Social Networks and the Decision to Insure*

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Abstract

Using data from a randomized experiment in rural China, this paper studies the influence of social networks on the decision to adopt a new weather insurance product and the mechanisms through which social networks operate. We provided financial education to a random subset of farmers and found a large social network effect on take-up: for untreated farmers, having an additional friend receiving financial education raised take-up by almost half as much as obtaining financial education directly, a spillover effect equivalent to offering a 15% reduction in the average insurance premium. By varying the information available to individuals about their peers' take-up decisions and using randomized default options, we show that the positive social network effect is not driven by the diffusion of information on purchase decisions, but instead by the diffusion of knowledge about insurance. We also find that social network effects are larger in villages where households are more strongly connected, and when people who are the first to receive financial education are more central in the social network.

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1 Introduction

It is well recognized that social networks can play fundamental roles in shaping human behavior and in affecting economic outcomes[1]. But how large these effects are and what mechanisms are at play are still incompletely understood and can be context specific. We use a novel experimental design to obtain clean measurements of the role and functioning of networks in the decision to adopt a new weather insurance product in rural China. Weather insurance is an important financial product that is hard for farmers to understand and has had particularly low spontaneous take-up in most countries. Social networks may play an important role in enhancing its diffusion: people can acquire knowledge about the product's benefits from their friends, be influenced by their decisions to adopt, and/or learn from their experiences with payouts after insured shocks have occurred.

We conducted a randomized experiment in rural China, which included 185 villages with 5300 rice-producing households. The product we are studying is a new weather insurance policy for rice farmers offered by the People's Insurance Company of China (PICC). Our experimental design allows us not only to identify and measure the causal effect of social networks on adoption, but also to test for the role of various channels through which social networks operate, including learning about the function and benefits of insurance products and learning about the purchase decisions of other farmers. Taking advantage of the substantial variation in network structure across villages and households, we are able to test the effects of social structure and initial conditions on the strength of social network effects. Finally, using household level price randomization, we calculate the price equivalence of the social network effect.

The paper provides an estimate of the value of social networks for insurance take-up by

[1] Existing studies have linked social networks with a wide range of activities, including risk sharing (Ambrus et al. (2010)), voting (Lazarsfeld (1944)), finding jobs (Pistaferri (1999); Munshi (2004)), building trust (Karlan et al. (2009)), financial decision-making (Duflo and Saez (2003); Hong et al. (2004)), technology adoption (Conley and Udry (2010); Goolsbee and Klenow (2002); Maertens (2012)), criminal behavior (Bayer et al. (2009); Glaeser et al. (1996)), productivity (Mas and Moretti (2009)), and participation in microfinance programs (Banerjee et al. (2012)). For a comprehensive review, see Jackson (2010).

measuring the spillover effect of financial education provided to a subset of farmers on the rest of the farmers in the village, who are untreated. To establish causality, we introduced the insurance product through four sessions in each village, in two rounds three days apart, with one simple session and one intensive financial education session in each round, randomly assigning households to one of these sessions. For each household, the social network variable is defined as the fraction of a group of friends (whose names were identified in a previous survey) who were invited to an early round intensive session. We find that, while financial education raised take-up by 43% in the first round, for second-round participants, having one additional friend who obtained first-round financial education increased take-up by almost half as much. The household level price randomization experiment shows that this effect is equivalent to decreasing the average insurance premium by 15%.

The magnitude of social network effects may depend on the social structure (Jackson (2008); Galeotti et al. (2010); Jackson and Yariv (2010); Banerjee et al. (2012)). By exploiting variations in both village and household level network characteristics, we show that the effect is larger in more clustered villages where households are more interwoven with each other, and when people in the first set to be financially educated are more central in the village network. We also find that households which are less frequently named as friends by other people, which are less easily reached by others, or which are less important in the village network, are more likely to be influenced by other people.

After observing a large and significant effect of social networks, it is natural to ask what information conveyed by social networks drives this effect. Do social networks matter in insurance adoption because they can diffuse knowledge among farmers about product benefits? Or is it because farmers learn about each other's purchase decisions through social networks and make their own decisions based on that? We find something surprising about what social networks do in these rural communities. They do not convey information about what other people do, even though others would like to obtain such information, but they do effectively convey information about what other people know. This result is obtained in the following manner. First, we compare the effect of financial education on insurance take-up and knowledge between the two rounds. We find that, in the second round, the effect of financial education is smaller, and that farmers understand insurance benefits better when they have a greater number of friends who received financial education. This means that there was diffusion of insurance knowledge from first-round educated farmers to second-round participants. Second, we exploit the exogenous variation in both the overall and individual take-up decisions generated by randomized default options to estimate whether or not subjects are affected by their peers' decisions. No significant effect was found, but, surprisingly, when we told farmers about other villagers' decisions, it actually mattered a lot to them. This suggests that, in this case, the main mechanism through which social networks affect decision-making is social learning about insurance benefits, as opposed to the influence of friends' purchase decisions.

This paper contributes to the social network literature on several fronts. Estimation of the causal effect of social networks is made challenging by the problem of correlated unobservables (Manski (1993); Manski (1995))[2]. To overcome this difficulty, experimental approaches were used by Duflo and Saez (2003), Duflo et al. (2008), Dupas (2010), Kremer and Miguel (2007), Kling et al. (2007), Kremer and Levy (2008), and Oster and Thornton (Forthcoming), etc. Non-experimental methods were used notably by Bandiera and Rasul (2006), Banerjee et al. (2012), Bertrand et al. (2000), Card and Giuliano (2011), Conley and Udry (2010), Foster and Rosenzweig (1995), Imberman et al. (2009), Munshi (2003) and Munshi (2004). Results vary greatly with both the product and the context considered. This paper uses randomized experimental methods to estimate the causal effect of social networks on decision-making, and the monetary equivalence of this effect, for a previously unexplored product and context.

Moreover, while the study of mechanisms through which social networks affect behavior is crucial from both theoretical and policy perspectives[3], only a few studies to date have shed

[2]Such as social norms, homophily, etc.

[3]In general, mechanisms through which social networks affect innovation adoption include social learning

light on this point. For example, Kremer and Miguel (2007) found negative peer effects, which effectively rules out explanations such as imitation and learning how to use the product. Banerjee et al. (2012) took advantage of differences in predicted patterns of behavior as a function of the diffusion of awareness of microfinance compared to the influence of others' decisions. They found that acquiring information from friends is the most important channel for microfinance decisions. By contrast, Maertens (2012) found that, concerning the adoption of Bt cotton, both acquiring knowledge from others about product profitability and imitating others matter. This paper probes this question by using experimental designs to directly identify a comprehensive set of generic channels through which social networks operate.

The paper also contributes to the literature on financial education. Although there exists correlational evidence suggesting that individuals with low levels of financial literacy are less likely to participate in financial markets (Lusardi and Tufano (2009); Lusardi and Mitchell (2007); Stango and Zinman (2009)), experimental evidence on the value of financial education is mixed. Duflo and Saez (2003) and Cole et al. (2011) found small or no effects of financial education on individual decisions, while Cai and Song (2011), Cole et al. (Forthcoming), and Gaurav et al. (2011) found positive and significant effects. In a context where insurance is new, and farmers have relatively low levels of formal education, our results show that lack of financial education is a major constraint on the demand for insurance, and that modest financial training can significantly improve take-up rates.

Finally, the paper sheds light on the challenge of how to improve weather insurance take-up. Insurance is important for farm households when production is exposed to substantial weather shocks[4]. Yet evidence from several countries shows that participation rates are sub-optimally low, even with heavy government subsidies[5]. Existing research has tested possible

about product benefits, imitation, and learning how to use the product.

[4]Formal insurance markets are important because informal insurance mechanisms cannot effectively reduce the negative impacts of regional weather shocks, and leave consumption susceptible to covariate shocks (Townsend (1994)). The absence of insurance markets can lead to highly variable household income and persistent poverty (Dercon and Christiaensen (2011); Jensen (2000); Rosenzweig and Wolpin (1993).

[5]For example, Giné et al. (2008) found a low take-up (4.6%) for a rainfall insurance policy among farmers in rural India in 2004, and Cole et al. (2011) found an adoption rate of only 5%-10% for a similar insurance policy in two regions of India in 2006.

explanations such as lack of trust, credit constraints, and ambiguity aversion (Giné et al. (2008); Cole et al. (2011); Bryan (2010)), but insurance demand remains low even after some of these barriers were removed in experimental treatments. We provide evidence on scalable instruments to improve uptake, such as combining intensive financial education to a subset of households with reliance on social networks to amplify the effect and boost participation rates, and combining subsidy or marketing strategies with social norms marketing in which we disseminate information to the full population about the behavior of peers[6].

The rest of the paper is organized as follows. Section 2 describes the background for the study and the insurance contract. Section 3 explains the experimental design. Sections 4 to 6 present the results, and section 7 concludes.

2 Background

Rice is the most important food crop in China. Nearly 50% of farmers produce rice and more than 60% of the Chinese people consume rice as their main staple food. In order to maintain food security and shield farmers from negative weather shocks, in 2009 the Chinese government requested the People's Insurance Company of China (PICC) to design and offer the first rice production insurance policy to rural households in 31 pilot counties[7]. The program was extended to 62 counties in 2010 and to 99 in 2011. The experimental sites for this study were two rice production counties included in 2010 in the insurance program from Jiangxi province, one of China's major rice bowls. In these two counties, rice production is the main source of income for most farmers. Because the product was new, no household had ever heard of or purchased such insurance before, and most of them had never interacted with PICC before. As a result, farmers, and even government officials at the village or town

[6]Field experiments have shown that social norms marketing, which tries to exploit people's tendency to imitate peers, has mixed effects on decision-making (Beshears et al. (2011); Cai et al. (2009); Carrell et al. (2011); Chen et al. (2010); Frey and Meier (2004); Fellner et al. (2011)). However, there is little evidence on how social norms marketing affects choices in products such as insurance.

[7]Although there was no insurance before 2009, if major natural disasters occurred, the government made payments to households whose production had been seriously hurt. However, the level of transfer was usually very limited and far from sufficient to help farmers resume production.

level, had very limited understanding of weather insurance products and were unfamiliar with the insurance company.

The insurance contract is as follows. The actuarially fair price is 12 RMB per mu per season[8]. The government gives a 70% subsidy on the premium, so farmers only pay the remaining 3.6 RMB per mu. If a farmer decides to buy the insurance, the premium is deducted from the rice production subsidy deposited in each farmer's bank account, with no cash payment needed[9]. The insurance covers natural disasters, including heavy rain, flood, windstorm, extremely high or low temperatures, and drought. If any of these natural disasters happens and leads to a 30% or more loss in yield, farmers are eligible to receive payouts from the insurance company. The amount of payout increases linearly with the loss rate in yield, from 60 RMB per mu for a 30% loss to a maximum payout of 200 RMB per mu[10]. The loss rate in yield is determined by a committee composed of insurance agents and agricultural experts. The average gross income from cultivating rice in the experimental sites is between 700 RMB and 800 RMB per mu, and the production cost is around 300 RMB to 400 RMB per mu. Thus, this insurance program covers 25% to 30% of the gross income or 50% to 70% of the production cost. With such a high level of subsidy, we can safely assume that it is optimal for all rice farmers to purchase the insurance.

[8] 1 RMB = 0.15 USD; 1 mu = 0.067 hectare. In the experimental sites, farmers produce two or three seasons of rice each year.The actuarially fair price was calculated based on the average probability of disaster and yield information at the national level. The disaster probability is lower in this particular province than the national average.

[9] Starting in 2004, the Chinese government has provided rice production subsidies to rice farmers in order to give them more production incentives. Each year, subsidies are deposited directly to the agricultural card in the rural credit cooperatives (the main rural bank of China).

[10] For example, consider a farmer who has 5 mu in rice production. If the normal yield per mu is 500kg and the farmer's yield decreased to 250kg per mu because of a windstorm, then the loss rate is 50% and he will receive 200*50% = 100 RMB per mu from the insurance company.

3 Experimental Design and Data

3.1 Experimental Design

We use a randomized experiment to identify the role of social networks in influencing insurance demand. The experiment was carried out in the spring of 2010, and includes 185 villages with $5,332$ households[11]. The experiment is used to answer three questions: What is the causal effect of social networks on the short-run demand for insurance? What is the monetary equivalence of the social network effect? What kind of information did social networks convey that is driving the effect?

The experiment was designed on the assumption that financial education reinforces insurance uptake, a fact that we will verify in the study. In order to generate household level variation in the knowledge and understanding of insurance products, two types of information sessions were offered to different households: simple sessions that took around 20 minutes, during which we only introduced the insurance contract[12]; and intensive sessions that took around 45 minutes and covered all information provided during simple sessions plus financial education to help farmers understand how insurance works and what are its expected benefits[13].

In each village, two rounds of sessions were offered to introduce the insurance program. During each round, there were two sessions, one simple and one intensive. The second round sessions were held three days after the first round, in order to allow second round participants to communicate with first round participants. The effect of social networks on insurance take-up is thus identified by looking at whether second round participants are

[11] In this experiment, "village" refers to the "natural village" in rural China, which is a smaller unit than "administrative villages".

[12] The simple session explains terms in the contract including the insurance premium, the amount of subsidy provided by the government, the responsibility of the insurance company, the maximum payout, the period of responsibility, rules of loss checking, and the procedures for making payouts.

[13] Some of the topics included in financial education are: How does the insurance program differ from a government subsidy? How much payout can you get under different conditions? What is the expected benefit or loss from purchasing insurance for five continuous years depending on different disaster frequencies and levels?

more likely to buy insurance if they had more friends exposed to financial education in first round intensive sessions.

The experimental design is illustrated in Figures 1.1 and 1.2. There are four randomizations in this experiment, two at the household level and two at the village level. The within-village household level randomizations are presented in Figure 1.1. First, households were randomly assigned to one of the four sessions: first round simple (T1), first round intensive (T2), second round simple (T3), and second round intensive (T4)[14]. This randomization is used to account for exogenous variations among second round participants in the proportion of their group of friends exposed to first round financial education, and hence helps identify the causal effect of social networks within villages.

Second, for each second round session, after the presentation and before participants were asked to make their final decisions, we randomly divided them into three groups and disseminated additional information that was different for each group. Farmers in groups U1 and U4 received no additional information from us but were directly asked to make take-up decisions; these farmers thus received exactly the same information from us as those in the two first round sessions (T1 and T2). To farmers in groups U2 and U5, we told what had been the attendance and the overall take-up rate at the two first round sessions in their village. To farmers in groups U3 and U6, we showed the detailed list of purchase decisions made in the two first round sessions, so that they knew specifically who purchased the insurance and who did not. This part of the experiment was designed to help determine the main mechanisms that drive the social network effect.

The village level randomizations are shown in Figure 1.2. First, we randomly divided villages into two types. In type I villages, all households faced the same price of 3.6 RMB

[14] Before doing randomizations, we first approached the leaders of each village to obtain a list with the names of all household heads and basic household characteristics. Households who did not grow rice were excluded. For all household-level randomizations in this experiment, we stratified the sample within each village according to household size and area of rice production per capita, and randomly assigned households to different treatment groups in each stratum. Only household heads were invited to attend one of the four sessions. No one could attend more than one session. In order to guarantee a high session attendance rate, we gave monetary incentives to village leaders and asked them to inform and invite household heads to attend these sessions.

per mu, while in type II villages, we randomly assigned seven different prices ranging from 1.8 to 7.2 RMB per mu to different participants[15]. Type II villages are used to measure the monetary value of the social network effect. The second village-level randomization was only within type I villages. We randomized the default option to buy in first round sessions. If the default was BUY, the farmer needed to sign off if he or she did not want to purchase the insurance; if the default was NOT BUY, the farmer had to sign on if he or she decided to buy the insurance[16]. Default options were the same in the two first round sessions within each village. The objective of offering different default options was to generate exogenous variations in the first round insurance take-up across villages which could be used in some estimations as an instrumental variable for first round purchase decisions[17].

In all cases, households had to decide whether to purchase the insurance individually at the end of the information session.

3.2 Data, Summary Statistics and Randomization Check

The empirical analysis is based on data from two surveys: the social network survey, which was carried out a few days before the experiment, and a household survey filled out after the uptake decisions had been made at the end of each information session. Because all rice households were invited to sessions, and more than 90% of them came to the sessions, this provides a detailed census of the population of these 185 villages. In total, $5,332$ households were surveyed.

[15]In all type II villages, farmers in second round sessions T3 and T4 received exactly the same information as households in first round sessions T1 and T2, respectively. No additional first round take-up information was provided after the presentation.

[16]During sessions where default = BUY, before insurance agents asked farmers to make decisions, instructors told them the following: "We think that this is a very good insurance product, and we believe that most farmers will choose to buy it, so it is more convenient for us to record who does not buy it rather than who buys it. So if you have decided to buy the insurance, there is nothing you need to do, as the premium will be deducted automatically from your agricultural card; if you do not want to buy it, then please come here and sign."

[17]According to Beshears et al. (2009), default options can influence households' financial decisions significantly. A possible reason is that households find it too complicated to make a decision by themselves, so they simply follow the default option as they think it is set as the default because it is a good choice. For more details, refer to Beshears et al. (2009).

The household survey includes information on demographics, rice production, income, borrowing, natural disasters experienced and losses incurred, experience in purchasing any kind of insurance, risk attitudes, and perceptions about future disasters[18]. It also contains questions that test farmers' understanding of how insurance works and its potential benefits. Summary statistics of selected household characteristics are presented in Panel A of Table 1. Household heads are almost exclusively male, and the average education level is between primary and secondary school. Rice production is the main source of household income, accounting for 73% of total income on average. 63% of the households had experienced some type of natural disasters in the most recent year, and the average yield loss rate was around 28%. Households are on average risk averse.

The social network survey asked the household head to list five close friends, either within or outside the village, with whom he/she most frequently discusses rice production and financial related problems[19]. The respondent was asked to rank these friends based on which one would be consulted first, second, etc. Relationships with each person named, topics that they usually talk about, and contact frequency were also elicited. Having the village census, we can fully characterize the village network. We use these data to construct two types of variables: social network financial education measures (Panel B) and social network structural characteristics (Panel C).

We use three types of household-level social network financial education measures (Panel B). The general measure is defined as the number of socially linked households who were invited to a first round intensive session (where financial education was provided), divided by the household's network size. Network size is uniformly equal to 5, the potential number of friends a household could name. Household A is said to be socially linked to B if A

[18]Risk attitudes were elicited by asking sample households to choose between a certain amount with increasing values of 50, 80, 100, 120, and 150 RMB (riskless option A), and risky gambles of (200RMB, 0) with probability (0.5, 0.5) (risky option B). The number of riskless options was then used as a measure of risk aversion. The perceived probability of future disasters was elicited by asking, "what do you think is the probability of a disaster that leads to more than 30% loss in yield next year?"

[19]Respondents can list any person except for their parents and children, because in many cases parents and children cultivate the same plots of rice together.

named B or B named A in the social network survey. As can be seen in Panel B, most households in fact listed 5 friends (on average 4.9). The social network financial education variable varies between 0 and 1, equal on average to 0.16. We construct two other social network financial education variables based on the strength of the link between households (Granovetter (1973)). The strong measure is defined as the number of bilaterally linked households that were invited to a first round intensive session, divided by network size. Household A and B are defined as bilaterally linked if they named each other as friends. The weak measure is defined as the number of second-order linked households that were invited to a first round intensive session, divided by the sum of friends' network sizes (25 in most cases). A second-order linked household is one that is named as a friend by one of your own friends. These three measures will be the main independent variables used to estimate the social network effect.

We also construct the village-level network structure and household-level network characteristics, with the idea that these network features may influence how well and how fast information diffuses between households, and hence provide sources of heterogeneity of the network effect on insurance uptake. We define five village-level network characteristics: network size, defined as the number of households in each village; segmentation of village network, measured by the fraction of "giant component", which is the share of households in the graph that are in the largest connected component; and three indicators of interconnectivity: (*i*) graph clustering rate, defined as the fraction of pairs of household friends that are friends of each other; (*ii*) transitivity, defined as the fraction of transitive triads (A is linked to B, B is linked to C, and C is linked to A) in the total number of triads; and (*iii*) reciprocity, defined as the fraction of bilaterally linked pairs of households in the total number of household pairs. Average values across the sample villages are reported in Panel C of Table 1. Villages have on average 32 households. They essentially include only one large connected group, with almost 99% of households in this main component. The average clustering rate shows that, in 18% of the cases where household i is connected to some households j and k, j and k are connected to each other. As for the transitive and reciprocal indicators, 21% of all possible households triads are connected to each other, and 17% of all possible pairs are bilaterally connected. These three indicators project the image of a dense level of connectivity among households of a village.

One can also characterize the importance of a given household in a network. We retain three indicators for this: (i) in-degree, which is the number of persons that named it as friend[20]; (ii) path length, which is the mean of the shortest paths to/from this household from/to any other household; and (iii) Eigenvector centrality, which measures a household's importance in the overall flow of information. This last indicator is a recursively defined concept where each household's centrality is proportional to the sum of its neighbors' centrality[21]. Average values for these variables are reported in Panel D. Each household is on average cited as a friend by three persons. The average path-length is around 3.5, which means that a household can be connected to any others in the village by passing on average through three to four households. These relatively short average paths reflect the intensity of network links in these villages.

Randomization checks are presented in Appendix A, Tables A1 and A2. Most household characteristics are balanced across the four different sessions. To check whether the price randomization is valid, we regress the five main household characteristics (gender, age, household size, education, and area of rice production) on a quadratic in the insurance price and a set of village fixed effects, in type II villages where price variation was implemented:

$$X_{ij} = \alpha_0 + \alpha_1 Price_{ij} + \alpha_2 Price_{ij}^2 + \eta_j + \epsilon_{ij} \tag{1}$$

Where X_{ij} is a set of characteristic of household i in village j, including gender, age, house-

[20] Although we use direct social network measures, only in-degree is considered here because out-degree is defined as network size, which equals five for most households.

[21] While measures such as degree are intuitive notions of graphical importance, they miss the key feature that a node's ability to propagate information through a graph depends not only on the sheer number of connections it has, but also on how important these connections are, which can be captured by the centrality measure. In Figure A1, Panel B illustrates an example where it is clear that i is a very important node, although a simple count of its friends would not carry this information.

hold size, education, and area of rice production. $Price_{ij}$ is the price faced by household i in village j, and η_j are village fixed effects. Results reported in Tables A1 and A2 show that all the coefficient estimates are small in magnitude and none is statistically significant, suggesting that the price randomization is valid.

4 Social Network Effect, Heterogeneity, and Network Structure

4.1 Estimation of the Social Network Effect

The average take-up rates in different information sessions are reported in Table 1, panel D. They show that, while the difference between the two first round sessions is substantial, there is almost no difference between the two second round sessions. Moreover, the take-up rate of second round sessions is much higher than that of first round simple sessions. This suggests that the financial education provided during first round intensive sessions improved farmers' take-up rates, and that, during the three days' time interval between the two rounds, there was substantial information diffusion from first round to second round participants.

We estimate the effect of social networks on insurance take-up, using the type I villages in which there was no price variation in the insurance offer (Figure 1.2). We first establish the effect of financial education using the sample of first round participants (simple session T1 vs. intensive session T2 in Figure 1.1) by estimating:

$$Takeup_{ij} = \beta_0 + \beta_1 Intensive_{ij} + \beta_2 X_{ij} + \eta_j + \epsilon_{ij} \quad (2)$$

where $Takeup_{ij}$ is an indicator of the purchase decision made by household i in village j, which takes a value of one if the household decided to buy the insurance and zero otherwise. $Intensive_{ij}$ is a dummy variable equal to one if the household was invited to an intensive sessions in village j and zero otherwise. X_{ij} includes household characteristics such as gender, age, education of the household head, rice production area, etc., and η_j are village fixed effects. Results in Table 2 show, first, that the take-up rate of first round intensive sessions (50%) is 15 percentage points higher than that of first round simple sessions (35%), suggesting the existence of a large and significantly positive financial education effect that increases the take-up rate by 43% in the first round.

Second, to estimate the social network effect, i.e., the spillover effect of first round financial education on second round participants, we focus on the sample of households that were assigned to second round groups U1 and U4 (where no first round take-up information was revealed). We test whether they are more likely to buy insurance if they have more friends who were invited to the first round intensive session by estimating:

$$Takeup_{ij} = \tau_0 + \tau_1 Network_{ij} + \tau_2 X_{ij} + \eta_j + \epsilon_{ij} \tag{3}$$

where the social network measure is defined as the fraction of the group of friends named in the social network survey who have been invited to a first round intensive session[22]. Because households are more likely to be exposed to information provided during financial education if more of their friends attended a financial education session, a positive social network effect is expected.

Estimation results are reported in Table 3. Column 1 shows a significantly positive effect of social networks on insurance take-up, with a magnitude of around 33.7 percentage points. This suggests that having one additional close friend attending a first round intensive session - raising the general network measure by 20% - increases a farmer's own take-up rate by 33.7*0.2 = 6.74 percentage points[23]. This is equivalent to more than 45% of the direct

[22]For example, if a household listed five friends, and two of them were invited to a first round intensive session, then the social network measure equals 0.4.

[23]In this experiment, there were no households who received no financial education and had no interactions with people who received financial education. We did another experiment to estimate the network effect in a more traditional way, with 52 villages and around 1,780 households. The design was as follows: we randomly selected 30 treatment villages within which we randomly invited a subset of households (group A) to attend a financial education session about the insurance program. Three days after the session, we visited the remaining households (group B) individually. In control villages, all households (group C) were visited door-to-door. We then measured the social network effect by estimating equation (3) based on groups B

financial education effect (Column 1 in Table 2). The result is robust to the addition of control variables (Column 2)[24]. Looking at the control variables suggests that older people, farmers with a larger production area, or those with more education are more likely to buy the insurance. Households who are more risk averse, or those who predict a higher probability of natural disasters in the following year, are also more likely to purchase insurance. In column 3, we test whether the magnitude of social network effects depends on whether a farmer received financial education himself. The social network effect is smaller in second round intensive sessions, indicating that people are less influenced by their friends when they have a better understanding of the product.

The magnitude of social network effects may depend on the strength of ties. To test this, we use the strong measure (bilateral links) and the weak measure (second-order links) of social networks and re-estimate equation (3). Results are reported in columns 1 and 2 of Table 4. Having one additional strongly linked friend attending first round financial education improves a farmer's own probability of taking the insurance by 8.5 percentage points, which is larger than the effect of the standard social links (6.7 percentage points). By contrast, friends with weak links are much less influential (column 2): the number of weakly linked friends receiving first round financial education does not have a significant effect on a farmer's own behavior. This means that households are not much influenced by friends' friends during a short period of time (three days in this case). In addition, we test whether the magnitude of the social network effect varies according to the relationship between the farmer and the person he or she named. Results in column 3 show that government officials have the largest effect in influencing their friends' purchase decisions, followed by neighbors and relatives.

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and C. We find a comparable effect: having one additional listed (strongly connected) friend attending the financial education increases one's own take-up by around 4% (5.5%), which equates to around 33% (50%) of the direct education effect.

[24]Because a small proportion of households named less than 5 friends in the social network survey, and these households might be different from other farmers in some aspects, we did a robustness check by excluding these households and re-estimating the social network effect. We found that the significance and magnitude of the social network effect remain almost the same.

The next question we ask is whether it is enough to have just one friend receiving financial education, or whether having more friends receiving financial education generates larger effects. We test the nonlinearity of the social network effect using the following equation:

$$Takeup_{ij} = \rho_0 + \rho_1 One_{ij} + \rho_2 Two_{ij} + \rho_3 More_{ij} + \rho_4 X_{ij} + \eta_j + \epsilon_{ij} \tag{4}$$

where One_{ij}, Two_{ij}, and $More_{ij}$ are dummy variables equal one if household i has one, two, or more than two friends assigned to the first round intensive session in village j, and 0 otherwise. Results presented in column 4 of Table 4 show that the magnitude of the social network effect increases with the number of friends receiving first round financial education. Specifically, among second round participants, the effect on insurance take-up of having two friends obtaining first round financial education is 20.6 percentage points; this is about 14 percentage points higher than the 6.2 percentage points effect of having only one friend financially educated in the first round. However, having more than two friends financially educated has only a slightly higher effect on take-up (7 percentage points) than having two.

In summary, these results tell us that providing financial education when introducing the insurance product improves the take-up significantly. More importantly, it has a large and significant spillover effect on insurance adoption by other farmers: among second round participants, having one more friend receiving financial education transmits 45% of the first order education effect. This effect is larger when the strength of connections is higher, and when transmission comes through friends working in the government.

4.2 Heterogeneity Related to the Social Network Structure

How efficiently can information be diffused, and to what extent can a farmer be influenced by other farmers? This may depend on network characteristics at both the village and the individual levels (Jackson (2010); Acemoglu et al. (2010); Allcott et al. (2007)).

Taking advantage of cross-village variation in network structure, we estimate how the magnitude of social network effects varies with a set of variables that capture village-level network structure using the following regression:

$$Takeup_{ij} = \eta_0 + \eta_1 Network_{ij} + \eta_2 VilNetCharact_j + \eta_3 Network_{ij} * VilNetCharact_j + \eta_4 X_{ij} + \epsilon_{ij} \tag{5}$$

where $VilNetCharact_j$ includes five measures of village-level network characteristics: village size (number of households), fraction in the giant component (the fraction of households that are in the main component), clustering (the fraction of pairs of a household's neighbors that are each other's neighbors), transitivity (the fraction of transitive triads in the total number of triads), and reciprocity (the fraction of mutually linked pairs in the total number of pairs). Results reported in Table 5 show that, in villages with a high clustering coefficient, the effect of social networks on insurance take-up is larger, suggesting that, in these villages, the spread of information might be easier and faster. None of the other measures of network connectivity significantly affect the magnitude of the social network effect. Considering all variables together in column 6 shows that the effect of clustering on the social network effect becomes stronger once other characteristics are controlled for.

We now look at heterogeneity of network effects across households, by interacting the social network variable with the different variables that characterize how influential or susceptible to be influenced a household may be. The estimation equation is as follows[25]:

$$\begin{aligned} Takeup_{ij} = \eta_0 + \eta_1 Network_{ij} + \eta_2 OwnCharact_{ij} + \eta_3 Network_{ij} * OwnCharact_{ij} \\ + \eta_4 NetCharact_{ij} + \eta_5 Network_{ij} * NetCharactij + +\eta_6 X_{ij} + \eta_j + \epsilon_{ij} \end{aligned} \tag{6}$$

where $OwnCharact_{ij}$ is the network characteristics of household i, and $NetCharact_{ij}$ is the average network characteristics of friends named by household i who attended the first round

[25] While Banerjee et al. (2012) studied the effect of group-level characteristics of initially treated households on village level microfinance participation, here we define injection point characteristics for each household's social links. We explain how the magnitude of social network effect depends on the characteristics of friends who were financially educated first and on each decision-making farmer's own importance in the village network.

intensive session in village j.

In this expression, the strength of network influence is:

$$\eta_1 + \eta_3 OwnCharact_{ij} + \eta_5 NetCharact_{ij}$$

This is a function of both a farmer's own characteristics and those of the farmer's network. A natural interpretation is that a farmer's own characteristics measure how susceptible the farmer is to influence his or her network, while the characteristics of the network measure how much the network influences the farmer. Because these are likely correlated with each other, we always consider them together in any estimation. Results in Table 6 indicate that a farmer's own characteristics are important: those who were named more often by other households (higher in-degree), who can be reached more easily (smaller path length), and who have a more important network position (higher eigenvector centrality), are less likely to be influenced by other people (interaction terms in columns 2, 4 and 6). As there are significant correlations between these individual-level network characteristics, we pool all these variables together in column 8. The significance of in-degree becomes much smaller once variables are pooled together. These characteristics not only affect the magnitude of the social network effect, but also directly affect the take-up decisions. Those who were named more often by others, who can be reached less easily, and who have a less important network position are more likely to buy insurance (Column 7).

Turning to the characteristics of friends treated in the first round financial education session, we see in column 8 that, even though the average in-degree and path length of one's friends do not influence the magnitude of the social network effect, their eigenvector centrality does. If the eigenvector centrality of the set of friends in first round financial education is one standard deviation larger (0.1), second round overall take-up is around 5 percentage points larger, and the effect on take-up of social networks (having one additional friend financially educated) is around 6.8 percentage points larger.

Who are these influential individuals with high centrality? Looking for correlates, we find that households with higher network centrality are usually better educated and with larger production size (Table A3). A reason they are more influential may be that they better understand the benefits of purchasing insurance and can explain them better. A reason they are less likely to be influenced by others may be that, as they are larger farmers, having insurance is more important to them and they purchase it regardless of what other people say. We present in Table A4 the role of heterogeneity of social networks based on these easily observable characteristics.

In summary, we verified that social networks are more effective at transmitting information in villages where households are more interwoven with each other, and when the people treated first are more importantly located in the village network.

5 Monetary Equivalence of the Social Network Effect

In order to better understand the importance of the social network effect, we assess its price equivalence using type II villages, where a price randomization was implemented. Specifically, we estimate the effect of varying subsidies on insurance demand, and test whether households are less sensitive to prices if they have more friends exposed to financial education. We then calculate the monetary equivalence of the social network effect, i.e., by how much should the premium be reduced in order to achieve the same effect as social networks on insurance take-up, based on estimated coefficients. A simple theoretical model of insurance demand, illustrating why social networks can potentially influence both the level and the slope of the insurance demand curve, is presented in Appendix B. The basic idea is that the benefits of insurance are not well known to farmers. Benefits are perceived as uncertain and with subjective expected value. As a result, the level and slope of the insurance demand curve are determined by farmers' perceptions and uncertainty about the expected benefits of the product, and by the distribution of the expected benefits at an aggregate level. For an individual farmer, how much he values the insurance product, and how certain he is about this value, may depend on his understanding of the product. This can be influenced by formal training or through learning from friends who are more knowledgeable than him about the product, and by experiencing the value of the product by himself or by observing friends who are using it. Moreover, how effectively information can be diffused through social networks determines how concentrated or dispersed is the distribution of farmers' expected product benefits As a consequence, we expect that the diffusion of information through social networks can affect both the level and the slope of the insurance demand curve.

In Figure 2, we compare the insurance demand curves of households who have an above-median (high) or a below-median (low) proportion of friends financially educated. The insurance demand curve is clearly higher and flatter, especially under high prices, when a high proportion of friends has been exposed to financial education in intensive sessions. We estimate this relationship with the following equation:

$$Takeup_{ij} = \gamma_0 + \gamma_1 Price_{ij} + \gamma_2 Network_{ij} + \gamma_3 Price_{ij} * Network_{ij} + \gamma_4 X_{ij} + \eta_j + \epsilon_{ij} \quad (7)$$

where $Price_{ij}$ is the price assigned to household i in village j, which takes one of seven different values ranging from 1.8 to 7.2 RMB per mu. Results presented in Table 7 show that increasing the price by 1RMB decreases take-up by 11.2 percentage points (Column 1). The interaction term between price and social network is significantly positive (Column 2), suggesting that households with more friends receiving financial education are less sensitive to price. Specifically, having one additional friend receiving financial education mitigates the price effect by 0.13*0.2/0.167 = 16%.

A concern with the above estimation is that, for households in the price experiment, some of their friends face lower prices than they do, while others face higher prices. A "fairness" concern may thus occur and affect the price elasticity of insurance demand. To control for this, we included two additional variables when estimating equation (7): the share of friends with prices higher or lower than one's own price. Results in column 3 show that the result changed only slightly.

We then calculate the price equivalence P of the social network effect by the following formula:

$$P = \frac{coef(Network_{ij}) + coef(Price_{ij} * Network_{ij}) * mean(Price)}{coef(Price_{ij}) + coef(Price_{ij} * Network_{ij}) * mean(Network)} * 0.2$$

Using estimated coefficients from columns 2 and 3, and the average value of Network (0.161) and Price (4.34) in these villages, we find that having one additional friend is equivalent to a 15% decrease in the average insurance premium.

6 Identifying the Social Network Effect Mechanisms

A natural question is why social networks matter. What is it that farmers learned from their informed friends that influenced their take-up decisions? Understanding these mechanisms is a prerequisite for making policy recommendations as to how governments or institutions can use social networks to obtain efficient outcomes. Generally speaking, social networks may influence the adoption of a new technology or a financial product because of three reasons: (i) people gain knowledge from their friends about the value or the benefits of a product (Kremer and Miguel (2007); Koher et al. (2001)); (ii) people learn from their friends how to use the product (Duflo and Saez (2003); Munshi and Myaux (2006); Kremer and Miguel (2007); Oster and Thornton (Forthcoming)); or (iii) individuals care about other people's decisions (Bandiera and Rasul (2006); Banerjee (1992); Beshears et al. (2011); Çelen et al. (2010); Ellison and Fudenberg (1993); Rogers (1995)). In this last case, farmers could be influenced by their friends' decisions because of scale effects (famers believe that they have greater leverage over the insurance company if more of them purchase the product at the same time), desire to imitate (farmers want to act like each other), or the existence of informal risk-sharing arrangements (a farmer's decision depends on the purchase decision of households from which the farmer borrows or to which the farmer lends).

Because insurance is a financial product rather than a technology, people do not need to learn how to use it. We thus focus on the role of the other two types of information that can be usefully conveyed by social networks: insurance knowledge and purchase decisions. If the reason that farmers are affected by their friends' exposure to financial education is that their understanding of insurance benefits is improved by learning from their friends, this means that insufficient knowledge of insurance impairs adoption; in that case, providing financial education would be crucial. On the other hand, if the network effect is driven by the influence of friends' purchase decisions, then using low-cost marketing strategies to guarantee a high adoption rate by pilot clients could significantly improve the take-up rate by follow-up customers.

To test the insurance knowledge mechanism, we follow two approaches. The first consists of comparing the magnitude of the financial education effect on insurance take-up and knowledge between first round (simple session T1 vs. intensive session T2) and second round sessions (simple session U1 vs. intensive session U4). Intuitively, if late participants can acquire enough information on insurance knowledge from early participants during the time interval between the two rounds, then, in the second round, the additional information given in the intensive session should make no difference relative to the simple session on take-up or knowledge of insurance. The estimation equations are as follows:

$$Takeup_{ij} = \omega_0 + \omega_1 Intensive_{ij} + \omega_2 Second_{ij} + \omega_3 Intensive_{ij} * Second_{ij} + \omega_4 X_{ij} + \eta_j + \epsilon_{ij} \quad (8)$$

$$Knowledge_{ij} = \omega_0 + \omega_1 Intensive_{ij} + \omega_2 Second_{ij} + \omega_3 Intensive_{ij} * Second_{ij} + \omega_4 X_{ij} + \eta_j + \epsilon_{ij} \quad (9)$$

where $Second_{ij}$ is a dummy variable indicating whether the household was assigned to one of the two second-round sessions, and $knowledge_{ij}$ is a measure of insurance knowledge, which is defined as the score that a household obtained on a ten question test. Results are presented in Table 8. Column 1 shows that, while financial education raises the take-up rate significantly in the first round (by 14 percentage points), it makes almost no difference in the second round. Similarly, financial education raises insurance knowledge by 31 percentage points in the first-round session, but not in the second-round (Column 3). Furthermore, levels of insurance take-up and knowledge are significantly higher in the second-round than in the first-round simple sessions, by an amount equivalent to 64% and 78% of the first-round intensive session effect, respectively.

The second approach looks at the networks specific to individuals, and tests whether households perform better on the insurance knowledge test when they had more friends attending first round financial education, by estimating the following equation:

$$Knowledge_{ij} = \lambda_0 + \lambda_1 Network_{ij} + \lambda_2 X_{ij} + \eta_j + \epsilon_{ij} \tag{10}$$

Results in column 4 of Table 8 show that having one additional friend assigned to first round intensive sessions improves the level of insurance knowledge by 7 percentage points. Furthermore, we test whether the effect is larger when one's friend better understands the materials provided during financial education, and as a result can better teach other people, by estimating:

$$\begin{aligned} Knowledge_{ij} = \lambda_0 + \lambda_1 Network_{ij} + \lambda_2 NetKnowledge_{ij} \\ + \lambda_3 Network_{ij} * NetKnowledge_{ij} + \lambda_4 X_{ij} + \eta_j + \epsilon_{ij} \end{aligned} \tag{11}$$

where $NetKnowledge_{ij}$ is the average insurance knowledge test score received by household i's friends who obtained first round financial education in village j. Column 5 in Table 8 shows that a farmer learns more from friends who had a better understanding of the information provided by financial education. These results support the argument that, during the three days between the two rounds of sessions, second round participants acquired insurance knowledge from the first set of people who were financially educated, and that such informal acquisition of knowledge improved insurance take-up significantly.

To estimate whether social networks conveyed information on purchase decisions, we directly test the effect of other people's decisions, i.e., the overall take-up rate in first round sessions, and friends' take-up rate in first round sessions, on second round participants' behavior. Consider first the effect of overall first round take-up:

$$Takeup_{ij} = \gamma_0 + \gamma_1 TakeupRate_j + \gamma_2 Reveal_{ij} + \gamma_3 TakeupRate_j * Reveal_{ij} + \gamma_4 X_{ij} + \epsilon_{ij} \quad (12)$$

where $TakeupRate_j$ is the overall take-up rate in first round sessions (T1 and T2) in village j, which is a continuous variable ranging from 0 to 1, and $Reveal_{ij}$ is an indicator of whether we told second round participants about the overall first round take-up rate. The hypothesis is that individuals are more likely to purchase insurance if they see higher take-up rates in previous sessions, because of either scale effect or imitation. However, OLS estimation cannot give a consistent estimation because unobservable variables such as social norms may affect both $TakeupRate_j$ and $Takeup_{ij}$.

Randomized default options in first-round sessions give significant and substantial variations in the overall first round take-up rates: the average take-up rate of "default = BUY" sessions is around 12 percentage points higher than that of "default = NOT BUY" sessions (Table 9, column 1)[26]. As a result, we can use the default option as an instrumental variable (IV) for first-round overall take-up rates. OLS and IV estimation results for the whole second round sample are presented in columns 2 and 3: farmers are more likely to buy insurance when the overall first round take-up rate is higher, but the effect is much smaller if we did not explicitly reveal that information, becoming insignificant with IV estimation. To see this more clearly, we break down the sample and re-estimate the influence of first round overall take-up rate in columns 4 and 5. Second round participants are not influenced by decisions

[26] Reasons why people follow the default option and which types of people are more likely to comply have been discussed in Brown et al. (2011) and Beshears et al. (2010). We find that people are less likely to follow the default option when they receive better information about the product: the default effect is smaller in intensive sessions than in simple sessions.

made by first round participants when this information is not revealed to them (column 4). However, they do care a great deal about what other farmers do: as suggested by column 5, if we disseminate first round overall take-up information during second round sessions, a 10% higher take-up rate in the first session can raise the take-up rate in second-round sessions by 4.3%, which is almost half of the first-round effect.

To see if friends' behaviors have similar effects on farmers' decisions as on overall take-up, we estimate the following equation using the sample of second round participants who did not receive take-up information and those who did receive from us the first-round decision list (U1, U3, U4, and U6 in Figure 1.1):

$$\begin{aligned} Takeup_{ij} = {} & \delta_0 + \delta_1 TakeupRate_j + \delta_2 TakeupRateNetwork_{ij} + \delta_3 Reveal_{ij} \\ & + \delta_4 TakeupRate_j * Reveal_{ij} + \delta_5 TakeupRateNetwork_{ij} * Reveal_{ij} + \delta_6 X_{ij} + \epsilon_{ij} \end{aligned} \tag{13}$$

where $TakeupRateNetwork_{ij}$ represents the take-up rate among friends of household i who attended first-round sessions in village j[27]. Similar to what has been discussed before, both $TakeupRate_j$ and $TakeupRateNetwork_{ij}$ are endogenous. While we still use the first round default option as IV for the overall first round take-up rate, we use Default times the ratio of network in first-round sessions (first round default options are more likely to influence the number of friends who purchase insurance if more friends are included in first round sessions) as an IV for $TakeupRateNetwork_{ij}$. Results in Table 10 show that decisions made by friends in a farmer's social network do not influence the farmer's own decision (column 4). This is not because farmers do not care about other villagers' decisions, as this information has a large and significant influence if we explicitly revealed it (column 5), but because, at least in this context, social networks did not convey this information[28].

[27]For example, if a household named five friends in the social network survey, four of them were assigned to the first round intensive session, and two of them decided to buy the insurance, then $TakeupRateNetwork_{ij}$ = 0.5.

[28]A qualitative analysis also confirms this argument. In the household survey, we directly asked people whether they know each of their friend's decisions. Only 9% of the households knew at least one of their

These results suggest an interesting regularity about the performance of social networks in traditional Chinese society: while networks are efficient in transmitting insurance knowledge, they do not convey information on purchase decisions. This is surprising, because farmers actually care a great deal about that information, something we know because of its significant effect on decision-making when explicitly revealed. We conclude that the short-run social network effect on insurance take-up is mainly driven by the diffusion of insurance knowledge, as opposed to channels related to the behavior of other people that may influence decision-making through scale effects, imitation, or informal risk-sharing.

Direct interviews with farmers, as well as behavioral studies (Qian et al. (2007)), reveal the presence of a strongly ingrained cultural factor which can explain the limited diffusion of information on take-up decisions: Chinese people care a lot about "face" (i.e., their public image, which is gained by performing social roles, that establishes respectability and deference from others), and disclosing purchase decisions carries the risk of "losing face." Specifically, farmers are reluctant to reveal their decisions because they are unsure of whether they have made the right choice and do not want to expose their potential lack of judgment or be liable for having influenced someone in making a bad decision as well. Social networks in Chinese villages are thus useful instruments for the diffusion of innovations as they effectively transfer knowledge from informed to uninformed related individuals. However, these networks suffer from the drawback that the deep-rooted concern with not losing face limits the circulation of information on an essential determinant of decision-making, namely knowing what peers have decided regarding adoption of the innovation.

7 Conclusions

This paper uses a randomized field experiment in rural China to analyze social network effects in the adoption of a new weather insurance product. We find strong evidence that social networks play important roles in affecting insurance take-up through social learning

friends' decisions.

mechanisms. Providing financial education to a subset of farmers has large and positive spillover effects on other farmers. This is driven by the diffusion of insurance knowledge through social networks rather than the diffusion of information on behavior. While people care a great deal about whether others in their social network have decided to purchase the new insurance product, this information is not conveyed by social networks, because people are concerned with potential loss of face if it turns out that they have made the wrong choice.

Several policy implications can be drawn from these results. First, providing financial education to a subset of farmers, and depending on social networks to multiply its effect on others, can substantially improve the overall insurance take-up rate. The choice of individuals targeted for financial education, based on the structure of social networks and the influence of particular individuals, can make a significant difference in the size of multipliers achieved. Second, these results cast some doubt about the common practice of providing heavy subsidies for innovative products to a sub-sample of potential customers in order to encourage take-up, with the hope that other people will follow their behavior. The fact that farmers do not communicate purchase decisions tells us that providing subsidies to a subset of the population may not be sufficient to achieve the expected outcomes. However, because we do see increased take-up when farmers are explicitly informed about the behavior of others, combining either education or subsidies for a targeted sub-population with social norms marketing, which disseminates information to the full population about the behavior of peers, may be an inexpensive way of expanding the take-up rate for innovative products.

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Appendices

A Supplementary Figures and Tables

Figure A1. Measure of Importance of a Household: In-Degree and Eigenvector Centrality

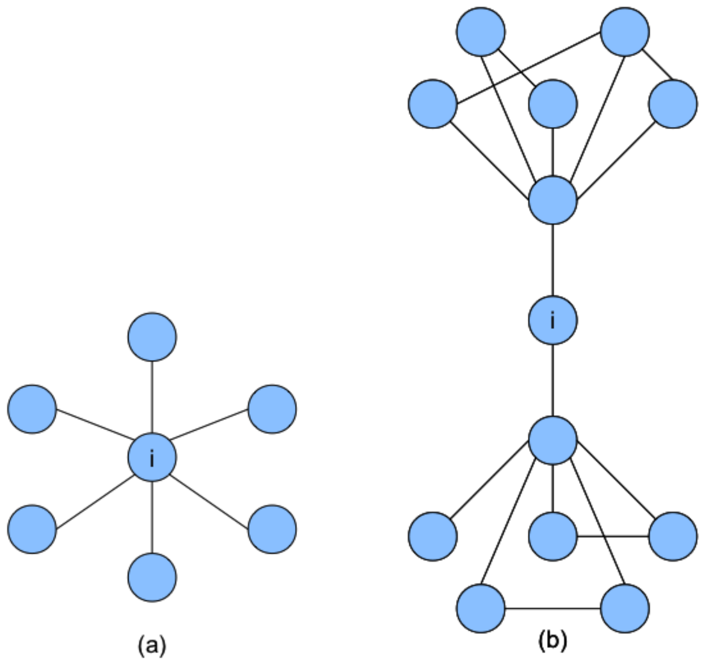


Table A1. Randomization Check: Session Assignments

	First Round		Second Round		P-Value
	Simple Session	Intensive Session	Simple Session	Intensive Session	
Gender of Household Head (1 = Male, 0 = Female)	0.908	0.923	0.91	0.915	0.5982
	(0.289)	(0.266)	(0.286)	(0.279)	
Age	51.489	51.091	51.724	51.592	0.6118
	(11.879)	(12.173)	(12.227)	(11.841)	
Household Size	4.902	4.856	4.943	4.945	0.7084
	(2.122)	(2.094)	(2.203)	(2.103)	
Education (0 = illiteracy, 1 = primary, 2 = secondary,	1.193	1.215	1.194	1.17	0.6471
3 = high school, 4 = college)	(0.859)	(0.85)	(0.866)	(0.839)	
Area of Rice Production (mu)	12.965	12.965	11.978	12.247	0.6263
	(15.25)	(26.307)	(14.397)	(21.882)	
Share of Rice Income in Total Income (%)	74.377	74.1	71.887	73.054	0.2812
	(33.878)	(33.553)	(36.015)	(35.414)	
Any Disasters Happened Last Year (1 = Yes, 0 = No)	0.624	0.633	0.634	0.632	0.9627
	(0.485)	(0.482)	(0.482)	(0.483)	
Loss in Yield Last Year (%)	27.042	27.683	27.601	27.651	0.9208
	(18.498)	(18.116)	(18.374)	(17.861)	
Number of Households	1079	1096	1587	1570	

Note: This table checks the validity of the within-village session randomization. Standard deviations are in parentheses. P-values reported are for the F-test of equal means of the four session groups. *** p<0.01, ** p<0.05, * p<0.1.

Table A2. Randomization Check: Price Randomization

	OLS Coeff on Price	OLS Coeff on Price Squared	P-Value Joint Test (Price and Price Squared)
	(1)	(2)	(3)
Gender of Household Head	0.007	0.001	0.4374
(1 = Male, 0 = Female)	(0.072)	(0.008)	
Age	-0.331	0.096	0.2317
	(1.961)	(0.209)	
Household Size	0.105	-0.013	0.8798
	(0.236)	(0.026)	
Literate	0.0113	-0.001	0.9845
(1 = Yes, 0 = No)	(0.07)	(0.008)	
Area of Rice Production (mu)	1.085	-0.123	0.7783
	(1.574)	(0.185)	
Number of Households	431		

Note: This table checks the validity of the price randomization. *** p<0.01, ** p<0.05, * p<0.1.

Table A3. Determinants of Household Level Social Network Characteristics

VARIABLES	In-degree	Out-Path Length	In-Path Length	Eigenvector Centrality
	(1)	(2)	(3)	(4)
Male	0.457***	-0.336***	-0.248	0.0179***
(1 = Yes, 0 = No)	(0.146)	(0.120)	(0.152)	(0.00558)
Age	-0.00650*	-0.00133	0.00559*	-0.000313**
	(0.00373)	(0.00355)	(0.00304)	(0.000142)
Household Size	0.0284*	-0.0406***	0.00761	0.00195***
	(0.0151)	(0.0131)	(0.0165)	(0.000624)
Rice Production Area (mu)	0.00961**	-0.00324	0.00882***	0.000306***
	(0.00435)	(0.00287)	(0.00273)	(0.000108)
Literate (1 = Yes, 0 = No)	0.372***	-0.173**	0.0489	0.00668*
	(0.0937)	(0.0869)	(0.102)	(0.00371)
Observations	4,811	4,245	4,811	4,811
Village Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.050	0.176	0.436	0.132

Notes: Robust clustered standard errors in parentheses. Village dummies are included in all estimations. *** p<0.01, ** p<0.05, * p<0.1

Table A4. Heterogeneity on the Social Network Effect: Household Characteristics

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Network Receiving 1st Round Financial Education	0.435***	0.888*	0.242**	0.0437	0.226**	0.0138	0.369***	0.764***
([0, 1])	(0.113)	(0.513)	(0.107)	(0.238)	(0.0954)	(0.125)	(0.0853)	(0.135)
Average Age	-0.000859	0.00150						
(friends in 1st round financial education)	(0.000831)	(0.00103)						
Average Age		-0.0269***						
*Network Receiving 1st Round Financial Education		(0.00782)						
Age (own)	0.00369***	0.00231	0.00384***	0.00384***	0.00389***	0.00388***	0.00367***	0.00379***
	(0.00123)	(0.00166)	(0.00122)	(0.00123)	(0.00121)	(0.00124)	(0.00123)	(0.00121)
Age (own)		0.00955						
*Network Receiving 1st Round Financial Education		(0.00659)						
Average Household Size			0.0105	0.00606				
(friends in 1st round financial education)			(0.00772)	(0.0104)				
Average Household Size				0.0357				
*Network Receiving 1st Round Financial Education				(0.0543)				
Household Size (own)	-0.00846	-0.00840	-0.00902	-0.0125	-0.00904	-0.00867	-0.00875	-0.00980
	(0.00674)	(0.00662)	(0.00676)	(0.00862)	(0.00674)	(0.00680)	(0.00677)	(0.00667)
Household Size (own)				0.0181				
*Network Receiving 1st Round Financial Education				(0.0341)				
Average Education					0.167**	0.00351		
(friends in 1st round financial education)					(0.0752)	(0.107)		
Average Education						0.673*		
*Network Receiving 1st Round Financial Education						(0.350)		
Education (own)	0.0818**	0.0751**	0.0867***	0.0864***	0.0838**	0.0593	0.0847***	0.0877***
	(0.0317)	(0.0313)	(0.0320)	(0.0320)	(0.0323)	(0.0378)	(0.0319)	(0.0316)
Education (own)						0.376		
*Network Receiving 1st Round Financial Education						(0.283)		
Average Rice Production Area (mu)							-0.000621	0.00420**
(friends in 1st round financial education)							(0.00118)	(0.00212)
Average Rice Production Area (mu)								-0.0242**
*Network Receiving 1st Round Financial Education								(0.0100)
Rice Production Area (own, mu)	0.00326***	0.00348***	0.00325***	0.00332***	0.00323***	0.00321***	0.00322***	0.00616***
	(0.00114)	(0.00108)	(0.00115)	(0.00115)	(0.00115)	(0.00113)	(0.00114)	(0.00145)
Rice Production Area (own, mu)								-0.0149**
*Network Receiving 1st Round Financial Education								(0.00704)
Male (1= Yes, 0 = No)	0.0404	0.0458	0.0330	0.0321	0.0385	0.0357	0.0384	0.0439
	(0.0673)	(0.0680)	(0.0670)	(0.0672)	(0.0672)	(0.0673)	(0.0671)	(0.0650)
Risk Aversion ([0, 1])	0.117**	0.116**	0.121**	0.122**	0.123**	0.122**	0.120**	0.130***
	(0.0494)	(0.0491)	(0.0500)	(0.0500)	(0.0495)	(0.0496)	(0.0492)	(0.0494)
Perceived Probability of Disaster ([0, 1])	0.00212**	0.00192**	0.00206**	0.00205**	0.00195**	0.00179**	0.00206**	0.00204**
	(0.000821)	(0.000820)	(0.000820)	(0.000818)	(0.000821)	(0.000839)	(0.000819)	(0.000803)
Intensive Financial Education Session	0.00705	0.0105	0.00593	0.00546	0.00756	0.00998	0.00743	0.00868
(1 = Yes, 0 = No)	(0.0330)	(0.0326)	(0.0329)	(0.0330)	(0.0328)	(0.0329)	(0.0328)	(0.0326)
Observations	1,255	1,255	1,255	1,255	1,255	1,255	1,255	1,255
Village Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.113	0.125	0.113	0.114	0.116	0.120	0.112	0.112
P-Value of joint-significance:								
%Friends in 1st round financial education		0.0000***		0.1131		0.0069***		0.0000***
Characteristics (friends in 1st round financial education)		0.0026***		0.3077		0.0202**		0.0562*
Characteristics (own)		0.0014***		0.31		0.0143**		0.0001***

Notes: Robust clustered standard errors in parentheses. Results in this table are based on the sample of participants in 2nd round sessions who did not receive 1st round take-up information from us. Social network is measured by the fraction of the five friends that a household listed who were assigned to a first round intensive session. Village dummies are included in all estimations. *** p<0.01, ** p<0.05, * p<0.1

B An Insurance Demand Model

In this section, we present an insurance demand model to explain why social networks can influence both the level and the slope of the insurance demand curve.

B.1 Individual Insurance Demand

A rural household i with wealth ω faces uncertainty about future production income due to possible natural disasters, which will cost him Z. Z is a random variable and follows a normal distribution $\mathcal{N}(\mu_z, \sigma_z^2)$. An insurance product can be purchased to hedge the risk at a premium P. However, due to unfamiliarity with the insurance program, each household has its own perception of the insurance benefit, which is denoted by $\epsilon_i \sim \mathcal{N}(\mu_{\epsilon_i}, \sigma_{\epsilon_i})$. Without insurance contract, the expected utility of the household is

$$\mathbb{E}\left(U(\omega - Z)\right)$$

If the household purchased the insurance contract, then its expected utility is

$$\mathbb{E}\left(U(\omega - P + \epsilon_i)\right)$$

Therefore, the household should purchase the insurance if and only if

$$\mathbb{E}\left(U(\omega - P + \epsilon_i)\right) \geq \mathbb{E}\left(U(\omega - Z)\right) \tag{14}$$

Assume that the household has a CARA utility function $U(X) = -e^{-AX}$, then

$$\begin{aligned}
\mathbb{E}\left(U(\omega - Z)\right) &= -e^{-A_i(\omega - \mu_z) + \frac{1}{2}A_i^2\sigma_z^2} \\
\mathbb{E}\left(U(\omega - P + \epsilon_i)\right) &= -e^{-A_i(\omega - P + \mu_{\epsilon_i}) + \frac{1}{2}A_i^2\sigma_{\epsilon_i}^2}
\end{aligned}$$

Replacing these in condition (14), we have

$$\begin{aligned}
& - e^{-A_i(\omega - P + \mu_{\epsilon_i}) + \frac{1}{2}A_i^2\sigma_{\epsilon_{ii}}^2} \geq -e^{-A_i(\omega - \mu_z) + \frac{1}{2}A_i^2\sigma_z^2} \\
\Longleftrightarrow & \ \omega - P + \mu_{\epsilon_i} - \frac{1}{2}A_i\sigma_{\epsilon_i}^2 \geq \omega - \mu_z - \frac{1}{2}A_i\sigma_z^2 \\
\Longleftrightarrow & \ P \leq \mu_z + \mu_{\epsilon_i} + \frac{1}{2}A_i\left(\sigma_z^2 - \sigma_{\epsilon_i}^2\right) && (15) \\
\Longleftrightarrow & \ \mu_{\epsilon_i} \geq P - \mu_z - \frac{1}{2}A_i(\sigma_z^2 - \sigma_{\epsilon_i}^2) && (16)
\end{aligned}$$

As a result, at the individual level, households with a higher expectation and a lower uncertainty of the value of the insurance product are more likely to buy it. Since receiving insurance knowledge through various means - either formal financial education or obtaining information from friends, or by observing friends purchasing insurance or receiving payouts, can all influence households' expectation of the product benefits and uncertainty about it, we expect that these factors have significant effects on individual insurance demand. Additionally, individuals who are more risk averse are more likely to buy the insurance.

B.2 Aggregate Insurance Demand

To study the determinants of the level and slope of the insurance demand curve, we assume that the perceived benefit of the insurance, μ_{ϵ_i}, is distributed with some CDF $F(.)$ and that the risk aversion coefficient and the variance is the same for all household, $A_i = A, \sigma^2_{\epsilon_i} = \sigma^2_\epsilon, \forall i$. Based on those assumptions, we can aggregate (16) to obtain the insurance demand curve:

$$Q(P) = 1 - F\left(P - \mu_z - \frac{1}{2}A(\sigma^2_z - \sigma^2_\epsilon)\right) \tag{17}$$

and the slope of the demand curve

$$\frac{\partial Q}{\partial P} = -f\left(P - \mu_z - \frac{1}{2}A(\sigma^2_z - \sigma^2_\epsilon)\right) \tag{18}$$

where $f(.)$ is the pdf. Equation (18) tells us that the perceived product benefits, the uncertainty about insurance benefits, and the dispersion on the valuation of the product, can affect the slope of the demand curve.

To give a specific example, let's look at Figure B1. f_l denotes the original distribution of the perceived expected value of the insurance contract in the population, with a corresponding demand curve D_l in Figure B2. For people who had more friends exposed to financial education or who received payouts, the distribution changes. First, these people may have higher perceived expected insurance benefits on average. Second, the distribution becomes more concentrated, i.e. smaller variance than before. In Figure B1, the distribution now shifts to f_h. As a result, the demand curve will shift upward. In the low price region, because the density of the pivotal value μ_{ϵ_i} is lower, the demand curve will be flatter, as indicated in the shaded region of Figure B2. The demand falls sharply over the price region where the corresponding pivotal value of μ_{ϵ_i} has high density, i.e. the concentrated region of the distribution f_h.

In order to derive the impact on the insurance demand curve of perceived benefits, dispersion on the product valuation, and the uncertainty about the benefits, we need to specify the distribution of μ_{ϵ_i}. Let $F(.)$ be the CDF of a Normal distribution with mean η and variance ψ^2, and $\Phi(.)/\phi(.)$ be the CDF/PDF of a standard normal distribution. Then $F(x) = \Phi\left(\frac{x-\eta}{\psi}\right)$ and $f(x) = \frac{1}{\psi}\phi\left(\frac{x-\eta}{\psi}\right)$. The demand curve in equation (17) becomes:

$$Q(P) = 1 - \Phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \tag{19}$$

and the slope of the demand curve is

$$S(P) \equiv \frac{\partial Q}{\partial P} = -\frac{1}{\psi}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \tag{20}$$

- Mean of perceived insurance benefit (η):

$$\frac{\partial Q}{\partial \eta}(P) = \frac{1}{\psi}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \tag{21}$$

$$\frac{\partial S}{\partial \eta}(P) = -\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi^3}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \tag{22}$$

  From equation (21) and (22), an increase in η has a positive level effect on the insurance demand curve, as $\phi(.)$ is positive everywhere. The impact on the slope of demand curve is more subtle. The slope will increase (demand curve will be flatter) if $P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta < 0$, and the slope will decrease (demand curve will be steeper) if $P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta > 0$.

- Dispersion of benefits valuation (ψ):

$$\frac{\partial Q}{\partial \psi}(P) = \frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi^2}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \tag{23}$$

$$\begin{aligned}\frac{\partial S}{\partial \psi}(P) =& \frac{1}{\psi^2}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \\ &- \frac{(P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta)^2}{\psi^4}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \\ =& \frac{\psi^2 - (P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta)^2}{\psi^4}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right)\end{aligned} \tag{24}$$

  From equation (23) and (24), an increase in ψ has a level effect on the demand curve. The direction depends on the sign of $P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta$: positive if $P - \mu_z -$

$\frac{1}{2}A(\sigma_z^2-\sigma_\epsilon^2)-\eta > 0$, negative if $P-\mu_z-\frac{1}{2}A(\sigma_z^2-\sigma_\epsilon^2)-\eta < 0$. The impact on the slope of the demand curve depends on the sign of $\psi^2-(P-\mu_z-\frac{1}{2}A(\sigma_z^2-\sigma_\epsilon^2)-\eta)^2$. The slope will decrease (demand curve will be steeper) if $\psi^2-(P-\mu_z-\frac{1}{2}A(\sigma_z^2-\sigma_\epsilon^2)-\eta)^2 < 0$, and the slope will increase (demand curve will be flatter) if $\psi^2-(P-\mu_z-\frac{1}{2}A(\sigma_z^2-\sigma_\epsilon^2)-\eta)^2 > 0$.

- Uncertainty about insurance benefits (σ_ϵ^2):

$$\frac{\partial Q}{\partial \sigma_\epsilon^2}(P) = -\frac{A}{2\psi}\phi\left(\frac{P-\mu_z-\frac{1}{2}A(\sigma_z^2-\sigma_\epsilon^2)-\eta}{\psi}\right) \tag{25}$$

$$\frac{\partial S}{\partial \sigma_\epsilon^2}(P) = \frac{P-\mu_z-\frac{1}{2}A(\sigma_z^2-\sigma_\epsilon^2)-\eta}{\psi^3}2A\phi\left(\frac{P-\mu_z-\frac{1}{2}A(\sigma_z^2-\sigma_\epsilon^2)-\eta}{\psi}\right) \tag{26}$$

From (25) and (26), the uncertainty about insurance benefits has a negative effect on the level of demand curve. However, the impact on the slope of demand curve depends on the sign of $P-\mu_z-\frac{1}{2}A(\sigma_z^2-\sigma_\epsilon^2)-\eta$. The impact is positive if $P-\mu_z-\frac{1}{2}A(\sigma_z^2-\sigma_\epsilon^2)-\eta > 0$, and it is negative if $P-\mu_z-\frac{1}{2}A(\sigma_z^2-\sigma_\epsilon^2)-\eta < 0$.

Figure B1. An Example of the Distribution of Perceived Insurance Benefits

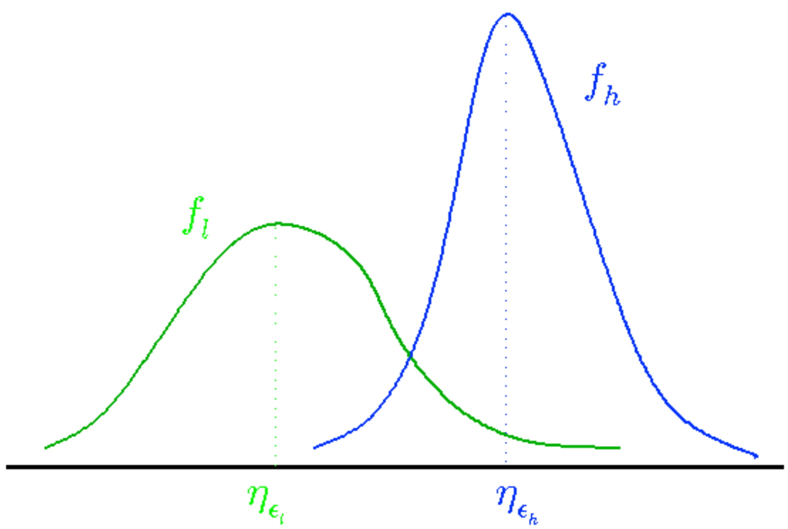


Figure B2. An Example of Insurance Demand Curve

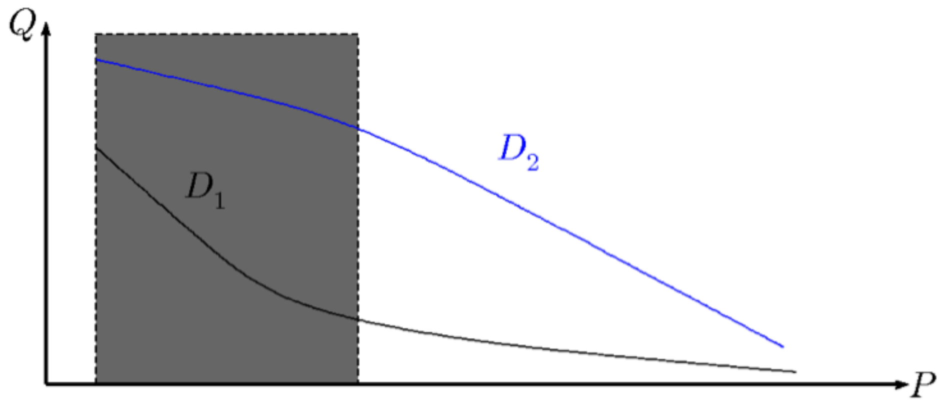


Figure 1.1. Experimental Design: Within Village, Household Level Randomization

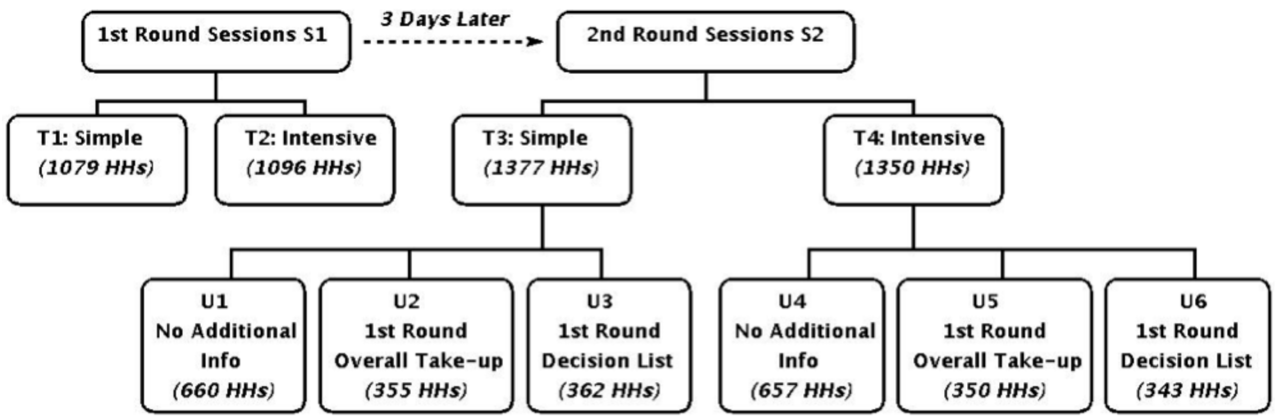
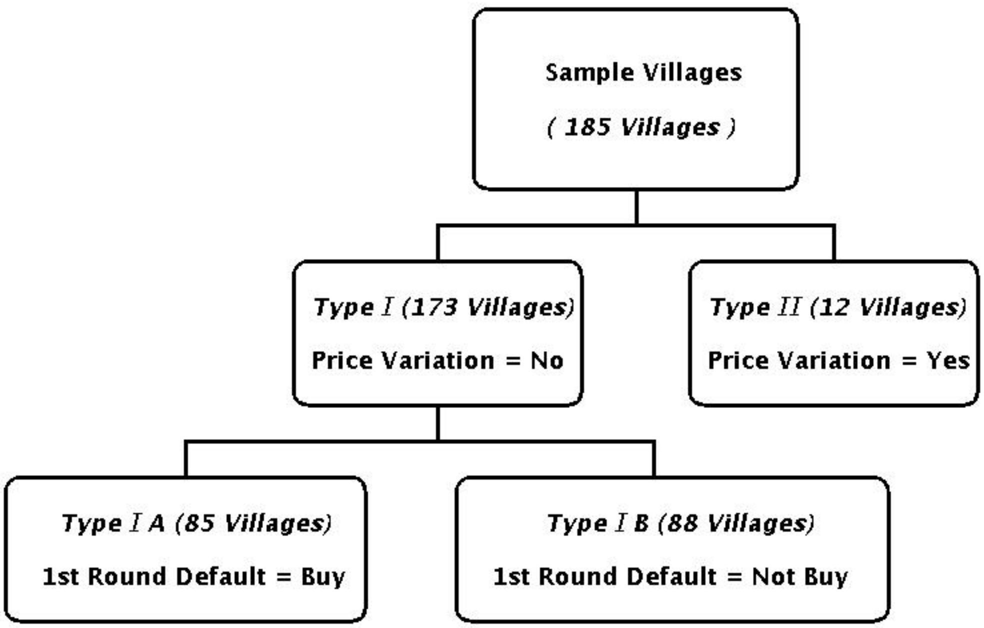
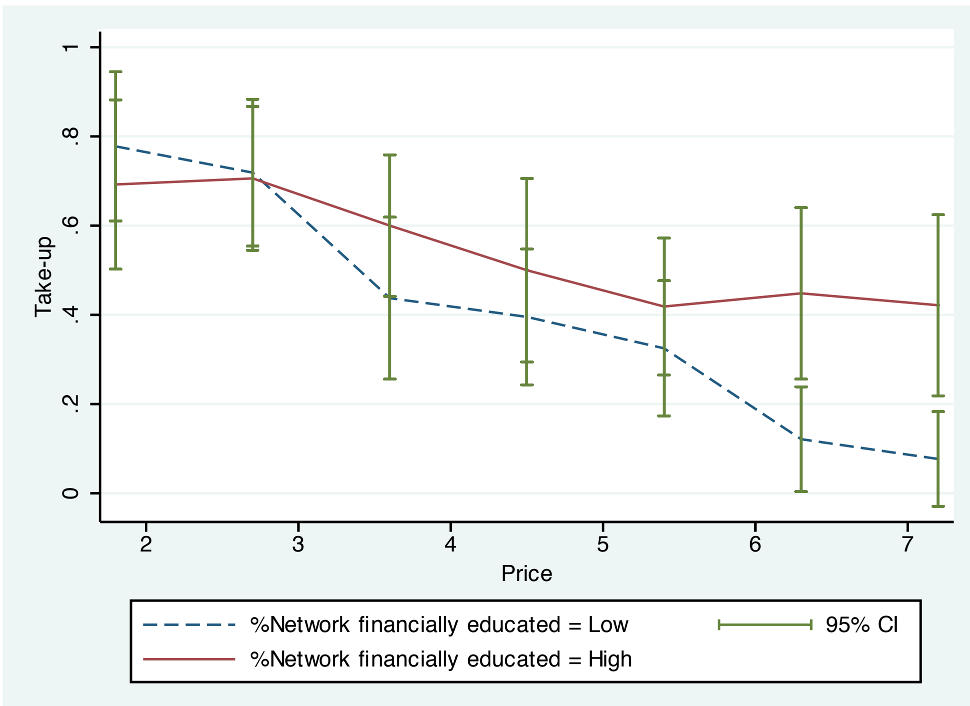


Figure 1.2. Experimental Design: Village Level Randomization



Notes: Randomizations within T3 and T4 are only available in type I villages where there was no price randomization. No additional first-round take-up information was offered to participants in T3 and T4 in type II villages.

Figure 2. Effect of Having Friends Attending Financial Education on Insurance Demand



Notes: This figure is based on the sample of households in type II villages where price randomization was implemented in year one. The variable %Network financially educated is defined as "high" if it is above the sample median and is defined as "low" if it is below the sample median.

Table 1. Summary Statistics

	Sample Mean	Sample Std. Dev
PANEL A: HOUSEHOLD CHARACTERISTICS		
Gender of Household Head (1 = Male, 0 = Female)	0.914	0.280
Age	51.494	12.032
Household Size	4.915	2.133
Education (0 = illiteracy, 1 = primary, 2 = secondary, 3 = high school, 4 = college)	1.192	0.853
Area of Rice Production (mu, 1 mu = 1/15 hectare)	12.635	19.921
Share of Rice Income in Total Income (%)	73.258	34.841
Any Disasters Happened Last Year (1 = Yes, 0 = No)	0.631	0.483
Loss in Yield Last Year (%)	27.507	18.199
Risk Aversion (0-1, 0 as risk loving and 1 as risk averse)	0.711	0.313
Perceived Probability of Future Disasters (%)	33.633	16.619
PANEL B: SOCIAL NETWORK FINANCIAL EDUCATION MEASURES		
Number of Friends Listed	4.893	0.510
General Measure: %Friends Attending 1st Round Financial Education	0.161	0.189
Strong Measure: %Mutually Listed Friends Attending 1st Round Financial Education	0.043	0.100
Weak Measure: %2nd order Friends Attending 1st Round Financial Education	0.154	0.114
PANEL C: SOCIAL NETWORK STRUCTURAL CHARACTERISTICS		
Village Size (Number of households)	31.962	9.839
Graph Clustering (Village level)	0.182	0.085
Fraction in Giant Component (Village level)	0.987	0.070
Transtivity (Village level)	0.213	0.067
Reciprocity (Village level)	0.168	0.054
In-Degree (Household level)	3.266	2.496
Path Length (Household level)	3.578	1.941
Eigenvector Centrality (Household level)	0.148	0.098
PANEL D: OUTCOME VARIABLE		
Insurance Take-up Rate (%), all sample	43.941	49.637
Insurance Take-up Rate (%), 1st round simple session	35.218	47.787
Insurance Take-up Rate (%), 1st round intensive session	50.365	50.021
Insurance Take-up Rate (%), 2nd round simple session	44.394	49.722
Insurance Take-up Rate (%), 2nd round intensive session	44.292	49.711
No. of Households: 5332		
No. of Villages: 185		

Table 2. Effect of Financial Education on Insurance Take-up

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)	
	(1)	(2)
Intensive Financial Education Session	0.149***	0.140***
(1 = Yes, 0 = No)	(0.0261)	(0.0259)
Male		0.0393
		(0.0476)
Age		0.00205*
		(0.00108)
Household Size		-0.00381
		(0.00514)
Rice Production Area (mu)		0.00161
		(0.000993)
Literate (1 = Yes, 0 = No)		0.0823***
		(0.0269)
No. of Observations	2,175	2,137
Village Fixed Effects	Yes	Yes
R-Squared	0.121	0.129

Notes: Robust clustered standard errors in parentheses. The estimation is based on the sample of participants in the two first-round sessions (T1, T2). *** p<0.01, ** p<0.05, * p<0.1

Table 3. Effect of Social Networks (General Measure) on Insurance Take-up

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)		
	(1)	(2)	(3)
Network Receiving 1st Round Financial Education	0.337***	0.348***	0.489***
([0, 1])	(0.0810)	(0.0779)	(0.105)
Intensive Financial Education Session		0.00643	0.0539
(1 = Yes, 0 = No)		(0.0329)	(0.0397)
Network Receiving 1st Round Financial Education			-0.301*
*Intensive Financial Education Session			(0.162)
Male		0.0374	0.0408
		(0.0673)	(0.0672)
Age		0.00374***	0.00384***
		(0.00123)	(0.00122)
Household Size		-0.00878	-0.00901
		(0.00677)	(0.00674)
Rice Production Area (mu)		0.00323***	0.00330***
		(0.00115)	(0.00114)
Literate (1 = Yes, 0 = No)		0.0844***	0.0841***
		(0.0320)	(0.0319)
Risk Aversion ([0, 1])		0.119**	0.114**
		(0.0494)	(0.0492)
Perceived Probability of Disaster ([0, 1])		0.00211**	0.00208**
		(0.000819)	(0.000819)
No. of Observations	1,274	1,255	1,255
Village Fixed Effects	Yes	Yes	Yes
R-Squared	0.087	0.112	0.115

Notes: Robust clustered standard errors in parentheses. Results in this table are based on the sample of participants in 2nd round sessions who did not receive 1st round take-up information from us (U1, U4) in type I villages. Social network is measured by the fraction of the five friends that a household listed who were assigned to a first round intensive session. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Heterogeneity of the Social Network Effect: Strength of Ties, Relationships, and Nonlinear Effects

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)			
	Strength of Ties		Relationships	Nonlinear Effects
	(1)	(2)	(3)	(4)
Network Receiving 1st Round Financial Education ([0, 1])				
- Strong social network	0.428**			
	(0.182)			
- Weak social network		0.0843		
		(0.149)		
Relationship with Friends Receiving Financial Education				
- Neighbors			0.336***	
			(0.105)	
- Relatives			0.291**	
			(0.134)	
- Government officials			0.528**	
			(0.258)	
Number of Friends Receiving 1st Round Financial Education				
- Equal to 1				0.0616*
				(0.0319)
- Equal to 2				0.206***
				(0.0398)
- Greater than 2				0.279*
				(0.156)
Male	0.0376	0.0397	0.0397	0.0432
	(0.0671)	(0.0680)	(0.0673)	(0.0667)
Age	0.00379***	0.00365***	0.00380***	0.00361***
	(0.00127)	(0.00127)	(0.00125)	(0.00122)
Household Size	-0.00838	-0.00836	-0.00875	-0.00812
	(0.00699)	(0.00694)	(0.00683)	(0.00669)
Rice Production Area (mu)	0.00281**	0.00288**	0.00331***	0.00339***
	(0.00120)	(0.00118)	(0.00114)	(0.00113)
Literate (1 = Yes, 0 = No)	0.0778**	0.0808**	0.0828**	0.0835***
	(0.0320)	(0.0321)	(0.0319)	(0.0317)
Risk Aversion ([0, 1])	0.121**	0.119**	0.117**	0.116**
	(0.0492)	(0.0488)	(0.0497)	(0.0498)
Perceived Probability of Disaster ([0, 1])	0.00220***	0.00217***	0.00211**	0.00202**
	(0.000829)	(0.000831)	(0.000819)	(0.000818)
Intensive Financial Education Session	0.000230	0.00305	0.00704	0.00467
(1 = Yes, 0 = No)	(0.0328)	(0.0330)	(0.0330)	(0.0329)
No. of Observations	1,255	1,255	1,255	1,255
Village Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.101	0.097	0.113	0.120

Notes: Robust clustered standard errors in parentheses. Results in this table are based on the sample of participants in 2nd round sessions who did not receive 1st round take-up information from us (U1 and U4 in Figure 1.1). Columns (1) and (2) report heterogenous effect of social networks depending on the strength of ties, where social network is measured in two ways: the strong social network is defined as the fraction of the five friends who were mutually listed and were assigned to the first round intensive session; the weak social network is defined as the fraction of second-order friends (friends' friends) who were assigned to the first round intensive session. Column (3) lists heterogenous effect of social networks depending on the relationship with friends. Column (4) shows nonlinear effects of social networks. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Heterogeneity of the Social Network Effect: Village Level Network Characteristics

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)					
	(1)	(2)	(3)	(4)	(5)	(6)
Network Receiving 1st Round Financial Education ([0, 1])	0.202	-0.727	0.0578	0.252	0.257	-1.616*
	(0.261)	(0.796)	(0.166)	(0.252)	(0.251)	(0.912)
Heterogeneity Effects:						
Number of Households:						
Direct effect	-0.00480**	-0.00403**	-0.00465**	-0.00424**	-0.00425**	-0.006**
	(0.00241)	(0.00184)	(0.00200)	(0.00213)	(0.00196)	(0.00257)
Interaction with Network	0.00433					0.008
	(0.00745)					(0.0078)
Fraction in Giant Component						
Direct effect		-0.194				-0.269
		(0.325)				(0.3379)
Interaction with Network		1.094				1.442*
		(0.812)				(0.7432)
Graph Clustering						
Direct effect			-0.490**			-0.636**
			(0.234)			(0.2957)
Interaction with Network			1.648**			2.783**
			(0.799)			(1.1831)
Transitivity						
Direct effect				-0.286		0.083
				(0.361)		(0.4313)
Interaction with Network				0.437		-1.387
				(1.116)		(1.486)
Reciprocity						
Direct effect					-0.224	0.0173
					(0.401)	(0.4696)
Interaction with Network					0.562	0.432
					(1.402)	(1.747)
Intensive Financial Education Session (1 = Yes, 0 = No)	0.0100	0.00913	0.0140	0.00644	0.0105	0.0133
	(0.0325)	(0.0326)	(0.0325)	(0.0322)	(0.0325)	(0.0325)
No. of Observations	1,255	1,255	1,255	1,255	1,255	1255
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.033	0.034	0.037	0.020	0.033	0.0404
P-Value of Joint-significance:						
Village Level Network Characteristics	0.0868*	0.382	0.083*	0.6639	0.8471	
Network Receiving 1st Round Financial Education	0.0002***	0.0001***	0.0000***	0.0001***	0.0002***	

Notes: Robust clustered standard errors in parentheses. Results in this table are based on the sample of participants in 2nd round sessions who did not receive 1st round take-up information from us (U1 and U4 in Figure 1.1). Social network is measured by the fraction of five friends that a household listed who were assigned to a first round intensive session. See text for definitions of village level social network characteristics. Household characteristics include gender, age and education of household heads, household size, rice production area, risk aversion, and perceived probability of future disasters. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Heterogeneity of the Social Network Effect:
Who is More Likely to be influenced and Who is More Influential?

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Network Receiving 1st Round Financial Education	0.316***	0.544***	0.419***	0.834***	0.165*	0.273	0.247**	0.462
([0, 1])	(0.101)	(0.189)	(0.107)	(0.213)	(0.0997)	(0.171)	(0.116)	(0.335)
Intensive Financial Education Session	0.00446	0.00821	0.0107	0.00926	0.00589	0.00908	0.00642	0.00613
(1 = Yes, 0 = No)	(0.0331)	(0.0330)	(0.0331)	(0.0328)	(0.0329)	(0.0328)	(0.0331)	(0.0327)
Heterogeneity Effects:								
Own in-degree								
Direct effect	0.00874	0.0235***					0.0207***	0.0244**
	(0.00566)	(0.00885)					(0.00772)	(0.0119)
Interaction with Network		-0.0860**						-0.0218
		(0.0397)						(0.0466)
Average in-degree								
Direct effect	0.00409	0.00209					-0.0214**	0.00538
	(0.00635)	(0.00850)					(0.00977)	(0.0208)
Interaction with Network		0.0186						-0.0770
		(0.0415)						(0.0768)
Own Path Length								
Direct effect			-0.0128*	-0.00530			-0.0120*	-0.00363
			(0.00729)	(0.00631)			(0.00714)	(0.00693)
Interaction with Network				-0.0680**				-0.0669**
				(0.0284)				(0.0333)
Average Path Length								
Direct effect			-0.0150	-0.000249			-0.0155	-0.0284
			(0.0124)	(0.0177)			(0.0129)	(0.0267)
Interaction with Network				-0.0666				0.165
				(0.0995)				(0.122)
Own Eigenvector Centrality								
Direct effect					-0.0472	0.422*	-0.497**	0.000288
					(0.174)	(0.235)	(0.234)	(0.335)
Interaction with Network						-2.836***		-2.427*
						(1.016)		(1.418)
Average Eigenvector Centrality								
Direct effect					0.492***	-0.0565	0.992***	0.177
					(0.157)	(0.225)	(0.244)	(0.515)
Interaction with Network						3.232***		3.416*
						(0.948)		(1.886)
No. of Observations	1,255	1,255	1,255	1,255	1,255	1,255	1,255	1,255
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.105	0.111	0.108	0.116	0.110	0.125	0.125	0.140
P-Value of Joint-significance:								
Network Receiving 1st Round Financial Education		0.01***		0.0002***		0.0003***		
Network Structure (of friends)		0.669		0.6202		0.0001***		
Network Structure (own)		0.0302**		0.0313**		0.0222**		

Notes: Robust clustered standard errors in parentheses. Results in this table are based on the sample of participants in 2nd round sessions who did not receive 1st round take-up information from us (U1 and U4 in Figure 1.1). Social network is measured by the fraction of the five friends that a household listed who were assigned to a first round intensive session. See definitions of social network characteristics in text. Household characteristics include gender, age and education of household head, household size, rice production area, risk aversion, and perceived probability of future disasters. *** p<0.01, ** p<0.05, * p<0.1

Table 7. Monetary Value of the Social Network Effect on Insurance Take-up

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)		
	(1)	(2)	(3)
Price	-0.112***	-0.167***	-0.151***
	(0.0162)	(0.0273)	(0.0306)
Network Receiving 1st Round Financial Education ([0, 1])	0.364***	-0.199	-0.241
	(0.0979)	(0.230)	(0.243)
Price * Network Receiving 1st Round Financial Education		0.130**	0.151**
		(0.0524)	(0.0520)
Male	-0.0739	-0.0711	-0.0740
	(0.0724)	(0.0724)	(0.0741)
Age	-0.00394	-0.00354	-0.00355
	(0.00230)	(0.00249)	(0.00233)
Household Size	-0.0241**	-0.0238**	-0.0237**
	(0.0102)	(0.00997)	(0.0102)
Rice production area (mu)	-0.00146	-0.00133	-0.00140
	(0.00316)	(0.00308)	(0.00295)
Literate (1 = Yes, 0 = No)	-0.0361	-0.0371	-0.0461
	(0.0830)	(0.0830)	(0.0933)
Risk Aversion ([0,1])	0.141*	0.144**	0.136*
	(0.0697)	(0.0652)	(0.0672)
Share of Friends with Higher Prices ([0,1])			0.0795
			(0.101)
Share of Friends with Lower Prices ([0,1])			-0.0911
			(0.0770)
No. of Observations	429	429	429
Village Fixed Effects	Yes	Yes	Yes
R-Squared	0.239	0.249	0.260
P-value of Joint-significance:			
Price		0.0000***	0.0013***
Network Receiving 1st Round Financial Education		0.0057***	0.0018***

Notes: Robust clustered standard errors in parentheses. Results in this table are based on the sample of second round session participants in type II villages where seven different prices ranging from 1.8 RMB to 7.2 RMB were randomly assigned on the household level. *** p<0.01, ** p<0.05, * p<0.1

Table 8. Did Social Networks Convey Insurance Knowledge?

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)		Insurance Knowledge ([0, 1])		
	(1)	(2)	(3)	(4)	(5)
Intensive Financial Education Session	0.141***		0.314***	-0.00129	
(1 = Yes, 0 = No)	(0.0259)		(0.0120)	(0.0167)	
Second round	0.0901***		0.245***		
(1 = Yes, 0 = No)	(0.0309)		(0.0142)		
Intensive Financial Education Session *Second round	-0.138***		-0.323***		
	(0.0422)		(0.0200)		
Network Receiving 1st Rround Financial Education		-0.106		0.356***	0.128
([0, 1])		(0.167)		(0.0475)	(0.103)
Network Receiving 1st Rround Financial Education		0.621***			0.312**
*Average Network Insurance Knowledge		(0.209)			(0.122)
Male	0.0477	0.0517	0.0425**	0.0393	0.0465
	(0.0343)	(0.0671)	(0.0187)	(0.0354)	(0.0352)
Age	0.00281***	0.00341***	-0.000846*	-0.000946	-0.00111
	(0.000843)	(0.00122)	(0.000435)	(0.000786)	(0.000783)
Household Size	-0.00485	-0.00825	0.00253	0.00221	0.00248
	(0.00427)	(0.00669)	(0.00247)	(0.00429)	(0.00425)
Rice Production Area (mu)	0.00167**	0.00313***	0.000457**	-0.000533	-0.000583
	(0.000788)	(0.00114)	(0.000198)	(0.000632)	(0.000621)
Literate (1 = Yes, 0 = No)	0.0777***	0.0785**	0.0868***	0.0852***	0.0822***
	(0.0201)	(0.0316)	(0.0119)	(0.0204)	(0.0206)
Risk Aversion ([0,1])	0.0934***	0.108**	0.0827***	0.0495*	0.0441
	(0.0265)	(0.0496)	(0.0139)	(0.0267)	(0.0269)
Perceived Probability of Disaster ([0,1])	0.000773	0.00209**	0.000553**	0.00145***	0.00144***
	(0.000521)	(0.000815)	(0.000277)	(0.000440)	(0.000441)
No. of Observations	3,433	1,255	3,259	1,255	1,255
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-Squared	0.093	0.118	0.233	0.132	0.137
P-value of Joint-significance:					
Intensive Financial Education Session	0.0000***		0.0000***		
Network Receiving 1st Round Financial Education		0.0000***			0.0000***

Notes: Robust clustered standard errors in parentheses. Estimation results in columns (1) and (3) are based on households who were assigned to first round sessions or those in second round session groups without additional information (T1, T2, U1, and U4 in Figure 1.1). Columns (2), (4) and (5) are based on households who were invited to second round sessions but did not receive any additonal take-up information (U1 and U4 in Figure 1.1). Insurance knowledge is the score that a household got in ten questions that we asked during household survey to test their understanding of insurance benefits. *** p<0.01, ** p<0.05, * p<0.1

Table 9. Effect of the Overall 1st Round Take-up Rate on 2nd Round Take-up

VARIABLES	First Stage: Overall 1st Round Take-up	Insurance Take-up (1 = Yes, 0 = No)			
		All Sample		No Information Revealed	Revealed 1st Round Overall Take-up
		OLS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
Default (1 = Buy, 0 = Not Buy)	0.121***				
	(0.0326)				
1st Round Overall Take-up Rate		0.388***	0.434**	0.0164	0.427*
		(0.0710)	(0.215)	(0.338)	(0.237)
No 1st Round Take-up Information Revealed		0.128***	0.181		
		(0.0405)	(0.135)		
1st Round Overall Take-up Rate		-0.307***	-0.431		
*No 1st Round Take-up Information Revealed		(0.0758)	(0.318)		
Male	0.0370	0.0395	0.0395	0.0363	0.0400
	(0.0490)	(0.0439)	(0.0439)	(0.0703)	(0.0532)
Age	0.00202*	0.00480***	0.00405***	0.00374***	0.00499***
	(0.00107)	(0.000886)	(0.000806)	(0.00123)	(0.00130)
Household Size	-0.00434	-0.00474	-0.00465	-0.00773	-0.00172
	(0.00515)	(0.00502)	(0.00508)	(0.00701)	(0.00690)
Rice Production Area (mu)	0.00159	0.00149**	0.00156**	0.00166	0.00152**
	(0.000972)	(0.000625)	(0.000651)	(0.00135)	(0.000596)
Literate (1 = Yes, 0 = No)	0.0868***	0.0751***	0.0832***	0.0757**	0.0802**
	(0.0265)	(0.0236)	(0.0228)	(0.0328)	(0.0373)
Intensive Financial Education Session		0.00750	0.00750	0.00671	0.00750
(1 = Yes, 0 = No)		(0.0180)	(0.0176)	(0.0318)	(0.0267)
Risk Aversion ([0,1])		0.122***	0.133***	0.131***	0.114***
		(0.0163)	(0.0162)	(0.0271)	(0.0261)
Perceived Probability of Disaster ([0,1])		0.00183***	0.00189***	0.00175*	0.00193**
		(0.000564)	(0.000572)	(0.000890)	(0.000805)
No. of Observations	2,137	2,674	2,674	1,296	1,296
Village Fixed Effects	No	Yes	Yes	Yes	Yes
R-Squared	0.120	0.100	0.096	0.098	0.135
P-value of Joint-significance:					
1st Round Overall Take-up Rate		0.0000***	0.116		

Notes: Robust clustered standard errors in parentheses. Column (1) present first stage results for IV estimation. Estimations from columns (2) to (5) in this table are based on the sample of 2nd round session participants. Columns (2) and (3) are based on the whole 2nd round sample; Column (4) is based on the sub-sample who received no extra information in addition to the presentation (U1 and U4 in Figure 1.1); Column (5) is based on the subgroup of households to whom we desseminated the first round take-up information (U2, U3, U4 and U6 in Figure 1.1). In IV estimations, Default options are used as the instrumental variable for the first round overall take-up rate. *** p<0.01, ** p<0.05, * p<0.1

Table 10. Effect of Friends' Decisions in 1st Round Sessions on 2nd Round Take-up

VARIABLES	First Stage: Network 1st Round Take-up Rate	Insurance Take-up (1 = Yes, 0 = No) All Sample		No Information Revealed	1st Round Decision List Revealed
		OLS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
1st Round Overall Take-up Rate		0.608***	0.441	0.257	0.691
		(0.109)	(0.605)	(1.376)	(0.664)
1st Round Network's Take-up Rate		-0.0152	0.567**	0.243	0.589**
		(0.0528)	(0.275)	(1.391)	(0.280)
No Information Revealed		0.256***	0.382**		
(1 =Yes, 0 = No)		(0.0554)	(0.193)		
1st Round Overall Take-up Rate		-0.544***	-0.679		
* No Information Revealed		(0.124)	(1.173)		
1st Round Network's Take-up Rate		0.0192	-0.0784		
* No Information Revealed		(0.0732)	(1.028)		
Default * Network in 1st Round Sessions	0.308***				
	(0.0593)				
Male	-0.00651	0.0554	0.0457	0.0247	0.0323
	(0.0410)	(0.0569)	(0.0597)	(0.0958)	(0.0746)
Age	-0.000656	0.00483***	0.00509***	0.00374**	0.00541**
	(0.000866)	(0.00106)	(0.00125)	(0.00162)	(0.00223)
Household Size	0.00365	-0.00409	-0.00495	-0.00814	0.00458
	(0.00453)	(0.00629)	(0.00662)	(0.00790)	(0.00993)
Rice Production Area (mu)	0.00169**	0.000819	-2.37e-05	0.000909	-0.00114
	(0.000771)	(0.00119)	(0.00139)	(0.00161)	(0.00201)
Literate (1 = Yes, 0 = No)	0.000523	0.0858***	0.0892**	0.0970**	0.0926
	(0.0262)	(0.0307)	(0.0342)	(0.0384)	(0.0613)
Intensive Financial Education Session	0.00101	0.0237	0.0231	0.0134	0.0465
(1 =Yes, 0 = No)	(0.0192)	(0.0240)	(0.0276)	(0.0361)	(0.0441)
No. of Observation	1,643	1,643	1643	983	660
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-Squared	0.163	0.088		0.047	
P-value of Joint-significance:					
1st Round Overall Take-up Rate		0.0000***	0.9241		
1st Round Network's Take-up Rate		0.9572	0.0355**		

Notes: Robust clustered standard errors in parentheses. Columns (1) - (3) are based on second round participants that received either no information or the decision list of first round sessions from us (U1, U3, U4 and U6 in Figure 1.1) . Column (4) is based on the sub-sample with no additional information (U1 and U4 in Figure 1.1), while column (5) is based on households to whom we provided with the decision list of first round participants (U3 and U6 in Figure 1.1). *** p<0.01, ** p<0.05, * p<0.1