Comparison of Targeting Methods for the Diffusion of Farming Practices: Evidence from Shrimp Producers in Viet Nam

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Abstract

This study examines which targeting method (i) improves the knowledge of good farming practices of the treated and their neighbors the most, (ii) enhances information sharing with their neighbors the most, and (iii) improves the farming knowledge of those who receive information from the treated. To test these research questions, we consider a case of shrimp farmers in Vietnam. This study identifies that simple random sampling (SRS) shows the highest increase in BMPs knowledge in comparison to other treatments. Second, systematically unaligned random sampling (SURS) shows a lower improvement in better management practices (BMPs) knowledge than SRS. On the other hand, unlike other groups, treated farmers in SURS increase their neighbors' scores. Third, social network targeting (SNT) increases information sharing between villagers in the treated village, but untreated farmers who receive information from treated farmers of the SNT group have a lower improvement score in their BMPs knowledge.

Keywords Better management practices; Betweenness centrality; Shrimp farming; Simple random sampling; Social network targeting; Systematic uniformly random Sampling

JEL Classification O12; D80; C32

1 Introduction

The diffusion of information on good farming practices plays a key role in improving agricultural productivity and promoting rural welfare in developing countries. Traditionally, the main channels to disseminate information to farmers have been the governments of developing countries through their extension officers. Nevertheless, the lack of information remains one of the reasons for farmers to adopt wrong or inefficient practices. Moreover, the problem of spreading inaccurate information also persists (The World Bank, 2007).

To overcome such problems, recent literature has focused on the role of farmers' social network on obtaining information. Banerjee et al. (2013) examine how participation in a microfinance program diffuses through social networks. They find that participation in a microfinance program is significantly higher when first-informed individuals about the program have higher community centralities. Beaman et al. (2015) examine the impact of network-based targeting on the diffusion of agricultural information. They find that information does not spread to people who are far from treated farmers in their social networks.

While existing studies have revealed the impact of social networks on the diffusion of information or technologies, it remains unclear as to what type of targeting method one should use in disseminating information in terms of delivering accurate information. This study uses individual-level data to identify a targeting method which can diffuse accurate agricultural information to farmers. This study examines which targeting method (i) improves the knowledge of good practices of the treated and their neighbors the most, (ii) enhances information sharing with their neighbors the most, and (iii) improves the farming knowledge of those who receive information from the treated.

To test these research questions, we consider a case of shrimp farmers in Vietnam. Shrimp farming is a profitable business for smallholders in developing countries. However, it is also challenging, and farmers frequently experience crop failures due to shrimp viral diseases (UNIDO, 2013). To reduce the risk of shrimp diseases, veterinary drugs are used by shrimp producers, but these often contain substances harmful to the human body, such as chloramphenicol, enrofloxacin, and ciprofloxacin. Thus, there have been attempts by the Vietnamese government and international communities to disseminate good aquaculture practices to Vietnamese shrimp farmers, better management practices (BMPs) being one of them. According to NACA (2016), well-designed and well-implemented BMPs support smallholder shrimp aquaculture to increase productivity by reducing the risk of shrimp disease outbreaks. Furthermore, our previous study regarding BMPs identify that receiving BMPs training has a significant and positive effect on reducing the use of these drugs.

A baseline survey was conducted in the Ca Mau province in southern Vietnam in September 2016 to collect information from 173 farmers. The data include information on farmers' social networks, psychological characteristics, and the knowledge level of BMPs, as well as their socio-economic characteristics. 40 shrimp farmers were invited to our BMPs workshop in December 2016 to disseminate BMPs to the farmers. 36 of the 40 invited farmers participated in the workshop. The participants were selected using three targeting methods and were divided into three groups based on the methods. Treatment group 1 includes farmers selected by SRS, while treatment group 2 includes individuals chosen by SURS using individual location information. Treatment group 3 is selected using SNT. Farmers in the SNT group have higher betweenness centralities than untreated farmers in the same village. The reason why this study employs betweenness centrality for SNT is that an individual with high betweenness centrality is an intermediary who plays an important role in the connection between other people in the same network. The individual has a large influence on information transfer through the network and is called a gatekeeper. Theoretically, providing information to the gatekeeper allows us to pass information to the highest number of people in the network (Brandes, 2008; Freeman, 1977; IBM, 2017). In August 2017, we conducted a follow-up survey to investigate how well farmers' knowledge of BMPs improved in comparison to the status before our treatment.

Using the balanced panel data and cross-sectional data, this study employs the difference in difference (DD), two-way fixed effects models, and control function estimator to test the research questions mentioned above. As a result, this study identifies that SRS shows the highest increase in BMPs knowledge in comparison to other treatments. Second, SURS shows a lower improvement in BMPs knowledge than SRS. On the other hand, unlike other groups, treated farmers in SURS increase their neighbors' scores. Third, SNT increases information sharing between villagers in the treated village, but untreated farmers who receive information from treated farmers of the SNT group have a lower improvement score in their BMPs knowledge.

These findings can conclude that SNT appears to be a method to disseminate information to more people, and SURS may be suitable to enhance the knowledge level of neighboring farmers. However, both the methods are less likely to deliver accurate information than SRS owing to the bias generated by the samplings.

The remainder of the study proceeds as follows. Section 2 describes Vietnam's shrimp industry, BMPs, reviews relevant extant literature on social network analyses, and a reciprocity index. Section 3 describes and explains the data used herein, presents the summary statistics, and describes our workshop and targeting methods. Section 4 describes the estimation methods used and the results are presented in Section 5. Finally, Section 6 concludes the study.

2 Previous Literature

2.1 Vietnam's Shrimp Industry and Better Management Practices

As a means of acquiring foreign currency, the Vietnamese government has been encouraging shrimp farming among farmers in southern Vietnam since market liberalization. Between 1990 and 2013, Vietnamese shrimp exports increased almost 18-fold in volume and 40-fold in monetary value. These figures suggest that the Vietnamese shrimp industry has achieved quantitative growth (FAO, 2016; UNIDO, 2013).

However, the problem of small farmers abandoning shrimp farming due to crop failures caused by shrimp viral diseases continues. Farmers use antibiotics to mitigate the risk of crop failures due to shrimp diseases, but such inputs contain substances harmful to the human body, such as chloramphenicol, enrofloxacin, ciprofloxacin, and oxytetracycline. Due to the residual antibiotics, the port rejection rate, or the share of Vietnamese shrimps that are rejected at the ports of importing countries, continues to grow. In addition, water pollution is occurring in rivers used for agriculture and as drinking water as some farmers discharge water in their ponds to the rivers without removing residual antibiotics (NACA, 2016; Suzuki & Vu, 2016; Taya, 2003; UNIDO, 2013).

To solve these problems, there have been attempts by the Vietnamese government and NACA to disseminate a guide for good aquaculture practices called BMPs. The purpose of BMPs is to improve farmers' management practices, and delivering increased profitability and environmental performance through the more efficient use of resources (Khiem, Simon, Nguyen, & Vo, 2010; Mantingh & V.H., 2008; NACA, 2016; UNIDO, 2013). According to NACA (2016), the application of BMPs by farmers significantly decreases shrimp mortality, and the pilot farmers' productivities are considerably higher than farmers who do not follow BMPs. Moreover, receiving

BMPs training has a significant and positive effect on reducing the use of those drugs. Reviewing the studies on BMPs, the spread of these practices appears to increase the output of small farmers and reduce port rejections arising from the presence of antibiotic residues.

2.2 Social Network Targeting

In developing countries, extension officers perform a role in transferring new techniques and information to farmers (Anderson & Feder, 2004). However, the provision of services through such official channels may be limited by reasons such as farmers' capabilities and residential areas. As a method to overcome such shortcomings, many studies in development economics have suggested peer learning or social learning for disseminating information to a wide range of farmers (Foster & Rosenzweig, 1995; Liverpool-Tasie & Winter-Nelson, 2012; Magnan, Spielman, Lybbert, & Gulati, 2015; Songsermsawas, Baylis, Chhatre, & Michelson, 2016).

Furthermore, recent studies have employed social network analysis to investigate the peer effects on agricultural information dissemination or technology adoption. According to Valente (2010), while random sampling is not suitable for measuring peer effects as sampling removes individuals from the social context, network analysis is useful for measuring the influence of a relationship on an individual's behavior. To investigate the spread of a microfinance program through social networks in each village, Banerjee et al. (2013) collected social network data from 43 villages in south India. They measured the eigenvector centrality[1] of the leader of each village using network data. Their result suggests that participation in a microfinance program is significantly higher when the village leaders have higher eigenvector centralities.

[1] The eigenvector centrality is a measure to indicate how important a node is in the sense of iterative paths through a network.

Beaman and Dillon (2018) employed network-based targeting to observe who benefit and who is excluded from the information transferred through social networks. They conducted social network census in 52 villages and selected farmers with the highest degree[2] or the highest betweennesses in each village as a treatment group. They provided short training on composting to farmers selected by the social targeting methods and random sampling, and provided informational placards about composting. Through a field experiment they found that information does not spread to people who are far from treated farmers in their social networks. However, they did not find that aggregate knowledge about composting differed across those targeting methods.

Kim et al. (2015) introduced their public health interventions to randomly selected villagers, villagers with the most social ties, or nominated friends of random villagers to assess which targeting methods produce the highest cascade or spillover effects, and hence maximize population-level behavior change. They found that the treatment group which included nominated friends increased the adoption of nutritional intervention by 12.2 percent in comparison to random targeting. On the contrary, targeting the most connected individuals did not increase adoption of either of the interventions. These results imply that targeting using the inherent characteristics of human social networks is a method to enhance the spread of intervention effects.

The existing studies reveal the impact of social networks on the diffusion of information. However, these studies do not provide answers on the best method to disseminate accurate information, although there is a concern that information dissemination through peers, not experts, may spread inaccurate information (Anderson & Feder, 2004). Therefore, this study compares various targeting methods to identify methods to accurately provide agricultural information to more farmers.

[2] The degree refers to the number of links to whom the node is connected.

3 Data Collection, Targeting Methods, and Workshop

3.1 Research Questions and Summary Statistics

Based on previous studies, this study poses three research questions. To test the research questions, this study considers a case of shrimp farmers in Vietnam and uses individual-level data to identify a targeting method which can diffuse accurate agricultural information to farmers.

Research Question 1

What are the targeting methods to improve the knowledge of good practices of the treated and their neighbors the most?

Research Question 2

What are the targeting methods to enhance information sharing with their neighbors the most?

Research Question 3

What are the targeting methods to improve the farming knowledge of those who receive information from the treated the most?

3.2 Summary Statistics

The study chooses four villages in the Phu Tan district, Ca Mau province as the study area as the province is currently the largest shrimp producer in Vietnam with an output of more than 145,000 tons in 2016, which is 23 percent of the country's total shrimp production. The value of the province's shrimp exports was approximately $1 billion in 2016, representing approximately 30 percent of Vietnam's total shrimp exports (VASEP, 2017). In the region, we conducted household surveys before and after a workshop as a part of the research project between the University of Tokyo and Foreign Trade University, Hanoi, Vietnam. As shown in Figure 1, the workshop for the dissemination of information on BMPs was held through a project in December 2016 in collaboration with the Ca Mau Province Office of the Ministry of Rural and Agricultural Development, Vietnam. A baseline survey was conducted for Vietnamese shrimp farmers in October 2016, and a follow-up survey was conducted in July 2017, collecting information from 173 households. In both the surveys, a farmer who is in-charge of shrimp farming in each family was requested to answer several questions regarding BMPs, which we prepared (see appendix 1 for the BMPs problems). The minimum (maximum) score is zero (17).

Table 1 summarizes 173 respondents' basic, psychological, and network characteristics, as well as their BMPs knowledge level. Overall, we observe that farmers have similar characteristics across villages. The average age of the interviewees is approximately 49 years old, and 86 percent of them are male. On an average, they have completed 8 years of formal school education and two people in their family are between the ages 16 and 60 years. The reason for choosing the range of 16 to 60 years is that they are likely to engage in income activities and participate in family decisions (The World Bank, 2004).

As will be explained elaborately in Section 3.3, we conducted the BMPs workshop for selected farmers in Villages A, B, and C, inviting them through different methods depending on the village. Village D is a pure control group. There is no notable difference in the basic characteristics between the villages, and the only difference in the statistics of shrimp production is the cost of shrimp farming. The cost of Village D is 4.85 billion VND, which is nearly 4 billion VND lesser than the average of other villages. In the BMPs test conducted in 2016, the average of Village B was approximately 1.7 points higher than those of other villages. Subsequent to our intervention in December 2016, the difference in the BMPs test scores between the treated villages (Villages A to C) and the untreated village (Village D) is much greater than in 2016. The other differences are that the average of Village A's logged reciprocity is lower than the other villages by 5, and considering the out-degree, the average of the treated villages, excluding Village C, decline from 2016. Village C's betweenness centrality increased largely in 2017 in comparison to 2016. This is owing to fact that the betweenness centrality of the treated in Village C increased significantly after the intervention. The average of their betweenness centralities rose from 2.92 to 48.19.

Another method of dividing farmers into groups is based on the canals they use. By nature, shrimp farming has a large potential for spillovers. As each farmer is connected through canals, one's action affects his/her neighbors. Even if one farmer faithfully implements water quality management of the pond following the BMPs guidelines, his/her shrimp pond may be contaminated by the behavior of the neighbors using the same canal. Therefore, to prevent shrimp diseases and increase productivity, cooperation among residents using the same canal is necessary. To analyze this aspect, we examine the relation between the status of shrimp harvest in 2017 and the BMPs score of canal groups in Table 2. Using the shrimp farming data of 2017, respondents are divided into a "harvest failure" group and a "successful harvest" group. The failure group includes farmers who put shrimp seeds into their ponds in 2017, but did not earn any revenue by selling shrimp that year. The other group includes farmers who sold their own shrimps and earned revenue in 2017. In total, there were 26 canals which the farmers in our sample use, and each farmer uses only one canal. The number of farmers who use the same canal varies from 1 to 19, with a mean of 6.65. The canal score *Min, Mean, Max,* and *SD* represent the score for canal groups which each respondent belongs to. While the mean, maximum, and standard deviation of the canal score are not statistically different between the two groups, a statistically significant difference is found in the canal score *Min*, which is higher in the successful group. This result implies that increasing the BMPs knowledge level of a farmer with the lowest level knowledge and using the same canal is likely to affect the productivity improvement of farms in the same cluster.

3.3 Targeting Methods and Workshop

The study implements a social network census in four villages in the Ca Mau province to ask all farmers in the village about the name of the farmers seeking advice on shrimp cultivation. As shown in Table 3, in 2016, 72 out of 80 farmers (90 percent) in Village A, 46 out of 52 farmers (88 percent) in Village B, 63 out of 76 farmers (83 percent) in Village C, and 47 out of 74 farmers (64 percent) in Village D were interviewed by me. In comparison to other villages, the number of respondents in Village D is relatively small, but as mentioned in Section 3.2, there is generally no notable difference between the characteristics of these villages. Nevertheless, this study should be careful when interpreting the estimation results using the sample as the difference in the response rates may introduce participation bias into our experiment.

Using the network information, a social network map of each village is drawn as shown in Figure 2. The direction of the arrows in those directed graphs indicates that each farmer nominates other farmers as his/her advisers. The size of the nodes indicates how high the betweenness centrality of each node is. The betweenness centrality is as follows:

$$BC_i(g) = \sum_{k \neq j : i \notin \{k,j\}} \frac{P_i(kj)/P(kj)}{(n-1)(n-2)/2} \tag{1}$$

where $BC_i(g)$ is the betweenness centrality of a node *i* and *n* is the number of nodes in a network; $P_i(kj)$ denotes the shortest paths between a node k and j that i lies on. $P(kj)$ denotes the total number of shortest paths between k and j (Freeman, 1977; Jackson, 2008).

To select treatment groups to participate in our workshop, villages are randomly assigned to be among one of the targeting methods, such as SRS, SURS, and SNT. According to Rogers (1962), the critical point, at which the adoption rate is accelerating, is approximately 16 percent in theory. Thus, we choose approximately 16 percent of all farmers in each village as our workshop participants. First, SRS is assigned to Village A. 15 shrimp farmers are randomly selected from the population list in the village.

Second, SURS is assigned to Village B. As depicted in Figure 3, we created a polygon grid on the map of Village B, and then marked the location of each farm on the map. The grid size is set at 1.5 km x 1.5 km as it is the size most suitable for choosing approximately 16 percent of the farmers in the village. Among the farmers in this village, the workshop participants are randomly selected in each block. The reason why the study employs SURS is that selecting a treatment group for each block appears to be the solution to the geographical obstacles mentioned below. The geographical features of the villages in the Ca Mau province are divided into several clusters due to the canals. Thus, it is challenging to visit other farms in the same village due to the canal, which may be an obstacle to the spread of information.

Third, SNT is assigned to Village C. The treatment group includes farmers whose betweenness centrality is in the top 20 percent of all the farmers in the village. A prerequisite for the use of betweenness centrality in targeting is the response of most of the network members as the centrality may change depending on the response rate of members. As 83 percent of the farmers in Village C responded to our network census in 2016, the value obtained from the survey appears to be close to the centrality of the whole network. Accordingly, we employ betweenness centrality for SNT. Another reason for using centrality in this study is that an individual with high betweenness centrality is an intermediary who plays an important role in the connection between other people in the same network. Finally, Village D is set as a pure comparison group, which means that none of the villagers are invited to our workshop.

A workshop on BMPs was held in the Ca Mau province on December 31, 2016. Table 3 summarizes that all the invited farmers in the SRS group, 8 out of 9 invited farmers in the SURS group, and 13 out of 16 invited farmers in the SNT group participated in our workshop. The participants were provided a leaflet on BMPs as well as a lecture on BMPs. There is a difference between the invitees and participants. As four farmers, who were invited but did not participate in our workshop, did not respond to the follow-up survey, they are excluded from the sample used for the analysis of the study. Thus, this study estimates the average effect of the treatment on the treated to find answers to the research questions mentioned previously.

In August 2017, a follow-up survey was conducted to measure changes in the knowledge level of BMPs and the adoption rate of water quality test kits. As shown in Table 3, among 228 respondents who responded to the baseline survey, 55 were excluded from the sample as they refused to respond to the follow-up survey or abandoned shrimp farming. While no one started using the kit after our intervention, the knowledge level showed a change. Most of the neighbors in the treatment group increased their BMPs knowledge level. This result indicates that our intervention had a spillover effect. In particular, the SURS village appears to have the highest spillover effect of our intervention as the BMPs knowledge level of all untreated farmers in the SURS village increased after our intervention.

3.4 Reciprocity

Apart from the common variables, we collected information to measure farmers' reciprocity. The literature on psychology or social networks has found that reciprocity is an important motive for information exchange in communities of practice (Lave, 1991; Lave and Wenger, 1991; Wasko, 2005; Wenger, 1998). Ethan and Schechter (2012) introduce an approach to measure reciprocity using variants of the dictator game, such as anonymous random game, revealed random game, anonymous chosen game, and revealed chosen game. The game is played in pairs. Each pair consists of a dictator and a recipient. The dictator receives 14,000 Guaranies and decides how much is to be shared with the recipient. The relationship between sharing in the four games and the four motives is as follows:

$$T_i = \begin{bmatrix} \tau_i^{AR} \\ \tau_i^{AC} \\ \tau_i^{RR} \\ \tau_i^{RC} \end{bmatrix} = \begin{bmatrix} B_i \\ B_i + D_i \\ B_i + S_i \\ B_i + D_i + S_i + R_i \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix}, \tag{2}$$

where *i* indexes an individual, T_i is the column vector of transfers made by the individual *i*, *B* is undirected altruism, *D* is directed altruism, and *S* is sanctions; τ indicates how much money the dictator gives to each recipient in each game. The reciprocity of individual *i* is equal to

$$R_i = \tau_i^{RC} - (\tau_i^{AC} - \tau_i^{AR} + \tau_i^{RR}) = \tau_i^{RC} - (B_i + D_i + S_i). \tag{3}$$

To measure individual reciprocity, we adopt their approach and conduct an experiment similar to that described above. However, the results may be different from their result as the dictators of our experiment receive play money instead of real money. This may have effects as the dictators may send more money to recipients in comparison to the case when the game is played using real money.

3.5 Risk preferences

To elicit individual risk preferences, either prospect theory (henceforth, PT) or expected utility theory (henceforth, EUT) approaches can be employed. PT adopts three parameters, such as risk aversion, loss aversion, and nonlinear probability weighting, for determining the shape of the utility function. On the other hand, EUT uses risk aversion as the sole parameter. Agricultural economists have debated which theory is most suitable to capture farmers' risk preferences (Kahneman & Tversky, 1979; Liu & Huang, 2013; Moscardi & Janvry, 1977; Tanaka et al., 2010). This study adopts Suzuki's approach, which follows EUT instead of PT, favoring the simplicity of this method to elicit individual risk preferences in order to create risk-aversion indices for farmers (Suzuki, 2015).

Each farmer's risk-aversion index is based on the results of a survey-based risk preference game (see Table 4). This risk preference game has six stages and two options, namely, projects A and B, with different probabilities of receiving prizes. To elaborate, farmers who choose project A, definitely win (100 percent chance) a prize at each stage, while if farmers select project B, they have a fifty-fifty chance of winning the reward. Apart from stage six, the amount of the prize associated with project B is higher than project A, but the risk is also higher. Because their decisions are considered irrational, we drop those observations where project B is chosen in stage 6. The risk-averse index, then, is as follows:

$$\sigma = \sum_{s=1}^{n} V_s \qquad (4)$$

where s denotes each stage of the risk preference game; V_s equals 1 if project A is chosen at stage s, and zero otherwise; and σ is the risk-averse index. The index ranges from 1 (least risk-averse) to 6 (very risk-averse).

4 Econometric Strategies

4.1 Regression Analyses

Using various estimation methods, this study empirically analyzes the research questions mentioned in Section 3.1. Balanced panel data is used in Equation (5)–(8), and cross-sectional data is used in Equation (9)–(11).

Since the study by Ashenfelter and Card (1985), the DD approach has become a popular method to estimate the causal effects of policy interventions (Ashenfelter & Card, 1985; Bertrand, Duflo, & Mullainathan, 2004; Wooldridge, 2007). According to Wooldridge (2007), the approach removes biases from the permanent difference between treatment and control groups, and from comparisons over time in the treatment group. Therefore, to estimate the effects of our treatment by comparing the treated and untreated, the DD estimation and two-way fixed effects with the DD are assessed by grouping the treatment groups into one group, rather than dividing them by targeting methods. The regression is as follows:

$$Y_{it} = \alpha + \beta_1 dT_{i\ or\ j} + \beta_2 X'_{it} + \gamma_1 T_t + \gamma_2 T_t \cdot dT_{i\ or\ j} + \eta_i + \lambda_t + \varepsilon_{it}, \qquad (5)$$

where the subscript i indexes the individual, j indexes the informer, and t indexes time. In the models for Question (i) and (iii), *Y* denotes the BMPs test score of individual i in t year, and the dependent variable *Y* for Question (ii) refers to individual *i*'s out-degree[3]—the variable's minimum (maximum) value is zero (three); dT_i is a dummy variable for our treatment which equals to one if individual *i* participates in our workshop and zero otherwise. In the model for Question (iii), dT_j equals to one if a farmer j, who provides BMPs information to individual i participates in our workshop; X' refers to individual *i*'s time-variant characteristics, such as *i*'s farming and household characteristics, and the risk-averse index is added only to the model for Question (ii). The index ranges from 1 (least risk-averse) to 6 (very risk-averse); *T* is a dummy variable indicating time which equals one if the intervention is performed and zero otherwise; η is the unobserved individual effect, λ is the time fixed effect, and u is the error term. The DD estimate $\hat{\gamma}_2$ can be expressed as follows:

$$\hat{\gamma}_2 = (\bar{Y}_{i,TRE,POST} - \bar{Y}_{i,TRE,PRE}) - (\bar{Y}_{i,COM,POST} - \bar{Y}_{i,COM,PRE}). \tag{6}$$

where the subscript *TRE* indicates that the individual is in the treatment group and *COM* is that the individual belongs to the comparison group. The *PRE* and *POST* subscripts represent before and after the treatment, respectively.

Second, this study assesses the difference in treatment effects between groups using DD estimation and fixed effect models with the DD estimate. The regression model is as follows:

[3] Out-degree is the number of outgoing links from a node to others.

$$Y_{it} = \alpha + \beta_1 dT_{i\ or\ j} + \beta_2 X'_{it} + \gamma_1 T_t + \delta_1 G_{i\ or\ j} + \delta_2 G_{i\ or\ j} \cdot dT_{i\ or\ j} + \delta_3 G_{i\ or\ j} \cdot T_t + \delta_4 G_{i\ or\ j} \cdot dT_{i\ or\ j} \cdot T_t + \eta_i + \lambda_t + \varepsilon_{it}, \tag{7}$$

where G is a categorical variable for targeting methods: 1 for SRS, 2 for SURS, 3 for SNT, and 4 for the pure comparison group. The DD estimate δ_4 is

$$\hat{\delta}_4 = (\bar{Y}_{i,TRE,G,POST} - \bar{Y}_{i,TRE,G,PRE}) - (\bar{Y}_{i,COM,G,POST} - \bar{Y}_{i,COM,G,PRE}) \tag{8}$$

where the subscript G represents SRS if the DD estimate is for SRS. In the case of the estimate for SURS, G indicates SURS.

Third, as a robustness check, the study employs the DD estimate again. Unlike Equation (5), in this model, the variable for targeting methods G is multiplied by the dummy for the treatment dT. The dependent variable Y is individual i's BMPs test score or out-degree after our treatment. Using the cross-sectional data, this study estimates regressions of the form

$$Y_{i,POST} = \alpha + \delta_1 G_{i\ or\ j} + \delta_2 G_{i\ or\ j} \cdot dT_{i\ or\ j} + \varepsilon_i. \tag{9}$$

The DD estimate δ_2 is

$$\hat{\delta}_2 = (\bar{Y}_{i,TRE,G} - \bar{Y}_{i,TRE,G}) - (\bar{Y}_{i,COM,G} - \bar{Y}_{i,COM,G}). \tag{10}$$

Furthermore, this study employs a control function estimator to estimate the effect of treatment after controlling the major variables. In addition to time-variant variables, time-invariant variables are added to the right-side of this model. The regression model is as follows:

$$Y_{i,POST} = \alpha + \beta_1 X'_{i,POST} + \beta_2 Z'_{i,POST} + \delta_1 G_{i\ or\ j} + \delta_2 G_{i\ or\ j} \cdot dT_{i\ or\ j} + \theta Y_{i,PRE} + \varepsilon_i \tag{11}$$

where Z' represents individual *i*'s time-invariant or omitted characteristics in fixed effects models, such as *i*'s gender, age, years of education completed, and farming experience. In the model for Question (ii), the variable for logged reciprocity is added. Variable reciprocity is used only for cross-sectional regression as the data on reciprocity of farmers was collected only in 2017. The dependent variable in this model is how many people does individual *i* provide information on shrimp cultivation to. Therefore, to avoid endogeneity problems, reciprocity is measured based on donating behavior, not information-sharing behavior. The method for obtaining the variable is described in Section 3.4.

4.2 Correlation Matrix

Table 5 presents the correlation matrix of all the independent variables used in the above models. The highest correlation is found between the continuous numerical variable for individual *i*'s age and the dummy for father’s occupation; however, it is only -0.38. The correlation between the categorical variable for targeting methods and other variables is less than 0.2. Most of the other correlations between the other controls are also lower than 0.2. Therefore, among the explanatory variables used in our analyses, there is no high correlation between the variables.

5 Estimation Results

5.1 Effect of each targeting method on the knowledge of BMPs of the Treated

Tables 6 and 7 show the estimation results for Question (i) using panel data and cross-sectional data, respectively. The dependent variable in the table is the BMPs test score of individual *i*.

In Columns (1) and (2), we consider the treatment of BMPs information workshop as one and examine the average effect of the treatment on the treated. We find that the coefficient of interaction term between treatment and time is insignificant, suggesting that the treatment did not have significant effect on BMPs score on an average. Column (1) of Table 6 shows the result of the DD estimation, indicating that the score after our intervention is 8.67 higher than the score in 2016, which is statistically significant at the 1 percent level. Column (2) is a fixed effects model with time-variant characteristics added to the independent variables used in Column (1). The result of the DD estimate in Column (2) is similar to that in Column (1).

Column (3) in Table 6 shows the result of the DD estimation to assess the difference in treatment effects between groups, and the result of the model with other explanatory variables added to the variables in Column (3) appears in Column (4) in Table 6. Village D, a pure comparison group, is used as the base level in the regressions. Coefficients on the interaction between group and time show that treated groups (i.e., SRS, SURS, and SNT) improved on BMPs scores in 2017 on an average and the effects are higher than the pure control village. Considering the SRS and SURS groups, the effects are statistically significant at 1% and 5% level, respectively. When we observe the treatment effects on treated farmers (i.e., interaction terms between group, treatment, and time), we find that most of them, except SURS in Column (3), are insignificant. This means that while farmers in the treated groups improved the score on an average, the increase was not significantly different between the treated and untreated farmers within the same village.

Essentially, the negative coefficients suggest that the increase was less for the treated. In particular, for the SURS group, the increase for the treated was 2.59 points lesser than the untreated (but the impact was still 0.57 more than the pure control group). The results suggest that there is a spillover effect between the treated and non-treated farmers within the treated villages. Except for SURS, the differences between the treated and untreated farmers in other groups are not statistically significant. Overall, the results shown in Column (4) are similar to those in Column (3). From the results of the two columns, it can be mentioned that the spillover effects from the treated to untreated are largest for the SRS group, followed by the SURS and SNT groups.

Table 7 summarizes the estimation results using cross-sectional data. The standard errors are clustered at the canal level. All the columns in the table indicate that the effect in the SRS group is approximately 0.80 lesser than that in the SURS group. These results are statistically significant at the 0.01 level. Similar to the results in Table 6, the differences between the treated and untreated farmers within the group are not statistically significant, except for the SURS group. The spillover effects from the treated to untreated farmers appear the highest in the SURS group, followed by the SRS and SNT groups.

5.2 Effect of Each Targeting Method on Information Sharing with Neighbors

The dependent variable in Tables 8 and 9 is the out-degree of individual i, which refers to how many farmers she/he provides the BMPs knowledge to. Each table has a column which contains a variable for the risk-aversion index and a column which does not contain it. As the variable may cause an endogeneity problem, we show the results of both the models.

Column (1) in Table 8 shows the result of the DD estimation, indicating that the increase in the out-degree of the treated farmer group is 0.05 lesser than the untreated farmer group. The results of the DD estimates in the three columns are statistically insignificant and similar in magnitude. In Columns (4)–(6), we find the interaction terms between group and time to be statistically significant at the 1% level for all groups. In particular, it is negative and statistically significant for the SRS and SURS groups, while it is positive and statistically significant for the SNT group. It means that information sharing was reduced in the SRS and SURS villages, while it was enhanced in the SNT village after the treatment. We also observe that the effects on treated farmers are insignificant (i.e., coefficients on the interaction terms between group, treatment status, and time), indicating that the effect of the treatment to enhance information sharing was not different between the treated and untreated farmers within the same group. Considering these results, we can state that after the treatment, information sharing was enhanced most in the SNT group, 0.87 higher than the pure control village, while the degree of information sharing was reduced for the SRS and SURS groups relative to the pure control group. This result is interpreted as reflecting the features of each targeting method. As the treated in SNT were originally active people in communicating with their neighbors, they became more active in sharing new information with their neighbors. The treated farmers in SRS and SURS, selected regardless of their communicative participation, have a lower betweenness centrality in 2016 (before our intervention) of 2 and 9 respectively, than those treated in SNT. The figure leads us to presume that the treated in the SRS and SURS groups were originally not as active as the treated in the SNT group in communicating with their neighboring farmers. During the fieldwork, we found that many farmers were reluctant to share farming information with other farmers. Many farmers mentioned that "because shrimp is very sensitive, if some problem occurs in our neighbors' ponds due to our advice, we cannot take responsibility." Thus, it may be that those with lower betweenness centrality strengthened this behavior of hiding information when they received new information, while those with higher betweenness centrality continued to spread information to others.

In Table 9, we again observe that the group dummies of SRS and SURS are statistically significant at the 1% level and negative across models. Controlling for the out-degree of 2016, farmers in the SRS and SURS groups decrease the out-degree in 2017 by approximately 2 units relative to the pure control village. SNT dummies are insignificant across the models. The effects on the treated farmers are also insignificant in most of the cases, except for SUR in Column (1). Overall, it can be stated that the effects on treated farmers were not different from those on untreated farmers within the village. In order to examine whether reciprocity plays a role in facilitating the out-degree, we included the variable for logged reciprocity in Column (5). It shows that if a person has a higher degree of reciprocity, she/he is likely to have a lower out-degree by approximately 0.08 units. This result is intuitive as having a higher degree of reciprocity means that the person offers something to others if she/he receives something from others.

5.3. Effect of Each Targeting Method on the Knowledge of BMPs of their Neighbors

The dependent variable in Tables 10–12 is BMPs test score of individual i, which is the same as the dependent variable for Question (i). The major difference between the models for Questions (i) and (iii) is that the models for Question (iii) employ the dummy variable dT_j for the treatment of informer j. To confirm the flow of information in each village, we asked farmers, "To whom (only shrimp farmer) do you advise on shrimp cultivation?." As the direction of selection is from an informer j to an individual i (information receiver), the explanatory variable dT_j can be treated as exogenous, which is not correlated with the error term of individual i.

The results in Columns (1) and (2) in Table 10 imply that treated informers have negative effects on the test score of individual *i*, although it is insignificant. However, when the treatment is separated into different groups as in Columns (3) and (4), we observe that it is positive for the SRS and SURS groups, and negative for the SNT group (i.e., interaction terms between groups, j's treatment status, and time). These coefficients show direct effects of spillovers from the treated to untreated farmers and is particularly strong in the SURS group, which is 2.9 and statistically significant at the 5% level. General spillovers can be observed from the interaction terms between group and time in the same columns, and these are positive and statistically significant for SURS and SRS. In addition to these general spillover effects, when a person's direct informer is treated, the BMPs score increases by 2.9 within the SURS group.

All columns in Table 11 again indicate that the test scores of individuals who receive information from the treated in SURS are 1.69–2.96 points higher than those informed by the untreated in the group. These results are statistically significant at the 5% level. The DD variables for the treated informer *j* in SRS and SNT have negative effects on their receivers' test scores and are not significant. These results are consistent with the panel models and confirm that the direct spillover effects are strong in the SURS group.

Table 12 shows the results using samples, including untreated farmers, only to show the direct spillover effects from treated to untreated farmers. In addition to direct spillover effects, when a person's direct informer is treated, the BMPs score increases by 2.3 within the SURS group. On the contrary, the BMPs score decreases by 2.2, if an untreated farmer nominates a treated farmer of the SNT as an advisor.

5.4 Robustness Checks

Table 13 describes the results of the robustness checks for Questions 1 and 3. In the table, the variables used in the estimations of Questions 1 and 3 are analyzed together. The table shows that the results are similar to those in Tables 6 and 10. The variables *Group*i's Treated*Time* are statistically insignificant. While the variable *SURS*j's Treated*Time* is not significant in Column (4), the variable is statistically significant in Column (3) and the magnitude is similar to the result in Table 10. These show that even after controlling for the treatment effects on treated farmers, direct spillover effects from the treated informer to an untreated farmer in the SURS group is high.

6 Conclusion

The study uses individual-level data to identify a targeting method which can diffuse accurate agricultural information to farmers. The data includes information on farmers' social networks, psychological characteristics, and the knowledge level of a good practice called BMPs, as well as their socio-economic characteristics.

On December 31, 2016, we held a workshop for disseminating BMPs. The participants were selected using three targeting methods and were divided into three groups based on the methods, such as SRS, SURS, and SNT. In August 2017, a follow-up survey was conducted to investigate how well farmers' knowledge of BMPs improved in comparison to the status before our intervention.

Using primary data, this study tested our research questions mentioned in Section 3.1, and found that: (1) while the treatment effect on treated farmers was weak or insignificant for most of our models, the SRS targeting method increases BMPs knowledge for all farmers in the village the most, followed by the SURS targeting method; (2) the SNT targeting method increases the degree of information sharing among villagers the most, while other targeting methods reduces information sharing; and (3) the SURS targeting method increases the BMPs knowledge of the information advisees of the treated farmers the most. These findings suggest that in order to spread accurate information to a wider group of farmers, the SRS and SURS targeting methods are better than the SNT targeting method. While the SNT targeting method is found to increase information sharing among farmers, the extent that the information is disseminated depends on the existing social network, and thus may not reach a wider group of farmers. Furthermore, the study found that reciprocity has a negative correlation with sharing information with many people. Reciprocity means helping others for mutual benefits. Therefore, it is presumed that people with strong reciprocity tend to be passive in information sharing. Considering the case of our study site, there are many factors which hinder frequent information exchanges among farmers, such as (i) the geographical characteristics that separate farmers from each other, (ii) information exchange using smart phones that is still not popular, and (iii) there is a strong traditional norm that people are not willing to exchange information, particularly about shrimp farming. These factors may have supported the effectiveness of the SURS targeting method that is based on geographical distance in our case.

Our findings shed light on the effective targeting methods for information diffusion. First, SURS may be suitable to enhance the knowledge level of neighboring farmers. However, we need to interpret the result carefully as systematic sampling tends to introduce bias into the sample rather than SRS. Second, while the SNT group is more active in informing BMPs knowledge to other farmers than other groups, the direct and indirect treatment effects of the SNT group on the diffusion of accurate information may be smaller than those of the other groups. WE presume that this is suggesting that the person with high betweenness centrality tends to receive and send a substantial amount of information through various channels and focuses on exchanging information frequently without distinguishing the quality of information.

Finally, we should note that there are several limitations to this study. One limitation is that the study does not handle regional or industrial heterogeneities. As our field experiment were conducted in only four villages, the estimation results may be due to the combined effects of the characteristics of each village and each targeting rather than the net effect of each targeting method. Therefore, a further study should be conducted in more regions and industries to clarify our research issues by eliminating the heterogeneities. Our findings suggest effective targeting methods to transmit information to more people or to spread accurate information to the untreated as well as the treated. It is hoped that they will contribute to improving farming practices in developing countries.

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Table 1 Basic, Farming, and Psychological Characteristic of each Village in 2017

	Village A (SRS)		Village B (SURS)		Village C (SNT)		Village D (Control)	
	Obs	Mean	Obs	Mean	Obs	Mean	Obs	Mean
Basic Characteristic								
Gender (Male = 1)	53	0.81	34	0.97	51	0.84	35	0.83
		[0.39]		[0.17]		[0.37]		[0.38]
Age	53	50.17	34	52.00	51	44.16	35	47.89
		[9.79]		[12.57]		[12.86]		[15.65]
Years of Education	53	7.70	34	7.26	51	8.49	35	8.26
		[2.59]		[2.69]		[2.63]		[2.42]
No. HM16 to 60	53	1.91	34	2.44	51	1.84	35	2.11
		[0.99]		[1.24]		[0.81]		[1.25]
Shrimp Production								
Farther Shrimp Farmer	53	0.23	34	0.09	51	0.25	35	0.11
(Yes=1)		[0.42]		[0.29]		[0.44]		[0.32]
Years of Shrimp Farming	53	6.25	34	6.24	51	6.94	35	6.97
		[3.65]		[3.04]		[3.00]		[2.88]
Shrimp farm size (ha)	53	0.60	34	0.57	51	0.58	35	0.63
		[0.37]		[0.36]		[0.42]		[0.42]
Cost (billion VND)	53	9.16	34	8.62	51	9.82	35	4.85
		[6.75]		[7.51]		[6.68]		[6.88]
Treatment	53	0.28	34	0.24	51	0.25	35	0.00
		[0.45]		[0.43]		[0.44]		[0.00]
Test score of BMP in 2016	53	1.58	34	3.44	51	2.00	35	1.54
(0 to 17)		[2.48]		[3.54]		[2.74]		[2.63]
Test score of BMP in 2017	53	11.64	34	12.79	51	10.02	35	8.34
(0 to 17)		[3.29]		[2.14]		[3.17]		[5.58]
Psychological Characteristic								
Logged Reciprocity	53	5.85	34	11.15	51	10.91	35	11.13
		[0.79]		[0.12]		[1.56]		[0.16]
Risk Aversion (1 to 6; 6 most risk averse)	53	5.85	34	5.97	51	5.47	35	5.54
		[0.79]		[0.17]		[1.36]		[1.31]
Network Characteristics								
Out-degree Centrality 2016	53	0.68	34	0.91	51	0.57	35	1.77
		[1.09]		[1.06]		[1.02]		[1.14]
Out-degree Centrality 2017	53	0.02	34	0.00	51	1.84	35	2.14
		[0.14]		[0.00]		[1.16]		[1.03]
Betweenness Centrality 2016	53	5.02	34	2.71	51	2.55	35	7.46
		[11.18]		[6.06]		[4.67]		[9.67]
Betweenness Centrality 2017	53	7.51	34	4.44	51	29.25	35	11.31
		[12.33]		[0.11]		[42.63]		[13.74]

Notes: Standard deviations are reported in brackets. Cost = cost of shrimp seed + cost of shrimp feed+ cost of permanent labors + cost of casual labors. Out-degree is measured using a question "To whom (only shrimp farmer) do you advise on shrimp cultivation?." Betweenness centrality is measured using a question "From whom (only shrimp farmer) do you obtain advice on shrimp cultivation?."

Table 2 The Test Score of the BMPs in 2016

	(a) Harvest Failure		(b) Successful Harv.		Diff
Variable	Obs	Mean	Obs	Mean	(a)-(b)
Canal Score Min	109	0.00	54	0.17	-0.17*
		[0.00]		[0.91]	(0.09)
Canal Score Mean	109	14.39	54	14.57	-0.19
		[2.50]		[2.92]	(0.44)
Canal Score Max	109	5.98	54	6.48	-0.50
		[1.80]		[2.00]	(0.31)
Canal Score SD	109	5.28	54	5.18	0.10
		[1.09]		[1.17]	(0.19)

Notes: Standard deviations are reported in brackets. Standard errors are reported in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%. Min is the abbreviation for minimum, Max is the abbreviation for maximum, SD is the abbreviation for standard deviation.

Table 3 Number of Invitees and Participants

	Targeting Method	**Total # of farmers**	**# of Respondents (Baseline)**	**# of Respondents (Follow-up)**	**Invited**	**Participated**
Village A	SRS	80	72	53	15	15
Village B	SURS	52	46	34	9	8
Village C	SNT	76	63	51	16	13
Village D	N/A (control)	74	47	35	N/A	N/A

Source: From own survey

Table 4 Risk Preference Game

	Project A	**Project B**	
	You obtain for sure:	50% chance of obtaining:	50% chance of obtaining
S1	1 million VND	2 million VND	0 VND
S2	1.2 million VND	2 million VND	0 VND
S3	1.4 million VND	2 million VND	0 VND
S4	1.6 million VND	2 million VND	0 VND
S5	1.8 million VND	2 million VND	0 VND
S6	2 million VND	2 million VND	0 VND

Table 5 Correlation Matrix of All Independent Variables

	Group	Treated	Treated advisor	Gender	Age	Education	Years of Shrimp Farming	Father Shrimp Farmer	No. of HM16 to 60	Shrimp farm size (ha)	Risk Aversion (1 to 6)	Logged Reciprocity
Group	1.00											
Treated	-0.21	1.00										
Treated advisor	-0.03	0.18	1.00									
Gender	-0.003	-0.07	0.08	1.00								
Age	-0.14	-0.04	-0.05	-0.03	1.00							
Education	0.12	0.01	0.02	0.17	-0.26	1.00						
Years of Shrimp Farming	0.10	-0.02	0.04	0.09	0.14	0.07	1.00					
Father Shrimp Farmer	-0.05	0.16	-0.05	-0.10	-0.38	0.13	-0.08	1.00				
No. HM16 to 60	0.01	0.01	-0.11	0.01	0.07	-0.01	-0.004	-0.13	1.00			
Shrimp Farm Size (ha)	0.02	0.07	0.01	-0.02	-0.05	0.22	0.17	-0.04	-0.03	1.00		
Risk Aversion (1 to 6)	-0.15	-0.03	-0.12	-0.04	0.08	-0.14	-0.03	-0.02	0.08	-0.15	1.00	
Logged Reciprocity	-0.03	0.05	0.05	-0.03	0.13	0.11	0.04	-0.16	0.002	0.04	0.27	1.00

Table 6 Effect of Each Targeting Method on the Knowledge of BMPs of the Treated: Panel Data

Dependent Variable: i's BMPs test score	DD1 (1)	FE with DD1 (2)	DD2 (3)	FE with DD2 (4)
Time	8.67***	8.79***	6.80***	7.00***
	(0.39)	(0.41)	(0.93)	(0.97)
SRS*Time			3.31***	3.26***
			(1.14)	(1.15)
SURS*Time			3.16**	2.81**
			(1.12)	(1.18)
SNT*Time			1.28	1.03
			(1.16)	(1.17)
i's Treated*Time	0.06	-0.08		
	(0.77)	(0.77)		
SRS*i's Treated*Time			-0.17	-0.31
			(1.29)	(1.32)
SURS*i's Treated*Time			-2.59*	-2.54
			(1.55)	(1.54)
SNT*i's Treated*Time			-0.23	-0.10
			(1.11)	(1.10)
Father Shrimp Farmer		-0.48		-0.43
		(0.61)		(0.60)
No. HM 16-60		0.43		0.29
		(0.30)		(0.28)
Farm Size		-1.00		-1.36
		(1.06)		(1.09)
Constant	2.06***	1.77*	2.06***	2.30**
	(0.17)	(1.03)	(0.16)	(1.00)
Joint-significance	0.00	0.00	0.00	0.00
Observations	346	346	346	346
R-squared	0.79	0.80	0.81	0.81
Number of id	173	173	173	173

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *i* indexes individual. SRS, SURS, and SNT is the abbreviation for simple random sampling, systematically unaligned random sampling, and social network targeting, respectively.

Table 7 Effect of each Targeting Method on the Knowledge of BMPs of the Treated: Cross-sectional Data

Dependent Variable: i's BMPs test score	DD2 (1)	CFE1 (2)	CFE2 (3)
Score 2016		0.17	0.11
		(0.11)	(0.12)
SRS	3.74***	3.62***	3.73***
	(0.80)	(0.76)	(0.77)
SURS	4.58***	4.37***	4.54***
	(0.82)	(0.90)	(0.93)
SNT	1.68**	1.55*	1.50**
	(0.82)	(0.76)	(0.72)
SRS**i*'s Treated	-1.55	-1.44	-1.10
	(1.58)	(1.69)	(1.59)
SURS**i*'s Treated	-0.55	-0.92***	-0.90***
	(0.34)	(0.32)	(0.28)
SNT**i*'s Treated	-0.03	-0.19	-0.32
	(0.94)	(0.65)	(0.57)
Father Shrimp Farmer		0.74	0.37
		(0.65)	(0.68)
No. HM 16-60		0.02	-0.00
		(0.17)	(0.18)
Farm size, t-1		0.05	-0.15
		(0.83)	(0.81)
Gender			1.24
			(0.94)
Age			-0.02
			(0.03)
Year of Education			0.17
			(0.10)
Years of Shrimp Farming			0.01
			(0.08)
Constant	8.34***	7.94***	6.94***
	(0.73)	(0.92)	(2.26)
Joint-significance	0.0001	0.0004	0.0006
Observations	173	173	173
R-squared	0.16	0.18	0.22

Notes: Standard errors in parentheses are clustered at the canal level. *** p<0.01, ** p<0.05, * p<0.1. *i* indexes individual. t-1 means one year ago. SRS, SURS, and SNT is the abbreviation for simple random sampling, systematically unaligned random sampling, and social network targeting, respectively.

Table 8 Effect of Each Targeting Method on Information Sharing with their Neighbors: Panel Data

Dependent Variable: i's out-degree	DD1 (1)	FE with DD1 (2)	FE with DD1&Risk (3)	DD2 (4)	FE with DD2 (5)	FE with DD2&Risk (6)
Time	0.08	0.10	0.08	0.37	0.43*	0.42*
	(0.13)	(0.13)	(0.13)	(0.24)	(0.24)	(0.24)
SRS*Time				-0.95***	-0.97***	-0.97***
				(0.30)	(0.29)	(0.29)
SURS*Time				-1.41***	-1.42***	-1.43***
				(0.32)	(0.31)	(0.31)
SNT*Time				0.87***	0.90***	0.89***
				(0.31)	(0.31)	(0.31)
i's Treated*Time	-0.05	-0.09	-0.07			
	(0.30)	(0.31)	(0.30)			
SRS**i*'s Treated*Time				-0.35	-0.43	-0.41
				(0.33)	(0.32)	(0.32)
SURS**i*'s Treated*Time				0.41	0.50	0.51
				(0.37)	(0.39)	(0.39)
SNT**i*'s Treated*Time				0.30	0.28	0.29
				(0.44)	(0.47)	(0.46)
Father Shrimp Farmer		0.36**	0.34*		0.30*	0.29*
		(0.18)	(0.18)		(0.15)	(0.16)
No. hm 16-60		0.01	-0.002		0.11	0.10
		(0.07)	(0.07)		(0.07)	(0.07)
Farm Size, t-1		0.01	0.01		0.35	0.35
		(0.44)	(0.43)		(0.30)	(0.30)
Risk Aversion			-0.10			-0.05
			(0.09)			(0.06)
Constant	0.94***	0.82**	1.42**	0.94***	0.40	0.71
	(0.06)	(0.35)	(0.64)	(0.05)	(0.26)	(0.47)
Joint-significance	0.92	0.96	0.98	0.13	0.07	0.08
Observations	346	346	346	346	346	346
R-squared	0.00	0.02	0.02	0.38	0.40	0.40
Number of id	173	173	173	173	173	173

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *i* indexes individual. t-1 means one year ago. SRS, SURS, and SNT is the abbreviation for simple random sampling, systematically unaligned random sampling, and social network targeting, respectively. Out-degree is measured using a question "To whom (only shrimp farmer) do you advise on shrimp cultivation?."

Table 9 Effect of Each Targeting Method on Information Sharing with their Neighbors: Cross-sectional Data

Dependent Variable:	DD2	CFE1	CFE2	CFE3	CFE4
i's out-degree	(1)	(2)	(3)	(4)	(5)
Out-degree 2016		0.16***	0.18***	0.18***	0.18***
		(0.05)	(0.06)	(0.06)	(0.06)
SRS	-2.12***	-1.97***	-2.00***	-2.01***	-2.00***
	(0.14)	(0.13)	(0.13)	(0.13)	(0.13)
SURS	-2.14***	-1.98***	-2.05***	-2.05***	-2.05***
	(0.14)	(0.16)	(0.16)	(0.17)	(0.16)
SNT	-0.43	-0.24	-0.21	-0.20	-0.23
	(0.36)	(0.34)	(0.36)	(0.37)	(0.35)
SRS* i's Treated	-0.03	-0.02	0.06	0.06	0.07
	(0.02)	(0.08)	(0.13)	(0.13)	(0.12)
SURS* i's Treated	8.84E-16*	-0.02	-0.02	-0.03	-0.02
	(4.42e-16)	(0.08)	(0.10)	(0.09)	(0.10)
SNT* i's Treated	0.52	0.41	0.36	0.36	0.39
	(0.36)	(0.47)	(0.46)	(0.46)	(0.43)
Score 2016		0.02	0.02	0.02	0.02
		(0.02)	(0.02)	(0.02)	(0.02)
Father shrimp farmer		0.10	0.16	0.15	0.13
		(0.13)	(0.14)	(0.13)	(0.14)
No. hm 16-60		-0.09	-0.09	-0.09	-0.09
		(0.07)	(0.07)	(0.07)	(0.07)
Farm size, t-1		0.24**	0.31**	0.31**	0.30**
		(0.12)	(0.14)	(0.15)	(0.14)
Gender			0.32*	0.32*	0.30
			(0.18)	(0.19)	(0.19)
Age			0.002	0.002	0.003
			(0.005)	(0.005)	(0.005)
Year of education			-0.02	-0.02	-0.02
			(0.02)	(0.02)	(0.02)
Years of Shrimp Farming			-0.02	-0.02	-0.02
			(0.01)	(0.01)	(0.01)
Risk Aversion				0.02	
				(0.06)	
Reciprocity					-0.08***
					(0.03)
Constant	2.14***	1.85***	1.70***	1.57***	2.59***
	(0.14)	(0.17)	(0.35)	(0.46)	(0.44)
Joint-significance	0.00	0.00	0.00	0.00	0.00
Observations	173	173	173	173	173
R-squared	0.63	0.66	0.67	0.67	0.67

Notes: Standard errors in parentheses are clustered at the canal level. *** p<0.01, ** p<0.05, * p<0.1. *i* indexes individual. t-1 means one year ago. SRS, SURS, and SNT is the abbreviation for simple random sampling, systematically unaligned random sampling, and social network targeting, respectively. Out-degree is measured using a question "To whom (only shrimp farmer) do you advise on shrimp cultivation?."

Table 10 Effect of Each Targeting Method on the Knowledge of BMPs of their Neighbors: Panel Data

Dependent Variable: *i*'s test score	DD1 (1)	FE with DD1 (2)	DD2 (3)	FE with DD2 (4)
Time	8.71***	8.84***	6.80***	7.02***
	(0.38)	(0.38)	(0.93)	(0.63)
SRS*Time			3.20***	3.16***
			(1.12)	(1.13)
SURS*Time			2.30**	1.95
			(1.13)	(1.19)
SNT*Time			1.90	1.69
			(1.18)	(1.17)
j's Treated*Time	-0.27	-0.36		
	(0.82)	(0.82)		
SRS**j*'s Treated*Time			0.30	0.05
			(1.42)	(1.38)
SURS**j*'s Treated*Time			2.90**	2.92**
			(1.16)	(1.38)
SNT**j*'s Treated*Time			-1.65	-1.66
			(1.13)	(1.14)
Father shrimp farmer		-0.51		-0.42
		(0.60)		(0.57)
No. hm 16-60		0.42		0.32
		(0.30)		(0.28)
Farm size, t-1		-1.04		-1.31
		(1.05)		(1.12)
Constant	2.06***	1.82*	2.06***	2.22**
	(0.17)	(1.05)	(0.16)	(1.01)
Joint-significance	0.00	0.00	0.00	0.00
Observations	346	346	346	346
R-squared	0.79	0.80	0.81	0.81
Number of id	173	173	173	173

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. *i* indexes individual. *j* indexes informer. t-1 means one year ago. SRS, SURS, and SNT is the abbreviation for simple random sampling, systematically unaligned random sampling, and social network targeting, respectively.

Table 11 Effect of Each Targeting Method on the Knowledge of BMPs of their Neighbors: Cross-sectional Data

Dependent Variable: *i*'s test score	DD2 (1)	CFE 1 (2)	CFE 1 (3)
Score 2016		0.18*	0.13
		(0.10)	(0.12)
SRS	3.47***	3.32***	3.55***
	(0.87)	(0.79)	(0.77)
SURS	4.30***	3.96***	3.999***
	(0.83)	(0.90)	(0.91)
SNT	1.76*	1.69*	1.79**
	(0.91)	(0.87)	(0.84)
SRS*j's Treated	-0.91	-0.53	-0.59
	(0.96)	(1.10)	(1.03)
SURS*j's Treated	1.69***	1.96***	2.96**
	(0.40)	(0.44)	(0.90)
SNT*j's Treated	-0.20	-0.45	-0.94
	(1.25)	(1.24)	(1.21)
Father shrimp farmer		0.58	0.19
		(0.77)	(0.75)
No. hm 16-60		-0.03	-0.04
		(0.20)	(0.21)
Farm size, t-1		-0.01	-0.18
		(0.83)	(0.79)
Gender			1.63*
			(0.95)
Age			-0.03
			(0.03)
Year of education			0.16
			(0.11)
Year of Shrimp Farming			-0.002
			(0.09)
Constant	8.34***	8.06***	7.06***
	(0.62)	(0.99)	(2.42)
Joint-significance	0.0001	0.002	0.001
Observations	173	173	173
R-squared	0.16	0.18	0.22

Notes: Standard errors in parentheses are clustered at the canal level. *** p<0.01, ** p<0.05, * p<0.1. *i* indexes individual. *j* indexes informer. t-1 means one year ago. SRS, SURS, and SNT is the abbreviation for simple random sampling, systematically unaligned random sampling, and social network targeting, respectively.

Table 12 Effect of Each Targeting Method on the Knowledge of BMPs of the Treated and their Neighbors: Panel Data & Untreated Farmers Only

Dependent Variable: *i*'s test score	DD1 (1)	FE with DD1 (2)	DD2 (3)	FE with DD2 (4)
Time	8.66***	8.76***	6.80***	6.97***
	(0.43)	(0.44)	(0.93)	(0.98)
SRS*Time			3.08**	3.06**
			(1.20)	(1.21)
SURS*Time			2.30*	2.59**
			(1.18)	(1.43)
SNT*Time			1.96	1.80
			(1.23)	(1.23)
j's Treated*Time	0.06	-0.11		
	(1.03)	(1.06)		
SRS**j*'s Treated*Time			1.46	1.46
			(1.17)	(1.10)
SURS**j*'s Treated*Time			2.30*	2.25
			(1.18)	(1.43)
SNT**j*'s Treated*Time			-1.99	-2.17
			(1.50)	(1.52)
Father shrimp farmer		-0.45		-0.21
		(0.63)		(0.63)
No. hm 16-60		0.32		0.24
		(0.34)		(0.32)
Farm size, t-1		-1.16		-1.40
		(1.11)		(1.15)
Constant	2.04***	2.07*	2.04***	2.35**
	(0.20)	(1.13)	(0.19)	(1.07)
Joint-significance	0.00	0.00	0.00	0.00
Observations	274	274	274	274
R-squared	0.78	0.79	0.81	0.81
Number of id	137	137	137	137

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *i* indexes individual. *j* indexes informer. t-1 means one year ago. SRS, SURS, and SNT is the abbreviation for simple random sampling, systematically unaligned random sampling, and social network targeting, respectively.

Table 13 Effect of Each Targeting Method on the Knowledge of BMPs of the Treated and their Neighbors: Panel Data

Dependent Variable: *i*'s test score	DD1 (1)	FE with DD1 (2)	DD2 (3)	FE with DD2 (4)
Time	8.71***	8.84***	6.80***	7.01***
	(0.42)	(0.42)	(0.93)	(0.97)
SRS*Time			3.25***	3.25***
			(1.19)	(1.20)
SURS*Time			2.90**	2.54**
			(1.16)	(1.22)
SNT*Time			1.86	1.63
			(1.21)	(1.21)
i's Treated*Time	-0.01	-0.02		
	(0.78)	(0.78)		
j's Treated*Time	-0.27	-0.35		
	(0.83)	(0.84)		
SRS**i*'s Treated*Time			-0.21	-0.32
			(1.26)	(1.26)
SURS**i*'s Treated*Time			-2.32	-2.28
			(1.58)	(1.57)
SNT**i*'s Treated*Time			0.23	0.38
			(1.19)	(1.20)
SRS**j*'s Treated*Time			0.33	0.09
			(1.36)	(1.28)
SURS**j*'s Treated*Time			2.30*	2.31
			(1.18)	(1.42)
SNT**j*'s Treated*Time			-1.70	-1.75
			(1.21)	(1.23)
Constant	2.06***	1.82*	2.06***	2.32**
	(0.17)	(1.05)	(0.16)	(1.03)
Time-variant Charac.	No	Yes	No	Yes
Observations	346	346	346	346
R-squared	0.79	0.80	0.81	0.82
Number of id	173	173	173	173

Notes: Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. *i* indexes individual. *j* indexes informer. SRS, SURS, and SNT is the abbreviation for simple random sampling, systematically unaligned random sampling, and social network targeting, respectively.

Figure 1 Timeline

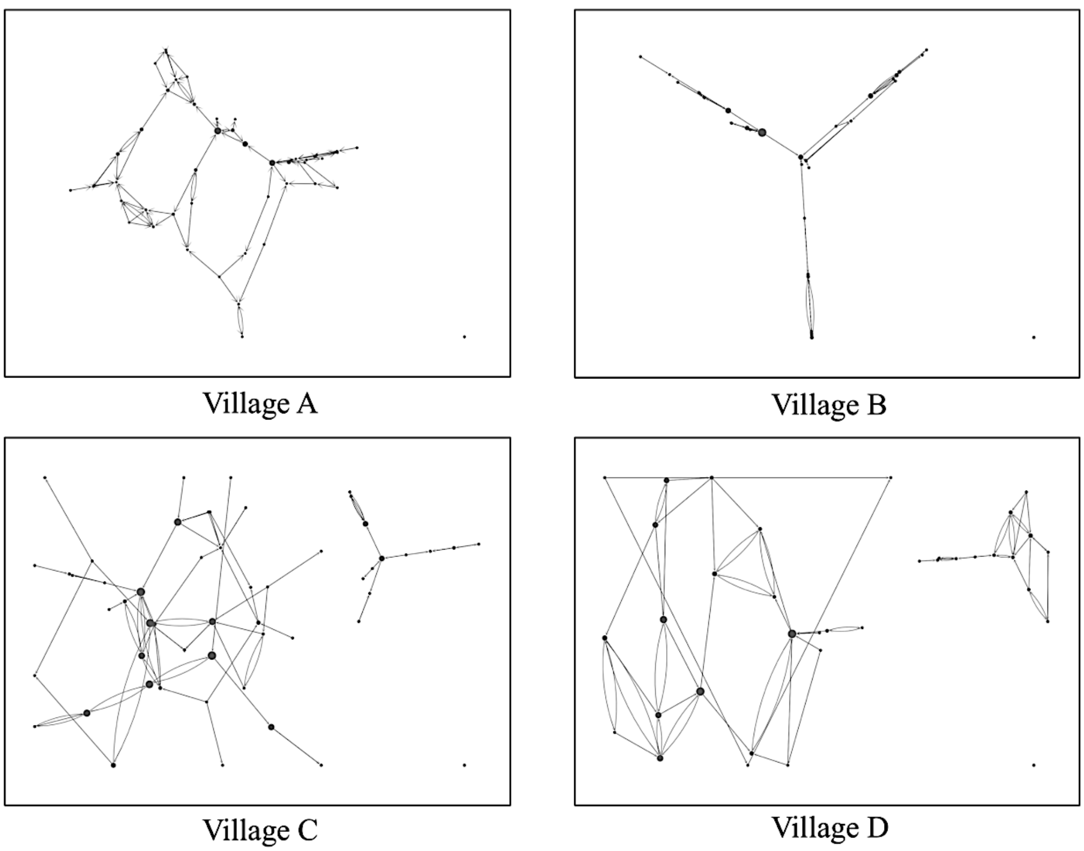
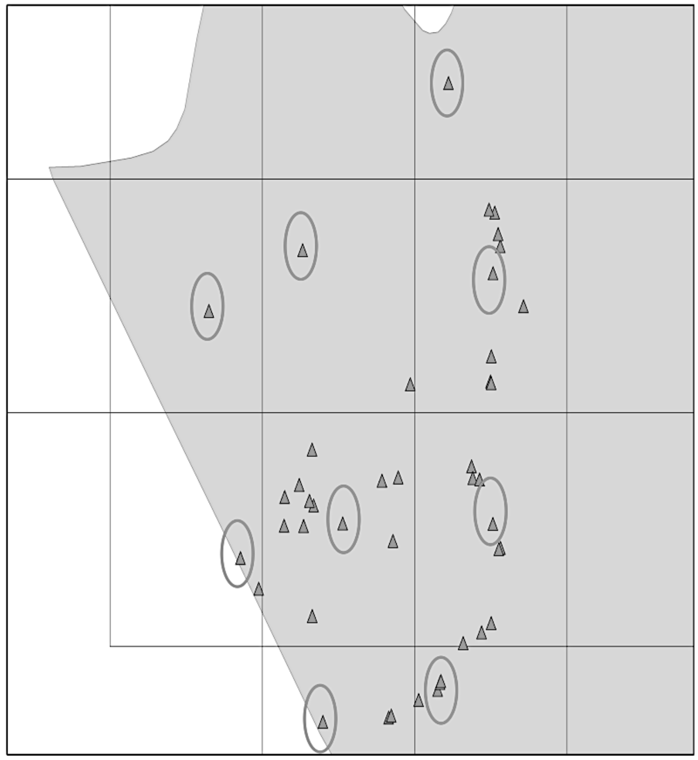


Figure 2 The Social Network of Each Village



Note: 1.5km x 1.5km grid

Source: From own survey

Figure 3 The Systematically Unaligned Random Sampling (SURS)

Appendix 1 BMPs Knowledge Test

I. Prohibited Elements

Q1 If imported shrimp contains some prohibited elements, EU, Japan, and the U.S., the major importers of Vietnamese shrimp, reject shrimp imports because the substance is harmful to the human. Do you know which chemicals are prohibited for use? (Yes/No)

1. Chloramphenicol
2. Enrofloxacin
3. Ciprofloxacin

99. I don't know

Q2 Choose prohibited elements among substances.

1. Sorbitol

3. Methionine
4. Ciprofloxacin
5. Lysine
6. Insorbitol
7. Enrofloxacin
8. Chloramphenicol
9. Bacillus licheniformis
10. Bacillus megaterium
11. Bacillus subtilis
12. Pediococcus acidilactici
13. Sodium selenite
14. Vitamin E

99. I don't know

II. Water Quality

Q1 Is the most suitable transparency when you measure transparency of your shrimp pond? *Answer the number (single-select)*

1. 20cm
2. 50cm
3. 30-40cm
4. 50-60cm
5. 1m20cm

99. I don’t know

Q2 What is the reason of 10cm transparency? (Yes/No)

1. Phytoplankton grows up considerably such that the water color becomes dark. In the water, too much organic substances exist. The bottom of the pond is dirty due to the feed surplus.
2. The water is clear because few phytoplankton exist in the water. The pond environment has poor nutrition. The use of chemistries decreases the number of phytoplankton. The water is polluted by the alum.

99. I don't know

Q3 What kind of problems may happen if transparency is 10cm? (Yes/No)

1. Oxygen is not enough in the early morning
2. The pH increases and fluctuates during the day
3. Natural feed for tiny shrimps is not enough
4. Shrimps grow up slowly
5. Shrimps become weak and more sensitive to diseases

99. I don't know

Q4 What kind of problems may happen if transparency is 50cm? (Yes/No)

1. Shrimps suffer stress and their ability of finding food is degraded
2. The algae in the bottom of the pond grow considerably
3. Shrimps are more sensitive to diseases
4. The NH3 concentration rises up

99. I don't know

Q5 What is the solution to 10cm transparency? (Multi-select)

1. Always maintain the high-water level (above 1.4 m)
2. Use the new water source with adequate number of phytoplankton
3. Use organic fertilizers
4. Use inorganic fertilizers
5. Use the bio products periodically
99. I don't know

Q6 What is the solution to 50cm transparency? (Multi-select)

1. Manage the amount of feed every day
2. Use the bio products periodically
3. Use the new water source with adequate number of phytoplankton
4. Use organic fertilizers
5. Always maintain the high-water level (above 1.4 m)
99. I don't know