NBER WORKING PAPER SERIES

FROM LEARNING TO DOING:
DIFFUSION OF AGRICULTURAL INNOVATIONS IN GUINEA-BISSAU

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Working Paper 26065
http://www.nber.org/papers/w26065

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2019

I am grateful for helpful suggestions from André Moreira, Inês Vilela, Julia Seither, Paulo Santos and Pedro Vicente. I would like to thank Pedro Santos, Patrícia Maridalho and the VIDA team for their cooperation and support. I wish to acknowledge the financial support provided by European Union and Camões-Instituto da Cooperação e da Língua, through the project "Kopoti pa cudji no futuro". This work was funded by Fundação para a Ciência e a Tecnologia (UID/ECO/00124/2013 and Social Sciences DataLab, Project 22209), POR Lisboa (LISBOA-01-0145-FEDER-007722 and Social Sciences DataLab, Project 22209) and POR Norte (Social Sciences DataLab, Project 22209). I would also like to acknowledge FCT for the PhD Scholarship PD/BD/105725/2014. The views expressed herein are those of the author and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 26065
July 2019
JEL No. O13,O31,O33,Q16

ABSTRACT

This paper analyzes the role of social networks in the diffusion of knowledge and adoption of cultivation techniques, from trainees to the wider community, in the context of an extension project in Guinea-Bissau. In order to test for social learning, we exploit a detailed census of households and social connections across different dimensions. More precisely, we make use of a village photo directory in order to obtain a comprehensive and fully mapped social network dataset. We find evidence that agricultural information spreads across networks from project participants to non-participants, with different networks having different importance. The most relevant connection is found to be between the network of people from which individuals would 'borrow money'. We are also able to disentangle the relative importance of weak and strong ties: in our context, weak ties are as important in the diffusion of agricultural knowledge as strong ties. Despite positive diffusion effects in knowledge, we found limited evidence of network effects in adoption behavior. Finally, using longitudinal network data, we document improvements in the network position of treated farmers over time.

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1 Introduction

Agricultural development through productivity improvements is often promoted as an effective means to reduce poverty amongst Africa's low-income population, for whom agriculture represents the main source of employment and livelihood. Despite some gains in recent years, agricultural productivity in the continent, and in sub-Saharan Africa in particular, remains low, lagging well behind the rest of the world. Although agricultural technologies are available that could significantly boost productivity, those have not yet been widely adopted in the region. Low access to extension services and to reliable information are among the most frequently mentioned barriers to technology adoption.

Agriculture development interventions aiming to increase agricultural productivity and yields have the potential to impact technology adoption beyond project participants, since it is expected that trained farmers will disseminate the techniques to the rest of the community. If true, social interactions may play a key role in mitigating information constraints and disseminating improved technologies.

This paper analyzes the role of social networks in the diffusion process of improved knowledge and, ultimately, adoption of cultivation techniques introduced by an agricultural extension project in Guinea-Bissau. The project focused on horticultural production and improved cultivation practices, with the aim of increasing food security and decreasing vulnerability through the diversification of crops and improvements in production practices.

We take advantage of this randomized intervention to study the diffusion of improved techniques from project participants to the wider community in one village in Guinea-Bissau. In particular, we test for spillover effects in terms of both knowledge and adoption of production practices over two agricultural seasons. In order to understand the mechanism through which both learning and adoption may occur, we collected a census of both households and their social relations across four dimensions – 'kinship', 'regular chatting', 'agricultural advice' and 'borrowing money' – allowing us to test for the relative importance of different channels. Our dataset contains two rounds of network data. We collected network data by first asking farmers to list their network contacts. Then, in a second stage, we used a photo directory as a visual aid to help respondents recall additional network links. This elicitation method allows us to capture results in a more detailed and fully mapped social network and an intuitive identification of farmers' weak ties – those who are mentioned only after visualizing the photo directory. Our results suggest that information externalities from the project participants to the rest of the community exist. Individuals with a link to a trained farmer experience increases in agricultural knowledge. Testing for the different information channels, not all network groups contribute equally for the diffusion of information. We find stronger network effects for those peers with links to farmers from whom they could ask for money in times of need. In contrast, we find evidence of a decrease in information exchange through a farmers kinship network. Furthermore, exploiting our measure of link strength, weak social links appear to be as relevant as strong links in the diffusion of information. Despite positive effects in knowledge, we found only limited evidence of social effects on adoption. Finally, we document network changes as a result of the intervention. In particular, we find evidence that the treatment led to an improvement in the network position of treatment farmers, with treated farmers becoming more central in the village social structure.

This paper relates to the literature on diffusion of information, technologies and behavior within social networks. Diffusion effects along social networks have been documented in a variety of settings, including health prevention (Oster and Thornton, 2012; Godlonton and Thornton, 2012; Apouey and Picone, 2014), educational outcomes (Bobonis and Finan, 2009; Fafchamps and Mo, 2017), financial decisions (Duflo and Saez, 2003; Cai, Janvry and Sadoulet, 2015; Banerjee et al., 2013), and agricultural practices (Foster and Rosenzweig, 1995; Munshi, 2004; Bandiera and Rasul, 2006; Conley and Udry, 2010; Van den Broeck and Dercon, 2011).

Our paper is closer in spirit to previous works on agricultural technology diffusion within social networks. Within that, Foster and Rosenzweig, (1995) was one of the early studies to investigate the effects of social learning in agriculture. In a study of adoption of high-yielding varieties in India, the authors found evidence of learning externalities not just via mimicking behavior, but through farmers learning from other farmers' experience. More recently, Bandiera and Rasul (2006) studied the adoption of sunflower seeds in Mozambique and provided further evidence of positive peer effects on adoption decisions. In a seminal paper, Conley and Udry (2010), were among the first to study peer-effects on agricultural technology adoption using explicit social network data. Focusing on pineapple producers in Ghana, they identified knowledge flows by asking farmers whether they had gone to a random selection of farmers in the village for agricultural advice. They also found evidence of farmers learning from one another, aligning their use of fertilizers with that of their most successful peers.

Although those and several other studies have found evidence of positive peer effects in technology adoption, unfortunately results have not always been as encouraging. Research has also shown that diffusion of knowledge and practices can be limited in some settings (Fafchamps and Quinn, 2016; Fafchamps and Söderbom, 2014) or non-existent (Duflo, Kremer and Robinson, 2011). And in some contexts, social network effects may even generate perverse outcomes, for example, creating incentives for delaying adoption and free-riding on the experimentation of others (Foster and Rosenzweig, 1995; Bandiera and Rasul, 2006; Maertens, 2017), or making technology adoption less likely altogether (Miguel and Kremer, 2007).

The remainder of this paper is structured as follows. Section 2 provides the context of the study setting. Section 3 describes the setting of the horticultural production project. Section 4 describes the data collection, and the network and outcome measures employed. In Section 5 we outline the estimation strategy. Section 6 presents the econometric results. Finally, in Section 7 we conclude.

2 Context

Guinea-Bissau, a country in West Africa with a population of approximately 1.8 million, is one of the poorest countries in the world, with a GDP per capita of 1450$PPP and 67 percent of its population living on less than $1.90 per day.[1] Agriculture is key to Guinea-Bissau's economy: it accounts for 69 percent of GDP and represents the primary source of income for 85 percent of its population. The agriculture sector is dominated by cashew nut production for export, by rice production for consumption, and by horticulture production on a smaller scale.[2] Rice is the main staple crop in the country and is widely grown, but rice productivity has remained relatively low.[3] Low productivity can be explained by several constraints faced by the agricultural sector ranging from erratic weather, scarce inputs and extension services, and weakened infrastructure. Years of poor harvest or shocks to cashew prices can leave subsistence farmers in a particularly vulnerable situation, as was the case in 2012, when a combination of poor cashew harvest, lower export prices and political instability led to a rise in food insecurity.[4] As for the horticultural sector, production has steadily increased, from 26,381 tons in 2005 to 33,420 tons in 2014.[5] In the Guinea-Bissau - Country' Economic Memorandum (2015), the World Bank identified horticulture as one of the agricultural sectors with greatest economic potential, and as a potential source of alternative income for rural households that would allow them to mitigate the risks posed by relying on a single cash crop.

The setting for this study was the village of Suzana, in the northwest region of Guinea-Bissau (Figure 1). Suzana is a rural village, with 354 households spread across 8 neighborhoods. The majority of households in Suzana are from the Felupe ethnic group, and most of the individuals in the village are subsistence farmers. As in other regions of the country, rice is the main crop, and cashew is produced on a smaller scale. Horticultural production is relatively scarce and is almost exclusively a female activity. Furthermore, there are no agriculture extension services in the region.

[1] World Development Indicators (2017), World Bank.
[2] See World Bank (2015).
[3] In 2014 rice productivity in Guinea-Bissau was 15.6 thousand hectograms per hectare, well below the average African level of 25.9 (FAOSTAT Database).
[4] See World Food Program (2013).
[5] FAOSTAT Database.

3 Agricultural intervention

In 2015, the international NGO 'VIDA' introduced an agricultural production project providing agricultural technical training and inputs to farmers in 6 villages of Guinea-Bissau, including Suzana. The project included training sessions on horticultural cultivation techniques, creation and management of farmers associations, and on the logistics of the supply chain to local markets. This study focuses specifically on the horticultural production component of the project. We take advantage of this intervention in order to study the diffusion effects of cultivation practices from the project participants to the rest of the community in the village of Suzana. In what follows we briefly describe the horticultural production component of the project and the selection of the project participants.

3.1 Horticultural production training

The horticultural production element of the intervention included three modules on cultivation techniques, which took place between November 2015 and February 2016, before the 2016 agricultural season (which runs from March to mid-July). The modules included a mix of theoretical and practical training sessions focusing mainly on improved production techniques. The training covered practices such as land preparation, irrigation, staking, pruning, soil enrichment, spacing, mulch, seed selection, nursery preparation and management, pest and disease management, organic pesticides, and post-harvesting handling. Although some of those practices were already familiar to farmers, most were newly introduced by the project.

3.2 Project participants

Project participants were selected by the female village leaders, who provided a list of progressive female farmers interested in participating in the intervention. That list of potential participants made up the sample of a randomized impact evaluation conducted on the project. Those were then randomly allocated to either the control or treatment group, with blocks being formed at the level of the village before randomization. In addition, female village leaders also attended the program. Results of the impact evaluation are not the main scope of this paper, but they are briefly addressed in the next sections. As mentioned in the previous section, this paper focuses only on the village of Suzana, where 35 farmers were assigned to the treatment group and participated in the project, while another 41 constituted the control group. As such those 76 individuals constitute the experimental subjects within Suzana village.

4 Measurement and data

We conducted two round of data collection, and each round included both a village census and a household survey. Survey respondents were the individuals responsible for the households' horticulture production - usually the female head of the household. The village census conducted includes questions on demographic characteristics, horticultural production patterns during the previous agricultural season, and household asset ownership. During the collection of the census data for first round of surveys, an enumerator took a photo of each respondent in order to compile a photo album of the village which was then used for the household survey. The household survey collected data on the individuals' network links, on horticultural production patterns during the previous agricultural season, and on practical horticultural knowledge and adoption.

The first village census took place in February and March 2016 and included all 354 households in the village. This was followed by the household survey and network data collection which took place between August and September of 2016, directly following the 2016 agricultural season. Regarding the second round of data collection, the census and second survey took place in November 2017, after the 2017 agricultural season. In the data collection points following the first survey, we were able to track over 90% of the initial respondents (345 in the second survey and 339 in the subsequent two out the 354 households). All data collection activities took place after the horticultural training intervention described in the previous section.

4.1 Network measures

During the household survey, which followed each of the census data collections, we collected data on each household's social network structure. Respondents were asked about all their social links in different contexts. This approach allows us to obtain a complete network map. Because the collection of such data is cumbersome and fraught with limitations, we proceeded in two steps.

We elicited the individuals' social links along four dimensions: i) kinship network, which is defined as individuals with whom the respondent has a kinship tie; ii) chatting network, which includes individuals the respondent regularly chats with; iii) agricultural advice network, which contains individuals the respondent would go to for agricultural advice; and iv) money-borrowing network, defined as the set of individuals the respondent could ask for money in times of need. The same set of four network questions were repeated to the respondent in the same order for each of the neighborhoods located in the village. With eight neighborhoods, respondents thus answered each set of network questions eight times. The order of the neighborhoods presented to each individual varied randomly.

The network links were collected through survey questions in a two-step procedure. We first asked farmers to name all individuals with whom they had a network link according to our four different social dimensions. This was done using an open question – i.e., not imposing a limit on the number of links the individual could list. This method might tend to capture only the individual's strong links, as those closer to the respondent are more likely to be named while those with whom the respondent interacts less frequently are more easily forgotten, i.e. a respondents weaker social links (Maertens and Barrett, 2012, Brewer, 2000).

To address this concern, we implemented a second step, where we used the village photo album collected during the first survey to prompt respondents and determine whether the respondent had any additional links not named previously – this provides a way that is both feasible and intuitive of identifying weak (and easily forgotten) links. The village photo album was organized by neighborhood, included the photo of one person per household (the household representative), and depicted all the households in the village.

To be more concrete, and using the kinship network as an example, we first elicited the kinship relationships from "memory" by asking: "Who are your family members that live in the neighborhood of «Catama» but outside of your household residence?" In the second step we asked the respondents to go through the photos of that neighborhood and asked: "Do you have any other family member living in the neighborhood of «Catama»?" This procedure was then replicated for the chatting network, which elicited the individuals with whom the respondent talked to on a regular basis (at least once a week). Again, this was followed by the agricultural advice network which elicited the individuals that the respondent would go to for agricultural advice. Lastly, the fourth network dimension was the borrowing money network which elicited the individuals that the respondent could ask for money in times of need.

For the latter two network dimensions, namely agriculture advice and borrowing money, we further recorded what we refer to as the effective link. While the statements above are phrased in such a way as to elicit the potential link (who *would* you go to), we also collect the effective link (who *did* you go to). In what follows, unless otherwise stated, agricultural advice and borrowing money refers to the network of potential links.

By eliciting the social networks in this manner we are implicitly capturing the strength of ties between individuals, since links elicited from "memory" are more likely to capture strong ties, while the remaining links prompted from the village photo album would more likely capture weak ties. In what follows, we define strong ties as the links provided from "memory", and weak ties as the links identified when aided by the photo album. Appendix A provides additional discussion and robustness checks on the measures of tie strength.

Finally, in addition to the aforementioned measurements, we also collected data on group membership, such as religious or self-help groups, as well as neighboring plots through GPS coordinates. In the results that follow we focus on the first four network variables described: kinship, regular chatting, agricultural advice and borrowing money.

4.2 Outcome measures

In our analysis of spillover effects we focus mainly on two outcome variables of interest: knowledge and adoption of agricultural practices. A list of 10 survey questions on production practices, based on the topics covered during the horticultural training, was used to measure the adoption of improved practices. These were then followed by 10 survey questions designed to measure the respondents' knowledge with respect to those same practices. Practices covered included land preparation, irrigation, nursery management, spacing, mulch, soil enrichment, pruning, staking, pest management and crop rotation. The practice adoption questions focused on whether respondents had adopted the aforementioned practices in the previous agricultural season, which had just finished. The practice knowledge questions tested respondents' knowledge on either how to apply the practice or their benefits. Responses to the two sets of questions were then used to construct two indices, one for production practice adoption and one for production practice knowledge, as the simple average of the z-scores for the relevant survey questions.[6] Table 1 provides a description of this variables.

< Table 1 around here >

As for the analysis of network changes, we focus on network centrality measures. To be more specific, we computed centrality measures in terms of in degree, out degree, betweenness and closeness centrality for the different network dimensions. Degree centrality captures how connected a farmer is. Betweenness describes the importance of an individual in connecting other farmers. Finally, closeness centrality captures how close an individual is to all other farmers in the network.[7] All centrality measures were standardized and therefore range between zero and one.

[6] The z-scores were computed by subtracting the mean and dividing by the standard deviation of the impact evaluation control group. Following Kling, Liebman, and Katz (2007) if an individual has a response to at least one of the 11 survey questions, then any missing value for the other variables are imputed by the group mean.
[7] In degree refers to the number of farmers the respondent mentioned as network partner, while out degree is the number of farmers that mentioned the respondent as a network partner. Betweenness is the number of shortest paths between farmers that pass through the individual. Closeness is calculated as the inverse of the distance between the individual an any other farmer.

5 Estimation strategy

We start our analysis by estimating the treatment effects for the outcomes of interest in the impact evaluation sample (progressive farmers). Given the random assignment of the treatment, the average treatment effects of the agriculture training program can be estimated using the specification:

$$Y_{it} = \alpha + \partial T_i + \varepsilon_{it}, \tag{1}$$

where Y_{it} represents the outcome variable of interest for individual i at time t. T_i is a binary variable which takes the value of one if the individual was assigned to the treatment group and zero otherwise.

The above specification can also be estimated using individual control variables:

$$Y_{it} = \alpha + \partial T_i + \gamma X_{i0} + \varepsilon_i, \tag{2}$$

where X_{i0} is a vector of individual and household characteristics, such as age, years of education, religion dummies, marital status, and household assets.

Average treatment effects are not the primary focus of this paper, however. Instead, we are interested in estimating the diffusion effects of the training program. Our village contains both progressive farmers (those selected to participate and which may be allocated a treatment or control status) and non-progressive farmers (the remaining farmers from the village population). We are interested in testing whether the knowledge and adoption behavior of non-progressive farmers is affected by the number of treated (progressive) farmers in their social networks. Our identification strategy uses the experimentally-induced variation in the number of treated farmers, conditional on the number of peer progressive farmers. We conduct a household level analysis employing the following specification:

$$Y_{it} = \alpha + \beta_T N_{i0}^T + \beta_P N_{i0}^P + \gamma X_{i0} + \theta \bar{X}_{j0} + \varepsilon_{it}, \tag{3}$$

where, N_{i0}^T is the number of links with treated individuals, and N_{i0}^P are the number links with all progressive farmers in individual i´s social network at time 0 (the first round of network data collection). The inclusion of N_{i0}^P ensures that the estimation of N_{i0}^T is not driven by the overall size of an individuals' network. Hence, N_{i0}^T captures the experimentally-induce variation in the number of treated peers. In addition, X_{i0} is a vector of individual and household characteristics, which include gender, years of education, marital status, religion, ethnic group, whether the household produced horticultural crops in the previous year, and household assets. $\bar{X}_{j0}$ captures the average individual and household characteristics of individuals i´s network members, which allows us to control for the fixed characteristics of the other farmers in the network. $\bar{X}_{jo}$ includes the proportion of female respondents, average years of education, proportion of married respondents, proportion of animists, proportion of respondents from the main ethnic group, proportion of households that produced horticultural crops in the previous year and household assets in individuals i´s network. The above specification was also expanded to analyze the effect of strong and weak links with treated individuals:

$$Y_{it} = \alpha + \beta_{sT} N_{i0}^{sT} + \beta_{wT} N_{i0}^{wT} + \beta_P N_{i0}^{P} + \gamma X_{i0} + \theta \bar{X}_{j0} + \varepsilon_{it}, \qquad \textbf{(4)}$$

where, N_{i0}^{sT} and N_{i0}^{wT} refer to the number of strong and weak links with treated individuals in i´s social network, respectively.

Next, we test diffusion of knowledge and adoption at the dyadic level. We follow the approach employed in Fafchamps and Söderbom (2014) and test for similarity of outcomes between progressive and non-progressive farmers. We take the directed dyad as the unit of observation, in which the direction of the link is taken into account, i.e. node i is linked to node j only if i reported j as a network partner. Note that since we are considering the direction of the link, a link from node i to node j is not the same as a link from node j to node i. Given that we are interested in estimating the influence of the treated nodes on the non-progressive nodes we exclude directed links reported by progressive nodes from the analysis. We estimate the following specification:

$$|Y_{it} - Y_{jt}| = \alpha + \beta_T L_{ij0}^{T} + \gamma_1 w_{ij0} + \gamma_2 (z_{i0} - z_{j0}) + \gamma_3 (z_{i0} + z_{j0}) + \varepsilon_{ijt}, \qquad \textbf{(5)}$$

where our outcome of interest is the absolute difference between Y_{it} and Y_{jt}. Y_{it} represents the outcome variable of interest for node i when i is non-progressive and Y_{jt} refers to the outcome variable of a progressive farmer (j). L_{ij0}^{T} is a binary variable that captures the existing links between a non-progressive and progressive farmer. It takes the value of one if i is non-progressive and j is treated, and zero if i is non-progressive and j is a control farmer. β_T takes negative values if dyads between non-progressive and treated farmers have more similar outcomes than dyads between non-progressive and control farmers. w_{ij0} is a vector of variables describing the relation between i and j, including whether the respondents have the same religion, belong to the same ethnic group have the same gender and the geographical distance between them. z_{i0} and z_{j0} captures the individual and household level characteristics of i and j, such as years of education, household assets, marital status and whether the household produced horticultural crops in the previous year. We follow Fafchamps and Gubert (2007) and include characteristics of the individuals in differences and in sums. This approach allows to control for the effects of the differences in characteristics of the nodes, as well as the combined effect of the characteristics in the outcome of interest.

The above dyadic level specification was also expanded to analyze the effect of strong and weak links with treated individuals:

$$|Y_{it} - Y_{jt}| = \alpha + \beta_{sT} L_{ij0}^{sT} + \beta_{wT} L_{ij0}^{wT} + \gamma_1 w_{ij0} + \gamma_2 (z_{i0} - z_{j0}) + \gamma_3 (z_{i0} + z_{j0}) + \varepsilon_{ikt}, \quad \textbf{(6)}$$

where, $L_{ij0}^{sT}$and L_{ij0}^{wT} are binary variables that capture existing links between a non-progressive and a progressive node, and the link is characterized as either strong or weak, respectively.

All coefficients are estimated under the OLS framework. We estimate robust standard errors in all regressions, except for the estimations in a dyadic framework where, following Cameron, Gelbach, and Miller (2011), we use two-way cluster-robust standard errors, clustered at both i and j.

6 Econometric results

We divide the analysis of econometric results into four parts. First, we present balance tests and descriptive statistics for the progressive and non-progressive farmers. We then move on to the analysis of the training program' effects on treated versus control progressive farmers. Third, we present the analysis of the network effects of the agriculture training program, using both household-level and dyadic specifications. Furthermore, we make use of our data in order to test for social learning across different network dimensions: kinship, regular chatting, agricultural advice and borrowing money. Lastly, document possible network changes as a result of the intervention.

6.1 Descriptive statistics

In this section we present descriptive statistics for the sample of respondents from the village of Suzana. The sample includes 76 progressive farmers split into 35 treated and 41 control individuals, and 271 non-progressive farmers remaining in the rest of the population (seven village leaders that attended the training were excluded from the analysis). Balance tests between the treatment and control groups are reported in the first two columns of Table 2. The last two columns present the descriptive statistics for non-progressive respondents and differences relative to the progressive. Table 2 is split into basic demographics, religion and ethnicity, occupation and network centrality variables. Figures 3 provide a visual representation of the network links among 54 households from one of the neighborhoods in the village. The networks of kinship, regular chatting, agricultural advice and borrowing money are depicted in Figure 3a, 3b, 3c and 3d, respectively.

< Tables 2 around here >

As expected, given the randomization procedure, we do not find any statistically significant difference between the treated and control groups of the progressive farmers. Looking at the demographic variables in Table 2, non-progressive respondents on average are approximately 54 years old and have 2 years of education. 86 percent of the non-progressive respondents are women, animism is the predominant religion, followed by catholicism, and the majority of individuals (87 percent) belong to the Felupe ethnic group. In terms of occupation, most of the individuals are farmers. Progressive farmers are younger, more likely to be married and catholic, and more central than the rest of the village.

6.2 Treatment effects

This section presents the results of the impact evaluation training program. Our two main outcomes of interest are the index of production practices knowledge and the index of production practices adoption described in section 4.2. Table 3 displays the estimates of treatment effects for each outcome of interest, specifications (1) and (2).

< Table 3 around here >

The treatment is estimated to have led to an increase in knowledge of 0.198- 0.288 standard deviations, in both time periods. There is also a clear positive and statistically significant effect of 0.200-0.264 standard deviations of the treatment on our measure of adoption. These results suggest that the treatment had the desired effect of increasing knowledge of agricultural practices in the treatment group which translated into an increase in adoption of those same practices.

6.3 Social network effects

We now turn to our analysis of the influence of social networks on farmers' knowledge and adoption of cultivation practices. We begin by employing the household level specification (3) and (4). For each outcome we present the results for five network variables, our four classifications of interest (kinship, regular chatting, agricultural advice and borrowing money) and 'all' links which refers to the union of all networks and thus, having a network link in any of the four dimensions. Tables 4 present the network effects on knowledge and adoption of practices for the household level analysis. Table 4a and 4b displays the short-run results, while Tables 4c and 4d focus on the medium-run results.

< Tables 4 around here >

As shown in Table 4a, the network effect differs considerably across network dimensions and link strength. On the one hand, we observe positive and statistically significant knowledge spillover effects in the regular chatting and borrowing money networks. These effects represent an improvement of 0.117-0.199 standard deviations in the z-score of an individual's knowledge index, statistically significant at the 1 percent level. This represents a positive spillover effect on the non-progressive farmers with positive knowledge spillovers for each additional progressive farmer in an individual's network which receives the treatment.

Both strong and weak links seem to be significant and there is no statistically difference between them. On the other hand, having a treated farmer in the kinship or agricultural advice network does not seem to translate to improvements in knowledge for the non-progressive population. The only exception is when we consider the link strength in the kinship network where weak links with treated farmers increase knowledge by 0.097 standard deviations, statistically significant at the 1 percent level.

In Table 4b we present the short-run results of network effects on practice adoptions. Looking at the table, we find only limited evidence of network effects in terms of an individual's adoption index. The links with treated individuals does not seem to have any statistically significant effect on agricultural adoption, except in for effects coming through the borrowing money network. This represents a 0.094 standard deviation increase in adoption, significant at 5 percent level.

We now focus our attention to the medium-run (two agricultural seasons after the treatment) with results presented in Tables 4c and 4d. Looking at Table 4c we can see that the diffusion of knowledge persisted over time in the borrowing money network, representing and improvement of 0.223 standard deviations in knowledge, statistically significant at the 5 percent level. Different than before, we also observe positive effects among agricultural advice peers and no effect in the regular chatting network. It is also worth noting the negative effect in the kinship network. Kin-treated farmers seem to reduce knowledge of their non-progressive kin members by 0.087 standard deviations, statistically significant at 10 percent level. One possible channel for this effect has to do with labor specialization among family members as a result of the treatment. From anecdotal evidences we know that extended family members help each other work in their plots in time intensive periods of the agricultural season, such as planting and harvesting. If treated farmers are perceived as having more knowledgeable agricultural practices because of the treatment, they may informally take on a larger share of the extended family's agricultural practices. Since kinship-based networks may have the strongest sense of trust between links, family members may choose to focus on other activities if they know they have a connection with a progressive farmer which received agricultural training. Consistent with this channel, in the larger impact evaluation conducted on this intervention we observe that trust within the family strengthens as a result of the treatment.

Finally, in Table 4d we document medium-run network effects in adoption. As before, we observe only limited diffusion of adoption through the network, with positive and statistically significant effects only observed in the agricultural advice network. These results, however, should be interpreted with caution, since the treatment might have changed the structure of the agricultural advice network. We address this potential network changes in the subsequent section.

Next, we test for knowledge and adoption similarities between non-progressive and progressive farmers in a dyadic framework. More specifically, we explore whether non-progressive farmers are more likely to know and adopt more similar practices as theirs treated peer farmers, in comparison to the control peer farmer. Our outcome of interest is the absolute difference between the progressive and non-progressive farmer's outcomes. Note that, if information and adoption diffuse from treated to non-progressive farmers, we would observe more similarities in outcomes between non-progressive and treated when comparing to non-progressive and control, and thus implying a negative coefficient in our variable of interest. We do this in a dyadic framework by employing specification (5) and (6).

< Table 5 around here >

Results for the short and medium-run outcomes are presented in Table 5. In line with the previous results, in the short-run, we observe the diffusion of knowledge in the regular chatting and borrowing money networks. Both of those effects are statistically significant at conventional levels. In addition, we also document diffusion effects in the agricultural advice, marginally significant at 10 percent level. When we extend our analysis to the medium-run, the coefficients for links with treated kin farmers is positive and statistically significant at the 1 percent level. This result provides robustness to the conclusion that having a kin-treated farmer seems to reduce knowledge of their non-progressive kin members. We do not find statistically significant results on the agriculture advice and borrowing money networks, even though, in line with previous results, point estimates are negative. As for the adoption outcome, we do not observe statistically significant effects in either time period.

Overall, the results described in this section are consistent with social effects existing in knowledge, although these differ considerably across network dimensions. However, despite the existence of positive externalities in knowledge, we have found limited evidence of social effects on adoption behavior.

6.4 Network change

Finally, we test for possible changes in the network structure as a result of the intervention. In particular, we focus on the sample of progressive farmer's and estimate average treatment effects in four network centrality measures – in degree, out degree, betweenness and closeness. We present the results for the different network variables of interest: kinship, regular chatting, potential and effective (real) agricultural advice, and potential and effective (real) borrowing money. Tables 6 present estimates of the treatment effects employing specifications (1) and (2). Tables 6a and 6b display the short- and medium-run results, respectively.

< Tables 6 around here >

We do not find any statistically significant difference in the networks of kinship, regular chatting, and potential and real borrowing money. Given that the treatment was focused on agriculture production, these results are unsurprising, and we thus focus on the effects of the real and potential agricultural advice networks. Looking at the short-run results in Table 6a, we observe that the treatment led to an increase in the in degree centrality for both the potential and effective agricultural advice network. This corresponds to an improvement of 0.008 and 0.004, respectively, statistically significant at 10 percent level in the preferred specification employing controls. Note that the inclusion of controls can help us in face of limited statistical power in our sample.

Moreover, in the effective agricultural advice network, betweenness and closeness centrality was found to increase by 0.004 and 0.008 in the treatment group. These effects are statistically significant at conventional levels. Lastly, to a certain extent, this improvement in network centrality seem to have persistent over time. In Table 6b we observe that treatment effects in the in degree centrality remained positive and statistically significant in the medium run, while betweenness centrality improved by 0.003 in the potential agricultural advice network.

Taken together, these results suggest that the treatment led to an improvement in the agriculture' network position of treated farmers.

7 Concluding remarks

This paper analyzes the role of social networks in the diffusion of cultivation techniques introduced by an agricultural project in Guinea-Bissau. In particular, we study the diffusion of knowledge and adoption of improved techniques from project participants to the rest of the community. To do so, we collected detailed census and network data in the village of Suzana and made use of a network elicitation mechanism that allowed us to obtain a comprehensive network map and a characterization of the strength of network ties. In addition, we elicited network membership across four different network dimensions (kinship, regular chatting, agricultural advice, borrowing money), allowing us to examine the role of each in knowledge and adoption diffusion.

Having established that the agricultural project increased knowledge and adoption of practices in project participants, we went on to investigate the prevalence of spillover effects to the rest of the community. Our results indicate that knowledge externalities do exist, particularly for those peers with links to farmers from whom they could ask for money in times of need. However, we find only limited evidences of network effects in adoption behavior. Furthermore, using our measures of link strength, we have found that weak social links – which conventional network measurements tend to fail to capture appropriately – appear to be as important as strong links in the dissemination of agricultural knowledge. This result highlights that weak ties can also be valuable sources of new information. Finally, our results show that the treatment led to an improvement in the network position of treatment farmers.

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Table 1: Production techniques

technique	knowledege	adoption
Land preparation	Best use for the stover and straws after land preparation	Use of stover and straws after land preparation
Irrigation	Advantages of early morning or late afternoon watering	Time of irrigation
Nursery Management	Best way to protect the nursery from sunlight	Sunlight protection
Spacing	Ideal spacing between onions	Spacing between onion plants
Mulch	Advantages of mulch	Practice of mulch
Soil enrichment	Awareness of different soil fertilizers	Use of organic soil fertilizers
Pruning	Advantages of pruning	Practice of pruning
Staking	Crops that need staking	Practice of staking
Pest and disease management	Awareness of organic pesticides	Use of organic pesticides
Crop rotation	Awareness of crop rotation	Practice of crop rotation

Table 2: Individual characteristics - differences across treatment, control and non-progressive groups

		control	difference to treatment group	non-progressive	difference to progressive group
basic demographics	**age**	39.439	2.955 (2.559)	53.795	-13.038*** (1.600)
	female			0.857	0.130*** (0.025)
	years of education	2.000	0.235 (0.633)	1.971	0.136 (0.369)
	married	0.780	0.014 (0.096)	0.485	0.301*** (0.056)
religion and ethnicity	**catholic**	0.293	0.148 (0.112)	0.250	0.110* (0.062)
	animist	0.585	-0.085 (0.117)	0.636	-0.089 (0.065)
	felupe	0.951	0.019 (0.045)	0.868	0.092*** (0.031)
occupation	**farmer**	0.902	-0.049 (0.077)	0.722	0.158*** (0.047)
	stays at home	0.073	0.074 (0.074)	0.183	-0.076* (0.043)
	vendor	0.024	-0.024 (0.024)	0.019	-0.006 (0.016)
network centrality	**in degree**	0.176	0.012 (0.019)	0.133	0.049*** (0.010)
	out degree	0.180	0.016 (0.019)	0.128	0.059*** (0.010)
	betweenness	0.003	0.001 (0.001)	0.002	0.002*** (0.000)
	closeness	0.585	0.009 (0.008)	0.561	0.028*** (0.004)

Note: Standard errors reported in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3: Treatment effect - Knowledge and adoption of production practices

		short-run				medium-run			
dependent variable ------>		knowledge		adoption		knowledge		adoption	
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
treatment	**coefficient**	0.198*	0.214*	0.254***	0.262***	0.288***	0.264***	0.200*	0.201*
	standard error	(0.116)	(0.113)	(0.095)	(0.096)	(0.091)	(0.089)	(0.121)	(0.122)
mean dep. variable (control)		0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
r-squared adjusted		0.022	0.021	0.069	0.043	0.022	0.021	0.021	0.034
number of observations		75	75	75	75	75	75	75	75
year		2 016	2 016	2 016	2 016	2 017	2 017	2 017	2 017
controls		no	yes	no	yes	no	yes	no	yes

Note: All regressions are OLS. The unit of observation is the individual. Non-experimental households are excluded from the observations. The dependent variables are an average of z-scores. 'treatment' is a dummy equal to one if the individual was assigned to the treatment group and zero otherwise. Controls are individual and household characteristics, which include years of education, marital status, religion, ethnic group and household assets. Robust standard errors reported in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4a: Knowledge of production practices

dependent variable ------>	knowledge									
network variable ------>	all		kinship		regular chatting		agricultural advice		borrowing money	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
links with treated	0.049		0.062		0.117***		0.055		0.199**	
	(0.033)		(0.040)		(0.043)		(0.048)		(0.081)	
strong links with treated		0.015		0.006		0.115**		0.044		0.202**
		(0.034)		(0.050)		(0.052)		(0.051)		(0.086)
weak links with treated		0.076***		0.097**		0.119***		0.107		0.185*
		(0.024)		(0.040)		(0.045)		(0.081)		(0.107)
links with experimental	0.002	0.003	-0.032	-0.021	-0.032	-0.032	-0.013	-0.016	-0.114**	-0.114**
	(0.021)	(0.019)	(0.030)	(0.030)	(0.025)	(0.025)	(0.044)	(0.045)	(0.055)	(0.055)
mean dep. Variable	-0.658	-0.658	-0.658	-0.658	-0.658	-0.658	-0.658	-0.658	-0.658	-0.658
F-stat p-value		0.077		0.023		0.923		0.402		0.867
r-squared adjusted	0.341	0.356	0.323	0.334	0.353	0.350	0.466	0.464	0.337	0.334
number of observations	260	260	260	260	260	260	260	260	260	260
year	2 016	2 016	2 016	2 016	2 016	2 016	2 016	2 016	2 016	2 016
controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: All regressions are OLS. The unit of observation is the household. Experimental households are excluded from the observations. The dependent variable is an average of z-scores. Controls are demographic characteristics and average demographic characteristics in the network. Demographic characteristics include include gender, years of education, marital status, religion, ethnic group, whether the household produced horticultural crops in the previous year, and household assets. Average demographic characteristics in the network include proportion of female respondents, average years of education, proportion of married respondents, proportion of animists, proportion of respondents from the main ethnic group, proportion of households that produced horticultural crops in the previous year and household assets in the network. Robust standard errors reported in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4b: Adoption of production practices

dependent variable ------>	adoption									
network variable ------>	all		kinship		regular chatting		agricultural advice		borrowing money	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
links with treated	-0.012		0.010		-0.014		-0.034		0.094**	
	(0.024)		(0.028)		(0.034)		(0.058)		(0.047)	
strong links with treated		0.006		-0.000		0.019		-0.038		0.104**
		(0.025)		(0.034)		(0.040)		(0.060)		(0.051)
weak links with treated		-0.015		0.017		-0.041		-0.015		0.058
		(0.021)		(0.030)		(0.037)		(0.080)		(0.065)
links with experimental	0.024	0.020	0.015	0.017	0.014	0.010	0.069*	0.068*	-0.042	-0.042
	(0.017)	(0.016)	(0.021)	(0.022)	(0.022)	(0.021)	(0.040)	(0.040)	(0.037)	(0.037)
mean dep. variable	-0.773	-0.773	-0.773	-0.773	-0.773	-0.773	-0.773	-0.773	-0.773	-0.773
F-stat p-value		0.432		0.520		0.128		0.762		0.488
r-squared adjusted	0.574	0.356	0.587	0.585	0.577	0.580	0.610	0.608	0.576	0.575
number of observations	263	260	263	263	263	263	263	263	263	263
year	2 016	2 016	2 016	2 016	2 016	2 016	2 016	2 016	2 016	2 016
controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: All regressions are OLS. The unit of observation is the household. Experimental households are excluded from the observations. The dependent variable is an average of z-scores. Controls are demographic characteristics and average demographic characteristics in the network. Demographic characteristics include include gender, years of education, marital status, religion, ethnic group, whether the household produced horticultural crops in the previous year, and household assets. Average demographic characteristics in the network include proportion of female respondents, average years of education, proportion of married respondents, proportion of animists, proportion of respondents from the main ethnic group, proportion of households that produced horticultural crops in the previous year and household assets in the network. Robust standard errors reported in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4c: Knowledge of production practices

dependent variable ------>	knowledge									
network variable ------>	all		kinship		regular chatting		agricultural advice		borrowing money	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
links with treated	-0.046		-0.087*		0.065		0.114**		0.223**	
	(0.040)		(0.049)		(0.059)		(0.056)		(0.093)	
strong links with treated		0.002		-0.106*		0.072		0.102*		0.219**
		(0.038)		(0.057)		(0.074)		(0.057)		(0.098)
weak links with treated		0.005		-0.076		0.059		0.164*		0.240*
		(0.034)		(0.054)		(0.057)		(0.096)		(0.131)
links with experimental	0.061**	0.039	0.101***	0.105***	0.004	0.003	-0.005	-0.007	-0.050	-0.051
	(0.026)	(0.025)	(0.037)	(0.036)	(0.035)	(0.035)	(0.057)	(0.057)	(0.072)	(0.072)
mean dep. variable	-0.818	-0.658	-0.658	-0.658	-0.658	-0.658	-0.658	-0.658	-0.658	-0.658
F-stat p-value		0.937		0.564		0.830		0.498		0.862
r-squared adjusted	0.280	0.272	0.296	0.294	0.298	0.294	0.305	0.302	0.306	0.302
number of observations	247	247	247	247	247	247	247	247	247	247
year	2 017	2 017	2 017	2 017	2 017	2 017	2 017	2 017	2 017	2 017
controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: All regressions are OLS. The unit of observation is the household. Experimental households are excluded from the observations. The dependent variable is an average of z-scores. Controls are demographic characteristics and average demographic characteristics in the network. Demographic characteristics include include gender, years of education, marital status, religion, ethnic group, whether the household produced horticultural crops in the previous year, and household assets. Average demographic characteristics in the network include proportion of female respondents, average years of education, proportion of married respondents, proportion of animists, proportion of respondents from the main ethnic group, proportion of households that produced horticultural crops in the previous year and household assets in the network. Robust standard errors reported in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4d: Adoption of production practices

dependent variable ------>	adoption									
network variable ------>	all		kinship		regular chatting		agricultural advice		borrowing money	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
links with treated	0.008		-0.015		0.048		0.140***		0.016	
	(0.026)		(0.029)		(0.035)		(0.038)		(0.047)	
strong links with treated		0.011		-0.044		0.039		0.145***		0.007
		(0.025)		(0.035)		(0.039)		(0.039)		(0.047)
weak links with treated		0.030		0.001		0.056		0.120		0.047
		(0.023)		(0.031)		(0.039)		(0.077)		(0.093)
links with experimental	0.020	0.014	0.036*	0.042**	0.010	0.010	0.007	0.008	0.027	0.027
	(0.018)	(0.017)	(0.021)	(0.020)	(0.022)	(0.022)	(0.038)	(0.039)	(0.037)	(0.037)
mean dep. variable	-0.753	-0.773	-0.773	-0.773	-0.773	-0.773	-0.773	-0.773	-0.773	-0.773
F-stat p-value		0.539		0.139		0.659		0.750		0.663
r-squared adjusted	0.379	0.383	0.379	0.383	0.387	0.385	0.441	0.608	0.393	0.391
number of observations	247	247	247	247	247	247	247	263	247	247
year	2 017	2 017	2 017	2 017	2 017	2 017	2 017	2 017	2 017	2 017
controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: All regressions are OLS. The unit of observation is the household. Experimental households are excluded from the observations. The dependent variable is an average of z-scores. Controls are demographic characteristics and average demographic characteristics in the network. Demographic characteristics include include gender, years of education, marital status, religion, ethnic group, whether the household produced horticultural crops in the previous year, and household assets. Average demographic characteristics in the network include proportion of female respondents, average years of education, proportion of married respondents, proportion of animists, proportion of respondents from the main ethnic group, proportion of households that produced horticultural crops in the previous year and household assets in the network. Robust standard errors reported in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: Knowledge and adoption of production practices

		short-run				medium-run			
	dependent variable ------>	knowledge		adoption		knowledge		adoption	
	network variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
all	links with treated	-0.050		0.053		0.118***		0.043	
		(0.045)		(0.052)		(0.043)		(0.068)	
	strong links with treated		-0.017		0.043		0.058		0.014
			(0.038)		(0.046)		(0.037)		(0.052)
	weak links with treated		-0.110**		0.039		0.069		0.005
			(0.044)		(0.046)		(0.055)		(0.056)
	mean dep. Variable (control dyad)	0.978	0.978	1.006	1.006	0.973	0.973	0.935	0.935
	F-stat p-value		0.043		0.916		0.876		0.823
	r-squared adjusted	0.295	0.297	0.529	0.529	0.205	0.203	0.228	0.227
	number of observations	3 358	3 358	3 369	3 369	3 193	3 193	3 193	3 193
kinship	links with treated	-0.052		0.064		0.177***		0.065	
		(0.051)		(0.056)		(0.048)		(0.071)	
	strong links with treated		0.001		0.088		0.170***		0.096
			(0.053)		(0.057)		(0.052)		(0.075)
	weak links with treated		-0.107*		0.040		0.184***		0.033
			(0.061)		(0.060)		(0.069)		(0.076)
	mean dep. Variable (control dyad)	1.022	1.022	1.019	1.019	1.010	1.010	0.959	0.959
	F-stat p-value		0.026		0.176		0.850		0.197
	r-squared adjusted	0.290	0.292	0.517	0.518	0.196	0.196	0.221	0.222
	number of observations	2 283	2 283	2 292	2 292	2 184	2 184	2 184	2 184
regular chatting	links with treated	-0.107**		0.046		0.052		0.002	
		(0.050)		(0.054)		(0.051)		(0.064)	
	strong links with treated		-0.087*		0.034		0.056		-0.012
			(0.053)		(0.055)		(0.056)		(0.063)
	weak links with treated		-0.147**		0.072		0.043		0.031
			(0.064)		(0.069)		(0.084)		(0.076)
	mean dep. Variable (control dyad)	0.941	0.941	1.033	1.033	0.922	0.922	0.935	0.935
	F-stat p-value		0.301		0.504		0.889		0.371
	r-squared adjusted	0.284	0.285	0.505	0.506	0.212	0.212	0.222	0.223
	number of observations	1 480	1 480	1 485	1 485	1 389	1 389	1 389	1 389
agricultural advice	links with treated	-0.103*		-0.070		-0.047		-0.044	
		(0.059)		(0.066)		(0.074)		(0.077)	
	strong links with treated		-0.075		-0.074		-0.039		-0.022
			(0.057)		(0.068)		(0.073)		(0.084)
	weak links with treated		-0.185**		-0.058		-0.071		-0.109
			(0.087)		(0.095)		(0.119)		(0.099)
	mean dep. Variable (control dyad)	0.684	0.684	0.727	0.727	0.683	0.683	0.795	0.795
	F-stat p-value		0.106		0.847		0.759		0.388
	r-squared adjusted	0.183	0.186	0.462	0.462	0.200	0.200	0.204	0.206
	number of observations	476	476	476	476	463	463	463	463
borrowing money	links with treated	-0.194***		0.062		-0.115		0.033	
		(0.068)		(0.069)		(0.079)		(0.091)	
	strong links with treated		-0.202***		0.030		-0.085		0.049
			(0.074)		(0.074)		(0.082)		(0.097)
	weak links with treated		-0.164**		0.183**		-0.228*		-0.028
			(0.077)		(0.089)		(0.120)		(0.105)
	mean dep. Variable (control dyad)	1.105	1.105	1.072	1.072	1.049	1.049	0.964	0.964
	F-stat p-value		0.628		0.058		0.204		0.417
	r-squared adjusted	0.328	0.328	0.563	0.566	0.275	0.277	0.284	0.285
	number of observations	514	514	516	516	493	493	493	493
	year	2 016	2 016	2 016	2 016	2 017	2 017	2 017	2 017
	controls	yes	yes	yes	yes	yes	yes	yes	yes

Note: All regressions are OLS. The unit of observation is the directed dyad. Observatios with directed links from progressive farmers nodes are not included. The dependent variable is an average of z-scores. Controls include characteristics of the dyad and of both nodes. Dyad controls include whether the respondents have the same religion, belong to the same ethnic group, have the same gender and the geographical distance between them. Node controls are individual and household characteristics, which include years of education, household assets, marital status and whether the household produced horticultural crops in the previous year. Two-way cluster-robust standard errors reported in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6a: Treatment effect - Short-run Network change

dependent variable ------>	out degree		in degree		betweenness		closeness	
network variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
kinship	0.002	0.008	0.010	0.014	-0.000	0.001	0.007	0.008
	(0.016)	(0.014)	(0.015)	(0.017)	(0.001)	(0.001)	(0.011)	(0.007)
mean dep. variable (control)	0.126	0.126	0.122	0.122	0.004	0.004	0.523	0.523
r-squared adjusted	-0.013	0.099	-0.008	0.069	-0.013	-0.015	-0.009	0.686
regular chatting	0.004	0.012	0.003	0.008	0.001	0.002	0.004	0.010
	(0.015)	(0.014)	(0.009)	(0.011)	(0.001)	(0.001)	(0.007)	(0.007)
mean dep. variable (control)	0.077	0.077	0.083	0.083	0.005	0.005	0.526	0.526
r-squared adjusted	-0.013	0.193	-0.012	-0.082	-0.009	0.093	-0.008	0.047
potential agricultural advice	-0.002	0.002	0.008	0.008*	0.002	0.003	0.004	0.005
	(0.006)	(0.007)	(0.005)	(0.005)	(0.002)	(0.003)	(0.005)	(0.005)
mean dep. variable (control)	0.030	0.030	0.029	0.029	0.006	0.006	0.319	0.319
r-squared adjusted	-0.013	-0.051	0.020	0.076	-0.007	-0.022	-0.006	-0.056
real agricultural advice	0.002	0.003	0.004	0.004*	0.004*	0.004**	0.007**	0.008**
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
mean dep. variable (control)	0.009	0.009	0.010	0.010	0.003	0.003	0.193	0.193
r-squared adjusted	-0.006	0.021	0.017	0.131	0.041	0.143	0.032	0.037
potential borrowing money	-0.006	-0.004	0.003	0.003	0.000	0.001	-0.008	-0.007
	(0.005)	(0.005)	(0.005)	(0.006)	(0.002)	(0.002)	(0.009)	(0.010)
mean dep. variable (control)	0.029	0.029	0.028	0.028	0.007	0.007	0.409	0.409
r-squared adjusted	0.010	0.054	-0.009	-0.048	-0.013	-0.074	-0.004	0.027
real borrowing money	0.003	0.003	0.001	0.001	0.003	0.002	0.001	0.000
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.009)	(0.010)
mean dep. variable (control)	0.004	0.004	0.006	0.006	0.001	0.001	0.191	0.191
r-squared adjusted	0.014	-0.059	-0.006	-0.028	0.025	0.088	-0.014	-0.017
number of observations	75	75	75	75	75	75	75	75
year	2 016	2 016	2 016	2 016	2 016	2 016	2 016	2 016
controls	no	yes	no	yes	no	yes	no	yes

Note: All regressions are OLS. The unit of observation is the individual. Non-experimental households are excluded from the observations. 'treatment' is a dummy equal to one if the individual was assigned to the treatment group and zero otherwise. Controls are individual and household characteristics, which include years of education, marital status, religion, ethnic group and household assets. Robust standard errors reported in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 6b: Treatment effect - Medium-run Network change

dependent variable ------>	out degree		in degree		betweenness		closeness	
network variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
kinship	-0.005	-0.002	-0.004	0.006	0.000	0.000	0.002	0.004
	(0.015)	(0.016)	(0.015)	(0.015)	(0.001)	(0.001)	(0.010)	(0.006)
mean dep. variable (control)	0.113	0.065	0.125	0.051	0.003	0.008	0.510	0.365
r-squared adjusted	-0.012	0.058	-0.013	0.101	-0.013	0.054	-0.013	0.595
regular chatting	0.005	0.009	0.006	0.011	0.001	0.001	0.004	0.007
	(0.010)	(0.011)	(0.010)	(0.011)	(0.001)	(0.001)	(0.005)	(0.006)
mean dep. variable (control)	0.071	0.128	0.078	0.053	0.004	0.006	0.502	0.509
r-squared adjusted	-0.011	0.000	-0.007	-0.080	-0.002	-0.075	-0.007	-0.067
potential agricultural advice	0.002	0.005	0.015	0.017*	0.003	0.003*	0.005	0.009
	(0.006)	(0.006)	(0.010)	(0.010)	(0.002)	(0.002)	(0.006)	(0.007)
mean dep. variable (control)	0.033	0.053	0.040	-0.057	0.005	-0.004	0.368	0.330
r-squared adjusted	-0.011	-0.005	0.020	0.136	0.024	0.021	-0.004	0.072
real agricultural advice	0.000	0.002	0.004*	0.004*	0.001	0.002	0.006	0.008
	(0.003)	(0.004)	(0.002)	(0.002)	(0.001)	(0.001)	(0.005)	(0.006)
mean dep. variable (control)	0.008	0.016	0.006	-0.013	0.001	-0.006	0.176	0.164
r-squared adjusted	-0.014	-0.024	0.030	0.163	0.017	0.024	0.004	-0.030
potential borrowing money	-0.001	-0.000	-0.003	-0.001	0.001	0.000	-0.004	-0.003
	(0.006)	(0.006)	(0.006)	(0.007)	(0.002)	(0.002)	(0.009)	(0.009)
mean dep. variable (control)	0.031	0.057	0.039	0.009	0.005	0.012	0.416	0.374
r-squared adjusted	-0.013	0.029	-0.011	-0.058	-0.008	-0.046	-0.011	0.189
real borrowing money	-0.000	0.000	-0.000	-0.001	-0.001	-0.000	-0.003	-0.006
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.009)	(0.009)
mean dep. variable (control)	0.004	0.008	0.006	0.004	0.002	0.006	0.188	0.188
r-squared adjusted	-0.013	0.091	-0.012	-0.087	-0.001	0.277	-0.012	0.031
number of observations	75	75	75	75	75	75	75	75
year	2 017	2 017	2 017	2 017	2 017	2 017	2 017	2 017
controls	no	yes	no	yes	no	yes	no	yes

Note: All regressions are OLS. The unit of observation is the individual. Non-experimental households are excluded from the observations. 'treatment' is a dummy equal to one if the individual was assigned to the treatment group and zero otherwise. Controls are individual and household characteristics, which include years of education, marital status, religion, ethnic group and household assets. Robust standard errors reported in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.

Figure 1: Map of Guinea Bissau

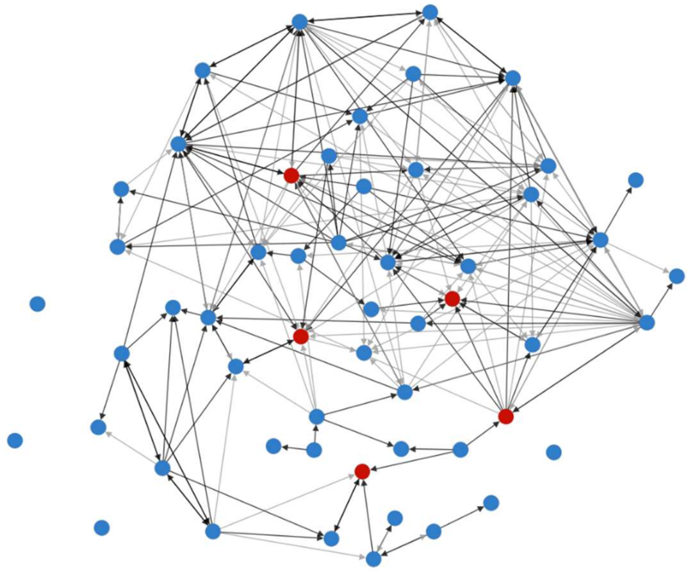

Figure 3a: Illustration of a kinship network

Note: Visual representation of the kinship links among 54 households from one of the neighborhoods in the village. Each node represents a household. Treated households are depicted as red nodes, while non-treated households are represented as blue nodes. The lines between nodes indicate the existence of a link and the direction of the link is illustrated by the arrow. Grey lines represent weak links and black lines represent strong links.

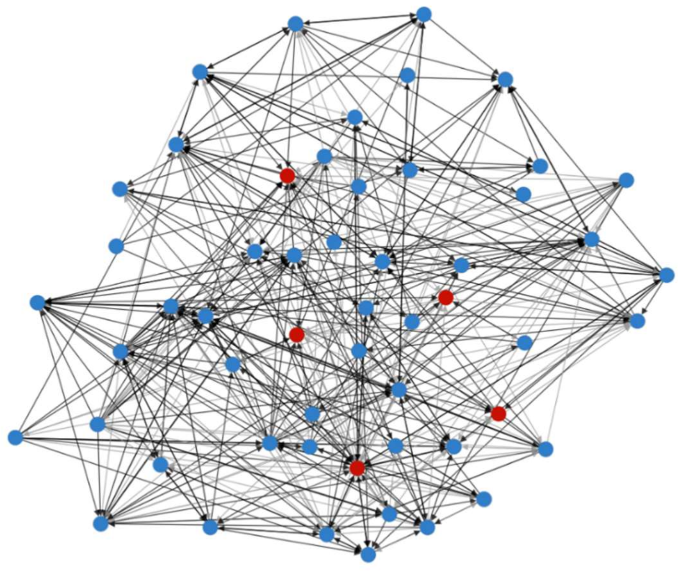

Figure 3b: Illustration of a regular chatting network

Note: Visual representation of the regular chatting links among 54 households from one of the neighborhoods in the village. Each node represents a household. Treated households are depicted as red nodes, while non-treated households are represented as blue nodes. The lines between nodes indicate the existence of a link and the direction of the link is illustrated by the arrow. Grey lines represent weak links and black lines represent strong links.

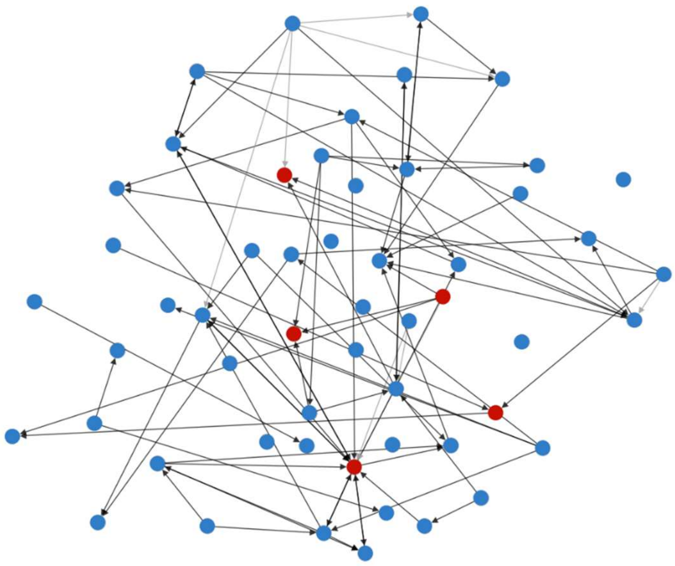

Figure 3c: Illustration of an agricultural advice network

Note: Visual representation of the agricultural advice links among 54 households from one of the neighborhoods in the village. Each node represents a household. Treated households are depicted as red nodes, while non-treated households are represented as blue nodes. The lines between nodes indicate the existence of a link and the direction of the link is illustrated by the arrow. Grey lines represent weak links and black lines represent strong links.

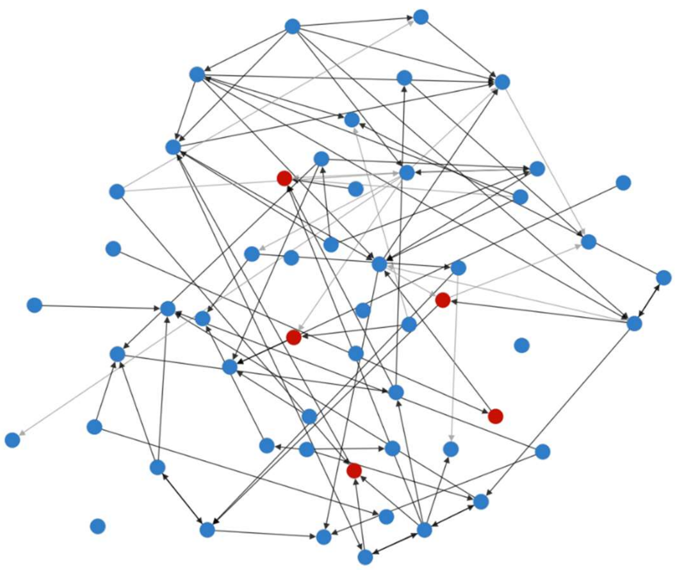

Figure 3d: Illustration of a borrowing money network

Note: Visual representation of the borrowing money links among 54 households from one of the neighborhoods in the village. Each node represents a household. Treated households are depicted as red nodes, while non-treated households are represented as blue nodes. The lines between nodes indicate the existence of a link and the direction of the link is illustrated by the arrow. Grey lines represent weak links and black lines represent strong links.

Appendix A

This appendix expands on our measure of tie strength presented in Section 3.1. As mentioned in the main text, recall-based elicitation methods of collecting network data might result in only capturing the individual's strongest ties. Given our elicitation method, we believe that the links elicited from memory would tend to capture stronger ties, while further links elicited with the album visual aid would more likely represent weak ones. According to Granovetter, 1973, in his seminal paper, "the strength of a tie is a (probably linear) combination of the amount of time, the emotional intensity, the intimacy (mutual confiding), and the reciprocal services which characterize the tie". In practice, different proxies have been used in order to characterize tie strength, such as reciprocity of the link and the number of mutual friends (Gee, Jones and Burke, 2017). As a robustness check, we test the relationship between our measure of tie strength and some of those proxies.

We follow a dyadic approach, using the directed dyad as the unit of observation. In this case the dyad is a pair of linked nodes and the directionality of the link is taken into account.[10] We estimate the following specification in a dyadic framework:

$$Y_{ij} = \alpha + \beta L_{ij}^{s} + \gamma_1 w_{ij} + \gamma_2(z_i - z_j) + \gamma_2(z_i + z_j) + \varepsilon_{ij}, \quad \textbf{(1)}$$

where Y_{ij} are the proxies for tie strength between nodes i and j: link reciprocity and the proportion of mutual ties. Link reciprocity is a binary variable, taking the value of one if there is a reciprocal relationship between nodes i and j, i.e. if both named the other as a network partner., and of zero if the relationship is unilateral, i.e. if node i named node j as a network partner, but not the other way around. The proportion of mutual ties of nodes i and j is the number of network partners common to i and j divided by the total number of network partners of both i and j. L_{ij}^{s} is a binary network variable that captures tie strength for directed links. It takes the value of one if the link was elicited from memory (strong link), and of zero if it was elicited with the album visual aid (weak link). w_{ij} is a vector of variables describing the characteristics of the dyad, including whether nodes i and j have the same religion, belong to the same ethnic group, are of the same gender, and the geographical distance between them. z_i and z_j are vectors of individual and household level characteristics of i and j, such as years of education, household assets, marital status, and whether the household produced horticultural crops in the previous year. We follow Fafchamps and Gubert (2007) and include the characteristics of the individual and household-

[10] Household i is linked to household j, if household i named household j as a network partner.

level characteristics as simple differences and in sums. By including the regressors in this manner we are able to account for the effects of the differences in characteristics of the nodes, as well as the combined effect of those characteristics. All estimations are OLS and we use two-way cluster-robust standard errors, clustered at both i and j, following Cameron, Gelbach, and Miller (2011).

We present the results for the aforementioned specifications in Tables A1.

< Table A1 around here >

As we can see from Table A1 having a strong kinship link in our measure is associated with a 3.7 percentage point increase in link reciprocity, and a 0.028 increase in the proportion of mutual ties. Both results are statistically significant at the 1 percent level. As for the network of regular chatting, a strong regular chatting link has a positive and statistically significant correlation with link reciprocity and mutual ties. These represent a 10 percentage points increase on link reciprocity and a 0.041 increase in the proportion of mutual ties. Regarding the network of agricultural advice, we see similar results in link reciprocity: a strong agricultural advice link increases the probability of the link being reciprocal by 4.5 percentage points, statistically significant at the 1 percent level. However, there is no statistically significant effect on the proportion of mutual ties. Lastly, in line with the results found before, a strong borrowing money link is associated with a 3.9 percentage point increase in link reciprocity and a 0.034 increase in the proportion of mutual ties between the nodes.

Overall, there is a positive correlation between strong links and link reciprocity for all network variables. Similar results arise using the proportion of mutual ties instead of reciprocity: having a strong link in any network category is generally associated with a higher proportion of mutual ties relative to weak links. The sole exception are agricultural advice links, for which coefficients are not significant. These results support our network definition of tie strength, i.e. that links recalled from memory are more likely to be strong than links recalled using the visual aid.

Table A1: Link strength

network variable ------>	strong kinship link	strong regular chatting link	strong agricultural advice link	strong borrowing money link
dependent variable	(1)	(2)	(3)	(4)
link reciprocity	0.037***	0.100***	0.045***	0.039***
	(0.012)	(0.011)	(0.016)	(0.015)
mean dep. Variable	0.312	0.132	0.074	0.083
r-squared adjusted	0.021	0.040	0.029	0.030
mutual ties	0.028***	0.041***	0.006	0.034***
	(0.004)	(0.005)	(0.011)	(0.011)
mean dep. Variable	0.295	0.267	0.421	0.388
r-squared adjusted	0.050	0.105	0.129	0.132
number of observations	12 571	7 604	2 010	2 665
controls	yes	yes	yes	yes

Note: All regressions are OLS. The dependent variables link reciprocity and regular chatting are binary. The dependent variable proportion of mutual ties is the number of mutual ties divided by the total number of ties in both i and j. Controls include characteristics of the dyad and of both nodes. Dyad controls include whether the respondents have the same religion, belong to the same ethnic group, have the same gender and the geographical distance between them. Node controls are individual and household characteristics, which include years of education, household assets, marital status and whether the household produced horticultural crops in the previous year. Two-way cluster-robust standard errors reported in parenthesis. * significant at 10%; ** significant at 5%; *** significant at 1%.