links)	Share of adopters among *i's* intensified network	0.16
		(0.29)
Network effect (group leaders)	Share of adopters among *i's* links to leaders	0.24
		(0.33)
Network effect (geographical)	Share of adopters among *i's* geographical network	0.12
		(0.27)
N		815

Note: All network effects are normalized by the total number of network members w_{ij} farmer *i* cited.

The intent-to-treat estimates show that our intervention has a positive effect on the individual decision to adopt KK15 (Table 3.7, model 1). Farmers assigned to the extension treatment are 23 percentage points more likely to adopt, compared to the control group. The individual intent-to-treat effects are robust to the inclusion of further control variables (Table 3.7, model 2). Our results further reveal that leaders have a 10 percentage point higher probability of being an adopter. Moreover, farmers with a larger agricultural information network at baseline are more likely to later become adopters, although the effect size is relatively small. Each additional agricultural information link at baseline – irrespective of adoption status – increases *i's* probability of adoption by one percentage point.

Our results suggest that network effects in general play a crucial role for the individual adoption decision. Furthermore, we observe heterogeneous effects depending on the chosen network definition (models (3) – (7) in Table 3.7). The share of adopters in the agricultural network at baseline (model 3) has a particularly large effect on the individual adoption decision: if all agricultural network links are adopters, *i*'s likelihood of also being an adopter are around 74 percentage points higher. Note that by using the baseline agricultural network, we rule out network changes induced by the intervention. In contrast, models (4) and (5) test the effect of newly formed agricultural links and intensified agricultural links, which have potentially been affected by the intervention. Interestingly, the share of adopters among newly formed links does not significantly contribute to the adoption decision of *i*. While the dyadic regression results revealed that the intervention significantly increases the likelihood of new link formation, these new links are apparently not the ones driving individual adoption decisions. Instead, networks that are characterized by stability over time, such as the intensified agricultural information network and the geographical network, have significant effects on the individual adoption decision (models (5) and (7)). Lastly, the group leader network has comparatively large effects on adoption, confirming the important role model function of group leaders. The larger the share of adopters among the group leaders with whom *i* exchanges agricultural information, the higher is the probability that *i* is an adopter as well (model (6)). Group leaders may in fact also play an essential role in driving other observed network effects. In particular, 43% of the intensified links to adopters and 37% of the geographical links to adopters are at the same time links to group leaders, whereas none of the newly formed links is a link to a group leader[15].

It can be seen across model specifications in Table 3.7 that once we control for network effects, the coefficient of the direct intent-to-treat effect on the individual adoption decision decreases. This suggests that the impact of the group-based intervention on individual adoption decisions is to an important part channeled through communication networks and group dynamics. Accordingly, our results confirm that fostering positive group dynamics plays an important role for successful technology delivery and that in particular group leaders assume critical role model functions in this process.

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[15] Overall, 43% of the agricultural network links at baseline are group leader links. Note that the network effects are based on links that are at the same time adopters. Therefore, the high percentages of links to group leaders are partly driven by the fact that group leaders are more likely to be adopters.

Table 3. 7 ITT, ITT with balance controls, ITT with controls and different network effects

	(1) KK15 adopter	(2) KK15 adopter	(3) KK15 adopter	(4) KK15 adopter	(5) KK15 adopter	(6) KK15 adopter	(7) KK15 adopter
ITT	0.232***	0.226***	0.0382**	0.203***	0.166***	0.0807***	0.182***
	(0.0365)	(0.0365)	(0.0154)	(0.0375)	(0.0325)	(0.0237)	(0.0332)
I is group leader		0.0927***	0.0853***	0.0975***	0.0926***	0.0884***	0.102***
		(0.0316)	(0.0306)	(0.0317)	(0.0300)	(0.0295)	(0.0336)
Agricultural network size of *i*		0.0117**	0.00689**	0.0132***	0.0102**	0.00591*	0.0103**
		(0.00464)	(0.00331)	(0.00448)	(0.00386)	(0.00343)	(0.00422)
Network effect (baseline)			0.717***				
			(0.0670)				
Network effect (new links)				0.160			
				(0.103)			
Network effect (intensified links)					0.258***		
					(0.0732)		
Network effect (group leaders)						0.436***	
						(0.0603)	
Network effect (geographical)							0.282***
							(0.0868)
Constant	0.00483	-0.128*	-0.164**	-0.147**	-0.150**	-0.143*	-0.132*
	(0.00478)	(0.0758)	(0.0646)	(0.0719)	(0.0679)	(0.0735)	(0.0772)
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes
N	815	815	815	815	815	815	815
R-squared	0.070	0.103	0.236	0.113	0.136	0.210	0.142

Note: *ITT* refers to the intent-to-treat effect and is a dummy turning 1 if *i* and *j* were treated. Coefficients and robust standard errors clustered at farmer group level in parentheses are shown. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Control variables for unbalanced baseline covariates are included (age in years, years of education).

3.5 Conclusion

In this essay, we set out to analyze how group-based extension influences agricultural information networks, and to what extent different forms of networks affect individual decisions to adopt the black bean variety KK15. This essay is among the first using detailed network panel data to illustrate network changes within farmer groups in response to randomized interventions. Our results show that group-based extension significantly increased link formation in comparison to the control group. We could also show that this increase in network activity is predominantly driven by the creation of new information exchange links. Furthermore, the intervention had a positive effect on the individual adoption decision, both directly and through communication networks. Our results thus confirm the importance of fostering positive group dynamics that are conducive to technology adoption. Testing different forms of networks, we were able to show that in particular stable networks, such as agricultural information links that intensified over time or links with neighboring agricultural plots, tend to be relevant in shaping individual adoption decisions. In addition, our results confirm the important role model function of group leaders in the technology adoption process. By shaping network activity, group-based extension can thus be an efficient approach for technology delivery as long as it succeeds in fostering positive group dynamics conducive to technology adoption. In this regard, our findings suggest that it is especially critical to reach out to group leaders and farm households in central locations as important multipliers that influence their peers through communication networks.

Our study is based on unique panel network data combined with a RCT, which allows us to relax the common assumption that networks are static and explicitly study the network changes induced by the intervention. However, when analyzing the impact of the intervention on individual adoption decisions our data does not allow separately identifying the direct *ITT* effect and the network effect. Previously used instruments that can help to identify endogenous network effects, such as the characteristics of *j's* network partners (Bramoullé et al. 2009; Comola & Prina 2017), are in our case not applicable. This is because we implemented treatment allocation and network data collection both at the same level of farmer groups, and therefore the persons j cites are very likely also connected to i. This problem could be circumvented if e.g. the village instead of the farmer group is used as a reference frame for network data collection, or if it is feasible to randomize the treatment at the individual level. Neither of these strategies was feasible in our case. Our research focuses on communication networks within farmer groups, and extending the collection of detailed census network data to the village level would have been very time consuming and only possible at the cost of reducing the number of clusters (farmer groups) studied. Random assignment at the individual level is by definition precluded when studying a group-based extension approach. One option is to add an individual randomized component, such as sending a text message reminder to a randomly selected sub-set of farmers, but in a community setting even small differences in how farmers are treated may lead to mistrust and conflict and therefore not be ethically feasible. We believe that for data collection in general, but network data, which is usually costly, in particular, researchers should carefully consider the existing network sampling strategies and the local setting to find the most feasible, context-specific solution allowing them to address their research questions. Based on the insights on group-based extension generated by our study, we encourage further research combining RCTs with panel network data to compare the role of network effects between different extension approaches, including group-based but also e.g. model farmer approaches. This would eventually allow deriving more general conclusions regarding the effectiveness of different extension approaches, while taking changes in communication networks and group dynamics explicitly into account.

3.6 Appendix A3

Table A3. 1 Additional effects of treatment 2 and treatment 3 on network changes

	Treatment 1 vs. Control	Treatment 2 vs. Treatment 1	Treatment 3 vs. Treatment 2
	AGRIC. at t_1	*AGRIC.* at t_1	*AGRIC.* at t_1
ITT	0.131**	-0.0540	0.0597
	(0.0560)	(0.0539)	(0.0529)
Constant	0.458***	0.589***	0.535***
	(0.0409)	(0.0383)	(0.0380)
Controls	No	No	No
Attrition	Yes	Yes	Yes
N_D	6,762	6,706	6,556

Note: Treatment 1: agricultural training, treatment 2: agricultural training plus nutrition training, treatment 3: agricultural training plus nutrition training, plus market training. NUTRITION is a dummy turning one if a nutrition link between *i* and *j* was reported at follow-up. *AGRICULTURE* is a dummy turning 1 if an agricultural link between *i* and *j* was reported at follow-up. Shown are OLS estimates and dyadic standard errors grouped by farmer group in parentheses. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A3. 2 Balance check of baseline covariates on dyadic level (undirected network)

	(1) Control	(2) Treatment	(3) Control-Treatment
	Mean (s.d.)	Mean (s.d.)	
Dependent variables			
Agricultural Link (1=yes)	0.73	0.73	0.00805
	(0.44)	(0.45)	(0.0364)
Proximity			
Both female (1=yes)	0.46	0.44	0.0223
	(0.50)	(0.50)	(0.0589)
Both male (1=yes)	0.13	0.22	-0.0890**
	(0.33)	(0.41)	(0.0349)
Kinship (1=yes)	0.28	0.37	0.0368
	(0.45)	(0.48)	(0.0291)
At least one is group leader (1=yes)	0.22	0.23	-0.0645
	(0.41)	(0.42)	(0.0523)
Plots sharing same border (1=yes)	0.08	0.09	-0.0136
	(0.27)	(0.29)	(0.0107)
Diff in:			
Land size in acre	-0.09	0.12	-0.204**
	(1.31)	(1.69)	(0.101)
Years of education	0.32	0.06	0.26
	(4.91)	(5.02)	(0.341)
Years of age	-1.03	0.39	-1.427
	(14.58)	(16.59)	(1.031)
Trust towards others	0.01	0.06	-0.0505
	(0.63)	(0.61)	(0.0449)
External links	0.11	0.36	-0.249
Sum of:			
Land size in acre	2.64	2.86	-0.224
	(1.55)	(1.85)	(0.209)
Years of education	18.28	17.02	1.263**
	(4.95)	(5.54)	(0.605)
Years of age	87.52	95.02	-7.503***
	(17.34)	(19.60)	(2.315)
Trust towards others	0.57	0.50	0.0693
	(0.65)	(0.62)	(0.0743)
External links	9.22	8.83	0.393
	(3.78)	(3.99)	(0.446)
N_D	1,705	4,954	6,659

Note: (3) shows OLS estimates and dyadic standard errors, grouped by farmer group in parentheses; External links refers to the number of persons that the respondents reported to share information with outside of their farmer groups. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A3. 3 Balance check of baseline covariates on individual level

	(1) Control	(2) Treatment	(3) Control-Treatment
	Mean (sd)	Mean (sd)	Difference in means (t-value)
Gender (1=male)	0.34	0.40	0.06
	(0.48)	(0.49)	(1.41)
Years of Education	9.14	8.52	-0.62*
	(3.50)	(3.72)	(-2.09)
Age in years	43.76	47.44	3.674***
	(11.35)	(12.75)	(3.68)
Agricultural knowledge	1.16	1.09	-0.07
	(0.98)	(1.02)	(-0.81)
Access to nutrition info (1=yes)	0.48	0.45	-0.0260
	(0.50)	(0.50)	(-0.65)
External links	4.60	4.40	-0.20
	(2.68)	(2.76)	(-0.90)
Group leadership position (1=yes)	0.27	0.31	0.04
	(0.45)	(0.46)	(1.18)
Land size (acres)	1.32	1.43	0.10
	(1.02)	(1.23)	(1.08)
Economic dependency ratio	1.71	1.74	0.03
	(1.19)	(1.25)	(0.28)
N	207	608	815

Note: External links refers to the number of persons who the respondents reported to share information with outside of their farmer groups. Access to nutrition information is a dummy variable, turning one if the respondent accessed nutrition information from an external source during the last 12 months. Agricultural knowledge is a score counting the number of selected pro-nutrition innovations that the respondent is aware of. Asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table A3. 4 Compliance rates with training attendance

Variable	Mean	s.d.	Number of farmers assigned to treatments
Group member attending treatment 1 (dummy)	0.798	0.402	203
Group member attending treatment 2 (dummy)	0.673	0.470	205
Group member attending treatment 3 (dummy)	0.630	0.484	200
Group member attending all treatments (dummy)	0.701	0.458	608
Share of sessions attended in treatment 1	0.486	0.357	203
Share of sessions attended in treatment 2	0.355	0.345	205
Share of sessions attended in treatment 3	0.308	0.342	200
Share of total training attended in all treatments	0.383	0.356	608

Note: Treatment 1: agricultural training, treatment 2: agricultural training plus nutrition training, treatment 3: agricultural training plus nutrition training, plus market training. Abbreviation s.d. refers to standard deviation. Attendance dummy turns 1 for members that at least attended one training session.

4 General conclusion

Technology adoption remains below expectations in SSA and a lacking access to information is one of the most important obstacles. To facilitate the access to new information, particularly on pro-nutrition technologies, extension services, as well as informal social networks, can play important roles. However, little is known about the flow of agricultural and nutrition information within farmer groups and the prominent and influential key persons embedded in these networks. This knowledge can however be crucial to cost-effectively deliver information regarding the attributes of pro-nutrition technologies to farmers. Therefore, this dissertation contributes to the literature by analyzing agricultural and nutrition linkages from a network perspective. We investigate the structure of nutrition and agricultural communication networks within farmer groups and characterize key persons within these networks. We also characterize persons who might be excluded from these networks. We further detect how agricultural communication networks are affected by the offer of group-based agricultural extension, and which role communication networks play for the individual adoption decision. This dissertation is one of the first using detailed data on nutrition and agricultural communication networks of farmer groups.

First of all, we find by analyzing the structure of communication networks for agriculture and nutrition that nutrition and agricultural information are shared within farmer groups. We also find that these agricultural and nutrition information networks overlap and often the same links are used for sharing nutrition and agricultural information. Based on these information synergies, we conclude that nutrition information can be transmitted through existing agricultural information networks. We recommend that promoting pro-nutrition innovations and nutrition information through agricultural extension may be a promising approach to make agriculture more nutrition-sensitive. Since nutrition information are so far only shared to a moderate extent within farmer groups and a large number of persons are excluded from nutrition information networks, there is room for nutrition training to sensitize group members and nudge further communication exchange about nutrition related issues.

Nudging communication may be particularly successful when working with farmer groups: one key conclusion of my dissertation is that agricultural communication networks of farmers can be positively influenced by group-based extension. This is relevant from a policy perspective since we find evidence that group-based extension has the positive side-effect of fostering positive group dynamics, besides being cost-effective. By fostering positive network activity, group-based extension can thus be an efficient approach for technology deliver. In addition, the delivery of group-based extension has a positive effect on the individual adoption decision, both directly and through communication networks.

Last, my dissertation analyzes the characteristics of farmers that are central for the communication about agriculture and nutrition. The results can help to develop targeting strategies for nutrition-sensitive extension programs: we found a large number of isolated persons – persons who do not share information on nutrition at all – and we recommend incentivizing the communication with these isolates. Encouraging links with less popular persons can increase the network's efficiency (Caria & Fafchamps 2015). Regarding gender, we have observed that men tend to share information with men and women with women. Sticking to people that are like oneself may limit ones exposure to new information and is hence not the most effective structure for communication networks (McPherson et al. 2001). Therefore we suggest encouraging cross-gender information exchange during extension sessions, if the local context allows. This is of special importance in times where diabetes, hypertension and obesity as well as undernutrition are prevalent in rural African communities, affecting both, men and women (Popkin et al. 2012). The essays pointed out, that group leaders and persons that are located in geographically central locations are key for communication networks and the adoption of technologies. I, therefore, recommend to additionally targeting central persons. Reaching out to these important people and making sure that they attend the extension sessions – through incentives or special invites – could contribute to improved information diffusion, and hence, increased project outreach.

4.1 Limitations and room for future research

Our first essay characterizes important persons for nutrition and agricultural communication, and our second essay identifies networks that foster the adoption of technologies. Both essays point out the importance of group leaders as well as centrally located persons. However our results remain to some extent suggestive. Future research could rigorously test whether additionally targeting the people we considered as targeting-worthy can help to make agricultural extension more effective. This can be done by for example designing randomized experiments that compare group-based extension approaches with approaches that use important persons (influencer such as leaders, or persons with farms located at central locations) within groups as additional target points. Hence, there is still room for future research on network targeting especially in the context of agricultural extension systems.

A few limitations concerning our experimental design need to be mentioned. The treatment assignment on group level had justifiable reasons: our research interest was on the group-based extension approach, offering only a few members training would be unethical and dealing with groups is cheaper than dealing with many dispersed individuals. However, the fact that only group members were interviewed does not allow separating training effects from the network effects. Further, commonly used instruments for the endogenous network effects such as the characteristics of *j's* contacts" (Bramoullé et al. 2009; Comola & Prina 2017) are in our case not suitable since our treatment allocation and network data collection took place on a group level. Therefore, persons farmer *j* cites are very likely also connected to farmer *i*. It would have been ideal to have selected the respondents on a village level so that we had network information not only from group members but also from other non-treated villagers. This would allow the use of instruments and identification of peer effects and we could have drawn a conclusion on spill-over effects. Even though, collecting detailed network data on a village level may be interesting, it is very costly and was beyond the scope of this project.

Due to the fact that the offered technology (black bean variety KK15) was not easily available on the market, little or no adoption behavior is observed in the control group. If the control group adopted the technology without the training, we would have had a more suitable counterfactual for our network effects.

The project's timeframe of three years is another drawback of our design since it is certainly too short to measure an economic impact of the intervention. The extension treatments began in March 2016 and the follow-up survey started in October 2016, which gave the farmers depending on the region, one, maximum two cropping seasons to decide whether to plant the black bean variety KK15. During the follow-up survey, the beans were not yet harvested in some areas, which makes it difficult to measure the economic impact of our interventions. However, even in a short-term, our intervention showed positive effects regarding technology adoption and an increase in social capital of farmer groups.

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General Appendix

Questionnaire 2016 (shortened version)

Questionnaire number (adda_hhid) ___________________

HOUSEHOLD SURVEY 2016

AGRICULTURE AND DIETARY DIVERSITY IN AFRICA: AN APPLICATION OF RANDOMISED CONTROLLED TRIALS IN KISII AND NYAMIRA, KENYA.

Goettingen University-Germany, University of Nairobi-Kenya and Africa Harvest Biotech Foundation International (Africa Harvest) are carrying out a research on different aspects of agricultural development. We are currently doing a survey which aims to provide more understanding about farmers' production and marketing decisions, and nutrition and health status. Your participation in answering these questions is very much appreciated. Your responses will be **COMPLETELY CONFIDENTIAL** and will only be used for research purpose. If you indicate your voluntary consent by participating in this interview, may we begin?

MODULE 0 – HOUSEHOLD ID !

TARGET PERSON: GROUP MEMBER OR HOUSEHOLD HEAD

MODULE 1: HOUSEHOLD DEMOGRAPHIC INFORMATION

MODULE 2: LAND HOLDING IN ACRES

MODULE 3: NON-LABOUR PURCHASED INPUT USE

MODULE 4: CROP UTILIZATION

MODULE 5: LABOUR INPUTS !

MODULE 6: VARIETY/BREED AWARENESS AND UP-TAKE !

MODULE 7: VARIETY/BREED ATTRIBUTES, KNOWLEDGE & PERCEPTION

MODULE 8: LIVESTOCK PRODUCTION AND MARKETING

MODULE 9: HOUSEHOLD ASSETS

MODULE 11: OTHER SOURCES OF INCOME AND TRANSFER

MODULE 12: NON-FOOD EXPENDITURE

MODULE 13: INFORMATION ON CREDIT ACCESS

MODULE 15: ACCESS TO SOCIOECONOMIC INFRASTRUCTURE !

MODULE 17: SHOCKS EXPERIENCENCED BY THE HOUSEHOLD !

TARGET PERSON: GROUP MEMBER

MODULE 18: SOCIAL CAPITAL ENDOWMENT

MODULE 14: COMMUNITY OUTREACH METHODS

MODULE 19: SOCIAL NETWORKS

TARGET PERSON: PERSON RESPONSIBLE FOR FOOD PREPARATION
!

MODULE 20: HOUSEHOLD FOOD CONSUMPTION !

TARGET PERSON: MOTHER OR CARETAKER OF CHILD BETWEEN THE AGE OF SIX TO 59 MONTHS

MODULE 21: CHILD QUESTIONNAIRE – ONLY ONE CHILD WILL BE CONSIDERED

1.! TARGET PERSON: FIRT INDIVIUDAL

MODULE 22/1- FIRST INDIVIDUAL QUESTIONNAIRE (1)

!!!! MODULE 23/1 - DECISION MAKING

2.! TARGET PERSON: SECOND INDIVUDAL

MODULE 22/1- SECOND INDIVIDUAL QUESTIONNAIRE (2)

!!!!MODULE 23/2 - DECISION MAKING

Questionnaire number (adda_hhid) ___________________

We are researchers from Göttingen University-Germany, University of Nairobi-Kenya and Africa Harvest Biotech Foundation International (Africa Harvest). We are conducting research that aims to improve the knowledge on agriculture-nutrition linkages in the African small farm sector. We are particularly interested in understanding the mechanisms through which farmers can effectively adopt agricultural technologies that may improve their nutrition and health. We are currently conducting the first round of the survey last year and now will do a follow-up round.

This informed consent is for smallholder farmers [like you] who belong to farmer groups and have engaged in farming activities during the last one year (October, 2015 to September, 2016). We are inviting you to participate in this research that mainly focuses on nutrition and health status of smallholder farmers in this area. We will ask you and some members of your household detailed questions on various topics related to agriculture, social networks, nutrition and health. We will also need to take measurements of the height and weight of selected adults and children below 5 years of age in your household. Your participation in this interview is entirely voluntary. Your responses will be treated with utmost confidentiality and the data will be used for research purposes only.

Do you have any questions that we need to clarify? [Make clarifications in case there are questions]If *No*, do you agree to take part in this survey, including the interviews and the measurements of adults and children?

If *Yes* let the potential respondent write name and sign below

Name_________________________________

Signature______________________________

Questionnaire number (adda_hhid) ___________________

MODULE 0 – HOUSEHOLD ID

1	Household ID		8	County	
2	Group ID		9	Sub-County	
3	Date of interview		18	Ward	
4	Start Time (24 Hr)		17	Division	
5	End time (24 Hr)		10	Village	
6	HH head Full Name		11	GPS Coordinates	
7	Cell phone number				

12	**First visit date**	
1=Interview completed 2= Interview partly completed 3= Specify		
14	**Enumerator Name**	
13	**Second visit date**	
1=Interview completed 2= Interview partly completed 3= Specify		
15	**Enumerator Name 1**	
16	**Enumerator Name 2**	

Questionnaire number (adda_hhid) ____________________

TARGET PERSON: GROUP MEMBER OR HOUSEHOLD HEAD

Respondent MEMID: ____

MODULE 1: HOUSEHOLD DEMOGRAPHIC INFORMATION *(reference period between 1st Oct 2015 and 30th Sep 2016)*

Household composition***: Please list all household members (All those who are under the care of household head in terms of food and shelter provision, and those who normally live and eat their meals together), starting with the household head.***

1	2	3	4	5	6	7	10	11	12	13	14
MEMID	**Name of the HH member**	**Gender** *M = 1 F= 0*	**R/ship with HH head (*Codes A*)**	**Age in years**	**Years of formal education (*Highest level attained*)**	**Marital Status** *(Codes B)*	**# of months in the last 12 months [NAME] has been away from home**	**Main Occupation based on time spent** *(Codes D)*	**Household farm labour contribution** *(for those above 16 years of age in the upper category) (Codes E)*	**How many hours per day are dedicated to farm activities? (hr)**	**If you had a larger farm how many hours per day would be dedicated to farm acitivities?**
			1								

Code A
1= Head
2=Spouse
3=Son/daughter
4=Father/mother
5=Sister/brother
6=Grandchildren
7=Grandparents
8=Step children
9=Step parents
10 = Father/mother-in-law
11 =Sister/brother-in-law
12 = House girl
13 =Farm labourer
16=Nephew/Niece
14 = Other relative
15= Other Unrelated

Code B
1= Married-monogamous
2= Married polygamous
3= Single
4= Divorced/separated
5= Widow/widower

Code D
0= None
1= Farming (crop + livestock)
2= Casual labour on-other farm
3= Casual labour off-farm
4= Self-employed off-farm
5= Salaried employment (civil servant etc)
6=Student/school
77= Other (Specify)______

Code E
1= Part time
2= Fulltime
3=Does not work on farm

Questionnaire number (adda_hhid) ____________________

MODULE 2: LAND HOLDING IN ACRES *(period between 1st Oct 2015 and 30th Sep 2016)*

2.1. How much land do you own in acres? ________________

2.2. How much of your total land is under homestead? _______________

2.3. Do you have a title deed for your land? ___________Yes=1 (all land), No=0 (no land), Partly=3

Land category	**Short rain season (Oct-Nov 2015)**		**Long rain season (Mar-Apr 2016)**	
	Cultivated	Fallow	Cultivated	Fallow
1. Own land (A)				
2. Rented in (B)				
3. Rented out (C)				
4. Total irrigated land				

2.4. What is the average cost of renting land per acre (Ksh/per year)? _________

Questionnaire number (adda_hhid) ___________________

CODES FOR MODULE 3

Codes A

1 Maize
2 Rice
3 Sorghum
4 Millet
5 Cassava
6 KK 15 Beans
7 Other Field beans
8 Bananas
9 Cabbage
10 Cowpea
11 Groundnut
12 Soybean
13 Sweet potatoes
14 Orange Fleshed Sweet Potatoes (OFSP)
15 Black night shade
16 Sugarcane
17 Pineapple
18 Jute Mallow (Omutere)
19 Amaranthas leaves (Emboga)
20 Pumpkin leaves
21 Sukuma wiki (Kales)
22 Carrots
23 Passion Fruit
24 Irish potato
25 Bean leaves
26 Tea
27 Onion
29 Coffee
30 Napier grass
31 Avocado
32 Spider Plant
33 Vine Spinache
34 Pumpkin
35 Trees
36 Mangoes
37 Guava
38 Wheat
39 Paw Paw
40 Tomatoes
41 Loquat
42 Green grams
43 Tree Tomato
44 Strawberry
45 Spring Onion
46 Desmodium
47 Spinach
48 Arrow Roots
49 Green Peas
50 Physallis/Gooseberry
51 Corriander
52 Capsicum
53 Pepper
54 Grass
55 Butternut
56 Lemon
57 Beetroot
58 Cumcumber
59 Water melon
60 Tree Seedlings
61 Raspberry
63 Pyrethrum
64 Cowpea Leaves
77 Other__________________
78 Other__________________
79 Other___________________

Codes B

0. Local
1. Improved
2. Mixture

Codes C

1. Kilogram
2. Litre
3. 90 Kg bag (40 Gorogoro)
4. 50 Kg bag
5. 25 Kg bag
6. Gorogoro (2.25 kg)
7. Debe (18 kg/ 8 Gorogoro)
8. Wheelbarrow
9. Ox-cart
10. Bunch (bananas)
11. Piece/number
12. Not yet harvested (for perennials only)
13. Stools
14. Glass (250 gr)
15. Suckers
16. Bucket
17. Ml
18. Spoonful
19. 5 kg bag
20. 10 kg Bag
22. Yellow paper bag
23. Grams
24. Pick up
25. Trees
26. Green paper bag
27. Lines
28. Packet (250g)
29. Crates
30. Bundle
31. Handful
32. Cuttings
33. Vines
35. Lorry
36. Seeds
37. Bushes
38. 45kg bag
39. Bottle top
40. Seedlings
41. Tonne
42. 500 Ml glass
45. Cobs
46. Poles
47. Crop failure
48. Black paper bag
77 Other (specify)________

Questionnaire number (adda_hhid) ___________________

MODULE 3: NON-LABOUR PURCHASED INPUT USE *(1st Oct 2015 and 30th Sep 2016 planting seasons, record separately by plots)*

1	2	3	12	4	5	6			7			8	9			10			11	
Plot Code (*Use alphabets in Cap*)	Crop Grown ***A***	Land under crop (*acre*)	Intercrop (1=Yes; 0=No)	Number of trees	Crop variety **B**	Seed **C**			Fertiliser(planting) (Fill once for intercrops) **C**			Oxen/ tractor hire Cost	Farm manure (Fill once for intercrops) ***C***			Pesticides/herbicides ***C***			Crop output ***C***	
						Qty	units	Price /Unit	Qty	Units	Price /Unit	Ksh	Qty	unit	Price /unit	Qty	units	Price /unit	Qty	Unit
Short Rains																				
	KK 15 (6)																			
Long Rains																				
	KK 15 (6)																			
Perennial Crops																				

Questionnaire number (adda_hhid) ____________________

CODES FOR MODULE 4 (*period between **1st Oct 2015 and 30th Sep 2016***)

Codes A

1 Maize
2 Rice
3 Sorghum
4 Millet
5 Cassava
6 KK 15 Beans
7 Other Field beans
8 Bananas
9 Cabbage
10 Cowpea
11 Groundnut
12 Soybean
13 Sweet potatoes
14 Orange Fleshed Sweet Potatoes (OFSP)
15 Black night shade
16 Sugarcane
17 Pineapple
18 Jute Mallow (Omutere)
19 Amaranthas leaves (Emboga)
20 Pumpkin leaves
21 Sukuma wiki (Kales)
22 Carrots
23 Passion Fruit
24 Irish potato
25 Bean leaves
26 Tea
27 Onion
29 Coffee
30 Napier grass
31 Avocado
32 Spider Plant
33 Vine Spinache
34 Pumpkin
35 Trees
36 Mangoes
37 Guava
38 Wheat
39 Paw Paw
40 Tomatoes
41 Loquat
42 Green grams
43 Tree Tomato
44 Strawberry
45 Spring Onion
46 Desmodium
47 Spinach
48 Arrow Roots
49 Green Peas
50 Physallis/Gooseberry
51 Corriander
52 Capsicum
53 Pepper
54 Grass
55 Butternut
56 Lemon
57 Beetroot
58 Cumcumber
59 Water melon
60 Tree Seedlings
61 Raspberry
63 Pyrethrum
64 CowPea Leaves

77 Other__________________
78 Other__________________
79 Other___________________

Codes C

1. Kilogram
2. Litre
3. 90 Kg bag (40 Gorogoro)
4. 50 Kg bag
5. 25 Kg bag
6. Gorogoro (2.25 kg)
7. Debe (18 kg/ 8 Gorogoro)
8. Wheelbarrow
9. Ox-cart
10. Bunch (bananas)
11. Piece/number
12. Not yet harvested (for perennials only)
13. Stools
14. Glass
15. Suckers
16. Bucket
17. Ml
18. Spoonful
19. 5 kg bag
20. 10 kg Bag
22. Yellow paper bag
23. Grams
24. Pick up
25. Trees
26. Green paper bag
27. Lines
28. Packet (250g)
29. Crates
30. Bundle
31. Handful
32. Cuttings
33. Vines
35. Lorry
36. Seeds
37. Bushes
38. 45kg bag
39. Bottle top
40. Seedlings
41. Tonne
42. 500 Ml glass
45. Cobs
46. Poles
47. Crop failure
48. Black paper bag
77 Other (specify)________

Codes D

1. Farm gate
2. Village market
3. Main market
4. Collection center
77. Other (specify)_________

Codes E

1. Own bicycle
2. Bodaboda
3. Hired truck
4. PSV
5. Donkey/oxen
6. Walking
7. Own truck
8. Taxi
77 Other (sp.)
99. NA

Code F

1. Male household head
2. Female household head
3. Female spouse
4. Joint decision
5. Male spouse
77 Other (specify)__________

Questionnaire number (adda_hhid) ___________________

MODULE 4: CROP UTILIZATION *(in the period between 1st Oct 2015 and 30th Sep 2016)*

1	2		3		4		5		6		7		8		9	11	10	12	13	14
Crop **Code A** (Aggregated crop)	Total Crop Output (Enter the total crop output from the plots)		Consumption		Saved as seed		Gift, tithe, donations, paid as wages		Stored		Quantity sold		Price		Point of most sales **D**	Main Mode of transport **E**	Travel time to the point of sale (minutes)	Who mostly decides revenue use? **F**	Who mostly decides technology use e.g. variety **F**	Who mostly decides how much of the total output is consumed by the household? **F**
	Qty	*Unit* **C**	*Qty*	*Unit* **C**	*Qty*	*Unit* **C**	*Qty*	*Unit* **C**	*Qty*	*Unit* **C**	*Qty*	*Unit* **C**	*Ksh*	*Unit* **C**						
Short rain																				
KK 15 (6)																				
Long rain																				
KK 15 (6)																				
Perennial crop																				

4.1 How easily can you access the market for sale of your produce (crop and or livestock)? *(Circle the applicable)*
1. Very easy 2. Easy 3.Difficult 4. Very difficult

4.2 Rank three most important market access constraints, if there exists any (***Prompt Codes G below***) 1._________________2._________________3.________________
Codes G:1. Poor infrastructure 2. Distant markets 3. Poor market prices 4. Cheating on quality standards/weighing scales 5.Lack of contracts or reliable buyers 6.Exploitative middlemen
77. Other (specify): _________________

4.7 In the last one year did you order: 1 KK15 ____ (1.Yes; 0. No); 2. Kuroiler chicken ____ (1.Yes; 0. No);

If the respondent is not growing KK 15 beans, skip to module 5

4.3 How easily can you market your KK15/beans? *(Circle the applicable)*
1. Very easy 2. Easy 3. Difficult 4. Very difficult

4.4 What is the **MAIN REASON** for your answer in 4.3 above *(Circle the applicable)*
1. Distance to market 2. Colour of beans 3. Prices 4. Yield 5. Taste 6. Pest and disease resistance 7. Cooking quality 8. Nutritional value
77. Others (specify)___________ -99 N/A

4.5 When did you first order the KK15 bean seed? Date __________________ Month______________

4.6 When did you receive KK 15 seeds for the first order? Date__________________ Month__________________

MODULE 5: LABOUR INPUTS *(01.Oct 2015 to 30. Sept 2016 planting seasons, record **total man hours** worked by plot)*

1	2	3	4	5
Plot code	Plot size in acres	Plot manager *(F=0, M=1; Joint=3)*	Ploughing & harrowing Planting & thinning Applying fertiliser, Pesticide application (1st and 2nd) Weeding (1st and 2nd) Harvesting /Threshing/shelling/bagging	
			Family	Hired
Short Rains				
A				
B				
C				
D				
E				
F				
G				
H				
Long Rains				
A				
B				
C				
D				
E				
F				
G				
H				

Questionnaire number (adda_hhid) ___________________

5.6 What is the average <u>daily wage rate</u> for men and women in this village? Men________ Ksh/per day Women__________Ksh/per day

5.7 Given all the family labour (manual) available in your household, what is the **maximum land size** in acres that you could potetntially cultivate and keep under livestock? _________________________________

MODULE 6: VARIETY/BREED AWARENESS AND UP-TAKE

	1	2	3	14	4	15	5	6	7	8	9	10	11	12	13
	New breed/variety/technologies	Have you ever heard of this variety/breed? *(1=Yes; 0=No) If No skip to the next technology*	**Main** source of information on the new variety/breed? **Codes A**	How easily can you obtain information from **main source**? **Code D**	Have you ever planted /kept this variety/breed? *(1=Yes; 0=No) If NO, skip to 5*	If yes, name the most important reason for adopting **Code E**	If No to Q4, what was the main reason? **Codes C** *Then Skip to Q10*	What was the **main** source of breed kept/variety planted that year? **Codes B**	Number of seasons the variety has been planted, **since first** planting?	Number of years /variety/breed has been planted/kept	If you did not plant this variety/keep breed in 2016 what was the main reason? **Codes C**	Will you plant the variety/ keep the breed in future? *(1=Yes; 0=No, 88=don't know) if Yes skip to Q12*	What is the main reason? **Codes C**	Are you aware of the nutritional value of this variety or breed? (yes = 1, No = 0)	If yes to Q12 what was the source of information? **Code Code A**
3	*Kuroiler chicken*														
4	*Beans(KK15)*														

Code A	**Code B**	**Code C**	**Code D**	**Code E**
1= Farmer Coop/Union 2= Farmer group 3= Extension staff/office 4= Other farmers (neighbours/relative) 5= Market (e.g. Agro vet/stockist) 6= Radio programs 7= Research centre (trials/demos) (*name___* 8= NGO/CBO *(name______* *9= Health centre/Practitioner* 77= Other*(specify______)*	1= NGO free *(name_______)* 2= NGO subsidy *(specify______)* 3= Extension staff demo plots 4= Other farmers 5= Market (Agrovet/local trader/stockist) 6= Farmer group/coop 7=Agricultural association/training centre 77= Other*(specify _________)*	1= Seed not available 2=Day old chicks not available 3=Lacked cash to buy seed/DOCs 4= Lacked credit to buy seed/DOCs 5= Prefer other varieties/breeds 6=Susceptible to diseases/pests 7=Poor taste 8=Low yielding/lays fewer eggs 9=Late maturing /longer maturity period 10=Low market prices/demand 11=High input requirements 12=Limited land to experiment/plant 13= Limited information 77= Other*(specify ______)*	1=Very easy 2= Easy 3=Difficult 4= Very difficult	1= Seed easily available 2= Day old chicks easily available 3= Availabiliy of cash to buy seed/DOCs 4= Availability of credit to buy seed/DOCs 5= Preference KK 15/Kuroiler 6= Resistance to diseases/pests 7= Good taste 8= High yielding/lays many eggs 9= Early maturing /shorter maturity period 10= High market prices/demand 11= Lower input requirements 12= Adequate land to experiment/plant 13= Sufficient information 14= Seed/DOC Subsidy 77= Other*(specify______)*

Questionnaire number (adda_hhid) ___________________

MODULE 7: VARIETY/BREED ATTRIBUTES, KNOWLEDGE & PERCEPTION

Instructions: Only ask the following questions to farmers who have ever heard or grown or kept the new technologies (listed below).

If *Yes*, ask for his/her perception of the performance of the technology (ies) against the listed attributes compared to his/her preferred local variety /breed. *Please mark the respondent's response with a **tick** in the appropriate cells below. If No, skip to the next module.*

	1	2				3			
		Kuroiler chicken				*Beans (KK15)*			
	Do you know the attributes of the following technologies? *Yes=1 No=0*	_________ *If No Skip to the next technology, IF Yes ask for the attributes*				_________ *If No Skip to the next technology, IF Yes ask for the attributes*			
	Technology attributes	*Better*	*Worse*	*No difference*	*Don't know*	*Better*	*Worse*	*No difference*	*Don't know*
1	Early maturity								
2	Yield								
3	Pest and disease resistance								
4	Marketability (demand)								
5	Cost of planting materials								
6	Market price received								
7	Cost of day old chicks								
8	Taste								
9	Lays more eggs								

7.8 How easily can you market your Kuroiler chicken*? (Circle the applicable)*
1. Very easy 2. Easy 3.Difficult 4. Very difficult 88. DNK

7.9 How easily can you market your Kuroiler eggs*? (Circle the applicable)*
1. Very easy 2. Easy 3.Difficult 4. Very difficult 88. DNK

7.10 What is the **MAIN REASON** for your answer in 7.8 above *(Circle the applicable)*
1.Early maturity 2.Pest and disease resistance 3.Maketability 4.Market price received 5. Cost of day old chicks 6. Taste 7. Lay more eggs 77.Others (specify) -99 N/A

7.11 What is the **MAIN REASON** for your answer in 7.9 above *(Circle the applicable)*
1. Taste 2 Price 3. Size 4. Colour of the yolk -99 N/A

Questionnaire number (adda_hhid) ____________________

MODULE8: LIVESTOCK PRODUCTION AND MARKETING

8.1 For the last **12 months *(1st Oct 2015 and 30th Sep 2016)***, please give details of revenue and cost of livestock production?

(Please include all animals on the farm last year also those that were later sold or died) If no livestock is owned skip to next module)

	1	2a	2b	3a	3b	4a	4b	5a	5b	6	7	8	9	10	11	12	13
	Animal species	Stock at the beginning of the period (01.Oct.2015) (*If 0, skip to the next*)		Changes over the years: Home consumption		Sales		Stock at the end of 30.Sep.2016		Cash expenditures between 10/15 and 9/16 Value in Ksh				Who decides sale?	Who decides revenue use?	Who decides technology use e.g. breed	Who mostly decides how much of the total output is consumed by the household?
		Unit	**Ksh**	**Units**	**Ksh**	**Units**	**Ksh**	**Units**	**Ksh**	**Veterinary treatment**	**Feed**	**Hired labor**	**Others, specify:**	**B**	**B**	**B**	**B**
1	Dairy cows/calves																
2	Cow/calves																
3	Goat																
4	Sheep																
5	Kuroiler/chicks																
6	Other chicken/chicks																
7	Donkeys																
8	Pigs																
9	Rabbits																
10	Ducks																
77																	
78																	

8.2 For the last **12 months *(01. Oct 2015 to 30. Sep 2016)***, please give details of production and revenue of the following livestock products?

	1	2		3		4		8		5	6	7
	Animal product/services	Quantity produced: Qty	Unit **A**	Quantity sold: Qty	Unit **A**	Quantity Consumed: Qty	Unit **A**	Other, specify: Qty	Unit **A**	Price per unit	Who decides sale? **B**	Who decides revenue use? **B**
1	Milk											
6	Kuroiler Eggs											
2	Other Eggs											
7	Kuroiler Manure											
3	Manure											
4	Honey											
5	Hide											
77	Others specify_________											

Code A: *1=Kilogram, 2=Litre, 3=90 Kg bag, 4=50 Kg bag, 5=25 Kg bag, 6=Gorogoro, 7=Debe, 8=Wheelbarrow, 9=Ox-cart, 10=Bunch (bananas), 11=Piece/number, 50=Tray, 77=Other (specify) ________*

Code B: *1=Male household head, 2= Female household head, 3=Female spouse, 4=Joint decision, 77= Others (specify)___________*

Questionnaire number (adda_hhid) ___________________

MODULE 9: HOUSEHOLD ASSETS *(Prompt for each item as listed below)*

9.1 As at September 2016, how many of the following items did the household own that are in **usable/repairable** condition?

To estimate the value ask the respondent how much they would be willing to buy the item in its current state if it were being sold to them

	ASSET	Total Quantity	Estimate total current value of the asset(s) if you were to buy it in its current state		ASSET	Total Quantity	Estimate total current value of the asset(s) if you were to buy it in its current state
1	Tractor			**2**	Slasher		
3	Car/Van			**4**	Axe		
5	Pickup			**6**	Panga		
7	Motorcycle			**8**	Hoes/Jembes		
9	Bicycle			**10**	Spades/shovel		
11	Television			**12**	Chemical spray pump		
13	Radio			**14**	Treadle pump		
15	Mobile Phone			**16**	Powered water pump		
17	Refrigerator			**18**	Mosquito net		
19	Solar panels			**20**	Greenhouse		
21	Generator			**22**	Water tank		
23	Chaff cutter			**24**	Store for farm produce		
25	Ploughs for tractor			**26**	Lanterns		
27	Reaper			**28**	Main house		
29	Ox-plough			**30**	Wheelbarrow		
31	Cart			**32**	Computer/laptop		
33	Livestock Kraal			**34**	Biogas digesters		
35	Other(specify_______			**36**	Other(specify_______		
37				**38**			

Questionnaire number (adda_hhid) ___________________

MODULE 11: OTHER SOURCES OF INCOME AND TRANSFER

11.1 Do you have off farm employment? _____________ (*1=Yes; 0=No*) *If NO, skip to 11.2.*

Please prompt the codes to make sure nothing is forgotten					
1	2	3	4	5a	5b
MEMID	Type of Occupation **A**	Average Number of days worked per month 10/15 – 9/16	Average Number of months worked per year 10/15 – 9/16	Earning per unit	
				Ksh	**B**

Code A: *1= Agricultural labour (casual+permanent), 2= Casual labour (non-agricultural), 3= Salary (Permanent non-agricultural employment)*
Code B: *1= Day, 2= Month, 3= Year, 4= Lump sum, payment, 77= Other, specify: _______________________________*

11.2 Do you have any other sources of income? _________ (*1=Yes; 0=No*) *If NO, please probe and skip to 12.*

	Please prompt the codes to make sure nothing is forgotten			
	1	2	3	4
	Categories	Code	Type of occupation	Amount /value received between Oct15/ Sept 16/ *for small businesses ask for profit (+) losses (-)*
1	Remittances/gifts/transfers/food aid	1		
2	Pension	2		
3	Small business	1	Brick making	
		2	Carpentry	
		3	Construction	
		4	Grain mill	
		5	Handicrafts	
		6	Beverage, local brew	
		7	Sales in shop, petty trade	
		8	Transport	
		77	Other, specify________________________	
4	Sales of forest products	9	Sale of wood and charcoal	
		10	Sale of wild nuts/fruits	
5	Other agric. Income	11	Sale of crop residues	
		12	Leasing out land	
		13	Renting out oxen for ploughing	
		14	Hiring out machinery services to other farmers	
		15	Dividends (T-bills, bonds, shares)	
		16	Tea bonus	
6	Other	35	Betting	

MODULE 12: NON-FOOD EXPENDITURE

Consider the **last year (Oct 15 - Sept 16)** generally how much has your HH spent on the items listed in a typical year (see specification indicated for each item)?

		1	2
		*Read out: Please exclude **Business Expenditures*** *Enter 88, if respondent does not know.*	How much did your household spend on [ITEM/SERVICE] during the last year (Oct. 15 – Sept 16)? Value in Khs
Non-food	1	Rent (housing)	
	2	Personal care supplies	
	3	Clothes, shoes and bags, accessories	
	4	Detergent/washing powder	
	5	Electricity	
	6	Other non-food	
Transportation + communication	7	Fuel, maintenance, insurance, and tax for motorbike/car	
	8	Public transport	
	9	Airtime (incl. MPESA)	
	10	Other transportation, communication	
	11		
	12		
Education	13	School fees, books, Student's dress/uniform, Tuition and rental fee	
	14	Other cost of schooling	
	15		
	16		
Health	17	Medicine, doctor fees	
	18	Other health cost	
	19		
	20		
Social	21	Celebration and funeral cost	
	22	Recreation and entertainment	
	23	Contributions (eg. Church, groups)	
	24	Tobacco (incl. snuff and miraa)	
	25	Insurance (eg. Car, life, health)	
	26	Remittances transferred to other HH	
	27	Other social cost	
	28		
	29		

MODULE 13: INFORMATION ON CREDIT ACCESS

13.1 Could you obtain credit if you needed it for the purpose of operational agricultural expenses (e.g. buying fertilizer paying for labour etc.)? ____________________*1=Yes, 0=No*

13.2 During the last ***12 months (Oct15 to Sep16)***, have you or any other household member received any credit to buy inputs, or received inputs on credit?_________________*1=Yes, 0=No*

13.3 If yes to 13.2, how much did you receive in Ksh? (___________________)
(*Include the value of inputs if inputs are provided on credit*)

13.4 How much went into purchasing inputs? (_______________)
(*Include the value of inputs if inputs are provided on credit*)

MODULE 15: ACCESS TO SOCIOECONOMIC INFRASTRUCTURE

1	2	3
Social facilities	**Distance to the nearest (km)**	**Most frequently used means of transportation to the facility** *(Use codes A below)*
1. Murram road		
2. Tarmac road		
3. Village market		
4. Main Agricultural input market		
5. Main agricultural product market		
6. Health centre		
7. Agric. Extension agent		

Code A: Means of transport Codes
1= Bicycle; 2= Motorbike; 3= Car; 4= Walk;
77= Others, (specify) ________

Questionnaire number (adda_hhid) ___________________

TARGET PERSON: GROUP MEMBER

Respondent MEMID: ___________________________

MODULE 18: SOCIAL CAPITAL ENDOWMENT

18.1 List all the groups you belong to (*Start with the sampled group)*

1	2	3	4	8	9	10	11
Group Name	Group Type **A**	Please name the most important group function **B**	Year joined	Participation in meetings in the reference period (Oct 15/Sep16) **D**	Your own role in the group **E**	Did the group receive any agricultural training during the reference period (Oct15/Sept16) Yes= 1; N0= 0	Who offered the training? AH= 1; Other= 0, AH+other= 2, DNK= 88

In case sampled group was not named in table above, answer 18.9, 18.10 and 18.11, otherwise skip to 18.2.

18.9 Are you still a member of the sampled group (NAME)? ________________ (Yes= 1; No= 0)

18.10 If no: Please shortly explain why you left the group: ____

18.11 In case, you received agricultural training from Africa Harvest in the sampled group: Who mostly informed you about the single training session (time and place)? ____________________________________ *(1= Group leader, 2= Other members, 3= Extension officer, 4= He was not informed, 77= Other, specify: _______________, -99= N/A)*

18.2. Do you personally exchange information with the local authorities/gov't agencies? ______ (1= Yes; 0= No)

18.6 Do you hold any of the other following positions: ____ *(Multiple answers possible)*

(0=No, 1= Village chief, 2= Village elder, 3= Nyumbakumi, 4= Religious leader, 77= Other_______________)

18.7 Are you a close relative to one of the mentioned positions *(1=Yes; 0=No)* ___________

18.8 If yes: Name position and relative: a. Position: _________ (Code 18.6) Relative _______ F

b. Position: _________ (Code 18.6) Relative _______ F

Codes A
1. Farmer cooperative
2. Farmers group
3. Women`s association
4. Youth association
5. Faith-based association/group
6. Funeral association/insurance group
7. Savings and credit group
8. Community based organization
9. Water users association
10. Informal labour sharing group
11. Widow/ widower
12. Family group
77. Other (______)

Codes B
1. Produce marketing
2. Input access or marketing
3. Seed production
4. Farmer research
5. Savings and credit
6. Welfare/funeral activities
7. Tree planting/Nursery
8. Soil & Water conservation
9. Faith-based organization
10. Input credit
77. Other (______)

Codes D
1. Always
2. Sometimes
3. Rarely
4. Never

Codes E
1. Official
2. Ex-official
3. Ordinary member

Code F
1. Parent
2. Spouse
3. Child
4. Brother/sister
5. Grandparent
6. Grandchild
7. Nephew/Nice
8. Uncle/Aunt
9. Cousin
10. Mother/father in low
11. Brother/Sister-in law
12. Other relative
13. Neighbour
14. Friend
15. Fellow villager
16. Attend same church/mosque
17. Business colleague
77. Other, specify _________

Questionnaire number (adda_hhid) ____________

MODULE 19: SOCIAL NETWORKS

Code A

1	Parent	**11**	Brother/Sister-in law
2	Spouse	**12**	Other relative
3	Child	**13**	Neighbour
4	Brother/sister	**14**	Friend
5	Grandparent	**15**	Fellow villager
6	Grandchild	**16**	Attend same church/mosque
7	Nephew/Nice	**17**	Business colleague
8	Uncle/Aunt	**77**	Other, specify___
9	Cousin		
10	Mother/father in low		

Questionnaire number (adda_hhid) __________________

19.1. General information about each group member									
1	2	3	4	5	6	7	8	9	32
MEM ID	Name of the group member	Do you know NAME? *(1=Yes; 0=No), (-99=N/A)*	Please specify your relationship to NAME **A**	Is NAME's plot bordering yours? *(1=Yes; 0=No)*	Do you know the kind of crops NAME grows? *(1=Yes; 0=No)*	Do you know the kind of livestock NAME keeps? *(1=Yes; 0=No)*	Did you lend or borrow any of the following production means from NAME between Oct15 and Sept16? 0=no 1=lend 2=borrow 3=lend &borrow		Do you exchange/ share food items? *(1=Yes; 0=No)*
							Seeds	Agric. Produce	

Questionnaire number (adda_hhid) ____________________

Code A

1 Very often
2 Often
3 Sometimes
4 Rarely

Code C

1 Preparation of meals
2 Choice of products
3 Nutritional state of children
4 Quantity of food
5 Composition of meals
6 Content of nutrition training
7 Balanced diet
77 Other, specify_______

Questionnaire number (adda_hhid) _________________

19.1. General Information about each group member						
1	**2**	**10**	**11**	**12**	**16**	**13**
MEM ID	Name of Group Member	If you suddenly needed money, would you ask NAME to lend it to you? *(1=Yes; 0=No),*	Inside of this group: who are the farmers who would adopt new cropping technologies **first**? *Please mark with X*	Inside of this group: who are the farmers who would adopt new livestock technologies **first**? *Please mark with X*	Have you visited NAME between Oct15/Sep16? *(1=Yes;0=No)*	Have you talked to NAME between Oct15/Sep16? *(1=Yes; 0=No), if no cross name out and skip to next person*

19.1. Specific interaction within the farmer group ***(remind respondent of nutrition definition)***							
1	**2**	**14**	**17**	**18**	**19**	**23**	**24**
MEM ID	Name of the Group Member	How often did you talk with NAME between Oct15/Sep16? **A**	Did you share information on nutrition with NAME? *(1=Yes;0=No) If no skip to 19*	Name the specific nutrition topic you mostly talked about with NAME **C**	Did you share information on agriculture with NAME between Oct15/Sept16? *(1=Yes; 0=No), if no, skip to next person*	Did you share information on Kuroiler chicken with NAME? *(1=Yes; 0=No)*	Did you share information on beans (KK 15) with NAME? *(1=Yes; 0=No)*

PLEASE USE THE 8 DIGIT MEMID (SEE GROUPLIST)

25. Who do you think is the **most informed person** among the group members concerning **nutrition** information?

    ____________________ MEMID

26. Who do you think is the **most informed person** among the group members concerning **agricultural** information?

    ____________________ MEMID

27. Why did you decide to become a group member? Give reason ____

28. Were you asked by another member to join the group ________ *(Yes=1, No=0)*

29. If yes: By whom? _________ ? MEMID

30. Have you introduced new people to this group? _____ *(Yes=1, No=0)*

31. If yes: Whom? MEMID__________ MEMID__________ MEMID__________

33. Please consider a situation where an organization offers agricultural training to your group.

    However, the agricultural extension officers will only train 3 persons of your group. These persons are supposed to forward the information to the group.
    Who do you think are the 3 most suitable persons of your group for this purpose?

    MEMID__________ MEMID__________ MEMID__________

34. Do you like this approach or would you prefer that all group members should be able to participate in the training?
    1=only 3 persons, 2= all group members

35. Now imageine the same situation, but the organization offers nutrition training to your group.

    However, the NGO will only train 3 persons of your group,
    Who do you think are the 3 most suitable persons of your group for this purpose?

    MEMID__________ MEMID__________ MEMID__________

36. Do you like this approach or would you prefer that all group members should be able to participate in the training?
    ___ 1=only 3 persons, 2= all group member

Questionnaire number (adda_hhid) ____________________

19.2. SPECIFIC INTERACTIONS OUTSIDE THIS COMMON INTEREST GROUP

19.2.1 Please name the persons outside of your common interest group you most frequently exchanged information about nutrition between Oct15/Sept16. Please name a maximum of 5 persons: OUT ID 1_____________ OUT ID 2_____________ OUT ID 3_____________ OUT ID 4_____________ OUT ID 5 ________________

19.2.2 Please name the persons outside of your common interest group you most frequently exchanged information about agriculture between Oct15/Sept16. Please name a maximum of 5 persons: OUT ID 6_____________ OUT ID 7_____________ OUT ID 8_____________ OUT ID 9_____________ OUT ID 10__________________

ID Section								
1	2	3	4	6	9	10	12	**11**
OUT ID	Name	NAME's gender *Male=1, female=0*	Please specify your relationship to NAME **A**	How often did you talk with NAME between Oct15/Sep16? **B**	Did you lend or borrow any of the following production means from NAME between Oct15 and Sept16? 0=no 1=lend 2=borrow 3=lend &borrow		Do you exchange/ share food items? *(1=Yes; 0=No)*	If you suddenly needed money, would you ask NAME to lend it to you? *(1=Yes; 0=No)*
					Seeds	Agric. Produce		
40								
40								
40								
40								
40								
40								
40								
40								
40								
40								

12. Who do you think is the **most informed person** among the ones named concerning **nutrition** information? ______________________OUT ID

13. Who do you think is the **most informed person** among the ones named concerning **agriculture** information? ______________________OUT ID

Code A									
1	Parent	**6**	Grandchild	**11**	Brother/Sister-in law	**16**	Attend same church/mosque	**Code B**	
2	Spouse	**7**	Nephew/Nice	**12**	Other relative	**17**	Business colleague	**1**	Very often
3	Child	**8**	Uncle/Aunt	**13**	Neighbour	**77**	Other, specify___	**2**	Often
4	Brother/sister	**9**	Cousin	**14**	Friend			**3**	Sometimes
5	Grandparent	**10**	Mother/father in low	**15**	Fellow villager			**4**	Rarely