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Effects of farmers' social networks on knowledge acquisition: lessons from agricultural training in rural Indonesia

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Abstract

Agricultural information is transferred through social interactions; therefore, ties to agricultural informants and network structures within farmers' local neighborhoods determine their information-gathering abilities. This paper uses a spatial autoregressive model that takes account of spatial autocorrelation to examine such network connections, including friendship networks and advice networks, upon farmers' knowledge-gathering abilities during formal agricultural training. We found that peer advice networks are important to support knowledge-gathering activities, while friendship networks are not. Further examination of network structures confirms that farmers who occupy a central position in their local neighborhood networks are found to perform better in learning outcomes to some extent, indicating that local network position is positively related to problem-solving ability in an unknown environment outside their locale.

1 Background

Access to information pertaining to agricultural knowledge is essential to develop farmers' abilities in maintaining and increasing farm productivity. Farmers who lack the means to acquire agricultural information from formal sources often rely on information within their informal social network (Boahene et al. 1999; Lyon 2000) and transfer agricultural knowledge through social interactions (Conley and Udry 2010). Social network approaches posit that an individual's behavior is influenced by relations, technical ties, and networks more than by the norms and attributes that an individual possesses (Yang and Tang 2003). Interpersonal interaction plays a significant role in facilitating learning processes as learners actively build knowledge by formulating ideas into words, which are built upon the reactions and responses of others. Despite the importance of networks as a means for information facilitation, Newman and Dale (2005) and Bodin et al. (2006) argue that "not all social networks are created equal." They highlight the importance of distinguishing between "bonding" (interactions between family members, friends, and neighbors) and "bridging" (extend outside the community and provide access to different information and resources) ties. Balancing connections to both ties equally may improve people's economic and social well-being (Wu and Pretty 2004;

Berrou and Combarnous 2012) and enhance community development and survival likelihoods after a natural disaster (Hawkins and Maurer 2010).

Some literatures have partially studied how the social structure of a village can affect the facilitation of social learning and adoption vis-a-vis improving the productivity of farmers (Foster and Rosenzweig 1995; Conley and Udry 2001; Romani 2003). However, these studies largely emphasize on final adoption and not the process of information solicitation. Literature exploring the effects of an individual's community network structure on learning mechanisms during knowledge transfer activities is still limited. Examining learning effectiveness requires a field experimental design to understand fully the role of an individual's network position in acquiring information, in addition to the incorporation of spatial aspects, because information transfer is often a function of geographic proximity. There has thus far been insufficient attention to investigations that combine the effects of an individual's network connections and network structure, as well as spatial processes, upon influencing knowledge-gathering mechanisms. We intend to fill this gap in the literature by arguing that while both personal and structural networks are equally important as positive determinants of information gathering, they may have differential effects in terms of the transmission of agricultural knowledge. Our contributions are threefold:

First, we conduct a field experiment in the context of farmers' learning during agricultural training to explore the effects of personal networks upon farmers' learning performance. To serve the purpose, we make a clear distinction between friendship networks and advice networks with both "bonding ties" (peers) and "bridging ties" (government official) as key determinants of farmers' learning performance. Bonding ties are interactions between family members, friends, and neighbors in tightly connected networks, while bridging ties extend outside the community and provide access to different information and resources (Putnam 2001; Woolcock 2001). Friendship networks are more socially oriented in nature, while advice networks consist of relations through which individuals share information, assistance, and guidance that are related to the completion of their work.

Second, we also examine how the structural properties of farmers' local networks affect learning outcomes during formal agricultural training. While individual learning is undoubtedly a personal cognitive activity, it is also very likely to be influenced by social forces in that a person's everyday interactions will tend to enhance or undermine learning (Bogenrieder 2002). To meet this objective, we investigate farmers' positions in their local neighborhood, how central their position is compared to others who belong to the same group, and how this affects learning outcomes.

Third, in the context of inferential regression analysis, we control for spatial autocorrelation as the explanatory variables are likely to be dependently distributed when farmers live close to each other. Spatial panel models are a powerful econometric tool for the estimation of spatially dependent cross-sectional time-series models.

We found that ties to peer advice networks correspond to better learning outcomes, and the centrality of an individual's position in a farming community strongly relates to their knowledge-gathering abilities to some extent. However, we also found that when the role of bridging ties is unfulfilled, irrelevant information that could potentially be adversarial for learning might be transferred instead. Learning is shaped not only by the

number of connections, but also by the quality of network sources and their relevance to the information being sought. Furthermore, farmers occupying central positions within their community may be more familiar with facilitating problem-solving activities as they are used to conducting effective coordination of actors and resources in their local network, resulting in better learning outcomes to some extent.

The paper is organized as follows: conceptual framework and hypotheses; data collection and experimental design; estimation methods; results; and finally our discussion and conclusions.

2 Conceptual framework

The way societies are organized and how they interact socially can have an impact upon information diffusion and farm productivity (Banerjee 1992; Besley and Case 1994; Foster and Rosenzweig 1995; Conley and Udry 2001). Networks essentially function as the exchange of information between individuals who share social and informational resources (Carlsson and Stankiewicz 1991). Networks can have both positive and negative implications that are assumed to be associated with an individual's performance. For instance, it has been revealed that advice relations were positively related to the facilitation of knowledge transfer (Bodin and Crona 2009), but adversarial networks may negatively affect learning performance and motivation (Baldwin et al. 1997). While these studies offer invaluable insights to understand better the role of networks, there is still a lack of clarity on the role of social structures in determining the extent and quality of information exchanges among neighbors. The dimensions of such relationships in learning or advice seeking among actors are not yet well understood, especially how social relationships constructed by interpersonal processes shape learning outcomes and may result in different kinds of information solicited.

In this paper, we test whether having more network ties can positively influence one's performance in knowledge acquisition during agricultural training. The network ties may take the form of friendship networks, advice networks from peers (termed "bonding ties"), or advice networks from government institutions (termed "bridging ties"). Furthermore, our second objective is to examine whether network centrality in farmers' locale affects their information acquisition abilities. Our hypotheses are as follows:

Hypothesis 1 Friendship networks, peer advice networks, and official advice networks tend to be positively associated with knowledge attainment during training.

Previous studies have reported positive associations between ties and networks among actors in facilitating knowledge transfers, in organizational settings (Reagans and Zuckerman 2008), in classroom settings (Frank et al. 2011), as well as in the context of natural resource management (Isaac et al. 2007; Bodin et al. 2006; Bodin and Crona 2009). Fundamentally, actors who have more connections and ties to other individuals may hold advantageous positions as these ties can serve as alternative ways to fulfill their needs, making them less dependent on other individuals. Because they have many ties, they may have access to and be able to call on more of the resources of the network, resulting in better possible information acquired during agricultural training.

We hypothesize that the number of friendship networks that a farmer has will be positively associated with their knowledge attainment during training. At the community level, friendship ties will similarly account for social capital (Adler and Kwon 2002), which is an asset enhancing the capacity of rural livelihood strategies, especially in the way it affects information sharing. Studies such as Ramirez-Sanchez and Pinkerton (2009) and Salpeteur et al. (2016) found that friendship networks play a key and flexible role as actors' social capital within and between communities in the context of natural resource management. In the context of this study, we expect that farmers with more social capital during training will have better learning outcomes because they can immediately activate their classroom network to aid them.

Peer advice networks, on the other hand, can also be classified as "instrumental ties" to reflect the fact that they involve cooperation to achieve some limited and immediate goals, which in this case amounts to the active pursuit of agricultural knowledge for the purposes of enhancing production. In the case of knowledge transfer, peer advice networks may be strongly attributed to such goals due to the active nature of knowledge seeking. Isaac et al. (2007) showed that particular farm management techniques relied on local ecological knowledge within the community, making the advice network from inside the community the primary source of knowledge of agroforestry management. In the classroom setting, peer advice networks can represent the ability or skill for information gathering. We expect farmers with stronger peer advice networks to perform better in learning outcomes due to their tendency to be more pro-active in information-processing and knowledge-gathering activities.

Acquiring new knowledge is a complex process which is mediated through establishing mutual ties with knowledge experts, even though challenges may still exist with respect to an actor's ability to receive knowledge (Prell and Lo 2016). To offset lacking capabilities on knowledge gains, actors tend to pursue others with more knowledgeable expertise than themselves (Frank et al. 2011), who mostly come from external links such as government institutions (Isaac et al. 2007). Hence, for successful knowledge transfer, we also expect that farmers with more ties to extension officials will accrue advantages from reciprocal knowledge exchange with experts (see, e.g., Burt (2004), Brown and Sonwa (2015)), which will translate into better learning outcomes.

Hypothesis 2 Centrality measures are positively associated with knowledge-gathering activities and learning, so less peripheral farmers will be more pro-active in information gathering, thus performing better during learning activities.

While the first hypothesis only examines unidirectional ties, we also provide an analysis of farmers' directed structural networks within their local farming communities. By having information on the directions, we can distinguish an individual's influence within their locale, and how their network position affects their information-gathering mechanisms. If an individual has many ties, they are considered prominent or having high importance, since many seek to connect with them. An individual, who nominates many others as their source of advice, is usually able to exchange information with many others or make many others aware of their opinion. This important feature of social network analysis can address the structural properties of social networks in explaining various

outcomes. Centrality, the extent to which a given individual is connected to others in a network, is the structural property most often associated with instrumental outcomes, including power (Moschitz and Stolze 2009) and innovation (Spielman et al. 2011).

A very effective measure of an actor's centrality and power potential is their degree (or number of directional ties relative to everyone's score in the locale). Freeman (1979) and Bonacich (1972) constructed centrality measures to ascertain which individuals in a network hold influential roles. Sparrowe et al. (2001) reported that individual centrality in an advice network is positively associated with individual performance. Innovation and performance can be enhanced if the actors occupy central network positions that provide access to new knowledge developed by other units, even though it may be dependent on an individual's capacity to replicate new knowledge (Tsai 2001). Therefore, in the context of this current work, we expect to see farmers with more centralized positions to be more pro-active in knowledge seeking, thus performing better during learning activities. Our dataset is available in Additional file 1.

3 Data collection

3.1 Fieldwork site

Our field site is located in Indonesia, in Lampung province. Lampung province, one of the largest coffee- and cocoa-producing areas in the country, has been facing problems such as aging plantations and traditional farming systems. Despite its importance in the country's exports, coffee and cocoa are mostly produced by smallholder farmers in Indonesia (Neilson 2008). Since 2009, the Ministry of Agriculture has carried out a national program to increase their productivity by reactivating the extension system in commodity-producing districts (Hasibuan et al. 2012). This takes the form of farmers' groups. Agricultural extension systems across Indonesia are officially regulated for all types of products under Law 16/2006 on Extension System for Agricultural, Fishery and Forestry (Neilson 2008). Farmers cultivating the same commodity and residing in the same or nearby neighborhoods are encouraged to form a farmers' group, which usually comprises 20–30 people. One or two extension workers are assigned to each group; they monitor farmers' progress and advise them at least once a month during group meetings. Government subsidies for new varieties, fertilizers, and even new agricultural knowledge are often disseminated through farmers' groups under the supervision of district government officials.

In the study area, coffee is considered an old commodity, as most farmers reported that the farmland was inherited from the previous generation. Cocoa plantations are relatively newer, as more and more coffee farmers have converted to cocoa in the past 10 years due to higher and more stable prices and relatively low maintenance compared to coffee. In 2009, the central government announced a national plan to increase cocoa productivity, called *Gerakan Nasional Peningkatan Produksi dan Mutu Kakao* (Gernas Kakao)[1] with 9 provinces constituting the initial target area. In 2011, the program developed substantially to target another 22 provinces including Lampung province. To support the *Gernas Kakao* program, the government recruited contract assistants as

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[1] Source: http://ditjenbun.pertanian.go.id/tanregar/berita-164-pembukaan-peningkatan-kapabilitas-tenaga-kontrak-pendamping-tkp-gernas-kakao.html accessed 2015/12/11.

extension officers who are in charge of assisting farmers and farmers' group to facilitate cocoa-growing activities. Extension agents were recent graduates from university agricultural departments and had undertaken many forms of agricultural training established by the national recruitment team. Due to this policy, most cocoa extension workers are much younger than coffee extension workers who have been working since before 2008.

Tanggamus district, our survey site, geographically lies at 104°18′–105°12′ east and 5°05′–5°56′ south. Tanggamus is one of the main coffee- and cocoa-producing districts in Lampung province. We chose this particular district due to its relevance to the national strategy to improve coffee and cocoa productivity, as well as professional contacts therein. We then chose two top coffee- and cocoa-producing subdistricts, Sumberejo and Pulau Panggung. Data from the local agricultural department listed 36 farmers' groups from these two subdistricts, from which we randomly chose 16 farmers' groups spanning across 14 villages for our survey. The data reported here were collected in two waves, in September 2012 and April 2013. In September 2012, we conducted face-to-face interviews with all the household heads in these 16 randomly selected farmers' groups. The agricultural department census registered 398 households in 2008; during this baseline survey, we succeeded in administering the survey to 312 households (~80%).

According to the baseline data, farmers' primary information sources are extension workers and fellow farmers in their farmers' groups. Local government officials and extension workers testified that farmers were never exposed to formal agricultural training as training is usually administered only for extension officials. Farmers in the district are also unlikely to travel frequently to the nearest city for either leisure or business. Given these facts, we decided upon social intervention in the form of institutionalized training in varying locations for the farmers.

3.2 Administration of agricultural training

In April 2013, we randomly invited 156 farmers to participate in 3-day training. The first day consisted of in-class lectures on coffee cultivation; the second day on cocoa cultivation; and on the third day we organized an educational trip. During this day trip, the farmers visited pilot farms, fields, and an exemplary local farmer while being guided by the lecturers. For heterogeneity purposes, we carried out the training in three locations: in Tanggamus, the district where the farmers reside (hometown); in South Lampung, a district producing coffee and cocoa located around 170 km from Tanggamus; and in Garut-Ciamis, a coffee- and cocoa-producing district in the neighboring Java island. Identical training material was given regardless of the location.

In the training, 39 farmers showed up to participate in their hometown location, 39 in the different district, and 42 in the inter-island training location (Table 1). These 120 participating farmers thus become our sample. Among them, coffee is cultivated by 95 farmers, cocoa by 68 farmers, with the subset of farmers who cultivate both coffee and cocoa numbering 47 people. Four farmers reported that since 2012 they no longer cultivate coffee or cocoa (Table 2); they are listed in government records as coffee and/or cocoa farmers according to a 2008 survey, and in the future, they may resume cultivation.

Table 1 Training participants according to training heterogeneity

Location	Category				Total
	Coffee farmers	Cocoa farmers	Both coffee and cocoa farmers	Neither	
Hometown (Tanggamus)	30	22	15	2	39
Intra-island (South Lampung)	32	22	15	0	39
Inter-island (Garut–Ciamis)	33	24	17	2	42
Total	95	68	47	4	120

Table 2 Training participants in three locations (Tanggamus, South Lampung, and Garut-Ciamis) in Indonesia

	Non-cocoa farmers	Cocoa farmers	Total
Non-coffee farmers	4 (3%)	21 (17.5%)	25 (20.8%)
Coffee farmers	48 (40%)	47 (39.2%)	95 (79.2%)
Total	52 (43.3%)	68 (56.7%)	120 (100%)

In the analysis, we group farmers trained in South Lampung (different district) and Garut-Ciamis (inter-island) together into a remote-location training category due to similarities in their training nature: Farmers trained in these remote venues spent 4 days in total in the training center, enabling them to interact intensively with their fellow trainees and extension workers.

Table 3 specifies descriptive statistics pertaining to our sample of coffee and cocoa farmers. In general, *t* test results show that no substantial differences are found in terms of demographic characteristics, wealth, or source of information between the two categories; however, years of experience in cultivating coffee (17 years on average) are significantly longer than cocoa (9 years on average). Cocoa farmers are also somewhat more educated than coffee farmers are, even though on average both did not complete middle school education. Cocoa farmers seem to use also slightly more organic and chemical fertilizer than coffee farmers, even though cocoa farmers employ more labor to some extent.

Effectively identical training was given regardless of the location. Two professional trainers from the Indonesian Coffee and Cocoa Research Institute were invited to give training lectures. Training materials and the lecturers were identical for each location, and training was controlled to produce similar environments. For instance, all lectures were conducted in similar classroom settings with a projector and a whiteboard, and the slides were kept the same throughout the whole training. Breaks and lunches were provided, and there were ice-breaking games in every session before starting the training.

Training was conducted first in the hometown location (between April 14–16 2013) and then in the different district (between April 18–20 2013) followed by the inter-island location (between April 22–24 2013). To examine learning effectiveness, farmers were given a ten-question quiz before and after the lecture by the trainers. The ten-question quiz was given in the morning before the training started, and once again, an identical exercise was given after the training ended on the same day. It applied to both coffee and

Table 3 Descriptive statistics

Variables	Coffee farmers				Cocoa farmers				*P* value of t-statistics
	Mean	Std. dev.	Min	Max	Mean	Std. dev.	Min	Max	
Demographic characteristics									
Years of experience of cultivating coffee (for coffee farmers) and cocoa (for cocoa farmers)	17.46	11.88	0	60	8.55	8.76	0	40	0.000***
Years of education of household head	7.90	3.22	0	16	8.42	3.24	3	16	0.312
Age of household head	44.27	11.30	21	80	44.88	9.78	28	75	0.720
Cultivated farmland (in Ha)	1.09	0.87	0	5	1.17	0.95	0	5	0.578
Log of farm income (in Rupiah)	16.26	1.08	13.08	18.61	16.38	1.04	13.91	18.61	0.479
Mobile phone possession (=1 if owning)	0.85	0.36	0	1	0.81	0.40	0	1	0.505
Native of Lampung (=1 if yes)	0.27	0.45	0	1	0.26	0.44	0	1	0.888
Second-generation migrant (=1 if yes)	0.60	0.49	0	1	0.59	0.50	0	1	0.899
No. of household members	4.23	1.70	1	12	4.27	1.73	1	12	0.883
Male ratio in the household	0.55	0.16	0.25	1	0.54	0.17	0.25	1	0.702
Agricultural inputs									
No. of hired labor	2.87	2.22	0	15	3.13	2.41	1	15	0.478
Annual usage of organic fertilizer (in Kg)	771.74	1079.33	0	5800	792.57	1018.07	0	4500	0.901
Annual usage of chemical fertilizer (in Kg)	193.00	232.87	0	1500	241.18	253.18	0	1500	0.211
Annual usage of fertilizer in total (in Kg)	964.74	1184.43	0	5800	1033.7	1137.58	0	4800	0.709
Information sources									
Knowing extension workers (=1 if yes)	0.85	0.36	0	1	0.84	0.37	0	1	0.863
No. of agricultural advice network	5.21	2.99	1	14	5.11	3.91	1	20	0.853
No. of advice network within the farmers group	3.67	2.81	0	12	3.83	3.79	0	19	0.757
Living nearby extension workers (within 15-min walking distance)	0.21	0.41	0	1	0.24	0.43	0	1	0.652
Observations	95				68				

***, **, and * signify statistical significance at the 1, 5, and 10% level, respectively

cocoa training. The quizzes before and after the lectures were exactly the same, and all the requisite information to score well on the quizzes were covered in the lectures. Trainers read aloud the quiz questions with multiple-choice answers, and farmers had to write down the answer on the form supplied. The maximum score was 10, the minimum 0. The lectures were principally about coffee and cocoa cultivation, including the preparation of seedlings, grafting, and cutting methods, the appropriate crops for shade trees and agroforestry, the usage of fertilizers, and ways to maintain post-harvest crops and productivity. Quiz questions for coffee and cocoa were similar, primarily pertaining to selecting high-yielding varieties, suitable shade trees, grafting methods, and pruning methods. The quiz questions are presented in Table 4, and the results are presented in Table 5.

4 Estimation methodology

4.1 Describing social networks

This paper particularly addresses the effects of social networks on learning performance during agricultural training, as discussed in the previous section. In this study, we categorize networks into personal networks and network structure of farmers' groups. We expect that network differences will play important roles during farmers' information gathering.

Table 4 Outlines of the quiz questions

No.	Coffee quiz	Cocoa quiz
1	Characteristics of Robusta coffee and Arabica coffee	Characteristics of the good seedlings for cocoa cultivation
2	Characteristics of the good seedlings for coffee cultivation	When to prepare the cocoa nursery
3	How to use seeds derived from cutting or grafting	Characteristics of the good seedlings for cocoa cultivation
4	The time to prepare shade trees	The time to prepare the shade trees
5	How to prepare the planting hole for coffee crops	Suitable crop types for shade trees for cocoa crops
6	Characteristics of suitable shade trees for coffee crops	Types of trimmings to form a strong branching of cocoa crops
7	Suitable crop types for shade trees for coffee crops	How to manage seedlings and fertilization of cocoa crops
8	Suitable crop for inter-cropping (agroforestry) for coffee crops	How to rehabilitate low productivity cocoa crops
9	How to perform single stem pruning for coffee crops	Signs of cocoa crops that are ready to be harvested
10	How to perform double stem pruning for coffee crops	How to improve productivity of cocoa crops

Table 5 Summary statistics of the outcome variable (test scores)

Variable	Before training				After training				P value of t-statistics
	Mean	SD	Min	Max	Mean	SD	Min	Max	
Coffee score	3.46	2.06	0	8	5.92	2.42	0	10	0.000***
Observation	95								
Cocoa score	7.62	1.45	4	10	8.73	1.53	4	10	0.000***
Observation	68								

***, **, and * signify statistical significance at the 1, 5, and 10% level, respectively

1. Personal networks

Personal networks take account of network ties or the number of people a farmer has in their network. Specifically, we decompose personal networks into the following constituents:

(NT1) Friendship networks   A friendship network is defined in terms of the number of farmers from the same farmers' group attending training at the same location. Farmers were randomly assigned to training locations, so they could not simply choose where, and with whom, they wanted to attend. Friendship network data were obtained in April 2013 during the administration of the quiz questionnaire and the training. For instance, Farmer A from Farmers' Group 1 has Farmers B and C who are also from the Farmers' Group 1 attending the hometown training. In this respect, Farmer A, B, and C from Farmers' Group 1 each have a friendship network of 2 people in this experimental context. Those who are in the friendship network, albeit coming from the same farmers' group, are not necessarily in the advice network.

(NT2) Peer advice networks   To solicit information regarding peer advice networks, we asked farmers during the face-to-face interviews in September 2012 to identify the people from whom they seek advice and information pertaining to coffee and cocoa farming. Peer advice networks are defined in terms of the number of people whom the farmers have so far consulted regarding coffee and/or cocoa cultivation from within their farmers' group.

(NT3) Official advice networks   Similarly, information regarding bridging ties was also solicited during these preliminary interviews in September 2012. From the people identified by farmers as forming their agricultural advice networks, we identified whether he or she was a government official or extension worker. Official advice networks are a function of the number of government officials or local extension service workers whom farmers consult regarding coffee and/or cocoa cultivation. Officials are considered an annex of farmers' local networks. They are more advanced in terms of knowledge, experience, and resources and often advise farmers on farming practices. In this study, we regard government officials and extension workers as bridging ties.

Network measurements in (NT1) to (NT3) only consider the number of people that farmers have sought information from; directional information is not solicited. Thus, furthermore, we examine the farmers' deeper network structures within their farming community as follows.

2. Network position in Farmers' groups

Network structures or network position in the farmers' group is measured based on information regarding advice networks from inside the farmers' group (peer advice networks). Farmers' groups usually consist of 20–30 farmers who have similar agricultural interests and live within close proximity to each other and typically facilitate agricultural information transfer from extension workers to farmers. The group regularly conducts
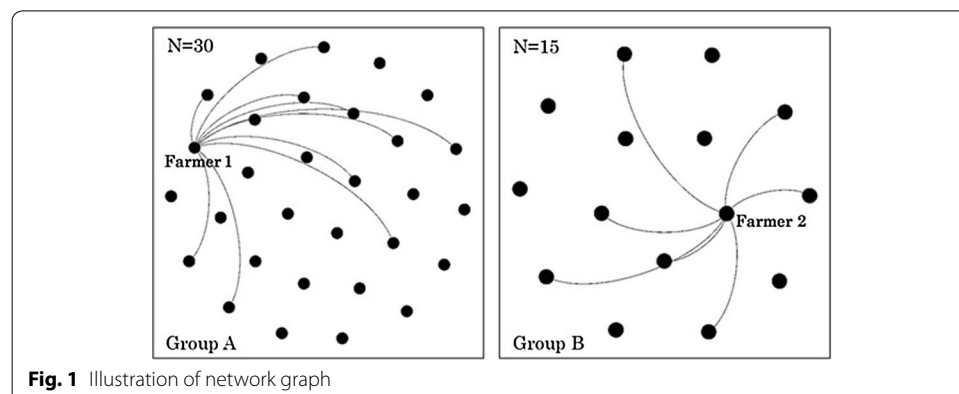
monthly meetings with extension workers to discuss farming practices. At the group level, farmers specify from whom they obtained information or talked to regarding agricultural practices; thus, the direction is outward.
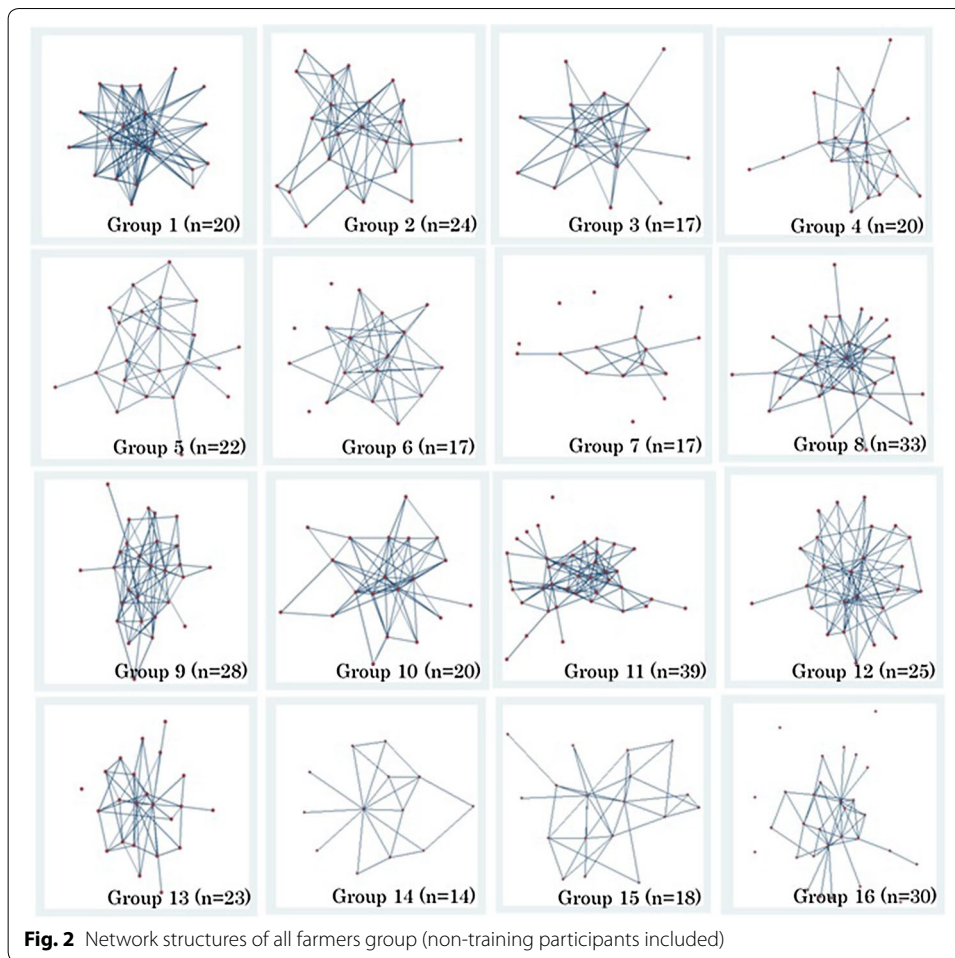
According to this information, we compute several centrality measures that incorporate information on all group members' knowledge-seeking directions in the farmers' group. The difference with peer advice networks (NT2), aside from the directional ties, is the ability to identify the individual's level of importance and influence within the group. For instance, Fig. 1 illustrates that Farmer No. 1 in group A may seem to be more influential when he solicited information from 10 members inside the group compared to Farmer No. 2 in group B who sought advice from only 7 members. However, group A has 30 members, while group B only has 15 members, making Farmer No. 2 more influential in his group than Farmer No. 1 even though Farmer No. 1 has a larger advice network in absolute terms.

The network structures for all 16 farmers' groups whose data were collected in the baseline survey are plotted in Fig. 2; this visualization derives from STATA programming as per Corten (2011). The red dot represents the vertex of each farmer, and the blue line corresponds to the edges. Group 1 has many members who are very active in soliciting information from each other, and the network seems dense. By contrast, there are 5 farmers in Group 7 who seem to be detached from the group, as they do not appear to seek advice from inside their farmers' group, indicating that communication within the group is not particularly intensive. Group 14, on the other hand, shows the presence of a sole influential person in the group; the other group members may not appear very active in information seeking from fellow members.

To measure network position within the farmers' group, we utilize information from peer advice networks (NT2). The information needed to construct centrality is the identifier of the individual who initiated the advice seeking (source) and the identifier of the individual who serves as the target of the advice seeking (target) from each farmers' group. We then compute three kinds of centrality measures that were initially developed by Freeman (1979) before later being made amenable in STATA by Miura (2012) and Cerulli and Zinilli (2014):

(NP1) Degree centrality Degree centrality measures the importance of a vertex by the number of its connections and was obtained from peer advice network information. A

Fig. 1 Illustration of network graph

Fig. 2 Network structures of all farmers group (non-training participants included)

farmer with a higher degree of centrality maintains more contacts with other farmers and is considered relatively influential in the farmers' network. Degree centrality is:

$$C(D^i) = \sum_{k \neq i}^{n} A_{i,j} \tag{1}$$

Degree centrality uses adjacency matrix A for unweighted networks, which is defined as a $|V| \times |V|$ matrix with entries $A_{i,j} = 1$ if and only if farmer i and j connects, else zero. The matrix $|V| \times |V|$ depends on the number of people in the farmers' group; if Farmers' Group 1 has 20 members, then the matrix would be $|20| \times |20|$.

(NP2) Closeness centrality   Closeness is based on the length of the average shortest path between a vertex and all vertices in the graph and was obtained from peer advice network information. A farmer who is close to other farmers can quickly interact and communicate with them without going through many intermediaries. Closeness centrality is computed as the inverse of the sum of geodesic distances from specific farmer i to the other $n - 1$ farmers. The closeness centrality of farmer i is:

$$C(C^i) = \left[\sum_{k \neq i}^{n} D_{i,j} \right]^{-1} \tag{2}$$

Closeness centrality used distance matrix D, which is defined as a $|V| \times |V|$ matrix with each entry of $D_{i,j}$ equal to the length of the shortest path between farmers i and j in the farmers' peer advice network data. A path is defined as a way to reach farmer j from farmer i using a combination of edges that do not connect through a particular farmer more than once. When i is not connected with any farmers, D_{ij} is defined to be infinity so that the closeness centrality of farmer i is zero. The matrix $|V| \times |V|$ depends on the number of people in the farmers' group; if Farmers' Group 1 has 20 members, then the matrix would be $|20| \times |20|$.

(NP3) Betweenness centrality   Betweenness is formulated based on the number of times a particular vertex lies "between" the other vertices in the network and was obtained from peer advice network information. It is the portion of the number of shortest paths that pass through the specific farmer divided by the number of shortest paths between any pair of farmers (Freeman 1977; Borgatti 1995). The betweenness centrality of specific farmer k measures gatekeeping and control of information in a network and is constructed as follows:

$$C(B^k) = \sum_{i \neq j \neq k \neq i}^{n} P_{ij}(k)/P_{ij} \tag{3}$$

Betweenness centrality used path matrix P, which is defined as a $|V| \times |V|$ matrix with P_{ij} entries being equal to the number of shortest paths between farmer i and j. If no paths exist between vertices i and j, P_{ij} is set to zero and P_{ii} is set to one. P_{ij} denotes the number of shortest paths from farmer i to j, and $P_{ij}(k)$ denotes the number of shortest paths from farmer i to j connecting via farmer k. The matrix $|V| \times |V|$ depends on the number of people in the farmers' group; if Farmers' Group 1 has 20 members, then the matrix would be $|20| \times |20|$.

Table 6 presents summary statistics for network variables, showing that there is no substantial difference across these variables between coffee and cocoa farmers. On average, farmers in both sets have 3 friendship connections during agricultural training; consult with 3 farming group members; and seek advice from less than 1 extension official. We use the standardized score of centrality measures to facilitate comparison among different centralization measures. A standardized centrality value of 1 (denoting 100%) means that the node connects with everyone in the group or that the person seeks advice from practically everyone in the farmers' group. Centrality measures show that cocoa farmers are slightly more active in information seeking, but this difference is not statistically significant. The majority of farmers used simple mobile phones that can only send and receive calls and short text messages. Only 1 farmer testified that his mobile phone could access the internet; hence, we do not take account of the internet usage of households for the possibility of information seeking.

Table 6 Summary statistics of the network variables

Variables	Coffee farmers				Cocoa farmers				P value of t-statistics
	Mean	SD	Min	Max	Mean	SD	Min	Max	
Friendship network	3.54	2.22	0	8	3.51	2.16	0	8	0.9315
Peers advice network	3.67	2.81	0	12	3.83	3.78	0	19	0.7569
Official advice network	0.8	1.33	0	5	0.69	1.34	0	5	0.6044
Betweenness centrality	0.05	0.078	0	0.404	0.065	0.11	0	0.679	0.3097
Closeness centrality	0.526	0.09	0.34	0.84	0.543	0.147	0.32	1	0.3623
Degree centrality	0.272	0.149	0.04	0.81	0.298	0.232	0.03	1	0.3854
Observation	95				68				

4.2 Estimation strategy

Farmers' modes of knowledge acquisition may be influenced by geographic proximity, because information transfer also occurred through nearest neighbor observations, with or without verbal exchange. This spatial dependency leads to the spatial autocorrelation problem, which violates an assumption of standard regression techniques that assume independence among observations. We collated the latitude and longitude of each household in order to compute a distance-based spatial weight matrix. To quantify the extent of spatial autocorrelation across variables, we utilized Moran's I global spatial autocorrelation test developed by Moran (1950) and Cliff and Ord (1981) as follows:

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(X_i - \overline{X})(X_j - \overline{X})}{\sum_i (X_i - \overline{X})^2} \quad (4)$$

where N is the number of spatial units indexed by i and j; X is the variable of interest; $\overline{X}$ is the mean of X; and w_{ij} is an element of a matrix of spatial weights. Values of I range from -1 to $+1$. Negative (positive) values indicate negative (positive) spatial autocorrelation. A zero value indicates a random spatial pattern. For the purposes of statistical hypothesis testing, Moran's I values can be transformed to Z-scores. The results are presented in Table 7. We found that the majority of explanatory variables are spatially correlated hence the importance of accounting for spatial error in the model.

Econometric models for panel data with spatial error processes have been proposed by Anselin (2001), Kapoor et al. (2007), and Baltagi et al. (2013). Using a spatial autoregressive (SAR) estimation that takes account of spatial autocorrelation, we modeled (NT1) to (NT3) with personal network independent variables as follows:

1. Effects of personal network on learning effectiveness

$$Y_{it} = \rho W Y_{it} + \beta_1 \text{Time}_t + \beta_2 \text{Personal Network}_{it}$$
$$+ \beta_3 \text{Time} \times \text{Personal Network}_{it} + \beta_4 X_{it} + \mu + \varepsilon_{it} \quad t = 1, \ldots, T \quad (5)$$

Equation 5 is a random-effects SAR model. W is the $n \times n$ matrix of spatial weights for each period of $t = 1$ before the training and $t = 2$ after the training, Y_{it} is the $n \times 1$ column vector of the dependent variable (test scores), and X_{it} is the $n \times k$ matrix of regressors. For each cross section, W describes the spatial arrangement of the n units and each

Table 7 Moran's I test for global spatial autocorrelation

Variables	Coffee farmers					Cocoa farmers				
	I	E(I)	SD(I)	Z score	P value*	I	E(I)	SD(I)	Z score	P value*
Coffee test scores	−0.005	−0.006	0.028	0.028	0.489	−0.047	−0.008	0.040	−0.974	0.165
Cocoa test scores						0.033	−0.008	0.039	1.063	0.144
Time × official advice network	−0.007	−0.006	0.027	−0.049	0.481	0.042	−0.008	0.039	1.274	0.101
Time × peers advice network	0.039	−0.006	0.028	1.611	0.054*	0.040	−0.008	0.040	1.195	0.116
Time × friendship network	0.091	−0.006	0.028	3.465	0.000***	0.193	−0.008	0.041	4.953	0.000***
Friendship network	0.423	−0.006	0.028	15.312	0.000***	0.126	−0.008	0.040	3.380	0.000***
Peers advice network	0.142	−0.006	0.028	5.306	0.000***	0.075	−0.008	0.040	2.070	0.019**
Official advice network	−0.017	−0.006	0.028	−0.396	0.346	0.154	−0.008	0.041	4.002	0.000***
Years of education of household head	0.056	−0.006	0.028	2.219	0.013**	0.037	−0.008	0.040	1.109	0.134
Living nearby extension official	0.138	−0.006	0.028	5.136	0.000***	−0.049	−0.008	0.040	−1.045	0.148
Motorbike possession	0.170	−0.006	0.028	6.336	0.000***	−0.095	−0.008	0.040	−2.156	0.016**
Mobile phone possession	−0.068	−0.006	0.028	−2.249	0.012**	0.112	−0.008	0.041	2.960	0.002***
Training outside hometown	0.184	−0.006	0.028	6.772	0.000***	0.040	−0.008	0.041	1.172	0.121
No of official attending training	0.070	−0.006	0.028	2.690	0.004***	−0.003	−0.008	0.041	0.110	0.456
Organic fertilizer (=1 if using)	−0.031	−0.006	0.028	−0.889	0.187	−0.059	−0.008	0.040	−1.274	0.101
Chemical fertilizer (=1 if using)	0.014	−0.006	0.028	0.724	0.235					
Years of experience cultivating coffee	0.019	−0.006	0.028	0.906	0.182					
Years of experience cultivating cocoa						0.148	−0.008	0.040	3.896	0.000***
Time × degree centrality	0.014	−0.007	0.033	0.615	0.269	0.035	−0.009	0.049	0.895	0.185
Degree centrality	0.076	−0.007	0.033	2.479	0.007***	0.128	−0.009	0.050	2.762	0.003***
Time × closeness centrality	0.003	−0.007	0.034	0.303	0.381	0.009	−0.009	0.050	0.367	0.357
Closeness centrality	0.123	−0.007	0.033	3.900	0.000***	0.145	−0.009	0.050	3.117	0.001***
Time × betweenness centrality	−0.011	−0.007	0.032	−0.131	0.448	0.011	−0.009	0.043	0.462	0.322
Betweenness centrality	−0.028	−0.007	0.033	−0.639	0.261	0.025	−0.009	0.047	0.734	0.231

***, **, and * signify statistical significance at the 1, 5, and 10% level, respectively

entry w_{ij} of W is greater than zero if units i and j can be considered as neighbors. We compute the matrix in STATA using the *spwmatrix* command by Jeanty (2010) which allows the creation and management of weight matrices. Then we run the SAR model in STATA using the *xsmle* command introduced by Belotti et al. (2013). The command automatically accommodates the longitudinal nature of the data; hence, users only need to provide the cross-sectional $n \times n$ weight matrix to estimate the model. Two methods of estimating spatial panel models have been categorized into GMM estimators, and quasi-maximum likelihood estimators, and *xsmle* can estimate models that fall into the second category. In the case of random effects, it is assumed that $\mu \sim N(0, \sigma_\mu^2)$ (Belotti et al. 2017).

For (5), where i indexes each farmer's id: Y_{it} is an outcome variable of interest, namely the coffee quiz scores for coffee farmers or cocoa quiz scores for cocoa farmers; α is a constant; $Time_t$ is an indicator for pre- and post-training periods (that is $Time_t = 1$ for post-training, else 0); Network is the number of personal networks held by farmers; and ε_{it} is a random error term. We use the quiz test scores before and after lectures in Y_{it} and conduct panel analysis; the panel nature takes into account time-invariant heterogeneities such as households' ethnicity, religion, and education. Networks with peers and experts do not change across waves. The variable of interest is the interaction term between Network and Time because we want to elucidate how networks play roles in information gathering during agricultural training. For this regression, we construct different estimations for both coffee and cocoa farmers and utilize a random-effects SAR model for our estimation. In cases where the key variables (X_{it}) do not vary much overtime, the random-effects model can take account of time-invariant determinants, thus efficiently eliminating any remaining serial correlation due to unobserved time-constant factors (Wooldridge, 2010).

With various network position indicators as independent variables (NP1) to (NP3), the estimation is as follows:

2. Effects of network position on learning effectiveness (only if farmers include any member of their farmers' group in their agricultural advice network)

$$Y_{i,t} = \rho W Y_{it} + \beta_1 Time_t + \beta_2 Centrality_{it} \\ + \beta_3 Time \times Centrality_{it} + \beta_4 X_{it} + \mu + \varepsilon_{it} \quad t = 1, \ldots, T \tag{6}$$

For (6), Y_{it} is the coffee quiz score for coffee farmers or cocoa quiz score for cocoa farmers; Centrality is the measure of closeness centrality, degree centrality, and betweenness centrality; similar to the above, Time is an indicator for pre- and post-training period (that is $Time_t = 1$ for post-training, else 0). For this estimation, our variable of interest is the interaction term between Centrality measures and $Time_t$, indicating the influence of a farmer's network position in their community upon their learning achievements. All centrality measures are derived from the adjacency matrix, so they constitute different mathematical computations using the same underlying data. In this paper, the centrality measures are highly correlated with one another; hence, we do not include them together in a single specification (see Valente et al. 2008).

5 Estimation results

5.1 Effect of personal networks on learning outcomes

Columns 1 and 2 of Table 8 present regression results of the influence of personal networks on knowledge acquisition for the case of coffee farmers. We found that after the lecture, the peer advice network variable is significantly associated with the coefficient of test score by 0.29 points. We did not find significant effects of friendship networks and official advice networks for coffee farmers. Additionally, the current usage of organic fertilizer is positively related to the coefficient of test score by 1.3 points, indicating that those who are familiar with the use of organic fertilizer are more likely to possess higher knowledge for effective production.

In the case of coffee, as an old commodity, knowledge regarding coffee production has been evolving across generations. Everyone is considered on par with each other when it comes to effective coffee production; hence, farmers' connections with their peer advice networks may positively reflect farmers' knowledge-gathering and information-processing abilities in unfamiliar situations such as formal training. Their experience with information solicitation within their local community might help them to acquire more knowledge from the training relative to those with fewer connections in the group.

Results for cocoa farmers are reported in columns 3 and 4. Similar to coffee farmers, peer advice networks are also associated with higher test score coefficients prior to the lecture by 0.103 and 0.162 points, respectively. In the case of cocoa farmers, the peer advice network coefficient is positive and significant before the lecture but insignificant after the lecture, meaning that the scores of farmers who are better networked in this respect were higher from the beginning. Farmers with greater peer advice networks may possibly, prior to the training, understand cocoa production better relative to others; hence, the increment on the score from the training is smaller than that for others with fewer connections. Current usage of chemical fertilizer is also attributed to better knowledge about effective agricultural practices, though the contrary applies to usage of organic fertilizer.

Further, those with ties to extension officials obtained lower scores by 0.3 points after the lecture compared to those with less of those ties. Both cocoa farmers and extension officials for cocoa are considered less experienced compared to the counterparts in the coffee domain; hence, there may be a possibility that some discrepancies occur between information transmitted by officials versus the knowledge presented during the lecture. When experts are inexperienced, advice networks may be adversarial to knowledge-gathering activities due to higher risks of irrelevant information being transmitted.

We revealed mixed findings that only partially supported the hypothesis: While peer advice networks are almost always beneficial for learning outcomes, official advice networks are negatively related to knowledge seeking to some extent, when the expert is not suitably well informed.

5.2 Effect of network position on learning

Delving deeper into farmers' network structures in their respective groups, we examined further effects on learning during training. The highest possible closeness, degree, and centrality score attainable is 1 if farmers practically mention everyone in their farmers' group as a source of agricultural advice, because we used the standardized centrality.

Table 8 Effects of personal network on knowledge acquisition

Variables	Coffee score (only for coffee farmers)		Cocoa score (only for cocoa farmers)	
	(1)	(2)	(3)	(4)
Time × peers advice network	0.291***	0.290***	−0.0247	−0.0243
	(0.0924)	(0.0922)	(0.0231)	(0.0233)
Time × official advice network	0.123	0.124	−0.295***	−0.298***
	(0.235)	(0.236)	(0.112)	(0.112)
Time × friendship network	−0.160	−0.159	−0.0552	−0.0539
	(0.132)	(0.132)	(0.101)	(0.101)
Time	3.136***	3.246***	2.002***	2.044***
	(0.658)	(0.666)	(0.362)	(0.367)
Peers advice network	−0.0742	−0.0474	0.103**	0.162***
	(0.0652)	(0.0640)	(0.0443)	(0.0413)
Official advice network	−0.163	−0.286*	0.0256	0.0151
	(0.151)	(0.146)	(0.128)	(0.118)
Friendship network	−0.0253	0.0457	0.0276	−0.00968
	(0.127)	(0.137)	(0.120)	(0.101)
Years of education of household head		0.111*		0.186***
		(0.0616)		(0.0433)
Living nearby extension Official (within 15-min walk)		0.0710		−0.218
		(0.559)		(0.375)
Organic fertilizer (=1 if using)		1.269***		−1.310***
		(0.480)		(0.385)
Chemical fertilizer (=1 if using)		−0.254		1.130***
		(0.454)		(0.369)
Mobile phone possession (=1 if owning)		−0.908*		0.688
		(0.542)		(0.484)
Motorbike possession (=1 if owning)		0.888		0.551
		(0.637)		(0.406)
Years of experience cultivating coffee		0.00586		
		(0.0182)		
Years of experience cultivating cocoa				0.00414
				(0.0155)
Constant	7.944***	5.476***	10.11***	7.253***
	(0.596)	(1.178)	(1.339)	(1.590)
$W \times Y_{it}$	−0.489***	−0.530***	−0.375***	−0.415***
	(0.124)	(0.129)	(0.143)	(0.160)
Farmers group fixed effects	Yes	Yes	Yes	Yes
Observations	172	172	128	128
Number of household ID	86	86	64	64
R-squared (within)	0.524	0.525	0.484	0.483
R-squared (between)	0.240	0.352	0.265	0.465

Results are based on random-effects spatial autoregressive (SAR) model. Heteroskedasticity-robust standard errors are in parentheses

***, **, and * signify statistical significance at the 1, 5, and 10% level, respectively

In columns 4–6 of Table 9, we found that all three network variables, namely degree, closeness, and betweenness centrality, are strongly associated with higher test scores for cocoa farmers before the lecture. Cocoa farmers who sought advice from everyone

Table 9 Effects of network position in farmers group on knowledge acquisition

Variables	Coffee scores (only for coffee farmers)			Cocoa scores (only for cocoa farmers)		
	(1)	(2)	(3)	(4)	(5)	(6)
Time × degree centrality	1.453			0.0370		
	(2.022)			(0.719)		
Time × closeness centrality		1.472			0.416	
		(3.363)			(1.223)	
Time × betweenness centrality			3.879			1.397
			(4.209)			(1.429)
Degree centrality	−0.0969			2.081**		
	(1.684)			(0.893)		
Closeness centrality		0.523			3.049**	
		(2.906)			(1.458)	
Betweenness centrality			−0.890			3.635**
			(3.087)			(1.688)
Time	3.842***	3.466*	4.027***	1.688***	1.483**	1.631***
	(0.796)	(1.841)	(0.598)	(0.348)	(0.749)	(0.270)
Living nearby extension official	0.306	0.292	0.276	−0.0927	−0.0828	−0.313
(within 15-min walk)	(0.493)	(0.492)	(0.498)	(0.427)	(0.426)	(0.421)
Years of education of household head	0.124**	0.123**	0.124**	0.165***	0.169***	0.155***
	(0.0622)	(0.0618)	(0.0605)	(0.0558)	(0.0567)	(0.0527)
Motorbike possession	1.024	1.050	1.000	−0.0379	0.0126	−0.367
(=1 if owning)	(0.703)	(0.701)	(0.714)	(0.352)	(0.374)	(0.354)
Mobile phone possession	−0.951*	−0.957*	−0.938*	0.808	0.770	0.619
(=1 if owning)	(0.495)	(0.492)	(0.488)	(0.550)	(0.577)	(0.590)
Organic fertilizer	0.930**	0.881**	0.946**	−1.177**	−1.206**	−0.949**
(=1 if using)	(0.428)	(0.438)	(0.423)	(0.490)	(0.509)	(0.457)
Chemical fertilizer	−0.658*	−0.648*	−0.655*	1.206***	1.155**	1.296***
(=1 if using)	(0.383)	(0.384)	(0.385)	(0.462)	(0.459)	(0.459)
Years of experience cultivating coffee	0.0117	0.0116	0.0122			
	(0.0176)	(0.0176)	(0.0170)			
Years of experience cultivating cocoa				0.00556	0.00392	0.00358
				(0.0173)	(0.0172)	(0.0168)
Constant	5.994***	5.646***	6.057***	8.184***	7.192***	9.572***
	(0.937)	(1.453)	(1.026)	(1.791)	(2.033)	(1.578)
$W \times Y_{it}$	−0.598***	−0.597***	−0.598***	−0.450***	−0.459***	−0.471***
	(0.144)	(0.143)	(0.144)	(0.151)	(0.149)	(0.150)
Farmers group fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	148	148	148	110	110	110
Number of household ID	74	74	74	55	55	55
R-squared (within)	0.475	0.472	0.479	0.454	0.456	0.461
R-squared (between)	0.400	0.402	0.399	0.474	0.460	0.489

Results are based on random-effects spatial autoregressive (SAR) model. Heteroskedasticity-robust standard errors are in parentheses

***, **, and * signify statistical significance at the 1, 5, and 10% level, respectively

in the group and close to them tend to have higher test scores, as testified by coefficients of 2.08, 3.05, and 3,6 points before lecture. After the lecture, the score increments become insignificant, suggesting that those with lower centrality scores made relative

gains during training. For the case of coffee, those with higher centrality scores are associated with higher test scores after the lecture, although this difference is not statistically significant.

The results indicate, to some extent, that farmers with a high degree of centrality may be good at adapting themselves to unknown situations and environments, thus supporting the second hypothesis. Centrality measures are often associated with power (Moschitz and Stolze 2009) and innovation in the rural community (Spielman et al. 2011), indicating that those with higher scores tend to be innately more capable in the context of agricultural management and therefore commanded respect from within the community. Actors with high centrality have a greater variety of choice since they are connected to a large number of other actors. In the context of rural innovation systems, Spielman et al. (2011) found that innovators' networks are more centralized and closer, denoting greater proximity (shorter walks) to other actors. Cocoa farmers, who inhabit more central positions in their communities, are found to be innately more capable of problem solving as well as more knowledgeable in effective agricultural management, making them more productive during learning activities.

6 Conclusions

This paper explores how farmers' social networks affect their information acquisition abilities. To serve our purpose, we conducted a quiz before and after agricultural training and explored how various social network variables influence learning outcomes. We demarcate social network ties into bonding and bridging ties, as well as into social and instrumental ties, and examine farmers' network structures within their farming group communities. We found that peer advice networks with instrumental features correspond to better learning outcomes. This is because in classroom settings, they represent farmers' adaptive capacity for knowledge-gathering processes in the new environment. Furthermore, an individual's position in their local farming community strongly relates to their information solicitation abilities. Findings in detail are discussed as follows:

First, peer advice networks are always advantageous for knowledge seeking in the classroom setting, but friendship networks have no significant effects. The majority of coffee farmers are experienced farmers to begin with; hence, those with more of these ties tend to experience more familiarity and confirmation of their current practices. On the other hand, as cocoa is a relatively new commodity compared to coffee, cocoa farmers with greater peer advice networks may possibly understand cocoa production better relative to others; hence, the increment on test scores following the training is significantly smaller than others with less developed networks. Advice relations were found to have stronger effects than simply friendship ties in the active pursuit of agricultural knowledge transfer due to their "instrumental" features; this corroborates the findings of Isaac et al. (2007).

Second, the quality of official advice networks vis-à-vis solicited information matters for learning facilitation to some extent depending on their years of experience. We found that official advice networks are adversarial for cocoa farmers but not for coffee farmers. Several possibilities arise to explain why knowledge-seeking characteristics are different between coffee and cocoa farmers, and more importantly, why official advice networks seem to have negative associations with cocoa farmers' knowledge attainment during agricultural training:

1. Cocoa extension workers in the area are still inexperienced compared to coffee extension workers. The Gernas Kakao program, which was implemented in early 2011, assigned contract workers with degrees in agricultural sciences. Most cocoa extension workers have been recruited recently, fresh from their studies. In the context of organizational settings, Eklinder-Frick et al. (2011) mentioned that bridging ties may contribute negatively to performance when the role of information broker is unfulfilled. This can result in irrelevant information being shared since the actors do not know each other well enough to differentiate low value from high value information.

2. Compared to coffee farmers, cocoa farmers in general are less experienced. Even when the correct ties are in place with the correct experts, challenges may still exist with respect to individuals' varying abilities to absorb the knowledge they receive from others. Given that knowledge is often complex, successful knowledge transfers often require that knowledge givers and receivers have a level of mutual understanding of one another, which, in turn, often requires reciprocal exchanges between actors for successful learning to occur (Burt 2004). This aspect may be absent in the case of the inexperienced cocoa farmers.

Third, an individual's position in their network structure in a community contributes positively to learning outcomes. Farmers who are in a central position in their farmers' group are strongly associated with higher test scores. Farmers with a high degree of centrality may be very good at facilitating problem-solving activities as they are used to conducting effective coordination of actors and resources in their local networks. They are more adept at solving problems even in the previously unknown environment, thus performing better in learning during agricultural training.

While it is easier, for the purposes of future information dissemination strategies, to approach influential farmers to help distributing new information in their local community, networks which have few members with very high centrality measures may have adversarial effects on learning, as they reduce the access of other actors to multiple sources of information (Abrahamson and Rosenkopf 1997). Another implication from this study highlights the importance of correct ties. Agricultural informants serving as "bridging ties" should preferably be more experienced and advanced than the advisee so that learning could be better facilitated and the risk of transferring irrelevant information could be minimized.

Additional file

Additional file 1. Dataset used for effects of social networks on knowledge acquisition.

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