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Diffusion of agricultural innovations in Guinea-Bissau

From learning to doing

Rute M. Caeiro*

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United Nations University World Institute for Development Economics Research
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Abstract: This paper analyses the pathways of technology diffusion through social networks, following the experimental introduction of new technologies in Guinea-Bissau. In the context of an agricultural extension project, we document both the direct effects of this intervention and subsequent diffusion from trainees to the wider community. In order to test for social learning, we exploit a detailed census of households and social connections across different social dimensions. In our first result, we show that trainees' knowledge and adoption rose immediately after training, remaining stable thereafter. Secondly, we show that agricultural information diffuses along social network links from project participants to non-participants. However, these effects are heterogeneous across different types of networks—the most relevant being a farmer's 'financial support'. Despite positive effects in knowledge, evidence of network impacts on actual adoption behaviour is more limited.

Key words: agriculture, technology adoption, social learning, social networks

JEL classification: O13, O31, Q16

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* UNU-WIDER, Helsinki, Finland; caeiro@wider.unu.edu

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Katajanokanlaituri 6 B, 00160 Helsinki, Finland

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1 Introduction

More than 70 per cent of Africa's low-income population live in rural areas and depend primarily on agriculture for their livelihood (Castañeda et al. 2016). Agricultural development through productivity improvements is therefore often promoted as an effective means to reduce poverty in the region. Despite some gains over recent years, agricultural productivity in sub-Saharan Africa remains low, lagging well behind the rest of the world (World Bank 2008). Although agricultural technologies that could significantly boost productivity are available, those have not yet been widely adopted in the region (Gollin et al. 2005). Poor access to reliable information is among the most frequently mentioned barriers to technology take-up. This issue can be particularly acute with technologies that are new or technically challenging and thus less likely to be adopted in the absence of information about their existence, implementation, or benefits (see Jack 2013; Magruder 2018). Information dissemination is therefore likely to be a key factor in boosting technology adoption, which can in turn foster productivity gains. To address existing information frictions, governments and other organizations have often relied on extension services, providing recommendations aimed at increasing agricultural productivity and yields. Extension interventions have the potential to impact technology adoption not only among project participants but also beyond, to the extent that trained farmers may disseminate knowledge to their peers. Social network contacts, because of their credibility and knowledge of local agronomic conditions, are often recognized as an important source of reliable information. This suggests that social networks are likely to have an important role to play in mitigating information constraints and disseminating improved technologies.

This paper analyses the role of social networks in the diffusion process of knowledge and, ultimately, the adoption of cultivation techniques introduced by a randomized agricultural extension intervention. 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.[1] We build on this experiment to identify, first, the direct effect of the extension intervention on the treated farmers and, second, the diffusion of improved techniques from project participants to the wider community in one village in Guinea-Bissau. To this end, a group of female progressive farmers were first chosen by the community to attend the extension training sessions and were then randomly assigned to either the treatment or control group. The extension training resulted in clear improvements in adoption and knowledge of improved practices among the treated progressive farmers, which persisted over two agricultural seasons. We then rely on within-village networks to investigate diffusion from treated progressive farmers to the non-progressive population. Our data set is especially comprehensive, tracking the village universe and their social connections over two years, and allows us to separate the importance of strong and weak ties. Our empirical approach exploits the exogenous variation in the intensity of exposure to treated farmers (i.e. in the number of treated farmers on an individual's social networks) to identify peer effects. We test for spill-over effects in both knowledge and adoption of production practices over two agricultural seasons.

In order to understand the mechanisms through which learning and adoption occur, we conducted a census of households and their social relations along different network dimensions. Specially, we distinguish among the 'kinship' network (i.e. households that are related through family links); 'chatting' network (i.e. individuals the respondent regularly chats with); 'agricultural advice'

[1] The practices included land preparation, irrigation, nursery management, spacing, mulch, soil enrichment, pruning, staking, pest management, and crop rotation.

network (i.e. farmers the respondent would go to for agricultural advice); and 'financial support' network (i.e. peers that the respondent could request money from in times of need). This categorization allows us to test for the relative importance of these different kinds of social links. These data were collected in two stages. First, we asked farmers to list their contacts in each of the aforementioned networks from memory. Then, in a second stage, we used a comprehensive photo directory, collected beforehand, as a visual aid to help respondents recall additional network links. This two-stage elicitation method provides an intuitive classification of farmers' ties into 'strong' and 'weak'—depending, respectively, on whether those were identified from memory or only upon visualizing the photo directory. This characterization allows us to identify how tie strength influences access to information.

Our results show that information externalities from 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 effect of different links, not all networks contribute equally to the diffusion of information though. We find stronger network effects for those individuals with links to farmers from whom they could request money in times of need ('financial support' network, as per the above classifications). In contrast, we find evidence of decreases in information within the 'kinship' network. Although seemingly counterintuitive at first glance, this effect could be explained by increased labour specialization among family members following the treatment—with treated farmers potentially taking on a larger share of the household's agricultural work, thereby freeing up other members to focus on alternative activities. Exploiting our measure of tie strength, we also find that strong ties appear to be as relevant as weak ties in the diffusion of information. These results suggest that the type of interaction may matter for information diffusion but not social proximity between individuals. Despite positive effects in knowledge, we find only limited evidence of social effects on actual adoption. Taken together, our results suggest that while information may be a necessary condition for technology adoption, it might not be sufficient, at least in our setting. Our results are robust to accounting for the dyadic nature of these links and to alternative specifications of the outcome variables.

Finally, we document network changes as a result of the intervention. Our analysis to detect network-level effects is based on individual-level specifications of the progressive farmers. Training led to a change in the position of treated farmers in the agricultural advice network, with those becoming more central in this social structure. Not surprisingly, these effects are only present in the agricultural network. These results indicate that the intervention encouraged the creation of agricultural communication links with the trained farmers, which in turn is likely to have fostered information dissemination.

This paper relates to the broader literature on diffusion of information, technologies, and behaviour within social networks.[2] Diffusion effects along social networks have been documented in a variety of settings, including health behaviour (Oster and Thornton 2012; Godlonton and Thornton 2012; Apouey and Picone 2014), education outcomes (Bobonis and Finan 2009; Fafchamps and Mo 2017), financial decisions (Duflo and Saez 2003; Cai et al. 2015; Banerjee et al. 2013), political behaviour (Giné and Mansuri 2018; Fafchamps et al. 2020; Batista et al. 2019), and agricultural practices (Foster and Rosenzweig 1995; Munshi 2004; Bandiera and Rasul 2006; Conley and Udry 2010).

[2] See Munshi (2004) and Chuang and Schechter (2015) for a comprehensive review.

The current paper is closer in spirit to previous works on agricultural technology diffusion within social networks.[3] Foster and Rosenzweig (1995) were one of the first to investigate the effects of social learning in agriculture. In a study of the adoption of high-yielding varieties in India, the authors found evidence of farmers learning from other farmers' experiences. 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, the authors found evidence of farmers learning from one another, aligning their use of fertilizers with that of their most successful peers. Beaman et al. (2018) studied social learning in diffusion of pit planting in Malawi. The authors identify entry points and show their effectiveness in promoting technology diffusion. Our paper innovates on this literature by investigating the role of network structures in the diffusion process. In particular, we test the role of different information channels in technology diffusion, which we measure using detailed data on kinship, chatting, agricultural advice, and financial support networks.

The literature on peer effects describes two main mechanisms through which peers can influence adoption decisions. First, individuals may be influenced merely by observing their peers' adoption decisions, either because of a desire to imitate or because adoption by peers affects individuals' perception of the value of technology (Bandiera and Rasul 2006; Beshears et al. 2015). The second, more complex mechanism relies on information transmission, where individuals learn from their peers about both the benefits and practical use of a technology (Conley and Udry 2010; Kremer and Miguel 2007; Oster and Thornton 2012). For example, farmers might learn from their peers about the profitability of a technology (Besley and Case 1994; Munshi 2004) or about the optimal input application (Foster and Rosenzweig 1995; Conley and Udry 2001). In this paper, we focus mainly on the information mechanism, as we separately attempt to measure both the diffusion of information and adoption.

Although the aforementioned studies have found evidence of positive peer effects in technology adoption, results have not always been as encouraging. As is the case with our paper, several other studies have found that diffusion of practices in particular can be limited or non-existent (Fafchamps and Quinn 2018; Fafchamps and Söderbom 2014). In the agricultural context, Munshi (2004), in a study in India, finds evidence of social learning in adoption of wheat but not of rice. Duflo et al. (2011), in a randomized field experiment among maize farmers in Kenya, found little evidence of peer effects in fertilizer adoption. In fact, in some contexts, social network effects may even generate perverse outcomes, such as 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 (Kremer and Miguel 2007; Miller and Mobarak 2014).

Our paper adds to the recent literature that uses complete social network data combined with exogenous variation in order to identify peer effects in the context of policy interventions. Estimation of peer effects faces several empirical challenges. A key concern relates to disentangling social interaction effects from pure correlated effects (Manski 1993). Individuals in the same peer group may behave similarly, not because they are influenced by others but because they might share similar characteristics. In order to overcome this issue, previous studies have either resorted to different econometric techniques in non-experimental settings (Foster and Rosenzweig 1995; Conley and Udry 2010; Munshi 2004; Bandiera and Rasul 2006) or, like us, relied on experimental

[3] Maertens and Barret (2012), Magruder (2018), and De Janvry et al. (2017) provide a review of peer effects in agriculture.

manipulation of treatment status (Fafchamps and Quinn 2018; Duflo and Saez 2003; Oster and Thornton 2012; Kremer and Miguel 2007; Godlonton and Thornton 2012; Dupas 2014). Further difficulties arise in correctly identifying network groups. Most previous studies rely on sampled networks, lacking comprehensive dyadic-level information. However, such an approach artificially truncates the network and can lead to non-classical measurement error (Santos and Barrett 2008; Chandrasekhar and Lewis 2011).[4] Similar to our paper, Beaman and Dillon (2018) and Cai et al. (2015) in an agricultural context and Kim et al. (2015) focusing on the adoption of health technologies employ both a social network census and a randomized controlled trial to identify peer effects. Beaman and Dillon (2018) and Kim et al. (2015) focus on which individuals should be targeted if the goal is to maximize social learning. Cai et al. (2015) identify the effect of social learning on adoption of crop insurance.

This paper also contributes to the literature by investigating the role of tie heterogeneity on peer effects. With respect to this, we use a novel characterization of connection strength between individuals to investigate the 'strength of weak ties' hypothesis, proposed by Granovetter (1973). Strong ties exist between individuals whose social circles tightly overlap, while weak ties are acquaintances or socially distant individuals. Granovetter (1973) showed that novel information about jobs tended to flow through weak ties rather than strong social ties. One possible explanation is that weak ties are more likely to be bridging ties, exposing individuals to different social circles and therefore more diverse information, including about jobs. Interestingly, in contrast with this literature, we find that both ties matter for agriculture information diffusion.

Finally, we contribute to the emerging literature on how social networks react in response to policy interventions (Comola and Prina 2021; Banerjee et al. 2018; Heß et al. 2020).

The remainder of this paper is structured as follows. Section 2 provides the context of the study. 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 gross domestic product (GDP) per capita of US$1,450 purchasing power parity and 67 per cent of its population living on less than US$1.90 per day (World Bank 2017). Agriculture is key to Guinea-Bissau's economy. It accounts for 69 per cent of GDP and represents the primary source of income for 85 per cent 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 (see World Bank 2015). Rice is the main staple crop in the country and is widely grown, but rice productivity has remained relatively low.[5] Low productivity can be explained by several constraints faced by the agricultural sector ranging from erratic weather, scarce inputs, and extension services to weakened infrastructure. Years of poor harvest or shocks to cashew prices can leave subsistence farmers in a particularly

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[4] There are, however, some notable exceptions that, similar to our case, use complete social network data from the census but do not exploit a randomized experiment (Banerjee et al. 2013; Van den Broeck and Dercon 2011; Blumenstock et al. 2016).

[5] 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).

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 (see World Food Program 2013). As for the horticultural sector, production has steadily increased from 26,381 tons in 2005 to 33,420 tons in 2014.[6] In the Guinea-Bissau Country Economic Memorandum (World Bank 2015), the World Bank identified horticulture as one of the agricultural sectors with the 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. Suzana is a rural village, with 354 households spread across eight neighbourhoods. 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 cashews are 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.

3 Agricultural extension intervention

In 2015, international non-governmental organization (NGO) VIDA[7] introduced an agricultural extension project providing agricultural technical training and inputs to farmers in six villages in the northwest region of Guinea-Bissau, including the focus of our study, Suzana. The project included group-level training sessions on horticultural cultivation techniques, creation and management of farmers' associations, and 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 project included three modules on production 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 group 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 training. That list of potential participants was then randomly allocated to either the control or treatment group. In addition, female village leaders also attended the training. This paper focuses only on the village of Suzana, where 35 farmers were randomly assigned to the treatment group and participated in the training, and another 41

[6] FAOSTAT Database.

[7] For more information, see http://vida.org.pt/en/.

constituted the control group. Results of the impact evaluation are not the main focus of this paper, but they are briefly addressed in the next sections.

4 Measurement and data

We conducted two rounds of data collection, each including both a village census and a household survey. The village census included questions on demographic characteristics, horticultural production patterns during the previous agricultural season, and household asset ownership. During the data collection of each census, 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 was directed at the individuals responsible for horticulture production—usually the female head of the household—and collected data on individuals' network links, horticultural production decisions during the previous agricultural season, and 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 that took place between August and September 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 per cent of the initial households.[8] 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 village's census, we collected data on households' social network. Respondents were asked about all their links with other residents of Suzana 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) financial support 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 neighbourhoods located in the village. With eight neighbourhoods, respondents thus answered each set of network questions eight times, but the order of the neighbourhoods 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 each of 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 (i.e. the respondent's weaker social links) are more easily forgotten (Maertens and Barrett 2013; Brewer 2000; Santos and Barrett 2008).

[8] Out of the 354 households in the village, we were able to follow 345 households in the second survey and 339 in the subsequent two.

To address these limitations, we implemented a second step, where we used the village photo album collected during each census to prompt respondents and determine whether the respondent had any additional links not named previously. The village photo album was organized by neighbourhood, included the photo of one person per household (the household representative), and depicted all the households in the village.[9] This second step provides a feasible and intuitive way of identifying weak (and easily forgotten) links.

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 neighbourhood of «Catama» but outside of your household residence?' In the second step, we asked the respondents to go through the photos of that neighbourhood and asked: 'Do you have any other family member living in the neighbourhood 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 for the agricultural advice network that elicited the individuals that the respondent would go to for agricultural advice. Lastly, the fourth network dimension was the financial support network that elicited the individuals that the respondent could ask for money in times of need.

For the latter two network dimensions, namely agricultural advice and financial support, we further recorded what we refer to as the effective link. While the statements depicted 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 financial support refers to the network of potential links.

By eliciting the social networks in this way, we are implicitly capturing the strength of ties between individuals because 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.

4.2 Outcome measures

In our analysis of spill-over 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

[9] In order to further minimize measurement error resulting from difficulties in matching names, the village photo album was also used in the first step, after the respondent finished listing all the peers. As such, there is no reason to believe there would be any difference in measurement error between the first and second step.

practice knowledge, as the simple average of the z-scores for the relevant survey questions.[10] Table 1 provides a description of these variables.

Table 1: Production practices

Practice	Knowledge	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

Source: authors' compilation.

Finally, we take advantage of the network data collected at two points in time to analyse changes in network structure, focusing 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.[11] All centrality measures were standardized and therefore range between zero and one.

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

[10] The z-scores were computed by subtracting the mean and dividing by the standard deviation of the impact control group. Following Kling et al. (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.

[11] In-degree refers to the number of farmers the respondent mentioned as a 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 and any other farmer.

average treatment effects of the agriculture training programme can be estimated using the specification:

$$Y_{it} = \alpha + \partial T_i + \gamma X_{i0} + \varepsilon_i, \tag{1}$$

where Y_{it} represents the outcome variable of interest for individual i at time t. T_i is a binary variable that takes the value of one if the individual was assigned to the treatment group and zero otherwise. 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 programme. Our village contains both progressive farmers (those selected by the village leaders to participate and were allocated either to 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 behaviour of non-progressive farmers is affected by the number of treated (progressive) farmers in their social networks. Our identification strategy relies on the fact that the number of treated peers is experimentally generated by the randomization, when conditioning on the number of peer progressive farmers.

We estimate these diffusion effects using the following specification:

$$Y_{it} = \alpha + \beta_T N_{i0}^T + \beta_P N_{i0}^P + \gamma X_{i0} + \theta \bar{X}_{j0} + \varepsilon_{it}, \tag{2}$$

where, N_{i0}^T is the number of links with treated individuals, and N_{i0}^P is the number of links with 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 the effect of N_{i0}^T is not driven by the overall size of the network. Hence, N_{i0}^T captures the exogenous variation in the number of treated peers. In addition, X_{i0} is a vector of individual and household characteristics that 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 analyse the effect of strong and weak links with treated individuals:

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

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 considered, i.e. node i is linked to node j only if i reported j as a network partner. Note that because we are considering the direction of the link, a link from node i to node j is not identical to 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:

$$|Y_{it} - Y_{jt}| = \alpha + \beta_T L_{ij0}^T + \gamma_1 w_{ij0} + \gamma_2 (z_{i0} - z_{j0}) + \gamma_3 (z_{i0} + z_{j0}) + \varepsilon_{ijt}, \quad (4)$$

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. A negative estimate of β_T is evidence that outcomes in dyads between non-progressive and treated farmers are more similar than in dyads between non-progressive and control farmers. In addition, we include w_{ij0}, 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. Finally, z_{i0} and z_{j0} capture 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 effect of the sum of the characteristics on the outcome of interest.

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

$$|Y_{it} - Y_{jt}| = \alpha + \beta_{sT} L_{ij0}^{sT} + \beta_{wT} L_{ij0}^{wT} + \gamma_1 w_{ij0} + \gamma_2 (z_{i0} - z_{j0}) + \gamma_3 (z_{i0} + z_{j0}) + \varepsilon_{ikt}, \quad (5)$$

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

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

6 Econometric results

We divide the analysis of econometric results into five 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 effects of the training programme on treated versus control progressive farmers. Third, we present the analysis of the network effects of the training programme, 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, chatting, agricultural advice, and financial support. Finally, we document possible network changes as a result of the intervention, followed by robustness tests.

6.1 Descriptive statistics and balance tests

In this section we present descriptive statistics and balance checks 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 who correspond to the rest of the population.[12] Balance tests between the treatment and control groups are reported in the first two columns of Table 2. The last two columns present the summary 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.

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

		Control	Difference to treatment group	Non-progressive	Difference to progressive group
Basic demographics	Age	39.439	2.955	53.795	-13.038***
			(2.559)		(1.600)
	Female			0.857	0.130***
					(0.025)
	Years of education	2.000	0.235	1.971	0.136
			(0.633)		(0.369)
	Married	0.780	0.014	0.485	0.301***
			(0.096)		(0.056)
Religion and ethnicity	Catholic	0.293	0.148	0.250	0.110*
			(0.112)		(0.062)
	Animist	0.585	-0.085	0.636	-0.089
			(0.117)		(0.065)
	Felupe	0.951	0.019	0.868	0.092***
			(0.045)		(0.031)
Occupation	Farmer	0.902	-0.049	0.722	0.158***
			(0.077)		(0.047)
	Stays at home	0.073	0.074	0.183	-0.076*
			(0.074)		(0.043)
	Vendor	0.024	-0.024	0.019	-0.006
			(0.024)		(0.016)
Network centrality	In-degree	0.176	0.012	0.133	0.049***
			(0.019)		(0.010)
	Out-degree	0.180	0.016	0.128	0.059***
			(0.019)		(0.010)
	Betweenness	0.003	0.001	0.002	0.002***
			(0.001)		(0.000)
	Closeness	0.585	0.009	0.561	0.028***
			(0.008)		(0.004)

Note: standard errors reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

[12] Seven village leaders that attended the training were excluded from the analysis.

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 two years of education, 86 per cent of the non-progressive respondents are women, animism is the predominant religion followed by Catholicism, and the majority of individuals (87 per cent) 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.

Social networks' characteristics are summarized in Table 3. The table reports the average number of links, and corresponding standard errors, within the village, with the progressive farmers and treated farmers. Figure 1 provides a visual representation of the network links among 54 households from one of the neighbourhoods in the village. The networks of kinship, chatting, agricultural advice, and financial support in the same neighbourhood are depicted in Figures 1a–1d, respectively.

Table 3: Descriptive statistics—network variables

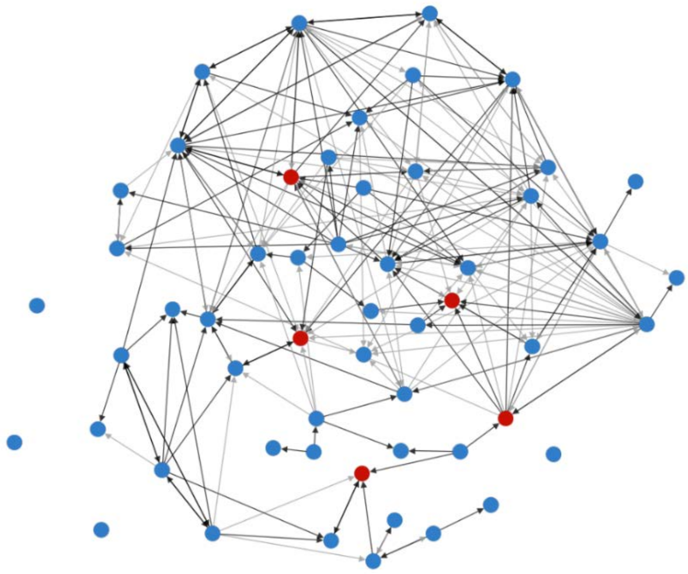
		Village	Links with progressive	Links with treated
All networks	Total	46.926	12.810	6.118
		(27.344)	(8.291)	(4.266)
	Strong	29.327	8.171	3.715
		(17.270)	(5.621)	(2.771)
	Weak	22.143	6.023	3.125
		(16.521)	(5.109)	(2.966)
Kinship network	Total	33.408	8.715	4.152
		(23.120)	(6.476)	(3.392)
	Strong	18.176	4.882	2.099
		(12.798)	(3.866)	(1.959)
	Weak	15.232	3.833	2.053
		(13.736)	(3.785)	(2.204)
Chatting network	Total	19.960	5.646	2.650
		(15.833)	(5.660)	(2.958)
	Strong	13.871	3.798	1.760
		(9.643)	(3.525)	(1.801)
	Weak	6.088	1.848	0.890
		(8.734)	(3.187)	(1.832)
Agricultural advice network	Total	4.324	1.810	0.924
		(6.105)	(2.763)	(1.559)
	Strong	3.364	1.357	0.707
		(4.849)	(2.139)	(1.308)
	Weak	0.960	0.452	0.217
		(2.078)	(1.144)	(0.601)

Financial support network	Total	7.081	1.962	0.947
		(6.189)	(2.288)	(1.350)
	Strong	5.879	1.654	0.757
		(4.947)	(1.930)	(1.092)
	Weak	1.202	0.308	0.190
		(2.354)	(0.796)	(0.594)

Note: table shows average number of links reported and corresponding standard errors in parentheses.

Source: authors' calculations based on experimental data.

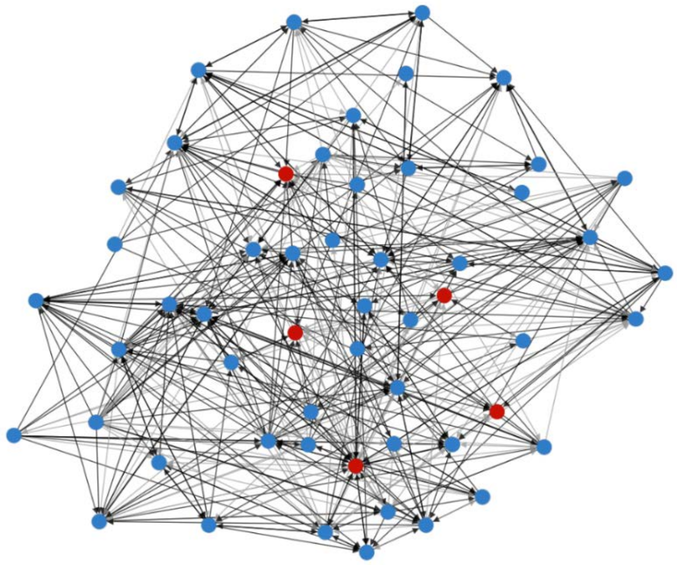
Figure 1a: Illustration of a kinship network



Note: visual representation of the kinship links among 54 households from one of the neighbourhoods 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.

Source: authors' illustration based on experimental data.

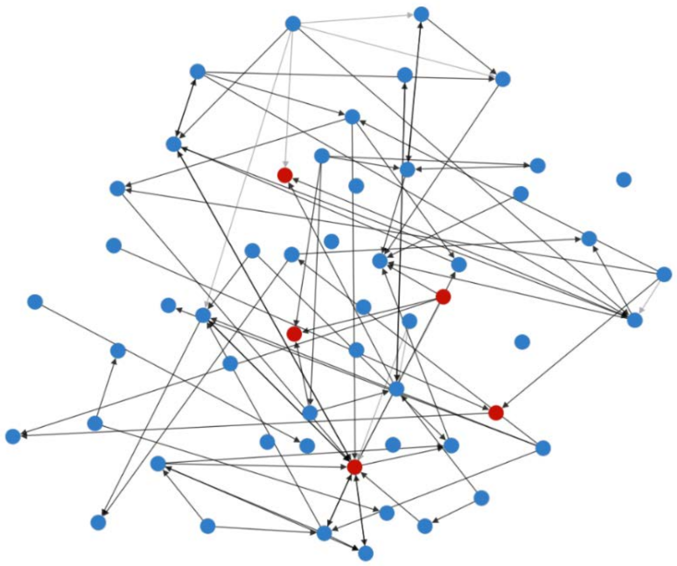
Figure 1b: Illustration of a chatting network



Note: visual representation of the chatting links among 54 households from one of the neighbourhoods 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.

Source: authors' illustration based on experimental data.

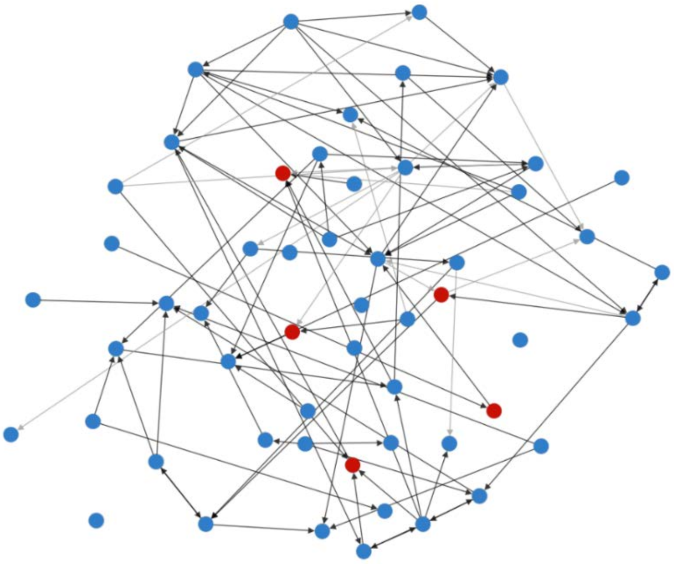
Figure 1c: Illustration of an agricultural advice network



Note: visual representation of the agricultural advice links among 54 households from one of the neighbourhoods 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.

Source: authors' illustration based on experimental data.

Figure 1d: Illustration of a financial support network



Note: visual representation of the financial support links among 54 households from one of the neighbourhoods 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.

Source: authors' illustration based on experimental data.

On average, respondents reported 47 links within the village, 13 with progressive and six with treated farmers, in any network dimension. The network with the highest density is the kinship network (10 per cent), while the agricultural advice network has the lowest (1.6 per cent).[13] Note that on average, individuals named four kinship, three chatting, one agricultural advice, and one financial support connections with treated farmers. Looking at the strong versus weak ties characterization, respondents reported, on average, 4.2 strong kinship ties, 2.7 strong chatting ties, 0.9 strong agricultural advice ties, and 0.95 strong financial support ties. A relatively large number of connections are only reported with the assistance of the village photo album (weak ties). This varies between 2.1 ties with treated farmers in the kinship network and 0.19 in the financial support network.

Finally, we turn our attention towards the balance tests regarding our main empirical strategy to estimate spill-over effects. Recall that identification is achieved by the fact that, conditional on the total number of peer progressive farmers, the number of treated farmers varies exogenously. To validate the conditional independence assumption, we document balance along observable characteristics. In particular, using a simplified version of specification (2), we regress the number of links with treated and progressive farmers (any network) on household characteristics. Results are presented in Table 4.[14]

[13] Network density refers to the proportion of possible ties that are actually formed.

[14] Table B3 in the Appendix reports the balance tests for the different network dimensions.

Table 4: Individual characteristics—balance across treated social links

		Number of links with treated
Basic demographics	Age	-0.065
		(0.578)
	Female	-0.011
		(0.014)
	Years of education	0.138
		(0.136)
	Married	0.012
		(0.019)
Religion and ethnicity	Catholic	0.020
		(0.017)
	Animist	-0.011
		(0.018)
	Felupe	-0.016
		(0.012)
Occupation	Farmer	0.008
		(0.014)

Note: standard errors reported in parentheses.

Source: authors' calculations based on experimental data.

None of the coefficients are statistically significant, offering support for the conditional independence assumption.

6.2 Treatment effects

This section presents the results of the impact evaluation of the training programme we follow in this paper. 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 5 displays the estimates of average treatment effects for each outcome of interest, while employing specification (1).

Table 5: Treatment effect—knowledge and adoption of production practices among progressive farmers

			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
	Controls		no	yes	no	yes	no	yes	no	yes

Note: all regressions are OLS. The unit of observation is the individual. Non-progressive 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 that include years of education, marital status, religion, ethnic group, and household assets. Robust standard errors reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

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 and an increase in adoption of those same practices in the treatment group.

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 estimating equations (2) and (3) with data at the household level. For each outcome we present the results for five network variables, i.e. our four classifications of interest (kinship, chatting, agricultural advice, and financial support) and 'all' links that refer to the union of all networks and, thus, having a network link in any of the four dimensions. Table 6 presents the network effects on knowledge and adoption of practices at the household level. Tables 6a and 6b present the short-run (one agricultural season after the treatment) effects, while Tables 6c and 6d focus on the medium-run (two agricultural seasons after the treatment) results.

Table 6a: Short run—knowledge of production practices among non-progressive farmers

Dependent variable ------>	Knowledge									
Network variable ------>	All		Kinship		Chatting		Agricultural advice		Financial support	
	(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 progressive	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
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: all regressions are OLS. The unit of observation is the household. Progressive 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 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

Table 6b: Short run—adoption of production practices among non-progressive farmers

Dependent variable ------>	Adoption									
Network variable ------>	All		Kinship		Chatting		Agricultural advice		Financial support	
	(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 progressive	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	263	263	263	263	263	263	263	263	263
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: all regressions are OLS. The unit of observation is the household. Progressive 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 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

Table 6c: Medium run—knowledge of production practices among non-progressive farmers

Dependent variable ------>	Knowledge									
Network variable ------>	All		Kinship		Chatting		Agricultural advice		Financial support	
	(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 progressive	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	-0.658	-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
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: all regressions are OLS. The unit of observation is the household. Progressive 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 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

Table 6d: Medium run—adoption of production practices among non-progressive farmers

Dependent variable ------>	Adoption									
Network variable ------>	All		Kinship		Chatting		Agricultural advice		Financial support	
	(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 progressive	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	-0.773	-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	247	247	247
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: all regressions are OLS. The unit of observation is the household. Progressive 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 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

As shown in Table 6a, the network effect differs considerably across network dimensions and link strength. We observe positive and statistically significant knowledge spill-over effects in the chatting and financial support networks. These effects represent an improvement of 0.117–0.199 standard deviations in the z-score of an individual's knowledge index, an effect that is statistically significant at conventional levels. This represents a positive spill-over effect on the non-progressive farmers with positive knowledge spill-overs for each additional progressive farmer in an individual's network who receives the treatment. Both strong and weak links seem to be significant, and there is no statistically significant difference between them.

As for the remaining dimensions, 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 5 per cent level.

In Table 6b we present the short-run results of network effects on practice adoption. We find only limited evidence of network effects in terms of an individual's adoption index. The links with treated individuals do not seem to have any statistically significant effect on agricultural adoption, except through ties with individuals in the borrowing money network. This represents a 0.094 standard deviation increase in adoption, significant at the 5 per cent level.

We now focus our attention on the medium run with results presented in Tables 6c (knowledge) and 6d (adoption). Our results show knowledge acquired through social networks did not fade away over time in the borrowing money network, representing an improvement of 0.223 standard deviations in knowledge, statistically significant at the 5 per cent level. Different than before, we also observe positive effects among agricultural advice peers and no effect in the chatting network. It is 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, which is statistically significant at the 10 per cent level. One possible channel for this effect has to do with labour specialization among family members as a result of the treatment. From anecdotal evidence, 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 more knowledgeable in agricultural practices because of the training, they may informally take on a larger share of the extended family's agricultural practices. Because 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 who received agricultural training. Consistent with this channel, in the larger impact evaluation conducted around this intervention, we observe that trust within the family increases because of the treatment.

Finally, in Table 6d 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 because the treatment might have changed the structure of the agricultural advice network. We address these potential network changes in the next section.

We now 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 practices in line with their treated peer farmers, when compared to their control peer farmers. 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 convergence in outcomes between non-progressive and treated when comparing to non-progressive and control, thus implying a negative coefficient in our variable of interest. We implement this in a dyadic framework by employing specification (4) and (5).

Table 7a: Knowledge and adoption of production practices among non-progressive farmers

		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
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
	Controls	yes	yes	yes	yes	yes	yes	yes	yes

Note: all regressions are OLS. The unit of observation is the directed dyad. Observations with directed links sent from progressive 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

Table 7b: Knowledge and adoption of production practices among non-progressive farmers (continued)

		Short run				Medium run			
Dependent variable ------>		Knowledge		Adoption		Knowledge		Adoption	
Network variable		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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
Financial support	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
	Controls	yes	yes	yes	yes	yes	yes	yes	yes

Note: all regressions are OLS. The unit of observation is the directed dyad. Observations with directed links sent from progressive 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

Results for the short- and medium-run outcomes are presented in Table 7. In line with the previous results, in the short run, we observe the diffusion of knowledge in the chatting and financial support networks. Both of those effects are statistically significant at conventional levels. In addition, we also document diffusion effects in the agricultural advice network, marginally significant at the 10 per cent level. When we extend our analysis to the medium run, the coefficients for links with treated kin farmers are positive and statistically significant at the 1 per cent 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 agricultural advice and financial support 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 the existence of social effects in knowledge, although these differ considerably across network dimensions. Despite the existence of positive externalities in knowledge, we have found limited evidence of social effects on actual adoption behaviour.[15]

6.4 Network change

We now turn to testing for possible changes in the network structure as a result of the intervention. In particular, we focus on the sample of progressive farmers 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, chatting, potential, and effective (real) agricultural advice and potential and effective (real) financial support. Table 8 presents estimates of the treatment effects employing specifications (1). Tables 8a and 8b display the short- and medium-run results, respectively.

Table 8a: Treatment effect—short-run network change among progressive farmers

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
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 financial support	-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 financial support	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)

[15] The main reasons for non-adoption reported by farmers were: 'not being familiar with the technique and its details' (46 per cent), followed by 'having only recently learnt about it and haven't started applying it yet' (27 per cent), and 'having doubts about the advantages of using it' (14 per cent).

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
Controls	no	yes	no	yes	no	yes	no	yes

Note: all regressions are OLS. The unit of observation is the individual. Non-progressive 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

Table 8b: Treatment effect—medium-run network change among progressive farmers

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
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 financial support	-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 financial support	-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
Controls	no	yes	no	yes	no	yes	no	yes

Note: all regressions are OLS. The unit of observation is the individual. Non-progressive 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

We do not find any statistically significant difference in the networks of kinship, chatting, or potential and real financial support. Given that the treatment was focused on agricultural 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 8a, 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 standard deviations, respectively, statistically significant at the 10 per cent 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 standard deviations in the treatment group. These effects are statistically significant at conventional levels. Lastly, to a certain extent, this improvement in network centrality seems to persist over time. In Table 8b, 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 standard deviations in the potential agricultural advice network.

These results suggest that the treatment led to a change in the agricultural network position of treated farmers, fostering the creation of new agricultural communication ties, which could in turn amplify the effect of the extension intervention.

6.5 Robustness

Our main results on diffusion of information and adoption are robust to different specifications of the outcome variable. Results are reported in Appendix Tables B1 and B2. First, we aggregate the knowledge and adoption variables using a simple count of the survey questions (Table B1). Second, we move from the intensive to the extensive margin and use knowledge and adoption magnitude instead of a binary indicator (Table B2). As before, these were then aggregated using a simple average of the z-scores. As we observe, our results remain very consistent across the different specifications, with clear knowledge spill-overs in specific network dimensions but only limited evidence of adoption along social networks.

One limitation of our diffusion results is that we do not have pre-intervention network data. On one hand, social networks might have been rewired as a result of the intervention, posing a threat to the identification strategy. On the other hand, as shown by Comola and Prina (2021), using pre-treatment network data might underestimate the true peer effects because it ignores the social network reshuffling. In the absence of pre- and post-intervention network data, we run a battery of balance tests to address the concern of endogeneity of our main results. Appendix Table B3 provides evidence of balance along observables for the number of treated peers in each network dimension. These results, coupled with the absence of average treatment effects in the centrality of the kinship, chatting, and financial support networks, help alleviate concerns that the underlying network structure of these social dimensions has changed as a result of the intervention. As for our results of peer effects on the agricultural advice network, where we observe improvements in the centrality measures, we acknowledge that our constructed variable does not allow us to disentangle the effect from the network change from the spill-over effect.

7 Concluding remarks

This paper analyses the role of social networks in the diffusion of production techniques introduced by an agricultural extension project in Guinea-Bissau. In particular, taking advantage of a randomized intervention, 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, chatting, agricultural advice, financial support), allowing us to examine the role of each in knowledge and adoption diffusion.

Having established that the training increased knowledge and adoption of practices of treated farmers, we went on to investigate the prevalence of diffusion effects to the rest of the community. Our results indicate that knowledge externalities 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 evidence of network effects in adoption behaviour. Furthermore, using our measures of link strength, we observe 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. Finally, our results show that the training led to an expansion of treated farmers' agricultural communication network, compared to the control group, as evidenced by the improvement in their network centrality position.

These results contribute to the debate on technology diffusion in developing economies, where formal institutions are scarce and social networks can play a critical role in technology transmission. First, our findings show that providing training on new technologies to a subset of individuals and relying on social networks to multiply its effects can improve overall knowledge about the technology, although this is not necessarily followed by adoption. Furthermore, our results suggest that when deciding the appropriate peer-based targeting in order to maximize diffusion, one also needs to consider which social dimension to target, as not every network dimension contributes equally to information transmission. Lastly, the results suggest that policy interventions—even if they are not set up explicitly to do so—might contribute to the rewiring of local social networks in a direction that improves access to information sources, thereby amplifying indirect treatment effects.

References

Apouey, B., and G. Picone (2014). 'Social Interactions and Malaria Preventive Behaviors in Sub-Saharan Africa'. *Health Economics*, 23(9): 994–1012. https://doi.org/10.1002/hec.3055

Bandiera, O., and I. Rasul (2006). 'Social Networks and Technology Adoption in Northern Mozambique'. *The Economic Journal*, 116(514): 869–902. https://doi.org/10.1111/j.1468-0297.2006.01115.x

Banerjee, A., A.G. Chandrasekhar, E. Duflo, and M.O. Jackson (2013). 'The Diffusion of Microfinance'. *Science*, 341(6144): 1236498. https://doi.org/10.1126/science.1236498

Banerjee, A., E. Breza, A.G. Chandrasekhar, E. Duflo, M.O. Jackson, and C. Kinnan (2018). 'Changes in Social Network Structure in Response to Exposure to Formal Credit Markets'. Available at SSRN: http://doi.org/10.2139/ssrn.3245656

Batista, C., J. Seither, and P.C. Vicente (2019). 'Do Migrant Social Networks Shape Political Attitudes and Behavior at Home?' *World Development*, 117: 328–43. https://doi.org/10.1016/j.worlddev.2019.01.019

Beaman, L., and A. Dillon (2018). 'Diffusion of Agricultural Information Within Social Networks: Evidence on Gender Inequalities from Mali'. *Journal of Development Economics*, 133: 147–61. https://doi.org/10.1016/j.jdeveco.2018.01.009

Beaman, L., A. BenYishay, J. Magruder, and A.M. Mobarak (2018). 'Can Network Theory-Based Targeting Increase Technology Adoption?' NBER Working Paper 24912. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w24912

Beshears, J., J.J. Choi, D. Laibson, B.C. Madrian, and K.L. Milkman (2015). 'The Effect of Providing Peer Information on Retirement Savings Decisions'. *The Journal of Finance*, 70(3): 1161–201. https://doi.org/10.1111/jofi.12258

Besley, T., and A. Case (1994). 'Diffusion as a Learning Process: Evidence from HYV Cotton'. Working Paper 228. Princeton: Princeton University.

Blumenstock, J.E., N. Eagle, and M. Fafchamps (2016). 'Airtime Transfers and Mobile Communications: Evidence in the Aftermath of Natural Disasters'. *Journal of Development Economics*, 120: 157–81. https://doi.org/10.1016/j.jdeveco.2016.01.003

Bobonis, G.J., and F. Finan (2009). 'Neighborhood Peer Effects in Secondary School Enrollment Decisions'. *Review of Economics and Statistics*, 91(4): 695–716. https://doi.org/10.1162/rest.91.4.695

Brewer, D.D. (2000). 'Forgetting in the Recall-Based Elicitation of Personal and Social Networks'. *Social Networks*, 22(1): 29–43. https://doi.org/10.1016/S0378-8733(99)00017-9

Cai, J., A. de Janvry, and E. Sadoulet (2015). 'Social Networks and the Decision to Insure'. *American Economic Journal: Applied Economics*, 7(2): 81–108. https://doi.org/10.1257/app.20130442

Cameron, A.C., J.B. Gelbach, and D.L. Miller (2011). 'Robust Inference with Multiway Clustering'. *Journal of Business and Economic Statistics*, 29(2): 238–49. https://doi.org/10.1257/app.20130442

Castañeda, A., D. Doan, D. Newhouse, M.C. Nguyen, H. Uematsu, and J.P. Azevedo (2016). 'Who Are the Poor in the Developing World?' Policy Research Working Paper 7844. Washington, DC: World Bank. https://doi.org/10.1596/1813-9450-7844

Chandrasekhar, A.G., and R. Lewis (2011). 'Econometrics of Sampled Networks'. Preliminary and incomplete paper.

Chuang, Y., and L. Schechter (2015). 'Social Networks in Developing Countries'. *Annual Review of Resource Economics*, 7(1): 451-472. https://doi.org/10.1146/annurev-resource-100814-125123

Comola, M., and S. Prina (2021). 'Treatment Effect Accounting for Network Changes'. *The Review of Economics and Statistics*, 103(3): 597–604. https://doi.org/10.1162/rest_a_00908

Conley, T.G., and C.R. Udry (2010). 'Learning About a New Technology: Pineapple in Ghana'. *American Economic Review*, 100(1): 35–69. https://doi.org/10.1257/aer.100.1.35

De Janvry, A., K. Macours, and E. Sadoulet (eds) (2017). *Learning for Adopting: Technology Adoption in Developing Country Agriculture*. Clermont-Ferrand: Fondation pour les études et recherches sur le développement international (Ferdi).

Duflo, E., and E. Saez (2003). 'The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment'. *Quarterly Journal of Economics*, 118(3): 815–42. https://doi.org/10.1162/00335530360698432

Duflo, E., M. Kremer, and J. Robinson (2011). 'Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya'. *American Economic Review*, 101(6): 2350–90. https://doi.org/10.1257/aer.101.6.2350

Dupas, P. (2014). 'Short-Run Subsidies and Long-Run Adoption of New Health Products: Evidence from a Field Experiment'. *Econometrica*, 82(1): 197–228. https://doi.org/10.3982/ECTA9508

Fafchamps, M., and F. Gubert (2007). 'Risk Sharing and Network Formation'. *American Economic Review*, 97: 75–9. https://doi.org/10.1257/aer.97.2.75

Fafchamps, M., and D. Mo (2017). 'Peer Effects in Computer Assisted Learning: Evidence from a Randomized Experiment'. NBER Working Paper 23195. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w23195

Fafchamps, M., and S. Quinn (2018). 'Networks and Manufacturing Firms in Africa: Results from a Randomized Field Experiment'. *The World Bank Economic Review*, 32(3): 656–75. https://doi.org/10.1093/wber/lhw057

Fafchamps, M., and M. Söderbom (2014). 'Network Proximity and Business Practices in African Manufacturing'. *The World Bank Economic Review*, 28(1): 99–129. https://doi.org/10.1093/wber/lht020

Fafchamps, M., A. Vaz, and P. Vicente (2020). 'Voting and Peer Effects: Experimental Evidence from Mozambique'. *Economic Development and Cultural Change*, 68(2): 567–605. https://doi.org/10.1086/700634

Foster, A.D., and M.R. Rosenzweig (1995). 'Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture'. *Journal of Political Economy*, 103(6): 1176–209. https://doi.org/10.1086/601447

Gee, L.K., J. Jones, and M. Burke (2017). 'Social Networks and Labor Markets: How Strong Ties Relate to Job Finding on Facebook's Social Network'. *Journal of Labor Economics*, 35(2): 485–518. https://doi.org/10.1086/686225

Giné, X., and G. Mansuri (2018). 'Together We Will: Experimental Evidence on Female Voting Behavior in Pakistan'. *American Economic Journal: Applied Economics*, 10(1): 207–35. https://doi.org/10.1257/app.20130480

Godlonton, S., and R. Thornton (2012). 'Peer Effects in Learning HIV Results'. *Journal of Development Economics*, 97(1): 118–29. https://doi.org/10.1016/j.jdeveco.2010.12.003

Gollin, D., M. Morris, and D. Byerlee (2005). 'Technology Adoption in Intensive Post-Green Revolution Systems'. *American Journal of Agricultural Economics*, 87(5): 1310–6. https://doi.org/10.1111/j.1467-8276.2005.00824.x

Granovetter, M.S. (1973). 'The Strength of Weak Ties'. *American Journal of Sociology*, 78(6): 1360–80. https://doi.org/10.1086/225469

Heß, S., D. Jaimovich, and M. Schündeln (2020). 'Development Projects and Economic Networks: Lessons from Rural Gambia'. *Review of Economic Studies*, 88(3): 1347–84. https://doi.org/10.1093/restud/rdaa033

Jack, K. (2013). 'Market Inefficiencies and the Adoption of Agricultural Technologies in Developing Countries'. White paper. Berkeley: Agricultural Technology Adoption Initiative (ATAI), JPAL (MIT)/CEGA.

Kim, D.A., A.R. Hwong, D. Stafford, D.A. Hughes, A.J. O'Malley, J.H. Fowler, and N.A. Christakis (2015). 'Social Network Targeting to Maximise Population Behaviour Change: A Cluster Randomised Controlled Trial'. *The Lancet*, 386(9989): 145–53. https://doi.org/10.1016/S0140-6736(15)60095-2

Kling, J.R., J.B. Liebman, and L.F. Katz (2007). 'Experimental Analysis of Neighborhood Effects'. *Econometrica*, 75(1): 83–119. https://doi.org/10.1111/j.1468-0262.2007.00733.x

Kremer, M., and E. Miguel (2007). 'The Illusion of Sustainability'. *The Quarterly Journal of Economics*, 122(3): 1007–65. https://doi.org/10.1162/qjec.122.3.1007

Maertens, A. (2017). 'Who Cares What Others Think (or Do)? Social Learning and Social Pressures in Cotton Farming in India'. *American Journal of Agricultural Economics*, 99(4): 988–1007. https://doi.org/10.1093/ajae/aaw098

Maertens, A., and C.B. Barrett (2013). 'Measuring Social Networks' Effects on Agricultural Technology Adoption'. *American Journal of Agricultural Economics*, 95(2): 353–9. https://doi.org/10.1093/ajae/aas049

Magruder, J.R. (2018). 'An Assessment of Experimental Evidence on Agricultural Technology Adoption in Developing Countries.' *Annual Review of Resource Economics*, 10: 299–316. https://doi.org/10.1146/annurev-resource-100517-023202

Manski, C.F. (1993). 'Identification of Endogenous Social Effects: The Reflection Problem'. *The Review of Economic Studies*, 60(3): 531. https://doi.org/10.2307/2298123

Miller, G., and A.M. Mobarak (2014). 'Learning About New Technologies Through Social Networks: Experimental Evidence on Nontraditional Stoves in Bangladesh'. *Marketing Science*, 34(4): 480–99. https://doi.org/10.1287/mksc.2014.0845

Munshi, K. (2004). 'Social Learning in a Heterogeneous Population: Technology Diffusion in the Indian Green Revolution'. *Journal of Development Economics*, 73(1): 185–213. https://doi.org/10.1016/j.jdeveco.2003.03.003

Oster, E., and R. Thornton (2012). 'Determinants of Technology Adoption: Peer Effects in Menstrual Cup Take-Up'. *Journal of the European Economic Association*, 10(6): 1263–93. https://doi.org/10.1111/j.1542-4774.2012.01090.x

Santos, P., and C.B. Barrett (2008). 'What Do We Learn About Social Networks When We Only Sample Individuals? Not Much'. Available at SSRN: https://doi.org/10.2139/ssrn.1141838

Van den Broeck, K., and S. Dercon (2011). 'Information Flows and Social Externalities in a Tanzanian Banana Growing Village'. *Journal of Development Studies*, 47(2): 231–52. https://doi.org/10.1080/00220381003599360

World Bank (2008). *World Development Report 2008: Agriculture for Development*. Washington, DC: World Bank.

World Bank (2015). *Guinea-Bissau - Country Economic Memorandum : Terra Ranca! A Fresh Start*. Washington, DC: World Bank.

World Bank (2017). 'World Development Indicators'. Washington, DC: World Bank.

World Food Program (2013). *Synthesis of Rapid Food Security Assessment in Guinea Bissau*. Rome: World Food Program.

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 et al. 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.[16] We estimate the following specification in a dyadic framework:

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

where Y_{ij} is the proxy 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 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 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-level characteristics as simple differences and 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 et al. (2011).

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

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

Table A1: Link strength

Network variable ---->	Strong kinship link	Strong chatting link	Strong agricultural advice link	Strong financial support 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 variable link reciprocity is 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. Two-way cluster-robust standard errors reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

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 per cent level. As for the network of chatting, a strong chatting link has a positive and statistically significant correlation with link reciprocity and mutual ties. These represent a 10 percentage point 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 financial support 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 is 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).

Appendix B

Table B1a: Short run—knowledge of production practices among non-progressive farmers

Dependent variable ------>	Knowledge									
Network variable ------>	All		Kinship		Chatting		Agricultural advice		Financial support	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Links with treated	0.201		0.252		0.485***		0.279		0.839***	
	(0.135)		(0.164)		(0.178)		(0.226)		(0.319)	
Strong links with treated		0.088		0.010		0.448**		0.244		0.840**
		(0.159)		(0.201)		(0.214)		(0.241)		(0.340)
Weak links with treated		0.304**		0.400**		0.515***		0.444		0.837**
		(0.143)		(0.162)		(0.183)		(0.347)		(0.418)
Links with progressive	0.010	0.033	-0.123	-0.076	-0.127	-0.123	-0.098	-0.109	-0.482**	-0.482**
	(0.085)	(0.086)	(0.121)	(0.121)	(0.103)	(0.104)	(0.205)	(0.208)	(0.222)	(0.223)
Mean dep. variable	5.288	5.288	5.288	5.288	5.288	5.288	5.288	5.288	5.288	5.288
R-squared adjusted	0.325	0.328	0.307	0.320	0.333	0.331	0.440	0.438	0.317	0.314
Number of observations	260	260	260	260	260	260	260	260	260	260
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: all regressions are OLS. The unit of observation is the household. Progressive households are excluded from the observations. The dependent variable is a simple count. Controls are demographic characteristics and average demographic characteristics in the network. Demographic characteristics 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

Table B1b: Short run—adoption of production practices among non-progressive farmers

Dependent variable ------>	Adoption									
Network variable ------>	All		Kinship		Chatting		Agricultural advice		Financial support	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Links with treated	-0.072		0.022		-0.087		-0.183		0.364**	
	(0.094)		(0.110)		(0.136)		(0.225)		(0.182)	
Strong links with treated		-0.016		-0.011		0.062		-0.203		0.392**
		(0.108)		(0.130)		(0.158)		(0.229)		(0.196)
Weak links with treated		-0.123		0.042		-0.210		-0.087		0.257
		(0.105)		(0.115)		(0.144)		(0.325)		(0.261)
Links with progressive	0.100	0.088	0.057	0.064	0.064	0.048	0.291*	0.285*	-0.157	-0.155
	(0.065)	(0.065)	(0.083)	(0.086)	(0.089)	(0.085)	(0.169)	(0.169)	(0.142)	(0.142)
Mean dep. variable	2.859	2.859	2.859	2.859	2.859	2.859	2.859	2.859	2.859	2.859
R-squared adjusted	0.537	0.537	0.548	0.546	0.539	0.545	0.569	0.567	0.538	0.536
Number of observations	263	263	263	263	263	263	263	263	263	263
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: all regressions are OLS. The unit of observation is the household. Progressive households are excluded from the observations. The dependent variable is a simple count. Controls are demographic characteristics and average demographic characteristics in the network. Demographic characteristics 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

Table B1c: Medium run—knowledge of production practices among non-progressive farmers

Dependent variable ------>	Knowledge									
Network variable ------>	All		Kinship		Chatting		Agricultural advice		Financial support	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Links with treated	-0.116		-0.263*		0.280		0.447**		0.576**	
	(0.126)		(0.150)		(0.182)		(0.178)		(0.294)	
Strong links with treated		-0.061		-0.308*		0.269		0.415**		0.578*
		(0.135)		(0.177)		(0.230)		(0.182)		(0.309)
Weak links with treated		-0.166		-0.237		0.289		0.587*		0.566
		(0.151)		(0.166)		(0.178)		(0.321)		(0.429)
Links with progressive	0.209**	0.198**	0.315***	0.324***	0.010	0.010	-0.048	-0.056	-0.096	-0.095
	(0.082)	(0.081)	(0.113)	(0.110)	(0.111)	(0.112)	(0.193)	(0.193)	(0.232)	(0.233)
Mean dep. variable	6.251	6.251	6.251	6.251	6.251	6.251	6.251	6.251	6.251	6.251
R-squared adjusted	0.303	0.302	0.315	0.312	0.312	0.317	0.332	0.329	0.313	0.310
Number of observations	247	247	247	247	247	247	247	247	247	247
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: All regressions are OLS. The unit of observation is the household. Progressive households are excluded from the observations. The dependent variable is a simple count. Controls are demographic characteristics and average demographic characteristics in the network. Demographic characteristics 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

Table B1d: Medium run—adoption of production practices among non-progressive farmers

Dependent variable ------>	Adoption									
Network variable ------>	All		Kinship		Chatting		Agricultural advice		Financial support	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Links with treated	0.039		-0.077		0.234		0.688***		0.082	
	(0.123)		(0.139)		(0.168)		(0.181)		(0.230)	
Strong links with treated		0.031		-0.215		0.190		0.710***		0.044
		(0.140)		(0.170)		(0.189)		(0.189)		(0.229)
Weak links with treated		0.047		0.005		0.274		0.590		0.226
		(0.144)		(0.151)		(0.190)		(0.377)		(0.452)
Links with progressive	0.101	0.103	0.179*	0.209**	0.052	0.055	0.048	0.053	0.146	0.143
	(0.084)	(0.085)	(0.101)	(0.098)	(0.107)	(0.107)	(0.185)	(0.185)	(0.176)	(0.175)
Mean dep. variable	2.657	2.657	2.657	2.657	2.657	2.657	2.657	2.657	2.657	2.657
R-squared adjusted	0.371	0.368	0.370	0.379	0.387	0.377	0.437	0.435	0.385	0.383
Number of observations	247	247	247	247	247	247	247	247	247	247
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: all regressions are OLS. The unit of observation is the household. Progressive households are excluded from the observations. The dependent variable is a simple count. Controls are demographic characteristics and average demographic characteristics in the network. Demographic characteristics 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

Table B2a: Short run—knowledge of production practices among non-progressive farmers

Dependent variable ------>	Knowledge									
Network variable ------>	All		Kinship		Chatting		Agricultural advice		Financial support	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Links with treated	0.040		0.052		0.106***		0.071		0.184***	
	(0.029)		(0.033)		(0.038)		(0.048)		(0.068)	
Strong links with treated		0.017		0.002		0.088**		0.064		0.187***
		(0.033)		(0.041)		(0.044)		(0.052)		(0.071)
Weak links with treated		0.061**		0.083***		0.121***		0.104		0.172**
		(0.031)		(0.032)		(0.039)		(0.072)		(0.088)
Links with progressive	0.002	0.007	-0.030	-0.020	-0.028	-0.026	-0.008	-0.011	-0.100**	-0.100**
	(0.017)	(0.017)	(0.024)	(0.024)	(0.020)	(0.021)	(0.040)	(0.041)	(0.046)	(0.046)
Mean dep. variable	-0.588	-0.588	-0.588	-0.588	-0.588	-0.588	-0.588	-0.588	-0.588	-0.588
R-squared adjusted	0.272	0.275	0.261	0.275	0.287	0.286	0.433	0.431	0.284	0.281
Number of observations	260	260	260	260	260	260	260	260	260	260
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: regressions are OLS. The unit of observation is the household. Progressive households are excluded from the observations. The dependent variable is a simple count. Controls are demographic characteristics and average demographic characteristics in the network. Demographic characteristics 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

Table B2b: Short run—adoption of production practices among non-progressive farmers

Dependent variable ------>	Adoption									
Network variable ------>	All		Kinship		Chatting		Agricultural advice		Financial support	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Links with treated	-0.012		0.007		-0.015		-0.031		0.081*	
	(0.021)		(0.024)		(0.031)		(0.052)		(0.042)	
Strong links with treated		0.003		0.005		0.018		-0.029		0.091**
		(0.024)		(0.029)		(0.035)		(0.055)		(0.045)
Weak links with treated		-0.025		0.008		-0.041		-0.039		0.042
		(0.024)		(0.025)		(0.033)		(0.073)		(0.054)
Links with progressive	0.022	0.019	0.016	0.017	0.016	0.013	0.061*	0.061*	-0.031	-0.031
	(0.014)	(0.014)	(0.018)	(0.019)	(0.019)	(0.018)	(0.035)	(0.035)	(0.032)	(0.032)
Mean dep. variable	-0.654	-0.654	-0.654	-0.654	-0.654	-0.654	-0.654	-0.654	-0.654	-0.654
R-squared adjusted	0.535	0.536	0.548	0.546	0.537	0.542	0.575	0.573	0.537	0.536
Number of observations	263	263	263	263	263	263	263	263	263	263
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: all regressions are OLS. The unit of observation is the household. Progressive 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 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

Table B2c: Medium run—knowledge of production practices among non-progressive farmers

Dependent variable ------>	Knowledge									
Network variable ------>	All		Kinship		Chatting		Agricultural advice		Financial support	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Links with treated	-0.029		-0.067		0.100*		0.120**		0.184**	
	(0.036)		(0.043)		(0.053)		(0.053)		(0.084)	
Strong links with treated		-0.007		-0.079		0.103		0.107**		0.186**
		(0.040)		(0.053)		(0.067)		(0.053)		(0.086)
Weak links with treated		-0.048		-0.061		0.097*		0.180**		0.177
		(0.042)		(0.047)		(0.052)		(0.092)		(0.122)
Links with progressive	0.054**	0.049**	0.079**	0.082**	-0.016	-0.017	-0.015	-0.019	-0.058	-0.058
	(0.024)	(0.024)	(0.034)	(0.033)	(0.033)	(0.033)	(0.057)	(0.057)	(0.067)	(0.067)
Mean dep. variable	-0.763	-0.763	-0.763	-0.763	-0.763	-0.763	-0.763	-0.763	-0.763	-0.763
R-squared adjusted	0.284	0.284	0.291	0.288	0.315	0.312	0.312	0.310	0.301	0.298
Number of observations	247	247	247	247	247	247	247	247	247	247
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: all regressions are OLS. The unit of observation is the household. Progressive 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 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

Table B2d: Medium run—adoption of production practices among non-progressive farmers

Dependent variable ------>	Adoption									
Network variable ------>	All		Kinship		Chatting		Agricultural advice		Financial support	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Links with treated	0.007		-0.021		0.049		0.144***		0.006	
	(0.026)		(0.028)		(0.035)		(0.036)		(0.047)	
Strong links with treated		0.004		-0.049		0.037		0.150***		-0.001
		(0.029)		(0.034)		(0.039)		(0.038)		(0.047)
Weak links with treated		0.009		-0.004		0.060		0.116		0.032
		(0.030)		(0.031)		(0.039)		(0.072)		(0.090)
Links with progressive	0.021	0.021	0.037*	0.043**	0.011	0.011	0.007	0.009	0.033	0.033
	(0.017)	(0.018)	(0.021)	(0.020)	(0.022)	(0.022)	(0.037)	(0.037)	(0.036)	(0.036)
Mean dep. variable	-0.737	-0.737	-0.737	-0.737	-0.737	-0.737	-0.737	-0.737	-0.737	-0.737
R-squared adjusted	0.365	0.362	0.367	0.371	0.378	0.376	0.432	0.430	0.385	0.383
Number of observations	247	247	247	247	247	247	247	247	247	247
Controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Note: all regressions are OLS. The unit of observation is the household. Progressive 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 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 parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.

Table B3: Individual characteristics—balance across treated social links

		Number of kinship links with treated	Number of chatting links with treated	Number of agricultural advice links with treated	Number of financial support links with treated
Basic demographics	Age	-0.562	0.996	-2.273	-0.447
		(0.682)	(0.805)	(2.007)	(1.163)
	Female	-0.015	0.026	-0.019	0.049
		(0.015)	(0.023)	(0.045)	(0.034)
	Years of education	-0.003	0.122	0.859	-0.089
		(0.124)	(0.193)	(0.540)	(0.278)
	Married	0.008	0.038	-0.061	0.041
		(0.022)	(0.026)	(0.050)	(0.046)
Religion and ethnicity	Catholic	0.009	0.020	0.020	0.020
		(0.020)	(0.024)	(0.035)	(0.037)
	Animist	-0.003	-0.009	-0.010	-0.010
		(0.020)	(0.026)	(0.037)	(0.039)
	Felupe	-0.003	-0.041**	-0.018	-0.014
		(0.007)	(0.018)	(0.041)	(0.018)
Occupation	Farmer	0.005	-0.021	0.015	-0.032
		(0.016)	(0.022)	(0.031)	(0.031)

Note: standard errors reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Source: authors' calculations based on experimental data.