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Buddhika N. Abeysinghe

Department of Agriculture

Ministry of Agriculture, Sri Lanka

Samanmalee Amarawansha

Department of Export Agriculture

Ministry of Agriculture, Sri Lanka

Takahiro Ito

Graduate School of International Cooperation Studies

Kobe University

Shinji Kaneko

Graduate School for International Development and Cooperation (IDEC)

Hiroshima University

Department of Development Policy
Division of Development Science
Graduate School for International Development and Cooperation (IDEC)
Hiroshima University
1-5-1 Kagamiyama, Higashi-hiroshima
7398529 Japan

Information Diffusion and the Role of Central Figures: Experimental Evidence of Network-based Agricultural Extension in Sri Lanka[*]

Buddhika N. Abeysinghe,[†] Samanmalee Amarawansha,[‡] Takahiro Ito,[§] and Shinji Kaneko[**]

Abstract

This study examines the effect of social networks and central figures in networks on information diffusion. Exploiting a government subsidy program and training workshops regarding the fair-trade and organic farming certifications in Sri Lanka, we conducted a randomized experiment to investigate the role of farmers' social networks and "key farmers" in information transmission to workshop non-participants and their application to the certifications. Key farmers are agricultural village leaders unofficially appointed by local government officials. The estimation results show that key farmers' involvement in the workshop amplifies information diffusion through social networks. In the treatment villages with key farmers involved, non-participants increase their knowledge of certifications and the likelihood of being a member of the applicant organization when directly connected with key farmers in their networks. Moreover, they are more likely to receive information goods from other peers in the network. However, in the control villages with key farmers uninvolved, direct connections with key farmers and farmers' networks do not influence the diffusion of information goods and knowledge and participation in the applicant group. These findings suggest that central figures' involvement is the key to the success of network-based programs.

Keywords: knowledge diffusion, certification application, key farmer, network-based agricultural extension, randomized experiment, Sri Lanka

JEL Codes: D83, Q16

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[†] Deputy Director, Department of Agriculture, Ministry of Agriculture, Sri Lanka.
[‡] Assistant Director, Department of Export Agriculture, Ministry of Agriculture, Sri Lanka.
[§] Corresponding author. Associate Professor, Graduate School of International Cooperation Studies, Kobe University, 2–1, Rokkodai-cho, Nada-ku, Kobe, Hyogo, 657-8501, Japan. E-mail: takahiro.ito@lion.kobe-u.ac.jp.
[**] Professor, Graduate School for International Development and Cooperation, Hiroshima University, 1-5-1, Kagamiyama, Higashi-Hiroshima, Hiroshima, 739-8529, Japan.

1. Introduction

A major concern government officials have recurrently had in agricultural societies is that farmers are not responsive to opportunities to adopt improved crop production technologies. Despite the availability of many established agricultural technologies and practices, the adoption rate remains considerably low in developing countries (Pierpaoli et al. 2013; Takahashi et al. 2019). Among several possible obstructive factors for technology dissemination, lack of access to information can be a significant barrier, especially for new technologies. Information diffusion is a vital first step in technology adoption; however, it is a significant weakness of developing countries, where institutions are often absent or weak (Anderson and Feder 2007; Aker 2011; Conley and Udry 2010; Foster and Rosenzweig 2010).

One method that has recently attracted attention to compensate the weakness and promote the diffusion of agricultural information in developing countries is to utilize social networks. [1] The so-called network-based agriculture extension includes farm field demonstrations and model-farmer training, where trainee networks serve as the mode of information diffusion. Since the seminal works of Foster and Rosenzweig (1995) and Conley and Udry (2001), studies on the role of social networks have surged (Munsi 2004; Bandiera and Rasul 2006; Kondylis, Mueller, and Zhu 2017; Conley and Udry 2010; Ramirez 2013; Maertens 2017; Di Falco et al. 2018; Beaman and Dillon 2018; Dar et al. 2019).[2] They documented anecdotal and empirical evidence that farmers learn through their social networks, not necessarily by observing every other farmer in the community. Information is localized and converted into common knowledge through personal ties (Vasilaky 2012), and network-based agricultural extension is expected to be more practical and cost-effective for information

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[1] See Takahashi et al. (2019) for the review on technology diffusion using social networks.

[2] Moreover, some studies indirectly examined the role of social networks on technology adoption by evaluating network-based extension programs. See, for instance, Vasilaky (2012), Beaman et al. (2018), Nakano et al. (2018), and Dillon et al. (2018).

diffusion (Feder and Umali 1993).

In this study, we explore the effectiveness of a network-based agricultural extension conducted in Sri Lanka. To this end, we implemented a randomized experiment in conjunction with government-run training workshops regarding the fair-trade and organic farming certifications. Research on the effectiveness of social network-based extension programs is in its infancy; thus, the available evidence remains sparse. Hence, this study contributes to the literature on network-based agricultural extension via the case of Sri Lankan spice farmers. Moreover, in estimating the network effect model, disentangling the network causal effect from possible biases due to correlated unobservables is a challenge (Manski 1993). While empirical studies of social network effects generally employ restricted models relying on identification assumptions,[3] the most rigorous approach is to randomize the networks or the introduction of new technology (knowledge) at the peer level. As detailed in Section 3.1 later, our experimental design ensures that the locations of workshop participants in village networks (and their knowledge regarding the certifications) are exogenously determined from observed and unobserved individual characteristics of non-participants. In the context of information or technology diffusion in agriculture, this study is the first attempt to isolate the causal network effect on information diffusion by utilizing a random intervention at the peer level.[4] Thus, this study provides new evidence on agricultural information diffusion in the literature on network effects.

The remainder of this paper proceeds as follows. In the next section, we present the background on organic and fair-trade certifications and spice farming in Sri Lanka. Section 3

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[3] The sources of social network effects can be divided into three in Manski's (1993) terminology: endogenous, contextual (exogenous), and correlated effects. In the literature, it has been often assumed that there are no correlated effects and only one of either endogenous or contextual effects.

[4] In fields other than agricultural information and technology diffusion in agriculture, several studies randomized network connections (Sacerdote 2001; Zimmerman 2003; Duflo and Saez 2003) or intervention at the peer level (Banerjee et al. 2012; Oster and Thornton 2012; Godlonton and Thornton 2012; Kremer and Miguel 2007).

explains the research design, including a verification of the identification assumption. Section reports 4 the estimation results, and the final section concludes.

2. Background

2.1. Fair-trade and Organic Certifications

In recent years, to promote environmental conservation and achieve sustainable consumption and production, several agricultural certification systems have been established worldwide. Fair-trade and organic farming certifications of interest are pioneers (Barham and Weber 2012), and the markets for both products have been growing steadily. The global market size for fair-trade and organic food products has grown to 7.3 and 75.7 billion euros, respectively, as of 2015 (Willer and Lernoud 2017).

Fair-trade is an alternative approach to conventional international trade. It aims to improve living conditions and the well-being of small (and often poor) producers and laborers in developing countries for sustainable development through trades at a "fair" price. The key players in the fair-trade supply chain are classified into three categories: certification organizations, producers, and traders. The most prevailing certification organization in Sri Lank, especially for coffee and spice products, is the Fair-trade Labeling Organization International (FLO). Producers include small farmer organizations and plantations, and traders include processing and export companies. Applicants must fulfill the requirements (Fair-trade Standards) mandated by the FLO to obtain the FLO certification. The requirements differ per product and classification of producers or traders. The certification process proceeds with the guidance and support of an FLO subsidiary, FLOCert. When applicant organizations are certified successfully, the certification lasts four years, during which they can trade their products at the global price. If the global price falls below a certain threshold, trading at a minimum floor price is guaranteed.[5] Moreover, during the three-year “certification cycle,” regular inspections are conducted once a year by FLOCert, where they audit the certified organization’s compliance per the requirements. When the cycle ends, the re-certification process starts. As of 2017, 34 Sri Lankan farmer organizations obtained a fair-trade certificate, covering approximately 30,000 farmers and laborers.

Organic certification aims to reduce the use of agrochemicals, such as chemical fertilizers and pesticides, and promotes “sustainable” agriculture. Many certification organizations provide organic certification services worldwide. Some are public, but most are private. These certification organizations have authorization from the International Organic Accreditation Service (IOAS), the authorization body of the International Federation of Organic Agriculture Movements (IFOAM).

As of 2019, Sri Lanka has eight international and one local certification agency (GoSL 2019). The requirements farmers must fulfill to obtain organic certification were formulated according to the guidelines provided by IFOAM. Farmer organizations then obtain organic certification through the pre-assessment, documentation review, and field audit provided by certification agencies. One certification cycle lasts for a couple of years, depending on the certification agency. Furthermore, regular inspections are conducted by the agency, either as announced or unannounced visits.

According to IFOAM statistics, the total area under organic agriculture in Sri Lanka in 2015 was 96,318 ha, the second-largest organic share to the total agricultural lands of a country in Asia (Willer and Julia 2017). Furthermore, Sri Lanka is considered the pioneer in the Asian region in introducing organically certified tea and cinnamon to the world market in

[5] Another major benefit of having the certification is the fair-trade premium additionally paid to the producer organization, which can be used for capacity building and community development. Regarding the cost of having the fair-trade certification, on the other hand. it mainly comprises the application and annual certification fees (after certification). These application and annual certification fees vary depending on products and the producer-trader category.

2017 (GoSL 2018d). The primary market channel of organic products in Sri Lanka is exports; destinations include European countries, the USA, Japan, Australia, and the Middle East (Vidanapathirana and Wijesooriya 2014). Currently, the Sri Lankan organic agriculture sector comprises nearly 8,695 producers, 189 processors, and 311 exporters (Willer and Julia 2017).

2.2. Spice Crop Sector and Subsidy Program in Sri Lanka

Spice products comprise Sri Lanka's fifth-largest export earner, accounting for 8 billion Sri Lanka Rupees (SLRs), or 30.7% of agricultural export earnings in 2017 (Central Bank of Sri Lanka 2017). Approximately 500,000 small farmers engage in spice cultivation, and over 30,000 tons of spice products are produced annually (GoSL 2018d). The main spice products are cinnamon, pepper, nutmeg, clove, cardamom, and mace. Simultaneously, several production issues have emerged. For example, degrading soil fertility, lack of water, limited market facilities, and low adoption rate of new technologies render spice farmers to be less profitable (Central Bank of Sri Lanka 2017).

The government has identified spice production as a key to improving export performance in the agricultural sector, given the high demand for organic spice products in the world market. Favorable climate conditions, higher contributions of the small-scale sector (70% of production is contributed by smallholders), and minimal use of agrochemicals provide a great opportunity for Sri Lankan farmers to convert to organic and fair-trade certified farming (GoSL 2018c).

Along with the national export policy launched in 2018, the Department of Export Agriculture (DEA) introduced an organic and fair-trade certification promotional program in September 2018 for small farms at the village level. The program includes holding training workshops to spice farmers and providing information and technical guidance regarding the certifications. Moreover, to increase the adoption rate for certifications and ensure small-scale farmers' participation, they introduced a subsidy that covers 50% of the application cost for certification (up to SLR 150,000 per farmer organization).

3. Research Design

3.1. Experiment and Household Survey

This study conducted a randomized experiment and household survey of spice farming households in three districts (Kandy, Mathale, and Nuwara Eliya) in the Central Province of Sri Lanka. These districts are located in the central part of the island, and their economies heavily rely on tea, spice, and vegetable cultivation. In particular, pepper, clove, cardamom, nutmeg, cocoa, and cinnamon are popular spice products in these districts.

Among the 49 spice-cultivating villages in Central Province, the DEA held one-day agricultural training workshops on fair-trade and organic certifications in 10 randomly selected villages in October 2018.[6] In each village-level workshop, randomly selected 45 spice farmers from the 2017 voter list were invited by post,[7] and the DEA provided them with specific information regarding fair-trade and organic certifications, including certification benefits, application procedures, certification requirements, and government subsidy programs. This information was also provided in leaflets distributed to workshop participants.[8] In addition to certification-related information, the DEA also provided general guidance on spice farming, including training on agronomic practices to improve the productivity of spice cultivation. The list of practices includes gap-filling, shade pruning, soil conservation, mulching, fertilizer application, and pest and weed control. The one-day training workshop took three to four hours.

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[6] During the same period, DEA conducted another training program in randomly-selected 20 spice farming villages. The content of the program in these villages are a part of the content of our program. Therefore, spillover from these villages into our study villages is less likely.

[7] The yearly voter list by the Election Commission of Sri Lanka includes the population aged 18 and over.

[8] The leaflets are written in the local language, Sinhalese (see Figure A1 in Appendix A).

We collaborated with the DEA to implement a randomized experiment in conjunction with the workshops in five villages randomly selected from the 10 villages.[9] We chose one leaflet distributor from each of the five villages (one distributor in one village) and asked them to distribute an additional 20 leaflets to respective villagers not invited to the training workshop. Moreover, to examine whether the distributor's position in the network matters in the diffusion of information goods, we differentiated the distributor type. Among the initial 10 villages, four included key farmers as participants, and six villages did not. We then randomly selected two villages from the former and appointed the key farmer as the distributor (treatment group). Regarding the six villages with no key farmers invited, we randomly chose three villages and appointed a randomly selected participant as the distributor (control group). All leaflet distributors were men (see Figure 1 for the flowchart of the experiment). The additional 20 leaflets consist of 10 leaflets about the fair-trade certification and 10 leaflets about the organic certification. Notably, the research team ensured that local officials provided no additional intervention in the study area.

[Insert Figure 1 here]

[Insert Figure 2 here]

After the experiment, we conducted an exhaustive household survey in the five villages in the treatment and control groups from December 2018 to January 2019. The survey was conducted in the Sinhala language by trained enumerators and the sample size is 901 households. Note that, among the 225 invited farmers in these five villages, 198 (88%) participated in the workshops, and invited non-participants (i.e., non-compliers) were also

[9] Note that the reason why we selected only five villages is simply due to budget constraints.

included in the survey. Figure 2 shows the locations of the five villages.

Note also that we could not conduct a baseline survey before the experiment mainly because of time constraints. When we joined the DEA project, the preceding training workshops had just started, leaving insufficient time and human resources to conduct the baseline survey. Thus, all information (including network connections) was collected after the interventions (see Figure 1), which may raise an identification issue in the network analysis because the social networks measured may reflect the endogenous network formation ex post facto. This situation is potentially a significant flaw for network analysis, as carefully discussed in a later section.

The questionnaire used in the survey comprised nine sections (seven pages), including questions regarding social network connections and subjective fair-trade and organic certification knowledge, in addition to standard questions about members' and households' characteristics. Table 1 reports individual and household characteristics, such as age, education level, and asset holding of the sample households in our dataset. The table also presents the same information calculated from provincial statistics for comparison in Column 2 (GoSL 2012; 2018a, 2018b). Respondents in our survey have quite similar characteristics to those in the provincial statistics. Although our study covers only five villages in Central Province, the table indicates that our study villages are not unusual villages in this province.

[Insert Table 1 here]

3.2. Empirical Framework

In the analysis, using a sample of workshop non-participants, we investigate information transmission to non-participants, using the following equation based on the linear network effect model:

$$(1) \qquad y_{ij} = \alpha_1(\bar{y}_{ij} \times Treat.\text{-}Village_j) + \alpha_2(\bar{y}_{ij} \times Cont.\text{-}Village_j) + \mathbf{x}_i\boldsymbol{\beta} + \bar{\mathbf{x}}_{ij}\boldsymbol{\gamma} + \delta \cdot Cxt.\text{-}Distributor_{ij} + \mu_j + \varepsilon_{ij},$$

where y_{ij} denotes the outcome variable regarding fair-trade and organic certifications of household i in village j; $\bar{y}_{ij}$ is the average outcome of peer households in the village networks; $\mathbf{x}_i$ is the control for a wide variety of household characteristics of household i; $\bar{\mathbf{x}}_{ij}$ are the average household characteristics of the peers; $Cxt.\text{-}Distributor_{ij}$ represents an indicator variable that takes unity if household i is directly connected to the leaflet distributor in village j and zero otherwise; μ_j denotes village-fixed effects; ε_{ij} captures unobserved components; and α_k $(k = 1,2)$, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ and δ are parameters to be estimated. Note that α_k and $\boldsymbol{\gamma}$**,** coefficients on the network variables are endogenous and contextual network effects, respectively. We allow the endogenous effect to vary according to the treatment status, whether key farmers were involved in the training program. We expect that key farmers enhance the spillover effects of agricultural training through the network via the leadership role in information diffusion regarding agricultural production (i.e., $\alpha_1 > 0$).

For the outcome variable (y_{ij}) in Equation (1), we use three different outcomes: (1) receiving a leaflet about fair-trade or organic certification, (2) fair-trade and organic certification knowledge, and (3) application for fair-trade or organic certification. Regarding farmers' subjective certification knowledge, we employed the sum of correct answers to 19 questions regarding certifications. The 19 questions were based on the information provided in the training and leaflets.[10] Regarding the leaflet receipt, enumerators checked whether households held a leaflet: If they reported that they received a leaflet but could not show it, enumerators confirmed whether they threw it away, passed it to another person, or misplaced it. Moreover, as a double-check, enumerators interviewed distributors to obtain the details of

[10] Moreover, to control respondents' cognitive ability, we also control the sum of correct answers to ten simple mathematics and general knowledge questions regarding domestic and international affairs.

those to whom they gave the leaflets. Note also that we did not prohibit the creation of photocopies of the leaflets; in some villages, photocopied leaflets were circulated.[11] Regarding the certification application, which is based on the group application principle, we obtained the names of all farmers participating in village applicant groups from the DEA.

Regarding the network variables in Equation (1), the average outcome ($\bar{y}_{ij}$) and average household characteristics ($\bar{\mathbf{x}}_{ij}$) of peer households in the village networks are calculated based on the following equation: $\bar{y}_{ij} = \left(W_{ij}' W_{ij}\right)^{-1} W_{ij}' Y_j$ and $\bar{\mathbf{x}}_{ij} = \left(W_{ij}' W_{ij}\right)^{-1} W_{ij}' \mathbf{X}_j$. W_{ij} is an $(n_j \times 1)$ vector, and its k-th element takes unity when household i has a direct connection to the k-th household and zero otherwise.[12] In this study, social networks denoted by W_{ij} are defined based on undirected connections, in which bilateral relations among farmers do not distinguish between senders and receivers. Y_j is an $(n_j \times 1)$ vector of all households' outcomes in the village, and $\mathbf{X}_j$ is an $(n_j \times k)$ vector containing all household characteristics in the village. Note that n_j is the number of households in village j. Thus, we implicitly assume that the network works only within the village. This is because we focus on the newly provided information on agricultural certifications, and, thus, diffusion from neighboring villages not included in the training experiment is virtually impossible. Therefore, this assumption is not just a simplification of reality but is also plausible in the present context.

Regarding the measurement of social networks, we investigated network connections in several dimensions by asking the following six questions:

N1. If you faced a farming problem, whom would you ask for advice or information?

N2. To whom do you give advice or information regarding a farming problem?

N3. To (from) whom do you give (receive) food products produced in your home garden without monetary payments and profits?

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[11] Specifically, six copies in a treatment village and ten copies in a control village were circulated.

[12] Note that the i-th element in W_{ij} is also zero.

N4. If you need rice, wheat, sugar, or other goods, to whom would you go?

N5. If you suddenly need 1,000 rupees, from whom would you ask for money?

N6. From whom do you ask for information about politics and government policies?

The questions N1 and N2 were asked separately for a) spice cultivation, b) vegetable cultivation, c) fruit crop cultivation, and d) tea or coconut cultivation.

Table 2 reports the summary statistics of the main empirical variables in the analysis. Note that we restrict the sample to those not invited to the training program and, therefore, the sample size is 676 (= 901−225). As discussed in the next subsection, by limiting the sample to the non-invitees, we attempt to eliminate the possible endogeneity caused by two-way interactions and isolate the network effect, β_k. Regarding household characteristics ($\mathbf{x}_i$) not reported here, we employ demographic characteristics, asset holdings, agricultural production, and other social connections (for the descriptive statistics of these variables, see Table B1 in Appendix B).

[Insert Table 2 here]

3.3. Check on the Validity the Identification Strategy

To identify the coefficients of interest, β_k, several concerns must be addressed. First, the possible interaction between y_{ij} and $\bar{y}_{ij}$ may raise the reflection problem (Manski 1993), causing the coefficients of $\bar{y}_{ij} \times Treat.\text{-}Village_j$ and $\bar{y}_{ij} \times Cont.\text{-}Village_j$ to be biased. The reflection problem in the endogenous effect stems from the two-way exchange of information; thus, if we can extract the information flow only from $\bar{y}_{ij}$ to y_{ij}, it is possible to eliminate the problem of the interaction. Thus, we address this issue by using a randomized training workshop program. Specifically, we employ the average outcome of the workshop participants in the network, denoted by $\bar{y}^*_{ij}$, as an instrument for $\bar{y}_{ij}$. The training provided information on the certifications to randomly invited farmers, and their certification knowledge is a key determinant of $\bar{y}_{ij}$. On the other hand, the sample farmers used in the analysis consist of those who were not invited to the training and, therefore, could not provide any additional information to the participants. Therefore, $\bar{y}^*_{ij}$ can be seen as an exogenous shifter of $\bar{y}_{ij}$ in the sense that it is not correlated with non-participants' potential knowledge. $\bar{y}^*_{ij}$ is calculated as $\bar{y}^*_{ij} = \left(W^{*\prime}_{ij} W^*_{ij}\right)^{-1} W^{*\prime}_{ij} Y^*_j$, where W^*_{ij} is an $(n_j \times 1)$ vector denoting household i's connections to workshop participants in village j and Y^*_j is an $(n_j \times 1)$ vector containing the participants' outcomes. We then utilize the instrumental variable (IV) regression technique, employing $\bar{y}^*_{ij} \times Treat.\text{-}Village_j$ and $\bar{y}^*_{ij} \times Cont.\text{-}Village_j$ as instruments for $\bar{y}_{ij} \times Treat.\text{-}Village_j$ and $\bar{y}_{ij} \times Cont.\text{-}Village_j$.

The second potential threat to identification is the issue of endogenous network formation. The formation of social networks with peers and neighbors is an outcome of household decisions, which may be the main source of bias due to the "correlated effect" (Manski 1993). However, the IV estimation explained above can essentially eliminate the influence of endogenous network formation. Even though the formation itself is endogenous and the network variable ($\bar{y}_{ij}$) is correlated with unobserved characteristics of members in the network, the outcome (knowledge and leaflet) provided to randomly invited farmers ($\bar{y}^*_{ij}$) is considered independent from unobservables.

Nevertheless, endogeneity in network formation may still be problematic in our research design. As explained in the previous subsection, we conducted the household survey after the experiment due to a time constraint. Hence, non-participants might have created new connections to participants to obtain information about the workshop and subsidy program. To address this possibility, when constructing the network variables ($\bar{y}_{ij}$, $\bar{y}^*_{ij}$), we exclude the networks for *agricultural* information sharing, specifically N1 and N2. The networks employed are those for lending food products or other goods, borrowing money, and sharing information on politics and government policies (N3 to N6). Thus, we assume that our experiment does not change the networks, except for the network to share agricultural information.

To check the validity of this identification assumption, we examine the possible impact of workshop participation on network formation. Table 3 reports the regression results where the dependent variables are the number of connections to workshop participants (Columns 1 and 2), and connections to non-participants (Columns 3 and 4). The table shows that the coefficients of participation are positive, implying that the workshop participants created new network connections after the training. In particular, when connections were measured based on the networks for agricultural information sharing (Columns 1 and 3), the coefficients are large. Thus, we cannot deny the possibility that our experiment altered the network connections in the study villages. However, when using the networks irrelevant to agricultural information sharing (Columns 2 and 4), the magnitude decreases. Although there is still a statistically significant relationship between workshop participation and network formation among participants (Column 2), the impact of workshop participation for connections between participants and non-participants is small and statistically insignificant (Column 4). We cannot strongly claim that new connections between participants and non-participants were not formed after the experiment, but potential influences from the endogenous network formation seem small.

In Figure 3, we present the network connections irrelevant to agricultural information sharing (i.e., N3 to N6) in the treatment (Panel A) and control villages (Panel B). Circles represent households (the numbers in the circles are the household IDs), and lines denote the links between households in the network. Moreover, yellow and green circles represent the key farmers and leaflet distributors. The figure also exhibits the persons with the highest degree (red circles), betweenness (blue circles), and eigenvector (black circles) centralities. As already mentioned, the key farmer in a village is an agricultural leader unofficially appointed by local government officials at the village level and is usually in the hub of village farmer networks. The figure shows that the key farmers in all villages are the central figures in the networks in terms of these three centrality measures.

[Insert Figure 3 here]

Furthermore, we verify the treatment exogeneity. The treatment in the experiment was whether key farmers were appointed to the leaflet distributors, which was implemented at the village level. Because of its randomness, we expect that the treatment status is independent of observed and unobserved household characteristics. However, we must verify this issue carefully since our sample villages are only five and the village-level heterogeneity might confound the treatment status by coincidence. Thus, to check this possibility, we conduct a balancing test and compare several key characteristics between the treatment and control groups (Table 4). In Panel A of Table 4, we compare the treatment and control villages on the observed household characteristics. The results show no statistically significant differences in household head's characteristics (Panel A), holding of durable consumer goods (Panel B), agricultural production (Panel C), and network connections (Panel E). Thus, the balancing test indicates that the households in the two groups are homogeneous.

[Insert Table 4 here]

4. Empirical Results

4.1. Diffusion to Non-Participants

We start by investigating the role of the key farmer and social network in information diffusion, focusing on information goods (i.e., leaflets of the fair-trade and organic certifications) and subjective certification knowledge. The estimation results for leaflet diffusion are presented in Columns (1) to (4) in Table 5, and those for knowledge diffusion are presented in Columns (5) to (8). Note also that we report the OLS results with and without village-fixed effects and their corresponding IV estimation results.

Looking at the first row in Columns (1) to (4), the coefficient estimates on “direct connection to distributor” are positive and statistically significant at the 5% level or less and considerably stable in all specifications. As expected, non-participants directly connected to the appointed distributor were more likely to receive the leaflet. We can also see the importance of the distributor connection for the diffusion of certification knowledge (Columns 5 to 8): farmers connected to the distributor chose two more correct answers to the 19 questions about certifications than farmers without a connection.

Turning to the network effect, the network has a significant impact on leaflet diffusion only in the treatment villages but not in the control villages. This indicates that the diffusion of information goods from the network is reinforced when key farmers participate in the training workshops and are appointed as leaflet distributors. On the other hand, we found no network effect for knowledge diffusion in either the treatment or control villages.

[Insert Table 5 here]

We then examine the effect of key farmers’ involvement and networks on the application of fair-trade and organic certifications. Table 6 shows that the network has no impact on the application, while the connection to the distributor consistently increases the likelihood of joining the village applicant group. If we interpret “Network × treatment village” as an indirect influence from the key farmer and “Direct connection to the distributor” as a direct influence, behavioral responses may be stimulated only through more direct interaction.

The following subsection further explores the role of key farmers in the direct connection.

[Insert Table 6 here]

4.2. Further Investigation on the Direct Connection to the Key Farmer

Table 7 reports the estimation results, including the direct connection to key farmers. We allow the coefficient to vary according to the treatment status (with key farmers involved or not) because key farmers in treatment villages were also distributors, while those in control villages were not.

[Insert Table 7 here]

Table 7 presents an interesting contrast in the role of the distributor's position in the network between leaflet diffusion and knowledge diffusion. When the leaflet distributor was a key farmer (i.e., the treatment villages), the direct connection to the distributor improves certification knowledge but not the likelihood of receiving a leaflet. However, when the leaflet distributor was randomly assigned to a farmer (i.e., the control villages), the direct connection to the distributor improves the likelihood of receiving a leaflet but not the certification knowledge. This result indicates that the key farmer varies the information transmission mode: to farmers in his network, he mainly transmits information orally; however, to farmers outside of his network, he mainly uses an information good (leaflet). Looking at the application for certifications, as in knowledge diffusion, the key farmer promotes the certification application mainly through direct communication.

Taken together, the estimation results suggest that key farmers promote the diffusion of information goods indirectly through village networks and further accelerates knowledge diffusion and application via direct communication. Thus, key farmer involvement is the key to the success of network-based programs.

5. Conclusion

This study examined key farmers' and social networks' role in the diffusion of leaflets and knowledge regarding fair-trade and organic certifications and application to them. It employed a field experiment, where workshop participants and leaflet distributors were randomly selected.

The main findings are as follows. Key farmers' involvement amplifies information transmission to workshop non-participants. Non-participating farmers in the treatment villages (with key farmers involved) are more likely to obtain certification knowledge and join the village applicant organization when directly connected with key farmers in their networks. However, in the control villages (with key farmers uninvolved), the direct connection with key farmers does not influence knowledge diffusion and farmers' application behavior.

These findings provide important policy implications for extending agriculture in developing countries, where social network-based agricultural extension methods have been practiced recently. That is, central figures' involvement is the key to the success of network-based extensions. The findings imply that farmers' knowledge and application behavior are accelerated through direct communication with their role model. However, a remaining issue is how to diffuse information to those with no connection to key farmers. Thus, future studies can examine and address this significant drawback of network-based extension.

References

Aker, Jenny C. 2011. "Dial 'A' for Agriculture: A Review of Information and Communication Technologies for Agricultural Extension in Developing Countries." *Agricultural Economics* 42(6): 631–647.

Anderson, Jock R., and Gershon Feder. 2007. "Agricultural Extension." In *Handbook of Agricultural Economics* Vol. 3, edited by Robert Evenson and Prabhu Pingali, 2343–2378. Amsterdam: Elsevier.

Bandiera, Oriana, and Imran Rasul. 2006. "Social Networks and Technology Adoption in Northern Mozambique." *The Economic Journal* 116(514): 869–902.

Banerjee, Abhijit, Arun G. Chandrasekhar, Esther Duflo, and Matthew O. Jackson. 2013. "The Diffusion of Microfinance." *Science* 341(6144): 1236498–1236498.

Barham, Bradford L., and Jeremy G. Weber. 2012. "The Economic Sustainability of Certified Coffee: Recent Evidence from Mexico and Peru." *World Development* 40(6): 1269–1279.

Beaman, Lori, Ariel BenYishay, Jeremy Magruder, and Ahmed Mushfiq Mobarak. 2018. "Can Network Theory-Based Targeting Increase Technology Adoption?" NBER Working Paper No. 24912. National Bureau of Economic Research. Cambridge.

Beaman, Lori, and Andrew Dillon. 2018. "Diffusion of Agricultural Information within Social Networks: Evidence on Gender Inequalities from Mali." *Journal of Development Economics* 133: 147–161.

Central Bank of Sri Lanka. 2017. "Economic and Social Statistic of Sri Lanka." Retrieved March 25, 2021, from https://www.cbsl.gov.lk/sites/default/files/cbslweb_documents/statistics/otherpub/Economic_%26_Social_Statistics_of_SL_2017_e.pdf

Conley, Timothy G., and Christopher R. Udry. 2001. "Social Learning through Networks: The Adoption of New Agricultural Technologies in Ghana." *American Journal of Agricultural Economics* 83(3): 668–673.

Conley, Timothy G., and Christopher R. Udry. 2010. "Learning about a New Technology: Pineapple in Ghana." *American Economic Review* 100(1): 35–69.

Dar, Manzoor H., Alain de Janvry, Kyle Emerick, Erin M. Kelley, and Elisabeth Sadoulet. 2019. "Endogenous Information Sharing and the Gains from using Network Information to Maximize Technology Adoption." CEPR Discussion Paper 13507.

Di Falco, Salvatore, Francesco Feri, Paolo Pin, and Xavier Vollenweider. 2018. "Ties that Bind: Network Redistributive Pressure and Economic Decisions in Village Economies." *Journal of Development Economics* 131: 123–131.

Dillon, Andrew, Maria Porter, and Aissatou Ouedraogo. 2018. "Social Network Targeting of Agricultural Technology: Adoption, Input Substitution and Yield Effects." Selected Paper Prepared for Presentation at the 2018 Agricultural & Applied Economics Association Annual Meeting, Washington, D.C., August 5-August 7.

Feder, Gershon, and Dina L. Umali. 1993. "The Adoption of Agricultural Innovations: A Review." *Technological Forecasting and Social Change* 43(3–4): 215–239.

Foster, Andrew D., and Mark R. Rosenzweig. 1995. "Learning by Doing and Learning from Others: Human Capital and Technical Change in Agriculture." *Journal of Political Economy* 103(6): 1176–1209.

——— 2010. "Microeconomics of Technology Adoption." *Annual Review Economics* 2(1): 395–424.

Government of Sri Lanka (GoSL). 2012. *Census of Population and Housing 2012—Final Report.* Department of Census and Statistics.

——— 2018a. *Household Income and Expenditure Survey 2016—Final Report.* Department of Census and Statistics.

——— 2018b. *General Report: Economic Census 2013/14 Agricultural Activities Sri Lanka*. Department of Census and Statistics.

——— 2018c. *National Export Strategy of Sri Lanka 2018 to 2022: Spices and Concentrates Strategy.* Ministry of Development Strategies and International Trade.

——— 2018d. *Spice Crop statistics*. Department of Export Agriculture.

Kondylis, Florence, Valerie Mueller, and Jessica Zhu. 2017. "Seeing is Believing? Evidence from an Extension Network Experiment." *Journal of Development Economics* 125: 1–20.

Manski, Charles F. 1993. "Identification of Endogenous Social Effects: The Reflection Problem" *Review of Economic Studies* 60(3): 531–542

Maertens, Annemie. 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.

Maertens, Annemie, and Christopher B. Barrett. 2013. “Measuring Social Networks' Effects on Agricultural Technology Adoption.” *American Journal of Agricultural Economics* 95(2): 353–359.

Mekonnen, Daniel Ayalew, Nicolas Gerber, and Julia Anna Matz. 2018. “Gendered Social Networks, Agricultural Innovations, and Farm Productivity in Ethiopia.” *World Development* 105: 321–335.

Nakano, Yuko, Takuji W. Tsusaka, Takeshi Aida, and Valerien O. Pede. 2018. “Is Farmer-to-Farmer Extension Effective? The Impact of Training on Technology Adoption and Rice Farming Productivity in Tanzania.” *World Development* 105 (2018): 336–351.

Ramirez, Ana. 2013. “The Influence of Social Networks on Agricultural Technology Adoption.” *Procedia-Social and Behavioral Sciences* 79 (2013): 101–116.

Sacerdote, Bruce. 2001. “Peer Effects with Random Assignment: Results for Dartmouth Roommates.” *Quarterly Journal of Economics* 116(2): 681–704.

Takahashi, Kazushi, Rie Muraoka, and Keijiro Otsuka. 2020. “Technology Adoption, Impact, and Extension in Developing Countries’ Agriculture: A Review of the Recent Literature.” *Agricultural Economics* 51(1): 31–45.

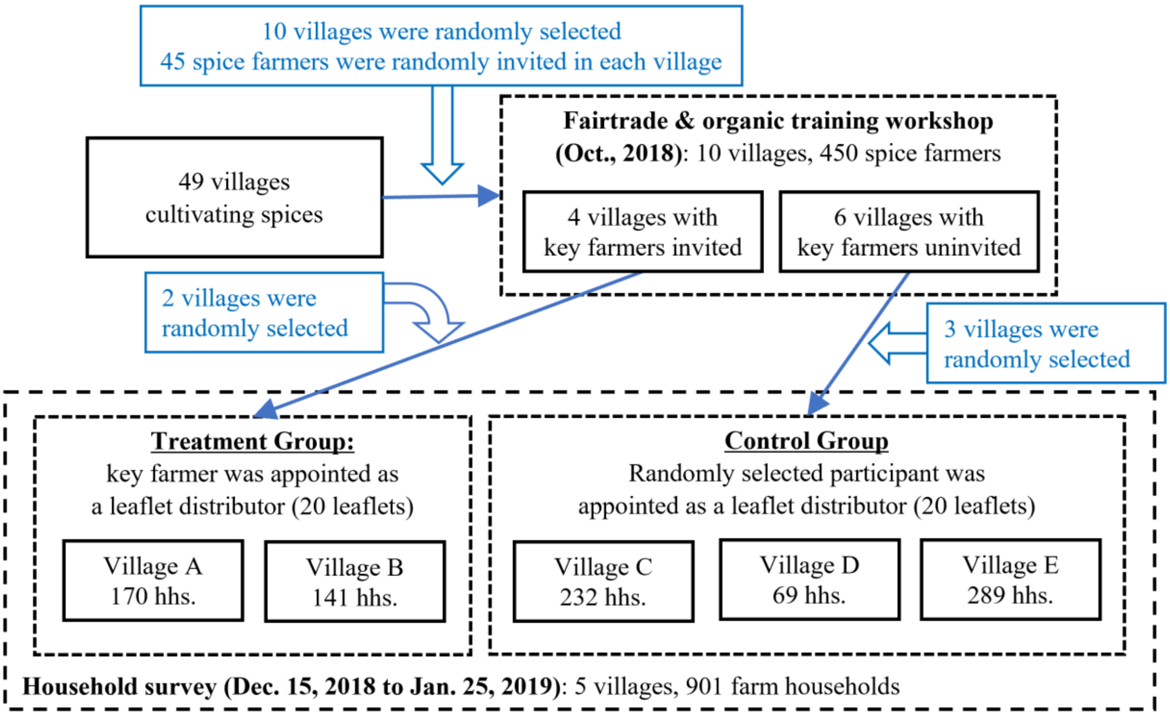
Vasilaky, Kathryn. 2013. “Female Social Networks and Farmer Training: Can Randomized Information Exchange Improve Outcomes?” *American Journal of Agricultural Economics* 95(2): 376–383.

Vidanapathirana, Ruvini, and Nalaka Wijesooriya. 2014. *Export Market for Organic Food: Present Status, Constraints, and Future Scope*. Hector Kobbekaduwa Agrarian Research and Training Institute. Retrieved March 25 2021, from http://www.harti.gov.lk/images/download/reasearch_report/new1/167.pdf

Willer, Helga, and Julia Lernoud. 2017. *The world of organic agriculture. Statistics and emerging trends 2017*. Research Institute of Organic Agriculture FiBL and IFOAM Organics International.

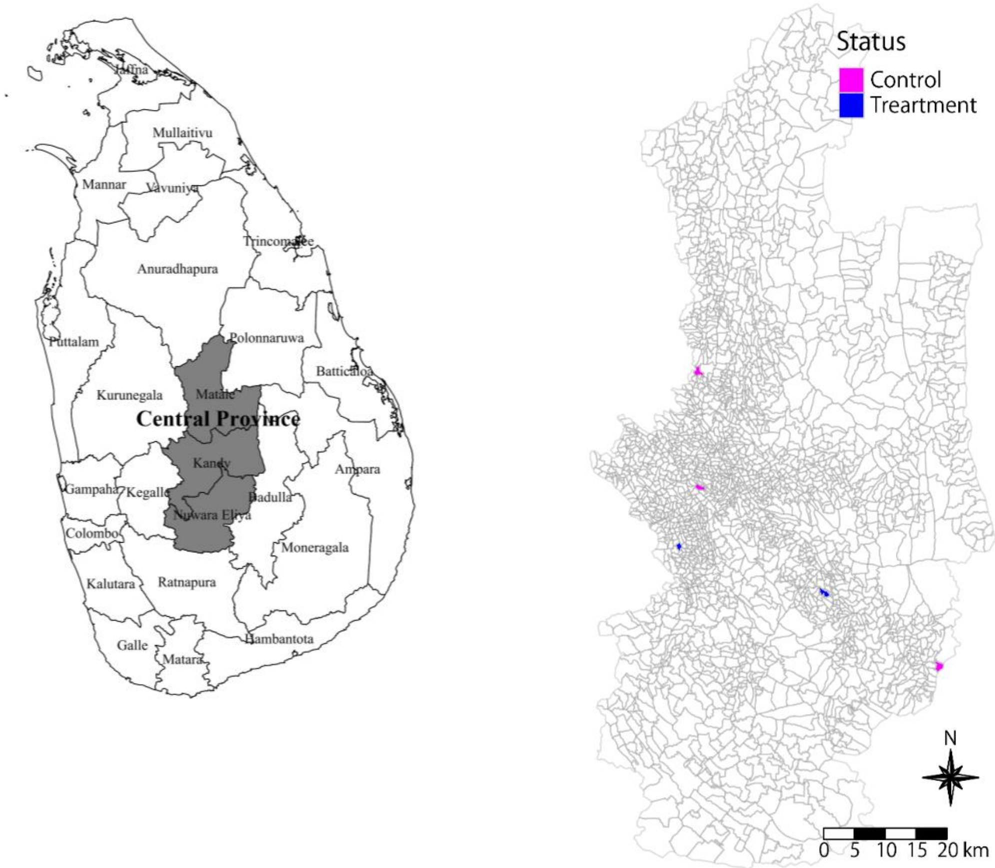
Figures and Tables

Figure 1. Research flowchart



Source: Authors' drawing.

Figure 2. The location of survey villages in Central Province

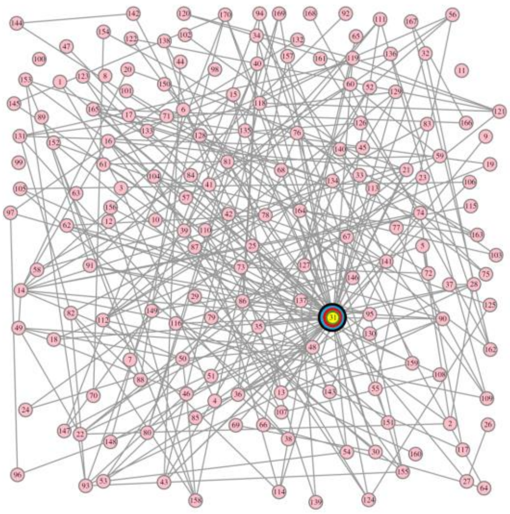


Source: Authors' drawing.

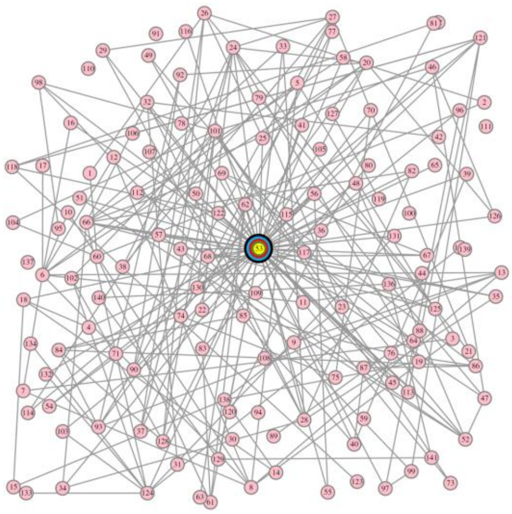
Figure 3. The social network in the study villages

Panel A: Treatment villages

(1) Village A (N = 170)

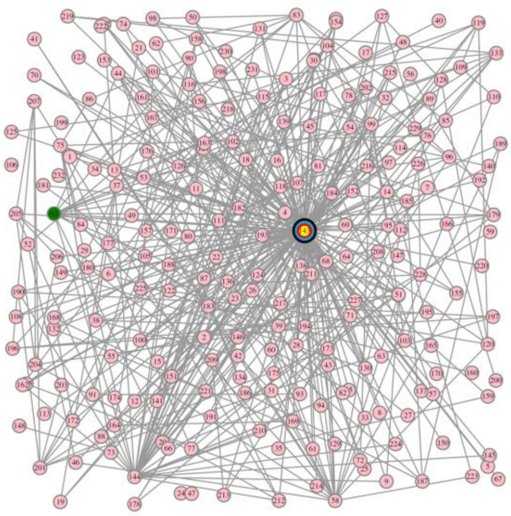


(2) Village B (N = 141)

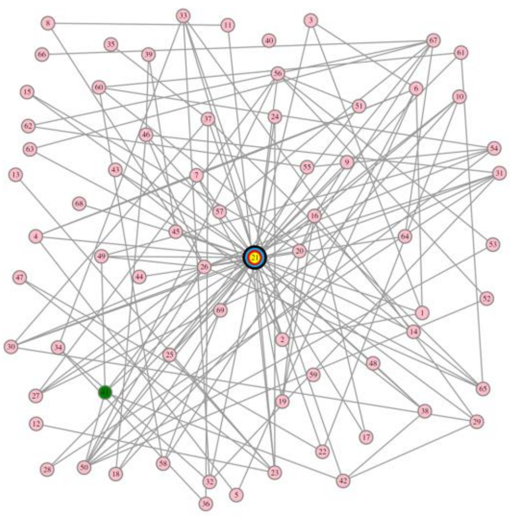


Panel B: Control villages

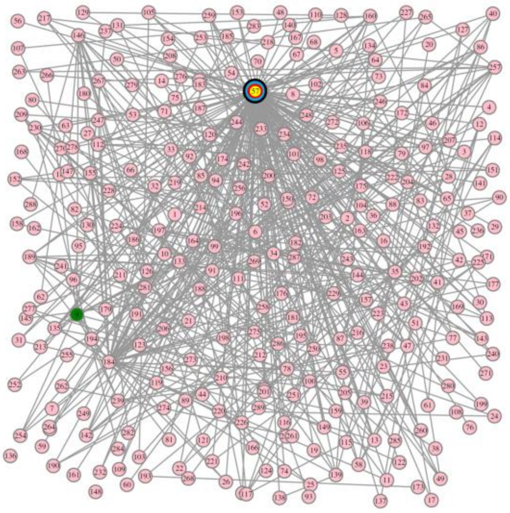
(1) Village C (N = 232)



(2) Village D (N = 69)



(3) Village E (N = 289)



Legend:

- : Key farmer
- : Leaflet distributor
- : Highest degree centrality
- : Highest betweenness centrality
- : Highest eigenvector centrality

Note: Circles represent households in the networks irrelevant to agricultural information sharing, while lines represent the links between the households.
Source: Authors' drawing from our survey data.

Table 1. Sample characteristics and comparison with provincial representative data

	Our survey data (NOBs = 901)	Representative data
	Mean	Mean
Age of agriculture workers	52.7	51.2 [a)]
Years of education of agriculture workers	8.982	8.121 [a), b)]
Land size (acres)	0.88	1.27 [a)]
Asset holding: households with		
1/4 acre of land or more	76%	62% [a), b)]
house made of permanent floor	95.2%	92.8% [c)]
house made of permanent wall	99.4%	96.6% [c)]
electricity	100.0%	88.7% [a)]
TV	89.1%	87.7% [c)]
radio	67.7%	73.1% [c)]
mobile phone	88.2%	89.1% [c)]
computer	12.4%	18.8% [c)]
automobile (car/van)	4.2%	7.7% [c)]
motorbike	20.2%	18.1% [c)]

Notes: This table compares the mean and percentage values of several social and economic characteristics between the sample in our survey and those in provincial representative surveys in the Central Province in Sri Lanka.

Source: Figures in Column 1 were calculated using data from the author's survey conducted on December 15, 2018, to January 25, 2019. Figures in Column 2 were based on a) the 2013–2014 economic census for agriculture activities in Sri Lanka (GoSL 2018b), b) the final report of the 2012 Census of population and housing (GoSL 2012), and c) the final report of the 2016 Household income and expenditure survey (GoSL 2018a).

Table 2. Summary statistics of main empirical variables

	N	Mean	Std. Dev.	Min	Max
Panel A: Dependent variable					
Knowledge about FT & ORG certifications	676	2.572	4.545	0	19
Receiving leaflet about FT/ORG certification	676	0.085	0.280	0	1
Application for FT/ORG certification	676	0.045	0.209	0	1
Panel B: Treatment and network variables					
Central famer village	676	0.326	0.469	0	1
N/w avg.: knowledge about FT & ORG certifications	676	5.803	5.054	0	19
N/w avg.: Receiving leaflet about FT/ORG certification	676	0.381	0.366	0	1
N/w avg.: Application for FT/ORG certification	676	0.126	0.256	0	1
Direct connection to key farmer	676	0.147	0.355	0	1
Panel C: Instrumental variables					
Part. avg.: knowledge about FT & ORG certifications	676	3.603	4.466	0	19
Part. avg.: Receiving leaflet about FT/ORG certification	676	0.304	0.350	0	1
Part. avg.: Application for FT/ORG certification	676	0.086	0.219	0	1

Notes: This table reports the number of observations, mean, standard deviation, minimum, and maximum of main variables used in the information diffusion, leaflet diffusion, and application of fair-trade and organic certification analysis.

Source: Authors' calculation from our survey data.

Table 3. Workshop participation and the formation of new networks

Dependent variable	Number of connections to participants in the network		Number of connections to non-participants in the network	
	Agricultural information-sharing networks (N1 + N2)	Other networks (N3 to N6)	Agricultural information-sharing networks (N1 + N2)	Other networks (N3 to N6)
	(1)	(2)	(3)	(4)
Workshop participation	1.955**	0.843**	1.988**	0.352
	(0.471)	(0.248)	(0.697)	(0.255)
HH characteristics	Yes	Yes	Yes	Yes
Village-fixed effects	Yes	Yes	Yes	Yes
Observations	901	901	901	901
R-squared	0.203	0.083	0.092	0.070

Notes: This table reports the estimates of network formation, where the dependent variable is the number of social network connections. Standard errors in parentheses are clustered at the village level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Authors' estimation from our survey data.

Table 4. Balancing test of household and network characteristics

	Control (training with key farmers uninvited)			Treatment (training with key farmers invited)			Difference	
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	(2) − (5)	Std. Err.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A) Household head's characteristics								
Age	455	52.116	13.062	221	53.226	12.665	−1.109	1.060
Female	455	0.202	0.402	221	0.249	0.433	−0.046	0.034
Years of education	455	8.476	3.458	221	8.375	4.121	0.101	0.302
B) Household characteristics								
Household size	455	3.14	1.398	221	3.14	1.526	0.004	0.118
# of sleeping rooms	455	2.971	1.020	221	3.081	1.133	−0.110	0.087
# of TVs	455	0.883	0.015	221	0.873	0.333	0.010	0.026
# of mobile phones	455	0.872	0.334	221	0.886	0.021	−0.014	0.027
C) Agricultural production								
Pepper production (Kg)	455	243.197	228.257	221	459.357	453.960	14.939	37.519
Land cultivated (acre)	455	0.854	1.220	221	0.842	0.776	0.012	0.090
D) Network characteristics								
# of connections	455	2.578	6.493	221	2.158	1.614	0.419	0.443
# of connections to invitees	455	0.813	0.848	221	0.755	0.833	0.057	0.186
Connection to key farmer	455	0.309	0.462	221	0.276	0.448	0.034	0.376

Notes: Columns 1 to 6 report the number of observations, mean, and standard deviation of the observed household treatment and control group characteristics. Columns 7 and 8 report the difference in means between the control and treatment groups and stand error, respectively.

Source: Authors' calculation from our survey data.

Table 5. Effect on the diffusion of leaflets and agricultural information

Dependent variables:	Receiving leaflets of certifications				Knowledge about certifications			
	OLS		IV		OLS		IV	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Direct connection to distributor	0.088**	0.087**	0.087***	0.087***	2.097*	2.127**	2.073***	2.098***
	(0.031)	(0.031)	(0.026)	(0.026)	(0.760)	(0.754)	(0.646)	(0.645)
Network (receiving leaflet or knowledge of peoples in the network)								
× treatment village (key farmer involved)	0.205***	0.206***	0.219***	0.221***	0.046	0.021	0.111	0.106
	(0.021)	(0.018)	(0.040)	(0.037)	(0.094)	(0.100)	(0.114)	(0.119)
× control village (key farmer uninvolved)	0.002	0.005	0.001	-0.003	-0.057	-0.078	-0.064	-0.077
	(0.019)	(0.014)	(0.033)	(0.035)	(0.056)	(0.045)	(0.073)	(0.073)
Treatment village	0.103***		0.087***		1.483**		1.461***	
	(0.022)		(0.026)		(0.487)		(0.428)	
HH characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HH average characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Village FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	676	676	676	676	676	676	676	676
R-squared	0.233	0.189	0.233	0.235	0.326	0.244	0.324	0.338
First-stage F statistics for:								
Network × control village			1,569.7	1,485.7			32.8	42.4
Network × treatment village			1,092.9	1,176.0			176.9	313.9

Notes: This table reports the coefficients of interest based on Equation (1). All standard errors in parentheses are clustered at the village level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Authors' estimation from our survey data.

Table 6. Effect on the certification application

	OLS		IV	
	(1)	(2)	(3)	(4)
Direct connection to distributor	0.071*	0.070*	0.071***	0.070***
	(0.031)	(0.031)	(0.027)	(0.026)
Network (certification application of peoples in the network)				
× treatment village	0.05	0.022	0.056	0.032
(key farmer involved)	(0.087)	(0.088)	(0.082)	(0.082)
× control village	0.066	0.056	0.051	0.054
(key farmer uninvolved)	(0.044)	(0.039)	(0.057)	(0.047)
Treatment village	0.029		0.030	
	(0.025)		(0.021)	
HH characteristics	Yes	Yes	Yes	Yes
HH average characteristics	Yes	Yes	Yes	Yes
Village FE	No	Yes	No	Yes
Observations	676	676	676	676
R-squared	0.135	0.126	0.135	0.152
First-stage F statistics for:				
Network × control village			4190.497	4445.454
Network × treatment village			6575.854	2636.658

Notes: This table reports the coefficient of interest based on Equation (1). All standard errors in parentheses are clustered at the village level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Authors' estimation from our survey data.

Table 7. Further checks on the role of the key farmer (IV estimation)

Dependent variables:	Leaflet		Knowledge		Application	
	(1)	(2)	(3)	(4)	(5)	(6)
Direct connection to						
distributor in control village	0.123***	0.124***	0.904	0.998*	0.043*	0.032
	(0.031)	(0.031)	(0.578)	(0.520)	(0.024)	(0.028)
key farmer (=distributor) in treatment village	0.047	0.043	3.403***	3.352***	0.103***	0.113***
	(0.030)	(0.031)	(0.790)	(0.807)	(0.018)	(0.020)
key farmer in control village	-0.012	-0.016*	0.522*	0.391	0.026	0.001
	(0.009)	(0.008)	(0.290)	(0.306)	(0.018)	(0.014)
Network (ave. outcome of peers in the network)						
× treatment village (key farmer involved)	0.229***	0.231***	0.090	0.087	0.049	0.024
	(0.040)	(0.036)	(0.107)	(0.112)	(0.081)	(0.080)
× control village (key farmer uninvolved)	-0.002	-0.006	-0.059	-0.069	0.048	0.061
	(0.035)	(0.036)	(0.074)	(0.074)	(0.060)	(0.050)
Treatment (key farmer involved) village	0.109***		1.982***		0.046**	
	(0.015)		(0.318)		(0.023)	
HH characteristics	Yes	Yes	Yes	Yes	Yes	Yes
HH average characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Village FE	No	Yes	No	Yes	No	Yes
Observations	676	676	676	676	676	676
R-squared	0.234	0.237	0.334	0.347	0.138	0.155
First-stage F statistics for:						
Network × control village	4,445.5	1,600.0	32.8	41.4	5,334.2	3,930.9
Network × treatment village	2,636.7	1,473.8	177.3	255.9	2,412.4	2,287.3

Notes: This table reports the coefficient of interest based on Equation (1) with additional variables. All standard errors in parentheses are clustered at the village level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Authors' estimation from our survey data.

Appendix A: Fair-trade and organic leaflets

Figures A1 and A2 present the leaflets we distributed during the training and experiments.

[Insert Figures A1 and A2 here]

Appendix B: Summary Statistics of Control Variables

Table B1 reports the summary statistics of all control variables ($\mathbf{x}_i$).

[Insert Table B1 here]

Panel A presents the demographic characteristics, indicating that the average age of household heads is 53 years, and the average family size is less than four members. Moreover, 89% of the households are headed by males, and household heads' average years of schooling is approximately 8.5 years. Further, 38% of the sample household heads are full-time farmers, while 24% of the sample engaged in farming with monthly wage employment.

Panel B describes household assets and housing characteristics. It shows that more than 95% of the villagers have well-constructed houses with two or more sleeping rooms. All households had electricity in the five villages. Considering housing equipment, more than 53% of the people use refrigerators in their homes, and 53% of households use rice cookers. Further, 89% of households have television, and 67% own radio sets. On average, 1.6 households use mobile phones, and more than 88% use mobile connections for their daily communication. Approximately 12% owned a computer on average. Most people in the five villages have motorbikes, accounting for about 20% of households, while 14.8% and 2.8% have three-wheelers and cars, respectively.

Pepper, nutmeg mace, clove, and cardamom are the main spice products of the five villages, the sales of which depend on the village- and regional-level collectors. The average cultivation spans 0.8 acres, varying from zero to 15 acres. The average yield of pepper was 306 kg (wet weight) per household in the 2018 harvesting year.

Panel D presents the social connections of households in the five villages. It indicates that 22% of the sample households connect with regional-level agricultural extension officers, and 59% can contact village-level extension officers. Moreover, 99% are members of a welfare society in the village, and 24% hold an official position in a welfare society. Further, on average, households spend 88, 21, and 16 minutes watching television, listening to the radio, and reading newspapers per week, respectively. Finally, 11% of the villagers exchange information with people outside of the village.

Figures and Tables in Appendices

Figure A1. Leaflet of the fair-trade certification

Figure A2. Leaflet of the organic certification

Table B1. Summary statistics of control variables

	N	Mean	Std. Dev.	Min	Max
Panel A: Demographic characteristics					
Household head’s general knowledge	676	6.500	2.132	0	10
Household head’s age	676	52.507	12.858	18	90
Female headed household	676	0.217	0.412	0	1
Household head’s years of education	676	8.443	3.685	0	17
Household head’s job: full time farmer	676	0.389	0.487	0	1
Household head’s job: wage employer	676	0.242	0.428	0	1
Household size	676	3.143	1.441	1	7
Panel B: Asset holding					
Live family own house	676	0.973	0.161	0	1
# of bed rooms in the home	676	3.008	1.061	0	9
Permanent roofing (0=cadjan, straw, leaf material)	676	0.994	0.076	0	1
Permanent floor (0=clay, sand)	676	0.946	0.224	0	1
Permanent wall (0=clay, cadjan, leaf material)	676	0.994	0.076	0	1
Electricity availability for lighting	676	1.000	0.000	1	1
Refrigerator	676	0.544	0.498	0	1
Rice cooker	676	0.541	0.498	0	1
TV	676	0.880	0.324	0	1
# of radios	676	0.686	0.47	0	2
# of mobile phones	676	1.588	1.021	0	6
# of fixed telephones	676	0.181	0.389	0	2
Computer	676	0.109	0.312	0	1
Motor bike	676	0.199	0.401	0	1
# of three-wheelers	676	0.146	0.385	0	3
Car	676	0.031	0.173	0	1
Panel C: Agricultural production					
Pepper yield (kg) per household	676	238.742	457.179	0	5000
Land use for cultivation (acer)	676	0.857	1.107	0	15
Panel D: Other social connections					
Contact with export agriculture officer	676	0.191	0.393	0	1
Contact with village agriculture officer	676	0.554	0.497	0	1
Bearing official position in village-level welfare society last 5 years (Bearing official position=1)	676	0.187	0.391	0	1
Time spend to watch TV last week (minutes)	676	89.361	74.875	0	600
Times spend to listen to the radio last week (minutes)	676	20.872	51.125	0	600
Time spend to read newspaper in last week (minutes)	676	15.196	31.126	0	180
Sharing agriculture information with outside people of the village	676	0.106	0.308	0	1