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Drivers of organic farming: Lab-in-the-field evidence of the role of social comparison and information nudge in networks in Vietnam

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ABSTRACT

This study examines factors determining farmers' investment in organic farming using a contextualized lab-in-the-field experiment with 220 small household farmers in Northern Vietnam. We focus on the role of network structure, information nudge, and social comparison between farmers using three types of networks: circle, star and complete. Our results suggest that, on average, around 64% of the land is invested in organic farming in the complete network in which each farmer is connected to all of the others, while only about 57% of the land is invested in the circle and star network. Moreover, social comparison (i.e., information about the average investment) performs better in a circle network than in a star network. Finally, information nudges about the socially optimal investment could encourage farmers' coordination in all three networks, particularly in the complete network with an increase in organic investment up to 76%.

1. Introduction

Conventional farming is a widely used method worldwide to produce the majority of the food we eat. However, this type of farming technique is currently facing several issues that may threaten its future. It is well known that pesticides and fertilizers lead to serious health problems for consumers and farmers. For example, cancer, one of the most deadly diseases in the world today, is directly linked to pesticide adulteration of the food we eat (Rodgers et al., 2018; Horrigan et al., 2002). In recent years, we have observed a relative increase in the adoption of organic farming in several developed countries due to the heightened awareness of health problems caused by the consumption of contaminated foods and the adverse effects of environmental degradation. However, in many developing countries, conventional farming is still widely accepted since it helps to provide sufficient food for the population and generates a surplus for exports, even though this practice is becoming increasingly unsustainable, as revealed by declining crop productivity, environmental degradation, chemical contamination. In certain developing countries like Vietnam, the situation is even worse: farmers use pesticides overtly and without restraint.

According to the report of the Vietnamese Ministry of Agriculture and Rural Development (MARD) (August 2018), Vietnam imported 79 million USD worth of pesticides and raw materials (about 1800 billion VND), raising the import value of pesticides and raw materials in the first eight months of 2017 to over 660 million USD (over 15,000 billion VND), an increase of almost 47% over the same period in 2016. Statistics show that Vietnam is importing more and more pesticides and raw materials. The import of pesticides and plant protection chemicals has continuously increased over the last few decades due to the expansion of cultivated areas and the intensive cultivation of many crops. However, excessive use of chemicals in agriculture has caused severe consequences for both the soil and the water and the quality of agricultural products (Savci, 2012). Therefore, it is essential to encourage farmers to limit the use of pesticides and move toward more sustainable agriculture.

Several studies have shown that the low rate of organic adoption in

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several developing countries like Vietnam is because organic farming comes with many benefits (e.g., environmental protection, higher income, lower external inputs, etc.), but also comes at costs to farmers (e.g., lower yields, higher labor inputs, market barriers, certification, etc.) (Jouzi et al., 2017). Thus, institutional and economic supports (e.g., to market organic produces or subsidies for certification) are necessary to help lower the costs, reduce market barriers and thus help encourage organic farming adoption. However, financial supports like subsidies (e.g., organic certification) have not been easily accessed by small household farmers who produce over 70% of the world's food needs, especially for small household farmers in several developing countries (Wolfenson, 2013).

Besides economic incentives, the low rate of adoption of organic agriculture is due in part to the lack of information on the part of farmers about the risks of chemical products and the lack of methods and benefits (Conley and Udry, 2010; Vandercasteelen et al., 2020). Nevertheless, other research has shown that even if farmers personally know that applying more chemicals to their plants is harmful, they are still willing to use pesticides over time to ensure a high level of productivity (Aktar et al., 2009). Government and social media have provided information about the harmful effects of chemical inputs, environmental degradation and contaminated food, not only to farmers but to consumers as well, but, unfortunately, these interventions have not yet had a significant impact on farmers' decisions (FAO, 2017).

Moreover, the existing literature has suggested cooperative approaches organizing small agricultural producers in groups or networks to enhance market opportunities, train them on sustainable farming practices and help them engage in credit schemes that could efficiently drive smallholder farmers toward organic farming (Markelova and Mwangi, 2010; Ito et al., 2012; Suh, 2015). Thus, our paper aims to contribute to the literature by investigating how social and network factors could influence small household farmers' decisions concerning organic farming. In particular, we focus on the role of social networks (i.e., linkages between farmers), information nudge about social optimal organic farming investment and the role of social comparison between farmers. We tested these ideas via *a contextualized lab-in-the-field* experiment in 2019 with 220 small household farmers in eight different villages in four different provinces in Northern Vietnam. The context was established based on the definition of organic farming and the fact that we only had farmers not involved in organic farming in our sample.

The first objective of our experiment is to examine whether the social connections among farmers could lead to connections in their behaviors. There is a growing literature on theoretical and empirical studies that focus on the impact of networks on individuals' behaviors (Ferguson, 2007; Hogset and Barrett, 2010; Santos and Pacheco, 2011). According to the theory of social and economic networks, individuals link together in a network such as a network of friendship or neighborhood in which they can interact and exchange information with others (Granovetter, 1983; Golub and Jackson, 2010). In agriculture, farmers are often linked to farmers' networks such as neighborhood farmers, friends or agriculture organizations to share information, ideas and reflections on new farming methods. Consequently, social networks could be an effective way to diffuse information related to organic farming (Fafchamps et al., 2020).

Second, we introduce social comparison treatment into the experiment to test how social comparison (i.e., information about the average group investment in organic farming) impacts individual farmers' investment decisions. Some studies have indicated that social concern (e.g., revealing an environmental commitment to the others in the network) can be used as a factor to influence farmers' decisions to adopt organic farming (Dessart et al., 2019; Mzoughi, 2011). In our study, we consider an intra-group comparison in which each farmer observes his or her group's average level of investment. It is assumed that when farmers receive information about the average investment of their groups, a social comparison exists such that an investment that is lower than the average would harm farmers' outcomes; inversely, a positive impact is the result of an investment that is higher than the average.

We finally introduce information nudge treatment into the experiment. The idea of using information nudges to shape individual behavior has been aggressively studied in the literature (Hotard et al., 2019; Brandon et al., 2019; Sudarshan, 2017). Our study theoretically observes that all farmers would be better off at social optimum, but this optimum is challenging to achieve because every farmer has the incentive to deviate and free-ride on other investments. Thus, we provide the information nudge about the socially optimal investment of each farmer and the optimal investment of his/her direct neighbor to the other farmers to determine whether or not it would help encourage farmers to adopt a positive attitude toward organic agriculture.

The remainder of this study is organized as follows. In Section 2, we discuss the theoretical framework and present theoretical predictions. Section 3 describes the *lab-in-the-field* experiment, including treatment, experimental procedure, the sample, and additional experimental questionnaires. Results are presented in Sections 4 and 5. Section 6 is devoted to a discussion and conclusion.

2. Determinants of organic farming adoption

Organic agriculture is widely recognized as being more beneficial to the environment, ecosystems, and individual health than conventional agriculture (Tuomisto et al., 2012; Muneret et al., 2018). From an economic perspective, organic farming has been developed as a solution to avoid chemicals and stays close to nature, produces healthier foods and contributes to consumer well-being (Huang et al., 2002; Horrigan et al., 2002). Therefore, self-dependency in terms of inputs can increase the profitability of farms and provide many solutions to prevent the destruction of the environment, pollution and social imbalances (Liu et al., 2016; Cui et al., 2018).

However, organic farming is slow to be adopted today, and it may take decades to reach widespread adoption, especially in many developing countries. As a result, previous studies have been conducted to examine numerous factors that could influence farmers' choices to embrace organic farming, including economic incentives (e.g., subsidies), socio-psychological factors (e.g., perception, norms or nudge) and demographic characteristics.

Economic incentives (e.g., subsidies for organic output and input pricing) are found to be a critical factor in persuading farmers to transition to organic agriculture (Pietola and Lansink, 2001; Kerselaers et al., 2007; Breustedt et al., 2011). For instance, researchers discovered that organic farms with low yields per hectare tend to convert to conventional farming compared to those with higher returns (Pietola and Lansink, 2001; Breustedt et al., 2011). Thus, agricultural policies that cut output prices and compensate for revenue losses are essential to improve farmers' incentives to switch to organic farming (Pietola and Lansink, 2001).

In addition to the economic incentives, numerous psychological theories of behavioral change in the literature, such as Social Cognitive Theory (SCT) and Theory of Planned Behavior (TPB), have been employed to predict individual behavioral intention and change. In particular, the TPB indicated that individuals' behaviors are medicated through their intentions which could be predicted by their attitudes, norms and perceived behavioral controls toward a specific behavior or action (Ajzen, 1991; Fishbein and Ajzen, 2011). Besides, the idea of reciprocal determinism is central to the SCT since it describes how behavior, personal factors and environment could interact and shape individuals toward more sustainable behaviors (Bandura, 1989, 2001). For instance, self-efficacy (i.e., people believe that they are capable of performing a recommended action) and outcome expectancy (i.e., people perceive a particular outcome of engaging in a specific behavior) could significantly influence individuals to take pro-environmental actions (Jugert et al., 2016; Lauren et al., 2016; Collado and Evans, 2019). Thus, according to the SCT, when people believe about the effectiveness of taking a particular action could lead to an expected consequence (i.e., higher outcome expectancy) and/or they are confident about their capacity to obtain the expected outcome (i.e., higher self-efficacy), they are more inclined to change or modify their behaviors in the recommended direction.

Besides the SCT, Rogers's first model of diffusion, namely Diffusion Of Innovation (DOI), suggests that individuals' decisions to adopt an innovation depend on the diffusion process, consisting of different elements, such as observability (i.e., an innovation is visible to potential adopters), relative advantage (i.e., an innovation is perceived as being superior to current practice), compatibility (i.e., an innovation is perceived to be consistent with social-cultural and belief), trialability (i.e., an innovation can be experimented with on a limited basis) and complexity (i.e., an innovation is difficult to use and understand) (Rogers, 1995, 2003; Rogers and Singhal, 2003). Although the DOI is classic and widely established, many studies on Rogers's theory indicated that individuals' choices to adopt an innovation are based on information process (i.e., information about an innovation is disseminated) (Tornatzky and Klein, 1982; Fiske and Taylor, 1991). Moreover, the number of adopters or adoptions during a time period is also critical to encourage adoption rate throughout most of the diffusion process (Bass, 1969).

In agriculture, socio-psychological factors (e.g., attitude, social expectation, personal norms, etc.) are found to be essential in driving farmers' perceptions and attitudes toward more sustainable farming practice and management. Research suggested that information acquisition from various sources, such as education, information channels, extension services and workshops, could positively influence the adoption of new farming practices (Genius et al., 2006; Wheeler, 2008). Furthermore, farmers' positive attitudes toward organic farming (e.g., farmers believe that organic farming is beneficial to the environment, health, etc.) could ease their investment and management in organic farming (Läpple and Van Rensburg, 2011; Läpple and Kelley, 2013). Additionally, farmers' risk perceptions (i.e., perceived risks) associated with the organic farming investment are a significant obstacle to encouraging organic farming conversion (Kallas et al., 2010; Sapbamrer and Thammachai, 2021). Notably, farmers less concerned about risk are more likely to endure risky scenarios, such as high input prices, market price volatility and market demand (Sapbamrer and Thammachai, 2021). Moreover, some studies suggested that the adoption of organic farming is also constrained by social expectation and farmers' ability (i.e., self-efficacy) (Kaufmann et al., 2009; Läpple and Kelley, 2013). For instance, improving social acceptance of organic farming is needed to shift farmers to promote the uptake of organic farming (Läpple and Kelley, 2013).

Numerous researches have shown that farm size, agricultural experience and education are favorable predictors of organic farming adoption (Läpple and Van Rensburg, 2011; Hoang-Khac et al., 2021; Sapbamrer and Thammachai, 2021). For instance, well-educated farmers often have a greater capacity to comprehend and appreciate the benefits of organic agriculture (Hoang-Khac et al., 2021; Sapbamrer and Thammachai, 2021). On the other hand, farmers' age results in a negative association with organic farming adoption (Suwanmaneepong et al., 2020; Sapbamrer and Thammachai, 2021) since older farmers are usually more risk-averse and have less time to invest for the long-term than younger farmers (Sapbamrer and Thammachai, 2021). Moreover, younger farmers often have more receptive minds and a greater understanding of the organic farming practice and thus have more possibilities to assess organic farming than older generations.

3. Theoretical model and predictions

In this section, we present the theoretical model used to assess farmers' behaviors in optimally allocating their investment in organic and conventional farming. Theoretical modeling helps us to construct experimental design and formulate theoretical predictions, which are empirically tested using data from the lab-in-the-field experiment.

3.1. Model

Consider a landscape consisting of a fixed number of N farmers. Each farmer i has a set of neighbors that she is connected with, denoted $N_i(d)$ (i.e., network of i). Each farmer has a fixed amount of land L and will face a decision problem of optimally allocating her investment in conventional and organic farming. We assume that the investment is the percentage of lands that a farmer can allocate to either conventional or organic agriculture. Let c_i and x_i be the farmer i's investment in conventional and organic agriculture, respectively. Thus, we have $c_i \in [0, 1]$, $x_i \in [0, 1]$ and $x_i + c_i = 1$.

Consider $f(.)$ as an increasing and concave revenue function, $f' > 0$, $f'' < 0$ and $f(0) = 0$. We also assume that the gross revenue in organic farming is higher than the gross revenue in conventional farming since organic farming comes with may benefits like higher income and lower external inputs. Total gross revenue for conventional and organic farming is $h(c_i) + f(x_i)$ where $h(c_i) = \beta f(c_i)$ with $\beta \in (0, 1)$. However, when engaging in organic farming, farmers have to pay an extra amount γx_i (e.g., due to higher labor inputs, market barrier and certification). By substituting c_i with $1 - x_i$, we can write the agent i's total payoff function (or net revenue) as follows:

$$\pi_i(x_i) = \beta f(1 - x_i) + f(x_i) - \gamma x_i \tag{1}$$

Let us consider that farmers organize in groups or networks (i.e., cooperatives) that help them enhance market opportunities, access lessons about organic farming practices, and engage in credit schemes. Thus, according to the social network theory, an organic farmer i would also benefit from the organic investment of his or her direct neighbors, $\delta \sum_j^N d_{ij} x_j$ with $\delta > 0$. We can, for instance, imagine that an organic farmer who has good market information might inform his organic peers about when and where to market their crops to receive high profits. The benefits would come from the market information and experience and greater labor-sharing opportunities in their networks (e.g., farmers in a network can help each other cultivate organic products) (Munasib et al., 2011). The peer effect can also be interpreted as the descriptive norm in that farmer who adopts sustainable agriculture may motivate their neighborhood farmers to adopt it as well because most individuals are "conditionally cooperative", i.e., people contribute to public goods only if others do so as well (Dessart et al., 2019).

Our model also takes the social comparison mechanism in which an organic farmer receives information about the average level of organic investment in the network into account. We assume that farmer i, who invests more in organic farming than the average of his or her group, would earn an amount $\eta(x_i - \frac{1}{N}\sum_j^N x_j)$ where $\eta > 0$, otherwise he or she would lose an amount $\eta(\frac{1}{N}\sum_j^N x_j - x_i)$. From a social perspective, the social comparison could be interpreted as the social factors such as social signaling or social norm that affect farmers' behaviors. Regarding social signaling, improving public image and status helps motivate farmers to adopt more sustainable practices such as organic and integrated farming (Dessart et al., 2019; White et al., 2019). The group's average investment could be seen as a norm or an expected investment amount. Those who invest more than this level would benefit from social signaling. On the contrary, farmers who invest less than the expected amount of investment would suffer from public punishment (e.g., public shaming).

Thus, we have farmer i's total payoff function as follows:

$$\pi_i(x_i) = \beta f(1 - x_i) + f(x_i) - \gamma x_i + \delta \sum_j^N d_{ij} x_j x_i + \eta(x_i - \frac{1}{N}\sum_j^N x_j) \tag{2}$$

where, $f(x) = a\,x - bx^2$, $a, b > 0$, $a > 2b\,x$ and $\delta, \eta > 0$.

Let $\mathrm{x}^* = (x_1^*, x_2^*, \ldots x_n^*)$. In the matrix formula, we have

$$\mathrm{x}^* = \frac{\alpha}{2(1+\beta)b}(I - \Phi)^{-1}\iota. \tag{3}$$

where, $\alpha = (1-\beta)a + 2\beta b - \gamma + \eta$, ι is the $n \times 1$ column matrix of one and $\Phi = \frac{\delta}{2(1+\beta)b}\mathrm{D}$ (see the detailed in Appendix A).

3.2. Theoretical predictions

According to Eq. (3), the equilibrium of organic investment depends on two terms: the fraction $\frac{\alpha}{2(1+\beta)b}$ and the network structure $\Phi = \frac{\delta}{2(1+\beta)b}\mathrm{D}$. This result suggests that the interconnections among farmers (adjacent matrix **D**) would have a positive impact on farmers' organic investment decisions since $\delta > 0$, which means that an agent who is connected to more organic neighbors (i.e., a neighbor who invests in organic farming) is more likely to invest in organic farming. In addition, the farmers' organic investment would also vary across different types of network structures, which are represented by the matrix **D**. We therefore establish our first prediction as follows:

3.2.1. Prediction 1 (role of networks)

Interconnection among agents via their social networks positively impacts their investment in organic farming. This impact varies across three different types of networks: star, circle, and complete.

In the experiment, we test our results with three different types of networks: a star, circle and complete network (see Fig. 1. The complete network is a decentralized network, which is the most straightforward situation in real life, where farmers care about the behaviors of all other farmers in their groups/communities. The circle network is also a decentralized one but with fewer connections, in which each farmer cares only about his/her two closest neighbors (i.e., two most important neighbors/friends). The star network is a centralized network where farmers care about the most important farmer in the network, the central farmer (i.e., the center). According to the theoretical model, we expect that network connections would positively impact individual behavior. The most substantial impact on farmers' organic investments would come from the complete network since it is the most connected network in this study.

Remark that the effect of social comparison on the equilibrium is captured by the parameter η. A higher value of η results in a higher equilibrium level of investment x^* (see Eq. (3)). Thus, we would expect that social comparison positively impacts farmers' organic investments. Since the effect of social comparison is independent of the network structure at the equilibrium (Eq. (3)), we would expect no significant difference in the effect of social comparison on individual behavior across networks. Our second prediction is as follows:

3.2.2. Prediction 2 (role of social comparison)

Social comparison positively impacts farmers' investments in organic farming. This impact is independent of network structure.

We observe that when optimal investment is higher than its equilibrium level, i.e., $\hat{x} > x^*$, then the farmers' payoffs at the social optimum are also higher than their payoffs at the Nash equilibrium. This means that all farmers would be better off if they coordinated at the social optimum. However, this Pareto optimum will not be easily achieved because farmers have incentives to deviate from the social optimum and earn higher payoffs if they know that others coordinate at the social optimum (see Table A.1 in Appendix A for the detailed numerical illustration). Thus, it is necessary to verify whether introducing the nudge information would increase the coordination among farmers. In our experiment, the nudge information (i.e., information about the socially optimal investment) is introduced in the case where farmers receive the social comparison treatment since we want to compare the effectiveness of social comparison and the combination effect (with both social comparison and information nudge) in promoting organic agriculture. This result leads us to the following prediction:

3.2.3. Prediction 3 (role of social comparison combined with information nudge)

Combining social comparison and information nudge has a positive impact on farmers' organic investments. This impact varies across different network structures: star, circle and complete.

4. The lab-in-the-field experiment

4.1. Treatments

There are two treatments in our experiment: social comparison (Sc) and the combination of social comparison and nudge (ScNd). The control is the *no treatment*, i.e., neither social comparison nor the combination of social comparison and nudge. We test these two treatments and the control in four different types of network structures (empty network, circle, star and complete network).

The control is the *no treatment* where subjects were invited to participate in a land management game without social comparison and nudge, but, even then, a network effect exists that influences the subjects' payoffs depending on the network structure (star, circle or complete network). We tested a total of 11 different treatments in the experiment (see Fig. 2). These 11 treatments were tested during 22 different experimental sessions, which means that each treatment was tested twice, and only one treatment was tested in each session. In the treatment "social comparison" (Sc), information about the average group investment was given. Hypothetically, subjects' payoffs are negatively (or positively) affected by the average group investment if their organic investments are lower (or higher) than the average. In the treatment "social comparison and nudge" (ScNd), subjects receive both information about the average group investment and the information nudge. The nudge for subjects is provided through information about the socially optimal investment for them and their direct neighbors.

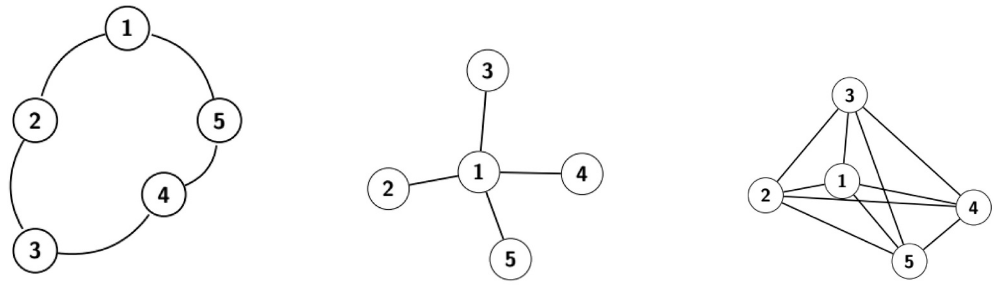
4.2. Experimental procedure

The experiment was initially run with a pilot in June 2019, followed by the field experiment in August 2019. The pilot was run with two groups of small household farmers (five subjects per group). In the pilot, farmers were assigned to a complete network and the "ScNd" treatment. The objective of the pilot was to test some outcomes of the theoretical predictions, our parameter assumptions, as well as the experimental instructions. The experiment was conducted using an IPad for each participant.[2]

The experiment consisted of four parts. In the first part, a standard lottery-choice task, identical for all sessions, was implemented to capture the subjects' sensitivity to risk (see details in Appendix B). In the second part, subjects were invited to participate in a simple organic investment game. The second part, also identical for all sessions, concerned the case of the empty network (B), no social comparison and no nudge (N) (i.e., no treatment) (see Fig. 2). The third part of the experiment differed from one treatment to another (see Fig. 2). The third part of the experiment concerns one of the 11 treatments mentioned in Fig. 2. There were 22 experimental sessions since each treatment was tested twice in two different villages. There were two groups of subjects (five subjects per group), and all of them were assigned to the same treatment. In the last part of the experiment, qualitative and quantitative information was collected from the subjects using survey questions. This part was identical for all sessions. A detailed experimental procedure is reported in Appendix B.

Note that in the second and third parts of the experiment, we chose a repeated game design in which subjects make repeated decisions in a single treatment, with earning feedback between rounds. The game was

[2] There were assistants during the experiment to help farmers use the IPad and understand the experimental instructions. During the experiment, only for farmers who had difficulty with the Ipad, the role of assistants in all 11 treatments was limited to reading instructions and questions and putting answers on the IPad like in a face-to-face interview.



(a) Circle (b) Star (c) Complete

Fig. 1. The three different network structures for $N = 5$.

Treatment variables	Empty network (B)	Network		
		Complete (Cp)	Circle (Cr)	Star (St)
No treatment (N)	-	Cp	Cr	St
Social comparison (Sc)	BSc	CpSc	CrSc	StSc
Social comparison and Nudge (ScNd)	BScNd	CpScNd	CrScNd	StScNd

Fig. 2. Two treatments and control in four different types of networks (11 treatments).

repeated five times for the second part and ten times for the third part. After each round, subjects assigned to a particular network structure received feedback of their direct neighbors' decisions depending on the different network structures. For instance, subjects in the circle network can observe the investment decision of their two direct neighbors, while those in the complete network have four direct neighbors and consequently receive the feedback of four other farmers' decisions. In the presence of treatments, subjects assigned to the "Sc" and "ScNd" treatments received information about the average group's investment after each round. Subjects assigned to the "ScNd" treatment received additional information about the socially optimal investment of all members in their group at the beginning of each round.

4.3. *Additional experimental questionnaires*

In addition to the preliminary experiments, we collected information from participants on a variety of socio-demographic characteristics. In particular, we collected information on age, gender, farm size, household size, type of residence, individual and household income, health, the highest level of education, marital status, number of children in the household, and individual attitudes toward risks, etc.

We also elicited information on several questions related to environmental concerns via 15 New Ecological Paradigm (NEP) questions to help us to identify the individual perceptions toward the environment (details of the NEP questions in Table D.4 in Appendix D) (Dunlap et al., 2000). The total NEP score is the aggregate score of these NEP questions, in which Cronbach's alpha is equal to 65.45%[3] and questions number 2, 4, 6, 8, 10, 12, 14 (even number questions) are reversely coded (Cronbach, 1951). There were also several other questions related to environmental concerns to capture participants' opinions and concerns toward the environment. All questionnaires are available in the Supplementary Materials.

4.4. *Sample*

In total, 220 small household farmers took part in the lab-in-the-field experiment. The 22 experimental sessions were divided equally across geographic locations, with ten farmers (five farmers per group) in each experimental session. The participants were all farmers living in rural areas, aged from 16 to 78 years, across eight villages of four different provinces (Vinh Phuc, Hung Yen, Hai Duong, Ha Noi) in Northern Vietnam (see Fig E.3 in Appendix E for the area of the experiment). These provinces around Hanoi were chosen because they produced the most agricultural products (vegetables, rice and fruits) for Northern Vietnam. The experiments were conducted in the village where the participants lived.

Farmers were 52-years-old on average. A total of 67% were women, and 39.1% were heads of households. They produced mainly vegetables (74.5%) and rice (52.7%). Only 33.2% and 27.7% of the farmers produced fruits and corn, respectively.[4] Most of the farmers in our sample were small household farmers with an average farm size of 2466 m^2. The following sections will present the descriptive statistics and analyze the average and individual decisions for the 11 treatments mentioned above.

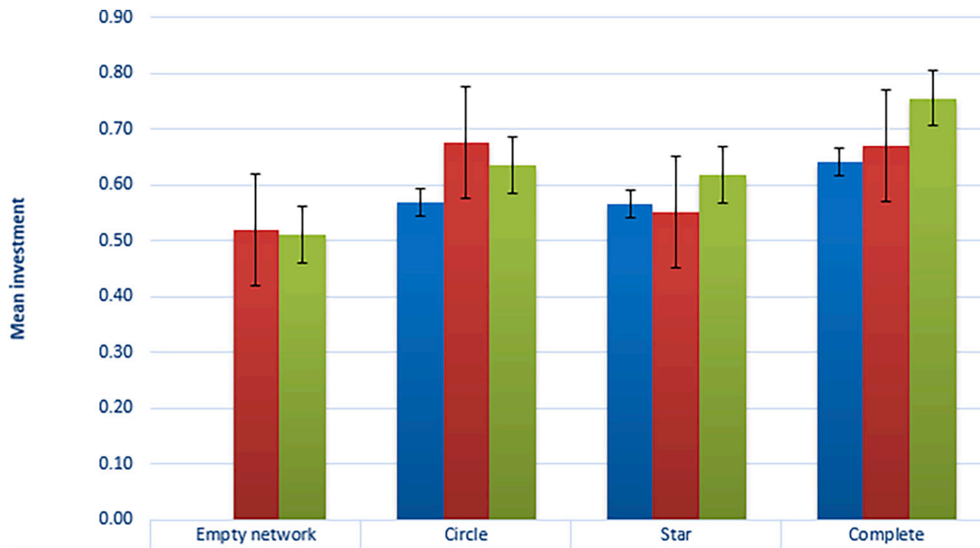
5. Analysis of average investment decisions

In this session, we undertook an analysis of the average investment per network and treatment. It should be recalled that the decision variable is the proportion of land investment in organic farming, ranging from 0% to 100%. The rest, which is not invested, is devoted to conventional farming. The distribution of the percentage of land invested in organic farming per network and treatment is shown in Table D.1 (in Appendix D) and in Fig. 3.

We examine the differences across treatments and networks using the non-parametric test. The Wilcoxon Rank Sum test (or Mann-Whiney

[3] Cronbach's alpha is equal to 65.45% in the reliability test, which suggests that 65.45% of the variance in the score is reliable.

[4] Note that the sum of these percentages is greater than 100% since each farmer may produce more than one crop.



	Empty network	Circle	Star	Complete
No treatment		0.57	0.57	0.64
Sc	0.52	0.68	0.55	0.67
ScNd	0.51	0.64	0.62	0.76

Fig. 3. Histogram of mean investment per network and per treatment.[11]

U test) was used to compare the choice of participants in two treatments and no treatment across four different networks (Mann and Whitney, 1947). The non-parametric test is presented in Tables 1 and 2.

5.1. Role of networks

In the situation of no treatment, which means that there is no social comparison or information nudge treatment, we observe that farmers invest more in organic farming in the presence of more network connections: On average, 64.1% of the land is invested in organic farming in the complete network in which each farmer is connected to all of the others, while only about 57% of the land is invested in the circle and star network in which there are fewer connections between farmers (Fig. 3 and Table D.1 in the Appendix). This result is confirmed by the Wilcoxon Rank Sum test (Table 1). In particular, farmers in the complete network invested an average of 7% more in organic farming than the circle and star networks.

However, surprisingly, there is no significant difference in organic investment between the circle and the star network (second column of Table 1). If we break down the farmers in the star network into two groups - farmers in the center and the corner of the star - we then observe that farmers in the center seem to invest more than the corner ones in organic farming, according to the Wilcoxon test statistic reported in Table D.2 (in Appendix D). The results indicate that farmers in the center invested an average of 10% and 13% more in organic farming than the circle and farmers in the corner, respectively. However, there is only one central farmer in the star network. This result leads to the fact that the corners have only one direct neighbor (i.e., the network connection is weak), and thus a weaker network (i.e., with fewer connections) results in a lower level of organic investment.

Therefore, in the case without any treatment, we could observe a positive impact of the network on farmers' investment decisions in organic farming. This result suggests that farmers seem to be influenced by their direct neighborhood farmers' decisions, and the greater number of direct links/connections means a higher level of organic investment. Prediction 1 is therefore validated.

5.2. Role of social comparison

In the presence of social comparison where farmers received information about their average group investment after each round, the circle and complete networks result in a sufficiently high level of organic investment (about 68% for the circle network and 67% for the complete network compared to 57% and 64% in the case without social comparison) (Fig. 3). Fig E.2 suggests that the social comparison treatment works effectively in the circle and complete networks (decentralized network) but that it is less effective in the star network (centralized network). Farmers in the star network invest just a little in organic agriculture (only 55.1% on average). Our theoretical prediction indicated that the effect of social comparison on farmers' decisions does not depend on the network structure. However, we observe that this is not the case in the experiment, even when every farmer in the same network received the same information about his or her group's average investment. One interpretation could be that in the experiment and the information about the average group investment, farmers assigned to the "Sc" treatment received different types of feedback about their direct neighborhood investment depending on the network structure. For instance, farmers in the complete network could observe all of the others' decisions, while those in the circle network could only observe the decisions of two direct neighbors. Thus, the social comparison treatment could play an essential role in a network with fewer connections.

In a star network, after each round, both farmers in the center and corner received information about the average organic investment of their group (i.e., the same information). The difference is that the center had information about the decisions of all the other farmers in the network, while the corners observed only the center's decision. Fig E.2 (in Appendix E) suggests that both the centers and corners followed the average group investment because of the asymmetric information. During the last period, the decisions of the corners seemed to converge to the Nash equilibrium (about 55% at the Nash equilibrium), while the centers followed the average group decision instead of choosing the Nash equilibrium strategy, i.e., about 71% of land invested in organic farming (Table A.1 in Appendix A). This result also suggests that the center seems to be more influenced by the average group decision than expected from the theoretical prediction.

Therefore, we can observe that the social comparison treatment works more effectively in a decentralized network with fewer connections (like a circle network) but performs worse in a centralized network (like a star). Therefore, Prediction 2 is only partially validated.

Table 1
Difference-in-mean between different network structures per treatment (Wilcoxon Rank Sum test).

	No treatment			SC			SC & Nudge		
	Circle	Star	Complete	Circle	Star	Complete	Circle	Star	Complete
Empty network	–	–	–	−0.16*** (0.000)	−0.03** (0.026)	−0.15*** (0.000)	−0.13*** (0.000)	−0.11*** (0.000)	−0.25*** (0.000)
Circle	–	0.00 (0.858)	−0.07*** (0.000)	–	0.13*** (0.000)	0.01 (0.778)	–	0.02 (0.179)	−0.12*** (0.000)
Star	–	–	−0.07*** (0.000)	–	–	−0.12*** (0.000)	–	–	−0.14*** (0.000)

Notes: The table reports the difference-in-mean and the p-value of the Wilcoxon Rank Sum test in parentheses. SC stands for the social comparison. * $p < 0.05$; *** $p < 0.01$.

Table 2
Difference-in-mean between treatments per network structure (Wilcoxon Rank Sum test).

	No network		Circle		Star		Complete	
	SC	SC & Nudge	SC	SC & Nudge	SC	SC & Nudge	SC	SC & Nudge
No policy	–	–	−0.11*** (0.000)	−0.07*** (0.000)	0.02 (0.156)	−0.05*** (0.000)	−0.03 (0.105)	−0.11*** (0.000)
SC	–	0.01** (0.013)	–	0.04** (0.043)	–	−0.07*** (0.000)	–	−0.08*** (0.000)

Notes: The table reports difference-in-mean and the p-value of the Wilcoxon Rank Sum test in parentheses. SC stands for the social comparison.** $p < 0.05$; *** $p < 0.01$.

5.3. Role of social comparison combined with information nudge

In the case of an empty network, according to the results in Table 2, the value 0.01 in the second column suggests that the farmers in the "Sc" treatment invest 1% more in organic farming than the ones in the "ScNd" treatment. This difference is statistically significant at the 5% level, suggested by the Wilcoxon Rank Sum test with the $p - value = 0.013$. This result means that in the case of an empty network, the additional information nudges about the socially optimal investment in organic farming results in a slight reduction in investment compared to the social comparison. This observation is in line with our theoretical result that the social optimum (46.11%) is lower than the Nash equilibrium (47.22%) (see Table A.3 in Appendix A).

While the "Sc" treatment performs more efficiently only in the decentralized network (like a circle network), the nudge implementation performs well in encouraging farmers' coordination in all three networks (circle, star and complete network), especially in the complete network with an increase in organic investment up to 76% (see Fig. 3). This is because farmers are more likely to coordinate with the nudge information in a more strongly connected network (like a complete network) than a weaker connected network (like a circle network). One interpretation could be that in a complete network, each farmer receives nudge information and observes the decisions of all the others (because they are all connected to each other). In contrast, in a circle network, each farmer receives nudge information about the optimal decision of two other farmers (who are the two direct neighbors) and observes only these two farmers' decisions. Thus, farmers in a complete network are more likely to cooperate with the nudge information when their action is observed by all other farmers in the network (Brick et al., 2017). Consequently, these observations confirm Prediction 3.

6. Analysis of individual decisions

In this section, we analyze the impact of different treatments on individual decisions, x_i. We adopt the fractional regression model to deal with dependent variable, which is defined on the closed interval $x_i \in [0, 1]$ (Papke and Wooldridge, 1996; Ramalho et al., 2011). Fig E.1 in Appendix E presents the distribution of individual investment decisions across different network structures. Detailed discussions about the fractional regression model are presented in Appendix C. Descriptive statistics are reported in Table D.3 (in Appendix D).

6.1. Role of networks

The results in Table 3 suggest that in the case of no treatment, *Complete * NoTreat* has a positive and significant impact on individual decisions compared to the circle network (i.e., *Circle * NoTreat* is a base category) across the three models in Table 3. This result is in line with the results on the average decisions reported in Table 1. The results also suggest that the *Star * NoTreat* is not significantly different from the *Circle * NoTreat*, while *Circle * NoTreat* is positive and statistically significant compared to the empty network. This result suggests that farmers are positively influenced by their direct neighborhood's organic investment, even in the case of no treatment. Thus, the network could play an essential role in promoting investment in organic farming. Therefore, Prediction 1 is validated since the results show that a network with more connections (i.e., complete network) is more effective in encouraging organic investment than the one with fewer connections.

Since the *Neigbor*$(t-1)$ have different impacts on individual behavior depending on the different network structures (i.e., farmers in different networks and different locations in a particular network have different numbers of direct neighbors), we break down our estimation into four different network structures presented in Table 4. We observe that *Neigbor*$(t-1)$ is statistically significant at the 5% level in only the circle network. We observe the statistically significant coefficient of *Center * Neighbor*$(t-1)$ in the star network. Our results in Table 3 show that farmers in the complete network invest more in organic farming than those in circle and star network, but the variable *Neighbor*$(t-1)$ in Table 4 is not significant in the complete network. This result indicates that farmers in dense networks do not care about their neighborhood investments. In other words, farmers who belong to a network with many neighbors invest more in organic farming because of the peer effect but perhaps because of psychological factors like altruism or because they know that their investment could benefit others. This result therefore suggests that farmers care more about their neighborhood investment (i.e., peer influence) in sparse networks (i.e., network with

[1] Sc stands for "social comparison" treatment. ScNd stands for "social comparison and information nudge" treatment.

Table 3
Estimation results of the pooled sample.

	Fractional regression model		
Variables	(1)	(2)	(3)
Star*NoTreat	−0.007	−0.007	0.005
	(0.128)	(0.129)	(0.149)
Complete*NoTreat	0.304**	0.307**	0.284*
	(0.133)	(0.134)	(0.163)
Empty network*Sc	−0.193*	−0.195*	−0.222
	(0.106)	(0.107)	(0.167)
Circle*Sc	0.463***	0.468***	0.534***
	(0.126)	(0.127)	(0.140)
Star*Sc	−0.072	−0.072	−0.032
	(0.136)	(0.137)	(0.209)
Complete*Sc	0.437***	0.441***	0.384**
	(0.104)	(0.105)	(0.152)
Empty network*ScNd	−0.236*	−0.238*	−0.120
	(0.136)	(0.138)	(0.202)
Circle*ScNd	0.282***	0.284***	0.404***
	(0.071)	(0.071)	(0.103)
Star*ScNd	0.207*	0.209*	0.267
	(0.115)	(0.115)	(0.165)
Complete*ScNd	0.853*	0.861*	0.802*
	(0.485)	(0.488)	(0.466)
Control variables			
Period		0.070***	0.070***
		(0.008)	(0.008)
Farm size (in log)			−0.063*
			(0.037)
Injunctive norm			0.015**
			(0.004)
Intercept	0.277***	−0.106	−0.724
	(0.101)	(0.103)	(1.000)
Observations	2200	2200	2200
Number of farmers	220	220	220
Log pseudo-likelihood	−1446.20	−1435.84	−1430.95
Pseudo R^2	0.016	0.023	0.026

Note: The dependent variable is the individual investment. Regressions with Circle*NoTreat which is circle network with no treatment, is a base category. NoTreat is no treatment. Sc and ScNd stand for the social comparison and social comparison & nudge treatment, respectively. Control variables are not reported including NEP, Female, Age, Education, Health, Individual income, Risk investment, Communist, Farmer association, which are not significant at 10% level.Bootstrapped standard errors in parentheses with 500 bootstrap replications. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 4
Estimation results of sub-groups of network structures.

	Fractional regression model			
Variables	Empty network	Circle	Star	Complete
Neighbor (t−1)		0.610***	0.083***	0.711
		(0.161)	(0.014)	(0.964)
Center			−0.507**	
			(0.262)	
Center*Neighbor (t−1)			0.966***	
			(0.266)	
Sc		0.315***	−0.051	0.217
		(0.109)	(0.175)	(0.261)
ScNd	0.014	0.209	0.225***	0.466
	(0.331)	(0.243)	(0.076)	(0.351)
Control variables				
Period	0.006*	0.055***	0.030***	0.097**
	(0.003)	(0.003)	(0.002)	(0.040)
Female	−0.151	−0.100	−0.602***	0.464***
	(0.210)	(0.302)	(0.059)	(0.115)
Age (in log)	0.280	0.139	−0.262***	1.793
	(0.801)	(1.035)	(0.081)	(1.126)
Health				
Good	0.013	−0.196	−0.168***	0.395**
	(0.254)	(0.301)	(0.015)	(0.177)
Very good	0.057	−0.102	−0.021	0.682**
	(0.284)	(0.230)	(0.047)	(0.264)
NEP	0.004	0.015	−0.018***	−0.022
	(0.012)	(0.011)	(0.005)	(0.020)
Injunctive norm	0.145	0.612**	0.092	0.694***
	(0.179)	(0.281)	(0.191)	(0.110)
Intercept	−2.101***	−0.645	2.497***	−9.021***
	(0.614)	(0.975)	(0.402)	(2.644)
Observations	400	540	540	540
Number of farmers	40	60	60	60
Log pseudo-likelihood	−276.19	−341.72	−359.45	−311.09
Pseudo R^2	0.003	0.029	0.017	0.053

The dependent variable is the individual investment. Regressions with no treatment as a base category. Control variables are not reported, including Individual income, Risk investment, Education, Farm size, Communist, Cooperative and Farmer association, which are not statistically significant at the 10% level. The detailed estimation results are reported in Table D.6 in Appendix C. Bootstrapped standard errors in parentheses with 500 bootstrap replications. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

fewer connections) than dense networks (i.e., network with more connections).

6.2. Role of social comparison

In the presence of the “Sc” treatment, the results in Table 3 show that the *Circle* * *Sc* and *Complete* * *Sc* are positive and significant, while *Star* * *Sc* is not significant and *EmptyNetwork* * *Sc* is negative and significant. This result suggests that the “Sc” treatment plays a role in promoting organic farming, but the effects of “Sc” are different in different network structures. The non-parametric test also confirms this result in Table 2.

According to the estimation results in Table 4, we find that the social comparison treatment is positive and significant only in the circle network. Fig E.2 shows that social comparison also has a positive impact on individual decisions in both circle and complete networks. This result suggests that the social comparison treatment positively impacts farmers’ investments in organic farming in the complete network, but its impact is not statistically different from the complete network without treatment.

Our results confirm that in the circle network, farmers who received the social comparison treatment allocated a higher percentage of lands to organic farming than farmers in other types of network structures. It should be noted that the circle and complete network are both decentralized networks, but each agent in the complete network has more connections compared to the circle. While the circle and complete networks are decentralized, the star represents the centralized network in which all agents are connected to the center, and there is no link between individuals in the corner. In our experiment, each farmer in the circle network only had two direct neighbors, and he or she could only observe the investment decisions of two direct neighbors after each round. However, in the complete network, each farmer is linked to all others, and he or she could thus observe all the others’ investment decisions even without social comparison. In the star network, only the centers could observe all the other farmers’ decisions. Thus, this implies that the social comparison does not significantly impact the individual investment in organic farming in the star and complete networks. Consequently, Prediction 2 is partially validated: the “Sc” treatment performs better in the decentralized network with fewer connections (like the circle network).

6.3. Role of social comparison combined with information nudge

We observe that the “ScNd” (social comparison combined with information nudge) treatment does not seem to perform well in the empty network but provides a positive and significant impact on farmers’ investments in organic farming in the presence of a network (Table 3). Table 3 shows that there is a negative impact of *EmptyNetwork* * *ScNd* on individual behavior compared to the baseline, which is *Circle* * *NoTreat*. Moreover, the first column of Table 4 confirms this result by indicating that the impact of "ScNd" on individual organic investment in the empty network is negligible. This result is in line with the theoretical prediction that there is no significant difference between the socially optimal investment and the Nash equilibrium in the empty network (Table A.3 in Appendix A).

The results in both Tables 3 and 4 indicate that in the presence of network connections, the treatment "ScNd" has positive and significant impacts on farmers' investments in organic farming in an only star network. This result suggests that it would be more efficient to provide the combination treatment to a centralized network (i.e., star network) rather than a decentralized one (i.e., circle and complete networks). Thus, this result aligns with our previous finding that farmers seem less likely to care about their neighborhood investment, especially when they are in a complete network. Since they care less about others, the nudge information about their optimal investment and their neighbors (e.g., in a circle network, the information is "the optimal decision for the whole group: each farmer chooses X equal to 83%".) could not significantly drive them to the socially optimal investment.

However, in the case of a star network, we observe that central farmers' investments strongly influence corner farmers in a star network (i.e., the interaction term *Center* * *Neighbor*$(t-1)$ is positively significant). Without information about the socially optimal investment, central farmers seem to invest less than the corner farmers in organic farming (i.e., variable *Center* is negatively significant). In a star network, the information displayed to farmers is "the optimal decision for the whole group is: Player 1 chooses X equal to 100%, and four other players choose X equal to 70.23%". This information helps drive the central farmers to invest more and thus increase the whole group's investment. Prediction 3 is therefore partially validated: the social comparison combined with information nudge performs well in only centralized networks like the star network.

7. Discussion and conclusion

Our results suggest that more connections (or links) in the network could result in higher investment in organic farming. This result is in line with the literature that reports that participants are more likely to coordinate in the presence of a network structure: a network with more connections is better than one with fewer connections in facilitating coordination (McCubbins et al., 2009). This result suggests that the network-based approach could be considered as a cost-effective method for the policymaker to incentivize the adoption of organic agriculture or new environmentally-friendly agricultural practices (Beaman et al., 2021).

As suggested in the existing literature, the intra-group comparison can lead to stronger cooperation in the public good provision (Bohm and Rockenbach, 2013). In our study, we also investigate the effect of intra-group comparison (i.e., social comparison treatment), but in the context of organic farming and in the presence of the network (i.e., connections exist among individuals). We find that the social comparison treatment significantly impacts farmers' organic investment decisions in organic farming in a circle network. In a complete network, when every farmer can fully observe all other farmers' decisions, providing social comparison treatment cannot sufficiently help promote the organic investment since the comparison effect among individuals in the network dominates the comparison effect of the social comparison treatment. Therefore, the results suggest that social comparison can be used to incentivize farmers to cooperate by investing in organic farming more effectively in a decentralized network with fewer connections (like a circle network).

In a network where only one farmer can fully observe the others' decisions (i.e., farmers in the center of the star network), the central farmers perform worse than expected in our theoretical prediction. In other words, the central farmers seem less likely to care about the corners since they invest less on average than the corner farmers. However, the decisions of central farmers in a star network are a good driver that could be used to promote the investment decisions of corner farmers since the corner farmers care a lot about the decision of the center. In the case of social comparison combined with information nudge treatment, the information nudge helps increase the investment decision of the central farmers and thus encourages farmers in the star network to move toward more environmentally friendly agriculture. Therefore, future studies would be more interesting to investigate this issue in greater detail, perhaps with two or more farmers in the center of the network (e.g., a bridge network). In our model, we have only one farmer in the center, and this could therefore make them less likely to sustain their behaviors when they observe that all the other farmers in the network have chosen a low level of organic investment.

In order to capture the causal effect of networks on farmers' behaviors, we consider the organic investment game with the given network structures (exogenous network) and allow the network to varying. Future studies should also take the endogenous structure of the network into account to capture which network pattern could result in a higher level of adoption of organic agriculture. Our results suggest a possibility of a *crowd in* effect since the effect of both social comparison and information nudge exceeds the effect of social comparison (Brandon et al., 2019). The mechanism of *crowding in and out* in social nudges (social comparison and information nudge) deserves our attention since it may have important implications in promoting sustainable agriculture.

One major issue concerns the recommendations that could be adopted to design public policies. They would be based not only on subsidies but more essentially on the information given to farmers (Van Campenhout et al., 2021). Firstly, it is crucial for farmers to understand the importance of their social links. In many instances, neighborhood farmers or local agricultural organizations are valuable sources of knowledge, information and advice for farmers. Consequently, policymakers and/or individuals themselves should always try to establish a channel for local farmers to promote farmer-to-farmer links. Moreover, agricultural extension services (locally or virtually) (e.g., mobile digitization extension services) could be pivotal to fostering organic agriculture cultivation. For instance, virtual extension services could facilitate farmers to get access to up-to-date information on current government plans and timely advice from scientists and specialists on their organic production.

Secondly, it is always challenging to observe the actual network structure in reality, and farmers cannot fully observe their neighbors' behaviors, actions, or decisions. In this situation, providing social comparison treatment like information about the average organic investment of the local groups or communities to farmers could stimulate self-evaluation and competition and could thus help incentivize farmers to behave positively towards organic farming. Finally, timely reminders about the importance of organic agriculture and the socially optimal organic investment (i.e., information nudge) can help increase farmers' awareness about organic agriculture and help them maintain commitments and schedules (Fabregas et al., 2019). As a result, it helps to nudge them towards bridging the gap between their intentions and actions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Network game and numerical illustration

A.1. Network game

Let us consider that there are N farmers; a typical farmer is denoted by i. Let $\mathbf{D}$ be an $N \times N$ adjacency matrix; its element d_{ij} represents the relationship between farmer i and farmer j. Each farmer i has a set of neighbors, denoted $N_i(d)$ (i.e., network of i). In the network of i, $d_{ij} = 1$ if $j \in N_i(d)$ and $d_{ij} = 0$ if $j \notin N_i(d)$. We also assume that the network is *undirected*, which requires that $d_{ij} = d_{ji}$. Thus, a set of neighbors such that i is linked to is referred to neighbors of i: $N_i(d) = \{j \setminus i : d_{ij} = 1\}$ or $N_i(d) = \{j | ij \in g\}$.

Each farmer will face a decision problem of how to optimally allocate his or her investment in conventional and organic farming. Let c_i and x_i be the farmer i's investment in conventional and organic agriculture, respectively. We assume that the investment is the percentage of lands that a farmer can allocate to either conventional or organic agriculture. Thus, each farmer's amount of investment is bounded: $c_i \in [0, 1]$ and $x_i \in [0, 1]$. Since the total investment for each farmer is $x_i + c_i = 1$, we can rewrite the investment for conventional farming c_i with a given x_i as $c_i = 1 - x_i$.

Let us consider the case that an agent i invests both in conventional farming (c_i) and organic farming (x_i) so that his/her total gross revenue is the sum of both revenues: $h(c_i) + f(x_i)$ where $h(c_i) = \beta f(c_i)$ with $\beta \in (0, 1)$. This means that the gross revenue in organic farming is higher than the gross revenue in conventional farming since organic farming comes with may benefits like higher income and lower external inputs. For the sake of simplicity, we can assume that $f(.)$ is an increasing and concave function, $f' > 0$, $f'' < 0$ and $f(0) = 0$. However, when engaging in organic farming, farmers have to pay an extra amount γx_i. The extra cost comes from higher labor inputs, market barrier and certification. By substituting c_i with $1 - x_i$, we can write the agent i's total payoff function as follows:

$$\pi_i(x_i) = \beta f(1 - x_i) + f(x_i) - \gamma x_i \tag{4}$$

We extend our model by taking the role of the social network into account since farmers in the same group or network could also interact with different other neighborhood farmers. In particular, we consider that social connections exist among farmers and that each farmer cares about the actions of his/her direct neighbors (i.e., peer effect). We assume that the peer effect is positive such that $\delta \sum_j^N d_{ij} x_j x_i$ where $\delta > 0$. This assumption captures the fact that an organic farmer i would benefit from the total organic investment of his or her direct neighbors $\sum_j^N d_{ij} x_j$. Parameter δ, which represents the magnitude of this effect, is assumed to be positive and homogeneous across agents.

Our model also takes the social comparison mechanism in which an organic farmer receives information about the average level of organic investment in the network into account (from both direct and indirect neighbors). We assume that farmer i, who invests more in organic farming than the average of his or her group, would earn an amount $\eta(x_i - \frac{1}{N}\sum_j^N x_j)$ where $\eta > 0$, otherwise he or she would lose an amount $\eta(\frac{1}{N}\sum_j^N x_j - x_i)$.

Considering social network and social comparison concerns, the payoff for agent i is as follows:

$$\pi_i(x_i) = \beta f(1 - x_i) + f(x_i) - \gamma x_i + \delta \sum_j^N d_{ij} x_j x_i + \eta(x_i - \frac{1}{N}\sum_j^N x_j) \tag{5}$$

where, $f(x) = a\,x - bx^2$, a, $b > 0$, $a > 2b\,x$ and δ, $\eta > 0$.

If each agent chooses x_i by maximizing his or her payoff, from the first order condition (F.O.C), we then have the Nash equilibrium x^* such that

$$x_i^* = \frac{(1-\beta)a + 2\beta b - \gamma + \eta}{2(1+\beta)b} + \delta \frac{\sum_{j=1}^n d_{ij}}{2(1+\beta)b} x_j^* \tag{6}$$

It should be noted that the game is strategy complementary $\frac{\partial x_i^*}{\partial x_j^*} = \delta \frac{\sum_{j=1}^n d_{ij}}{2(1+\beta)b} > 0$ for $\delta > 0$.

Let $\mathrm{x}^* = (x_1^*, x_2^*, \ldots x_n^*)$. In the matrix formula, we have

$$\mathrm{x}^* = \frac{\alpha}{2(1+\beta)b}\iota + \frac{\delta}{2(1+\beta)b}\mathrm{D}\mathrm{x}^* \tag{7}$$

where, $\alpha = (1-\beta)a + 2\beta b - \gamma + \eta$ and $\boldsymbol{\iota}$ is the $n \times 1$ column matrix of one. Let $\Phi = \frac{\delta}{2(1+\beta)b}\mathrm{D}$. If the $\boldsymbol{\Phi}$ is invertible, we then have the equilibrium that is equal to:

$$\mathrm{x}^* = \frac{\alpha}{2(1+\beta)b}(I - \Phi)^{-1}\iota. \tag{8}$$

Thanks to this closed-form solution, we can calculate the equilibrium of each agent based on the information of the given network structure $\boldsymbol{\Phi}$. In other words, the equilibrium solution varies across different networks, the different positions of the agents inside the network and the number of direct links. Note that the condition of the convertibility of matrix $(I - \boldsymbol{\Phi})$ can be achieved if the determinant of $(I - \boldsymbol{\Phi})$ is non-singular. This condition always holds for the circle and complete network because these networks are regular graphs, and according to Hall's theorem, every d-regular graph is invertible (Aharoni and Haxell, 2000; West, 2001). Moreover, we can also prove that the determinants of $(I - \boldsymbol{\Phi})$ for all three network structures (circle, star and complete) are non-zero.[5]

Consider that there is a utilitarian social planner who maximizes the total individual payoffs (considered as social welfare). His or her maximization problem is as follows:

[5] In particular, $det(I - \boldsymbol{\Phi}) = 0.9389$ for the circle network, $det(I - \boldsymbol{\Phi}) = 0.9506$ for the star network and $det(I - \boldsymbol{\Phi}) = 0.8467$ for the complete network with parameter assumptions in Appendix A (see Table A.1).

$$max_x W(g,d) = max_{x_1,x_2,\ldots,x_N} \sum_{i=1}^{N} \pi_i(x_i,d) \tag{9}$$

$$= max_{x_1,x_2,\ldots,x_N} \sum_{i=1}^{N} \{\beta(a-b) + [(1+\beta)a + 2\beta b - \gamma]x_i \tag{10}$$

$$+\delta \sum_{j=1}^{N} d_{ij}x_i x_j - (1+\beta)bx_i^2 + \eta(x_i - \frac{1}{N}\sum_{j}^{N} x_j)\} \tag{11}$$

Consequently, according to the F.O.C, the socially optimal investment in organic farming is equal to

$$\widehat{\mathrm{x}} = \frac{\widehat{\alpha}}{2(1+\beta)b}(I-2\Phi)^{-1}\iota \tag{12}$$

where, $\widehat{\alpha} = (1-\beta)a + 2\beta b - \gamma + \eta\frac{N-1}{N}$.

We can observe that for a sufficiently large value of N, $\widehat{\alpha} \to \alpha$. Thus, the socially optimal investment $\widehat{\mathrm{x}}$ is then higher than the investment at the Nash equilibrium $\mathbf{x}^*$, $\widehat{\mathrm{x}} > \mathrm{x}^*$. Since we have $\Phi = \frac{\delta}{2(1+\beta)b}\mathrm{D}$, a higher value of δ leads to a larger difference between $\widehat{\mathrm{x}}$ and $\mathbf{x}^*$. Therefore, in the experiment, we need to impose a sufficiently high value of δ in order to observe the difference between farmers' decisions at the social optimum and the Nash equilibrium. Note that a higher value of δ also means a stronger impact of the peer effect on individual behavior.

A.2. A numerical illustration

To illustrate the theoretical model, let us consider a numerical example with the parameter assumption reported in Table A.1. We consider that each farmer will decide to invest the percentage of his or her farming land in organic agriculture, $x \in [0, 1]$ (i.e., from 0% to 100%). We also consider that $\beta = 0.8$, which means that the benefit of organic farming is 20% higher than that of conventional farming. "Cost and benefit analysis" literature suggest that income from organic farming varies from 20-30% higher than conventional farming at a low level of subsidy, and 50% at the highest subsidy level (Urfi et al., 2011). We assume that the parameter of the revenue function $a = 2$ and, thus, given the assumption that $f'(x) \geq 0$, b must be ≤ 1 for $x = 1$. In order to make the game more interesting, we consider that in the absence of a network and social comparison, it is optimal to invest less than 50% of the land in organic farming (i.e., $x^* < 0.5$) and thus it is therefore necessary that $\gamma = 0.5$ since this assumption holds for $\gamma > 0.45$. For the social comparison parameter, we chose $\eta = 0.2$ since the existing literature suggests that the impact of social comparison on individual behavior varies from 20% to 30% (Vogel et al., 2015; Jiang and Ngien, 2020). The peer parameter is equal to 0.4 since δ must be ≥ 0.4 in order to obtain a difference of at least 0.2 in the Nash equilibrium and social optimum in the circle network (Table A.1), which is required for the information nudge treatment, as discussed in our theoretical model in Section 2. Table A.1 (in the presence of social comparison), Table A.2 (in the case of no social comparison) and Table A.3 (in the empty network) present the equilibrium and payoffs associated with two different organic land investment decisions (Nash equilibrium and social optimum) in a five-player game.

The results of the Nash equilibrium, social optimum and payoffs are calculated using Eqs. (2), (3) and (12), respectively. Our results in Table A.1 indicate that this five-player game has a unique Nash equilibrium. In the complete network, the payoff for each farmer at the Nash equilibrium is 193.1. However, the Nash equilibrium is not Pareto optimal. By coordinating at the social optimum, each farmer would earn an amount equal to 210, whereas this optimum is difficult to achieve because each farmer has the incentive to deviate if he or she knows that the other farmers will choose the optimal strategy. Specifically, farmer i would deviate from playing at the Nash equilibrium and earn a slightly higher payoff of 211.1. The other farmers would then suffer a loss equal to $210 - 188.4 = 21.6$. Therefore, the dominant strategy is that every farmer coordinates at the Nash equilibrium and earns a payoff equal to 193.1. Similarly, the same logic is applied to the circle and the star networks. However, in the case of the empty network, we observe that the Nash equilibrium is higher than the social optimum in the presence of social comparison. This is because there is a negative externality of the social comparison.

Table A.1
Nash equilibrium and social optimum in the presence of social comparison.

Parameter values				
Difference in revenue between conventional and organic farming: $\beta = 0.8$. Parameters of the revenue function $f(x) = a\,x - bx^2$: $a = 2$ and $b = 1$. Extra cost for organic investment: $\gamma = 0.5$. Peer parameter: $\delta = 0.4$. Comparison parameter: $\eta = 0.2$. Number of agents per network: $N = 5$.				
Equilibrium in the presence of social comparison				
		Star		
	Circle	Center	Corner	Complete
Nash equilibrium	0.6071	0.7175	0.5519	0.85
Social optimum	0.83	1.00	0.7023	1.00
Farmer i's payoff				
		Star		
Farmer i's/	Circle	Center	Corner	Complete

(continued on next page)

Table A.1 (*continued*)

Farmer *i*'s payoff								
			Star					
Farmer *i*'s/	Circle		Center		Corner		Complete	
other choices	Nash	Social	Nash	Social	Nash	Social	Nash	Social
other choices	Nash	Social	Nash	Social	Nash	Social	Nash	Social
Nash	**134.2***	141.4	**160.9***	175.8	**123.1***	126.4	**193.1***	211.1
Social	124.3	**135.6**^{e}	145.4	**167.1**^{e}	118.4	**123.4**^{e}	188.4	**210**^{e}

Notes: * and ^{e} stand for farmer *i*'s payoff at the Nash equilibrium and the social optimum, respectively.

Because of the sub-optimality of the Nash equilibrium, our objective is to introduce the information nudge about the socially optimal level of investment to the farmers in the experiment to examine whether the nudge treatment could help encourage farmers to move toward more sustainable agriculture. It should be noted that in Table A.1–Table A.3, in order to facilitate the computation as well as the theoretical analysis, we assume that all agents are identical. In this case, all of the agents' direct and indirect neighbors (four other agents) play the same strategies at the equilibrium. Indeed, the actual situation would be more complicated if all of the agents' strategies were different. However, this assumption still makes sense in reality because agents usually take what both direct and indirect neighbors would do into account when making their decisions. In the experiment, agents participate in a ten-period repeated game.

Table A.2
Nash equilibrium and social optimum in the case of no social comparison.

Equilibrium in the presence of social comparison				
		Star		
	Circle	Center	Corner	Complete
Nash equilibrium	0.5357	0.6331	0.4870	0.75
Social optimum	0.75	0.9807	0.6346	1.00

Farmer *i*'s payoff								
			Star					
Farmer *i*'s/	Circle		Center		Corner		Complete	
other choices	Nash	Social	Nash	Social	Nash	Social	Nash	Social
Nash	**131.7***	140.8	**152.2***	167.1	**122.7***	129.5	**181.3***	211.3
Social	123.4	**136.3**^{e}	130.4	**153.6**^{e}	118.8	**127.6**^{e}	170	**210**^{e}

Equilibrium and payoffs are calculated with the same parameter as in the case of the presence of social comparison. * and ^{e} stand for farmer *i*'s payoff at the Nash equilibrium and the social optimum, respectively.

In the case of no social comparison, agents can observe the previous decision of their direct neighbors after each round. For instance, agents in the circle observe the decisions of two direct neighbors, while those in the complete network observe the decisions of four direct neighbors. In the presence of social comparison, agents will receive additional information about the average group organic investment. The information nudge provides agents with information about the optimal investment strategy at the beginning of each round. In this way, we can explore the impact of information about their neighbors' previous choices on their likelihood of choosing the Nash equilibrium strategy and coordinating on the socially optimal outcome.

Table A.3
Nash equilibrium and social optimum in the empty network.

Equilibrium in the empty network		
	No social comparison	Social comparison
Nash equilibrium	0.4167	0.4722
Social optimum	0.4167	0.4611

Farmer *i*'s payoff				
Farmer *i*'s/	No social comparison		Social comparison	
other services	Nash	Social	Nash	Social
Nash	**111.3***	111.3	**110.7***	110.9
Social	111.3	**111.3**^{e}	110.7	**110.9**^{e}

Notes: Equilibrium and payoffs are calculated with the same parameter as in the case of presence of social comparison. * and ^{e} stand for farmer *i*'s payoff at the Nash equilibrium and the social optimum, respectively.

Appendix B. Detailed experimental procedure

One week before the experiment, the local authorities in each village contacted farmers either directly or by sending letters to invite them to the experiment without knowing its content.

Upon arrival at the experimental session, farmers were given detailed information about the experiment and the monetary incentives. The farmers were informed that they would be paid after participating in the survey, and one farmer would receive at least 120,000 VND[6] depending on their performances.

At the beginning of the experiment, subjects were invited to read the experimental instructions and the experimenters explained the different parts and the monetary incentives. The experimenters and assistants helped the subjects understand the instructions after reading them. They then had to answer a quiz to test their understanding of the instructions.

The experiment consists of four parts. In the first part of the experiment, we ran a lottery-choice task to capture the subjects' sensitivity to risk. Each farmer was given 50,000 VND (Vietnam Dong)[7] to invest in a lottery. Subjects made their decisions on the IPad screen (see an example in Fig E.4 in Appendix E). At the end of the experiment, subjects were invited to individually make a draw (by tossing a coin), and the lottery winner was the one who had chosen heads. Subjects were told at the beginning of the first part that lottery winners would receive a triple amount of their investment; otherwise, they would lose the investment and keep the amount that was not invested. The amount of money not invested is used as a relative indicator of risk aversion.

In the second part of the experiment, farmers were told that their investment would not affect any of the others' decisions and that their payoffs depended only on their personal level of investment. In particular, each farmer was given a similar amount of agricultural land (denoted L). They were invited to allot a proportion of their land to organic farming (denoted as X and ranging from 0% to 100%), and the rest of the land that was not allotted to organic farming was devoted to conventional farming ($L - X$). For each unit of X, the farmer's payoff was calculated using Eq. (2) and the parameter assumptions in Table A.1. Note that farmers earned 500 VND for each unit of payoff. Thus, individual payoffs (in terms of VND) are given by the following function:

$$\pi = 40,000 + 75,000X - 90,000X^2 \tag{13}$$

In this part, there was no peer influence, no social comparison and no information nudge. Depending on their level of investment (X), farmers could receive a payoff ranging from 40,000[8] (for $X = 0$) to 55,625[9] (for the Nash or optimal investment $X = 41.67\%$). Subjects did not receive any information about the optimal decision or the payoff range. Subjects were told that their outcomes depended only on their personal decisions. The experiment was repeated over five periods, and subjects could observe their payoffs in each round (see Fig E.5 in Appendix E). Before starting the second part in which the simple organic investment game was played, experimenters introduced the definition of organic farming to the farmers. The definition is written as follows:

> "Organic agriculture is a production method that excludes the use of most chemicals (such as pesticides and fertilizers often used in conventional agriculture since the beginning of the 20th century), GMOs (Genetically Modified Organisms) and crop preservation by irradiation. Organic farming contributes to reducing environmental impacts (for example, reducing water pollution and protecting soil fertility, etc.) and improving food quality."

In the third part, farmers were informed that each individual was assigned to a position in a particular network of five participants (star, circle, complete or empty network). There were two groups per session (since there were ten participants per session). Only the farmers knew their positions, and thus nobody had any information about who would be their neighbors (either direct or indirect) or which group they were in. This position would be fixed determined for all ten periods of the experiment. Experimenters also explained the particular network structure that they were assigned to and the direct and indirect neighbors/links. They were also informed that there were peer effects due to the network links. Farmers would benefit from their direct neighborhood investments. They were told that there would be feedback after each round and that each farmer could observe the investment decision of his or her direct neighbors. The explanation of the role of networks is summarized as follows:

> "Organic farmers would benefit from the total organic investment of their direct neighbors. This benefit would result from the market information that an organic farmer who has good market information might share with his organic peers about when and where to market their crops to receive high prices. The peer benefits would also come from positive experiences and considerable labor-sharing opportunities in their networks. From a social perspective, farmers who adopt organic agriculture may motivate their neighboring farmers to adopt it as well because most individuals are "conditionally cooperative"."

For example, in the treatment *St*, the payoff function of farmer 2 (see the network structure in Fig. 1) is written as follows:

$$\pi_2 = 40,000 + 75,000X_2 - 90,000{X_2}^2 + 20,000X_2X_1, \tag{14}$$

where X_1 is the investment in organic farming of farmer 1. Farmer 1, the central farmer in the star network, is farmer 2's direct neighbor.

In the presence of social comparison (Sc), experimenters informed farmers that there would be peer effects depending on the network structures (star, circle or complete network) and the social comparison. The peer effect was explained in the same way as previously described. After each round, there was also feedback, and each farmer would receive information about his or her group's average investment decision. Regarding the social

[6] Equivalent to about 5 USD.
[7] Equivalent to almost 2 USD.
[8] Equivalent to 1.7 USD.
[9] Equivalent to 2.4 USD.

comparison, it was explained as follows:

"Farmers would receive information about the average organic investment of the whole group (including themselves and their direct and indirect neighbors) after each round. Organic farmers who invested less would then suffer a negative impact on the payoff. This negative impact would be calculated accordingly by the given payoff function".

As previously mentioned, we assumed that for an investment lower than the average, there is a negative impact of social comparison on the outcome, and for an investment higher than the average, the effect of social comparison on the outcome is positive. For farmer 2 concerned by social comparison in the star network, his or her previous payoff function (Eq. (14)) becomes:

$$\pi_2 = 40,000 + 75,000X_2 - 90,000{X_2}^2 + 20,000X_2X_1 \\ +10,000(X_2 - (X2 + X_1 + X_3 + X_4 + X_5)/5). \tag{15}$$

If we consider the circle network, π_2 is written as follows:

$$\pi_2 = 40,000 + 75,000X_2 - 90,000{X_2}^2 + 20,000X_2(X_1 + X_3) \\ +10,000(X_2 - (X2 + X_1 + X_3 + X_4 + X_5)/5), \tag{16}$$

where, X_1 and X_3 are the investment in organic farming of farmers 1 and 3 (farmer 2's direct neighbors in the circle network).

In the presence of an information nudge (ScNd), farmers were informed that information would appear on the screen at the beginning of each round: their optimal investment and that of all the other farmers in their group. If every farmer followed the instruction to choose the optimal level of investment, then all farmers would earn the optimal profit/payoff. Each farmer could decide to follow or not this information. Similar to the second part, each participant can make a simulation of their decision and see their expected payoff (for example, see Fig E.6 in Appendix E). This information would appear every time at the beginning of each round. For example, in the star network, the information was displayed as follows:

"The optimal decision for the whole group is: player 1 chooses X equal to 100% and four other players choose X equal to 70.23%".

They can decide to follow or not this information. After each round, farmers would receive feedback concerning information about the investment decision of their direct neighbors.

Appendix C. Econometric model

Since our dependent variable is the individual decision or the percentage of individual organic investment ranging from 0 (0%) to 1 (100%), the fractional regression model is applied to capture the fractional nature of the dependent variable. In the fractional logit model, we specify the set of regressors as $Z_i = (Exp_i, Socio_i, Psy_i)$. The descriptive statistics of our variables are reported in Table D.3.

The fractional model with the dependent variable x_i as a fraction bounded between zero and one, i.e., $x_i \in [0, 1]$, has the following structure:

$$E(x_i|Z_i) = H(Z_i\beta), \tag{17}$$

where Z_i represents a set of regressors including explanatory variables (Exp_i), socio-economic control variables ($Socio_i$) and psychological control variables (Psy_i). For the logistic link-function $H(.)$ satisfying $0 < H(.) = \frac{\exp(.)}{1+\exp(.)} < 1$ (Wooldridge, 2009), the fractional logistic model can be written as follows:

$$E(x_i|Z_i) = \frac{e^{Z_i\beta}}{1 + e^{Z_i\beta}}. \tag{18}$$

The proposed estimator for β is the Quasi Maximum Likelihood Estimator (QMLE), which maximizes the following Bernoulli log-likelihood function (McCullagh, 1989):

$$l_i(\beta) = x_i\log[H(Z_i'\beta)] + (1 - x_i)\log[1 - H(Z_i'\beta)]. \tag{19}$$

Since there is the non-linear estimation of the conditional mean, the fractional logit model performs well if there are not many observations at the boundary levels; otherwise, two-part models are often a better solution (Ramalho et al., 2011). We observe that the majority of individual investments fall inside the interval (0, 1) and only some small proportion of organic investment is left-censored at 0% and right-censored at 100% (see Fig E.1). Additionally, the estimation results with the Tobit regression model are also reported in Table D.6 (in Appendix D). The standard errors of the fractional and Tobit regression are estimated with 500 bootstrap replications and eight village clusters.

Appendix D. Tables

Table D.1
Mean investment per network and per treatment.

	Empty network	Circle	Star	Complete

(continued on next page)

Table D.1 (*continued*)

	Empty network	Circle	Star	Complete
No treatment	–	0.568	0.567	0.641
		(0.197)	(0.132)	(0.190)
Sc	0.520	0.677	0.551	0.671
	(0.111)	(0.185)	(0.115)	(0.220)
ScNd	0.510	0.636	0.618	0.756
	(0.112)	(0.176)	(0.175)	(0.193)

The standard deviation is in parentheses. Sc stands for "social comparison" treatment. ScNd stands for "social comparison and information nudge" treatment.

Table D.2
Difference-in-mean between different circle, complete and the center/corner of the star network per each treatment (Wilcoxon Rank Sum test).

	No treatment			Sc			ScNd		
	Center	Corner	Complete	Center	Corner	Complete	Center	Corner	Complete
Circle	−0.10***	0.03	−0.07***	0.12***	0.13***	0.01	−0.06**	0.04**	−0.12***
	(0.000)	(0.094)	(0.000)	(0.000)	(0.000)	(0.778)	(0.048)	(0.016)	(0.000)
Center	–	0.13***	0.03	–	0.01	−0.11***	–	0.10***	−0.06
		(0.000)	(0.595)		(0.435)	(0.000)		(0.000)	(0.171)
Corner	–	–	−0.10***	–	–	−0.12***	–	–	−0.16***
			(0.000)			(0.000)			(0.000)

Notes: The table reports the difference-in-mean and the *p*-value of the Wilcoxon Rank Sum test in parentheses. Sc stands for "social comparison" treatment; ScNd stands for "social comparison and information nudge" treatment. Center and corner are presented for the subset of only center and corner farmers in the star network. ** $p < 0.05$; *** $p < 0.01$.

Table D.3
Descriptive statistics.

	Definitions	Mean	Std.Dev	Min	Max
Dependent variables					
Individual decision	Percentage of land invested in organic farming	0.57	0.19	0	1
Explanatory variables					
Neighbor (t−1)	Log of total direct neighborhood investment in the previous period.	0.45	0.63	−2.30	1.38
Sc	=1 if an individual is assigned to the social comparison treatment.	0.30	0.46	0	1
ScNd	=1 if an individual is assigned to social comparison and information nudge treatment.	0.24	0.43	0	1
Center	=1 if an individual is a central player in the star network.	0.04	0.19	0	1
Control variables					
Period	Experimental period.	5.5	2.87	1	10
Socio-demographic variables					
Female	=1 if an individual is female.	0.67	0.47	0	1
Age (in log)	Log of individual age.	3.94	0.21	2.77	4.36
Age (in years)	Individual age.	52.40	9.92	16	78
High school	=1 if an individual graduated from vocational school (1 to 2 years after high school).	0.30	0.46	0	1
College/university	=1 if an individual graduated from college or university.	0.11	0.31	0	1
Good health	=1 if an individual stated that she had a good health.	0.40	0.49	0	1
Very good health	=1 if an individual stated that she had a very good health.	0.22	0.41	0	1
Medium income	=1 if an individual is in the middle income group (monthly earnings from 4 to 8 millions VND).	0.33	0.47	0	1
High income	=1 if an individual is in the high income group (monthly earnings > 8 million VND).	0.04	0.20	0	1
Farm size (in log)	Log of household farmer's farmland size.	7.45	0.81	4.99	10.0
Farm size (in m^2)	Household farmer's farmland size.	2466.17	2903.83	147	23,040
Communist	=1 if an individual is a member of the communist party.	0.18	0.38	0	1
Farmer association	=1 if an individual is a member of a farmer's association.	0.88	0.32	0	1
Cooperative	=1 if an individual is a member of a farmer's cooperative.	0.68	0.47	0	1
Psychological variables					
NEP	Aggregate score of individual 15 New Environmental Paradigm questions.	46.87	4.45	36	63
Risk investment (in log)	Log of individual investment in the lottery choice task.	10.1	0.82	0	10.8
Injunctive norm	=1 if the respondents believed that the adoption of organic farming is approved by most of the other villagers.	0.79	0.40	0	1

Table D.4
The 15 NEP scale items and their response distributions (in percentage).

NEP scale items	Strongly disagree	Partly disagree	Unsure	Partly agree	Strongly agree	Corr
1: "We are approaching the limit of the number of people the earth can support".	7.27	39.09	4.55	35.00	14.09	0.441
2: "Humans have the right to modify the natural environment to suit their needs".[a]	6.36	14.55	0.45	55.45	23.18	0.535
3: "When humans interfere with nature, it often leads to disastrous consequences".	6.82	44.09	3.64	33.64	11.82	0.466
4: "Human ingenuity will ensure that we do not make the earth unlivable".[a]	2.73	10.00	3.18	62.27	21.82	0.419
5: "Humans are severely abusing the environment".	6.36	25.91	2.27	41.82	23.64	0.387
6: "The Earth has plenty of natural resources if we just learn how to develop them".[a]	2.73	1.36	1.36	58.18	36.36	0.456
7: "Plants and animals have as much right as humans to exist".	0.91	5.00	1.82	56.82	35.45	0.485
8: "The balance of nature is strong enough to cope with the impacts of modern industrial nations".[a]	14.55	44.55	6.36	26.82	7.73	0.340
9: "Despite our special abilities, humans are still subject to the laws of nature".	0.45	4.09	1.82	53.64	40.00	0.414

(*continued on next page*)

Table D.4 (*continued*)

NEP scale items	Strongly disagree	Partly disagree	Unsure	Partly agree	Strongly agree	Corr
10: "The so-called "ecological crisis" facing humankind has been greatly exaggerated".[a]	2.27	45.91	10.00	35.00	6.82	0.356
11: "The Earth is like a spaceship with very limited room and resources".	0.45	12.27	3.64	59.09	24.55	0.375
12: "Humans were meant to rule over the rest of nature".[a]	3.64	24.55	5.91	52.27	13.64	0.380
13: "The balance of nature is very delicate and easily upset".	1.82	19.09	5.91	64.09	9.09	0.390
14: "Humans will eventually learn enough about how nature works to be able to control it".[a]	2.73	15.00	1.82	65.45	15.00	0.399
15: "If things continue on their present course, we will soon experience a major ecological catastrophe".	0.91	8.18	3.18	63.18	24.55	0.485
Total NEP score.	Mean = 46.87 and SD = 4.455.					
Cronbach's alpha			0.6545			

Notes: [a] Reverse coded.The column Corr represents the item-total correlation, which tells us how much each item correlates with the total NEP score. Cronbach's alpha is equal to 65.4% in the reliability test, which suggests that 65.4% of the variance in the score is reliable.

Table D.5
Correlation matrix of explanatory variables by different networks (with Pearson's correlation test).

	Empty network	Circle network		Star network			Complete network	
	Sc	Neighbor(t-1)	Sc	Center	Neighbor(t-1)	Sc	Neighbor(t-1)	Sc
Center	–	–	–	1.00	–	–	–	–
Neighbor(t−1)	–	1.00	–	0.83 (0.00)	1.00	–	1.00	–
Sc	1.00	0.21 (0.00)	1.00	0.00 (1.00)	0.00 (0.93)	1.00	−0.06 (0.150)	1.00
ScNd	−0.15 (0.00)	0.06 (0.166)	−0.50 (0.00)	0.00 (1.00)	0.06 (0.117)	0.5 (0.00)	0.18 (0.00)	−0.50 (0.00)

Notes: The p-value of the Pearson correlation test statistics are in parentheses. The Pearson correlation test statistics suggest that there are correlations between the "Sc" and "ScNd" treatments and between direct neighborhood investment $Neighbor(t-1)$ and Center. However, the correlation coefficients of these variables are not too large, except for the correlation between center and $Neighbor(t-1)$ in the star network.

Table D.6
The full estimation results.

	Empty network		Circle		Star		Complete	
Variables	Fractional	Tobit	Fractional	Tobit	Fractional	Tobit	Fractional	Tobit
Neighbor (t−1)			0.610***	0.143***	0.083***	0.019	0.711	0.185**
			(0.161)	(0.033)	(0.014)	(0.027)	(0.964)	(0.098)
Center					−0.507**	−0.099		
					(0.262)	(0.076)		
Center*Neighbor (t−1)					0.966***	0.200**		
					(0.266)	(0.094)		
Sc			0.315***	0.072***	−0.051	−0.011	0.217	0.048*
			(0.109)	(0.023)	(0.175)	(0.014)	(0.261)	(0.023)
ScNd	0.014	0.003	0.209	0.048**	0.225***	0.054***	0.466	0.112
	(0.331)	(0.013)	(0.243)	(0.021)	(0.076)	(0.020)	(0.351)	(0.101)
Control variables								
Period	0.006*	0.001	0.055***	0.012***	0.030***	0.007***	0.097**	0.019***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)	(0.040)	(0.004)
Female	−0.151	−0.038	−0.100	−0.020	−0.602***	−0.143***	0.464***	0.098***
	(0.210)	(0.015)	(0.302)	(0.019)	(0.059)	(0.021)	(0.115)	(0.023)
Age (in log)	0.280	0.068*	0.139	0.032	−0.262***	−0.060	1.793	0.402***
	(0.801)	(0.035)	(1.035)	(0.047)	(0.081)	(0.054)	(1.126)	(0.061)
Education								
High school	0.106*	0.026*	0.234	0.055**	−0.074	0.017	−0.122	−0.021
	(0.053)	(0.013)	(0.655)	(0.027)	(0.158)	(0.014)	(0.110)	(0.023)
College	0.173**	0.042	−0.043	−0.009	–	–	−0.359	−0.072*
	(0.108)	(0.028)	(0.337)	(0.036)			(0.539)	(0.041)
Health								
Good	0.013	0.003	−0.196	−0.047*	−0.168***	−0.039**	0.395**	0.091***
	(0.254)	(0.016)	(0.301)	(0.021)	(0.015)	(0.016)	(0.177)	(0.025)
Very good	0.057	0.014	−0.102	−0.025	−0.021	−0.005	0.682***	0.151***
	(0.284)	(0.021)	(0.230)	(0.021)	(0.047)	(0.024)	(0.264)	(0.027)
Individual income								
Medium	0.045**	0.011	−0.049	−0.010	0.012	−0.001	0.285*	0.058**
	(0.020)	(0.015)	(0.581)	(0.016)	(0.017)	(0.022)	(0.145)	(0.022)
High	−0.336***	−0.084***	0.270	0.065	–	–	0.118	0.023
	(0.004)	(0.027)	(0.326)	(0.060)			(0.179)	(0.031)
Farm size (in log)	0.071***	0.017**	−0.087*	−0.018	0.010	0.003	−0.218	−0.038*
	(0.005)	(0.008)	(0.357)	(0.015)	(0.032)	(0.010)	(0.205)	(0.016)
Communist	−0.041	−0.009	0.227***	0.051***	−0.050	−0.013	−0.098	−0.036

(continued on next page)

Table D.6 (*continued*)

	Empty network		Circle		Star		Complete	
Variables	Fractional	Tobit	Fractional	Tobit	Fractional	Tobit	Fractional	Tobit
	(0.363)	(0.035)	(0.414)	(0.017)	(0.063)	(0.021)	(0.318)	(0.035)
Farmer association	−0.057	−0.014	0.032	0.006	0.385***	0.094**	−0.077	−0.022
	(0.498)	(0.017)	(0.461)	(0.023)	(0.033)	(0.040)	(0.253)	(0.038)
Cooperative	−0.267	−0.065***	0.077	0.016	−0.202**	−0.047**	−0.194	−0.040*
	(0.202)	(0.020)	(0.111)	(0.018)	(0.052)	(0.023)	(0.394)	(0.021)
Risk investment (in log)	0.007	0.002	−0.038	−0.006	0.006	0.001	0.356*	0.073***
	(0.306)	(0.004)	(0.063)	(0.020)	(0.034)	(0.015)	(0.205)	(0.024)
NEP	0.004	0.001	0.015	0.003*	−0.018***	−0.004***	−0.022	−0.005*
	(0.012)	(0.001)	(0.011)	(0.001)	(0.005)	(0.001)	(0.020)	(0.003)
Injunctive norm	0.145	0.036**	0.612**	0.140***	0.092	0.021	0.694***	0.148***
	(0.179)	(0.015)	(0.281)	(0.025)	(0.191)	(0.015)	(0.110)	(0.025)
Intercept	1.566	−2.101**	0.308	−0.744	1.022***	2.203*	−1.610***	−9.460***
	(1.012)	(0.875)	(0.315)	(1.500)	(0.278)	(1.157)	(0.394)	(1.856)
Observations	400	400	540	540	540	540	540	540
Log (pseudo)−likelihood	−276.19	315.05	−341.720	185.6	−359.45	373.29	−311.09	66.94
Wald $\chi^2(q)$	104.93***	106.67***	200.51***	217.62***	228.51***	251.93***	248.77***	289.36***
q	18	18	20	20	20	20	20	20
Pseudo R^2	0.003	−0.059	0.029	−0.742	0.017	−0.325	0.053	2.570

Note: The dependent variable is the individual investment. No treatment is a base category.Bootstrapped standard errors are in parentheses with 500 bootstrap replications.* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Appendix E. Figures

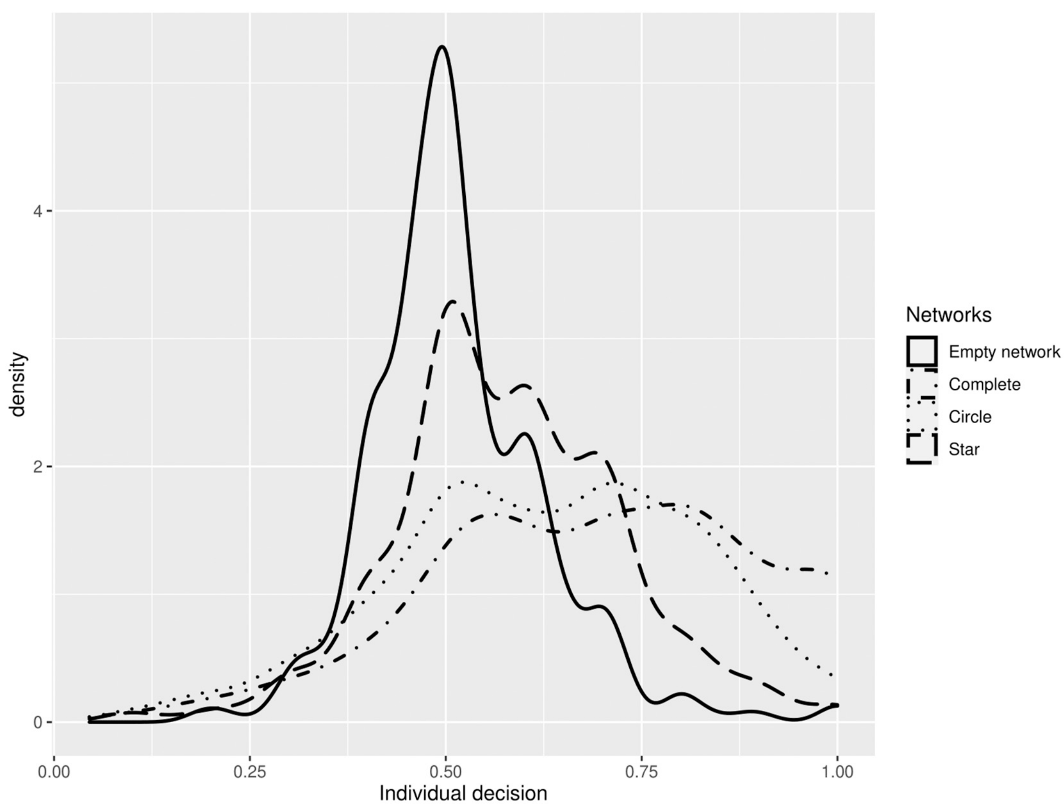


Fig E.1. Density plot of individual decisions by different networks.

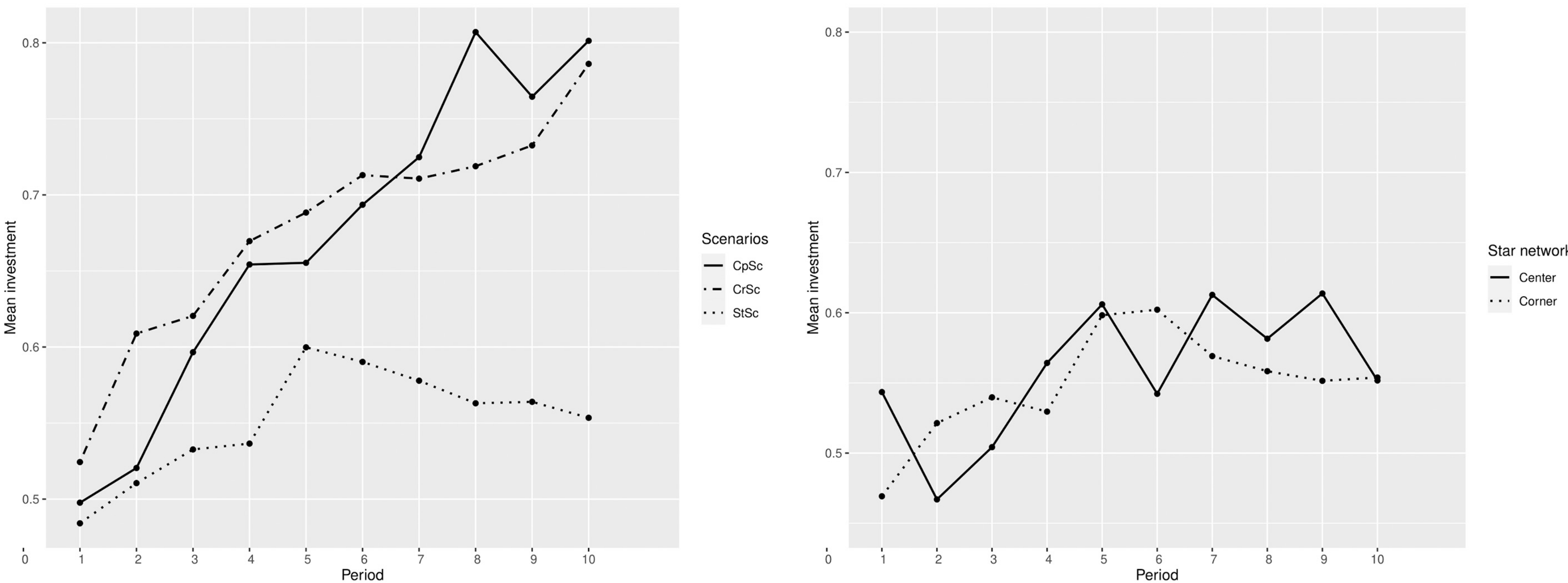


Fig E.2. Mean investment over periods (with social comparison treatments).

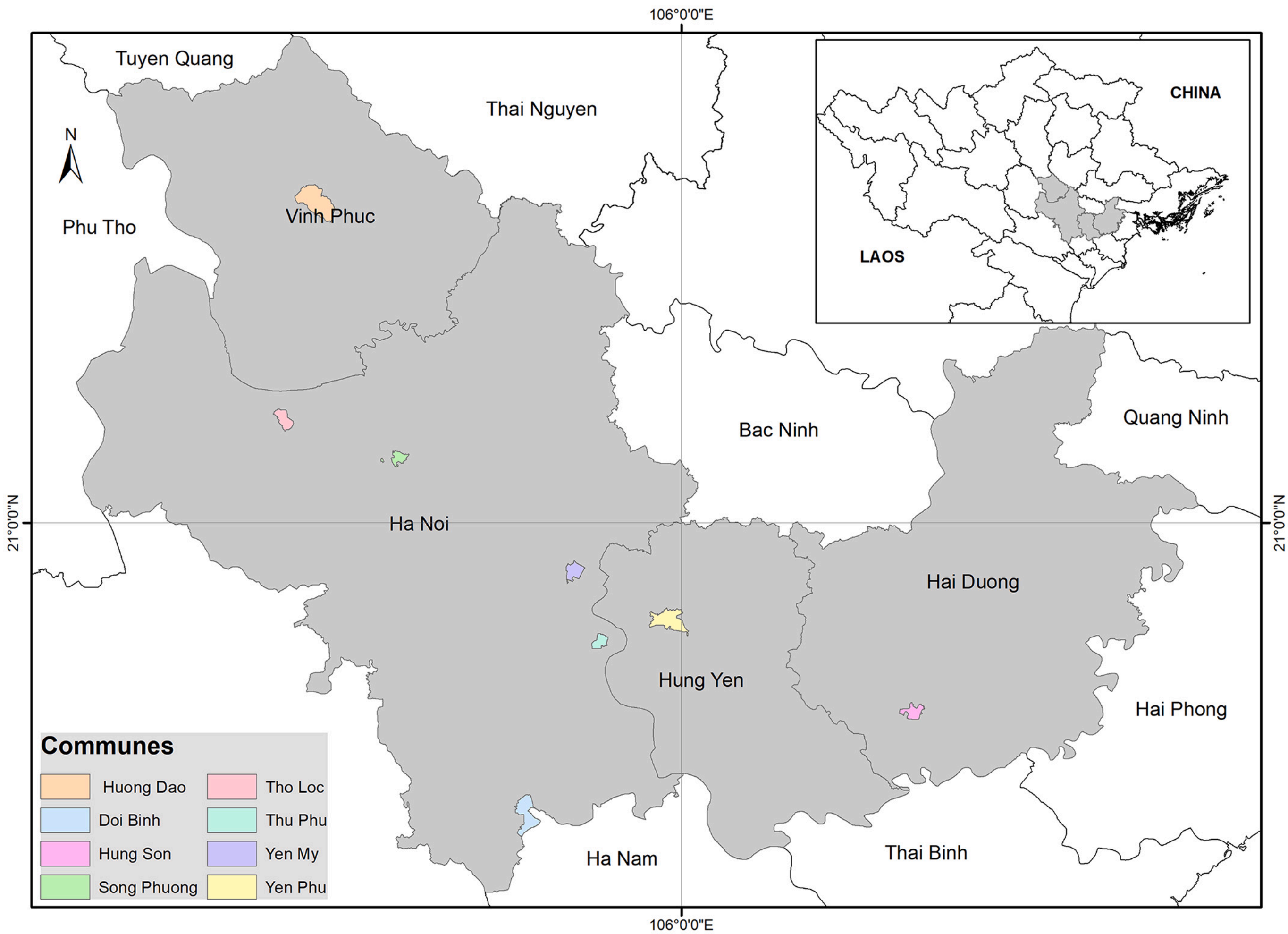


Fig E.3. Survey areas.

Fig E.4. The first part of the experiment (lottery-choice task).

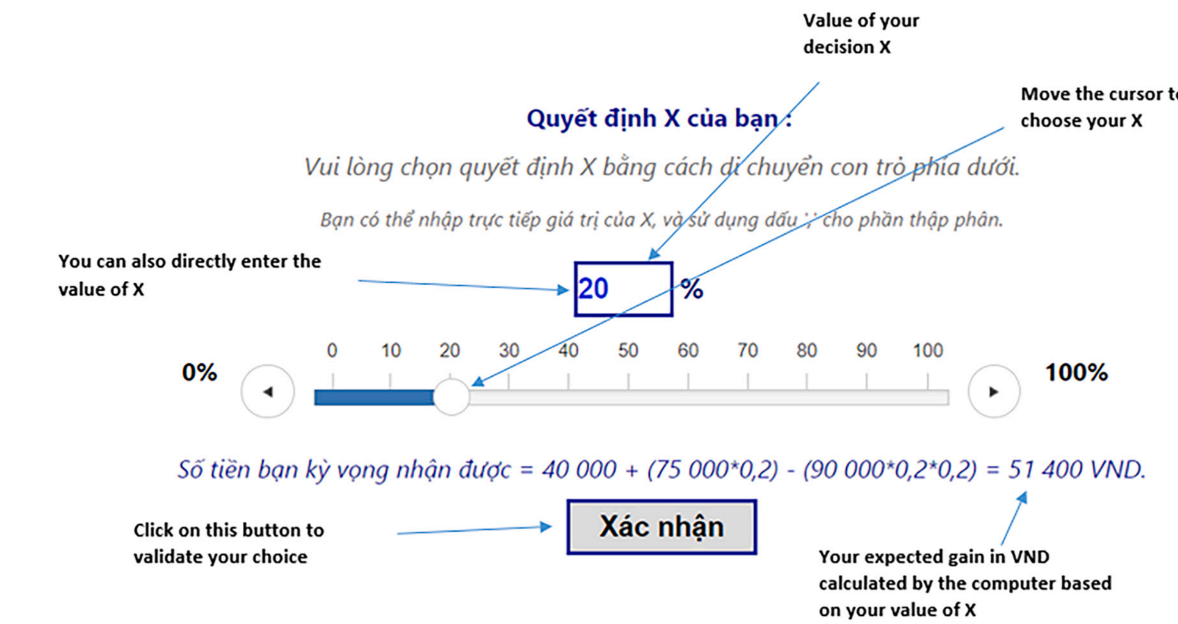


Fig E.5. The second part of the experiment (simple organic investment game).

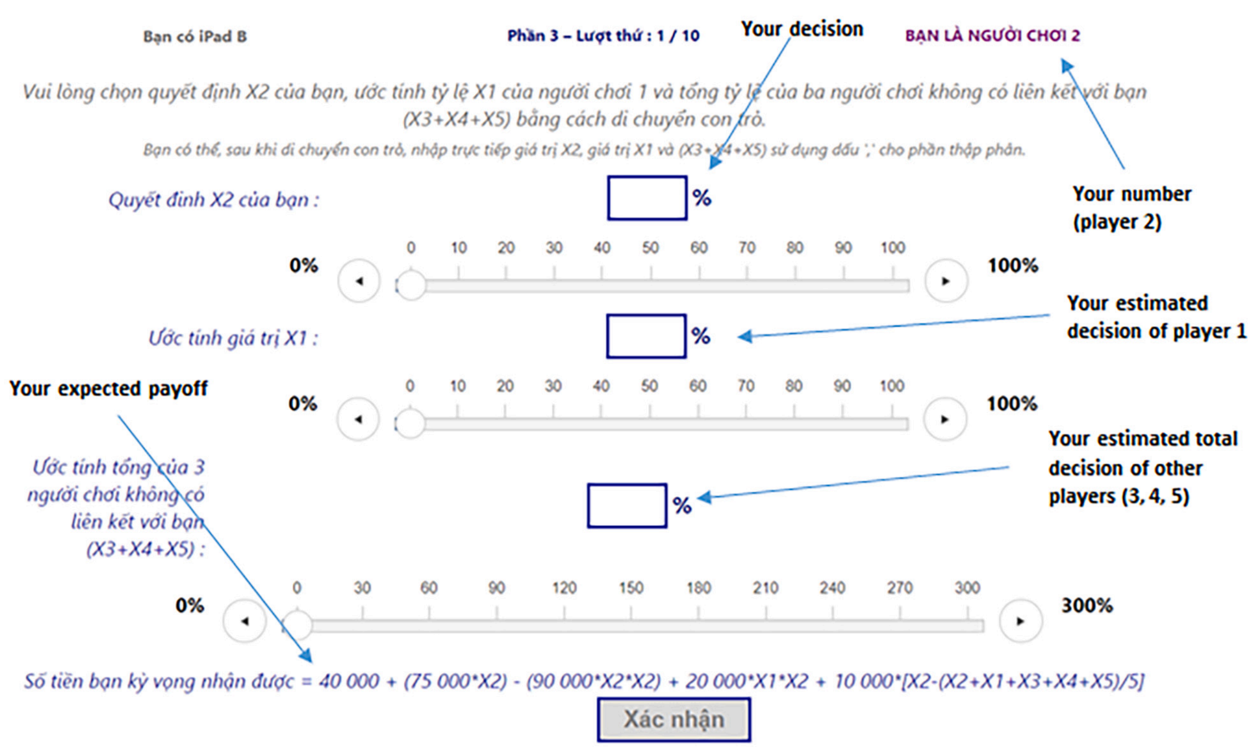


Fig E.6. The third part of the experiment (an example of the StSc treatment).

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