Social Networks and the Decision to Insure: Evidence from Randomized Experiments in China*

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Abstract

Using data from a two-year 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. In the first year, I provided financial education to a random subset of farmers and found a large social network effect on insurance take-up: for untreated farmers, having an additional friend receiving financial education raises take-up by almost half as much as obtaining financial education directly, a spillover effect equivalent to offering a 12% reduction in the average insurance premium. By varying the information available to subjects about their peers' take-up decisions and using randomized default options, I show that the positive social network effect is not driven by scale effects, imitation, or informal risk-sharing, but instead by the diffusion of insurance knowledge. One year later, social networks continue to affect insurance demand: observing an above-median share of friends receiving payouts increases insurance take-up at a rate equivalent to about 50% of the impact of receiving payouts directly. I also find that social network effects are larger in villages where households are more strongly connected, and when the people who receive financial education first are more central in the social network.

Keywords: Social network; Insurance; Demand; Learning
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1 Introduction

It is well recognized that social networks play a fundamental role in shaping human behavior and have important effects on economic outcomes[1]. But how large are social network effects in practice, and what are the underlying mechanisms? In this paper, I investigate this topic in the context of the introduction of a new weather insurance product in rural China. This kind of insurance product is important for households in agricultural communities where production is exposed to substantial weather shocks[2]. However, evidence from several countries shows that participation rates are sub-optimally low, even with heavy government subsidies[3]. One approach to increasing take-up might be to exploit social network effects, which can be an important factor in decisions on whether or not to adopt new and unusual financial products: people may learn about benefits of a product from their friends, imitate their decisions, or respond to their experience.

With data from a two-year randomized experiment in rural China, which includes 185 villages and about 5300 households, I study the influence of social networks on the demand for insurance, both in the short term and over longer periods[4]. The product I am studying is a new weather insurance policy for rice farmers offered by the People's Insurance Company of China (PICC). The novel experimental design allows me not only to identify the causal effect of social networks, but also to test various mechanisms through which social networks operate, including learning about the function and benefits of insurance products, scale effects, imitation, informal risk-sharing, and learning from friends' payout experiences. Additionally, taking advantage of the substantial variation in network structure across villages and households, I am able to test the effect of social structure and initial conditions on the strength of social network effects. Furthermore, using household level price randomization, I calculate the price equivalence of the social network effect.

I begin by investigating the value of social networks for insurance take-up using the

[1]Existing studies have linked social networks with activities and outcomes including risk sharing (Ambrus et al. (2010)), voting (Lazarsfeld (1944)), finding jobs (Munshi (2004)), trust (Karlan et al. (2009)), financial decision-making (Duflo and Saez (2003); Hong et al. (2004)), technology adoption (Conley and Udry (2010)), etc. For comprehensive discussion and references, see Jackson (2010).

[2]Formal insurance markets are important because informal insurance mechanisms cannot effectively reduce the negative impacts of regional weather shocks, and they 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)).

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

[4]Most papers are focused on studying ways to improve the initial participation rate, but there is no rigorous study about how to maintain high take-up rates over time as subsidies are gradually removed, which is essential for generating a substantial welfare impact on households.

experiment implemented in year one. Specifically, if only a subset of farmers were offered financial education about the product, would this have a spillover effect on untreated farmers? To establish causality, I randomly assigned households in each village to early versus late round sessions, and simple versus intensive (including financial education) sessions. For each household, the social network variable is defined as the fraction of a group of friends (named in a social network survey) who were invited to an early round intensive session. I find that, while financial education raises take-up by 43% in the first round, for second-round participants, having one additional friend who obtained first round financial education increases take-up by half as much. I use a household level price randomization to show that this effect is equivalent to decreasing the average insurance premium by 12%.

The magnitude of the social network effect may depend on social structure (Jackson (2008); Jackson and Yariv (2010)) as well as on the initial conditions (Banerjee et al. (2011)). By exploiting variations in village and household level network characteristics, I show that the effect is larger in more clustered villages where households are more interwoven with each other, and when the first set of people to be financially educated are more important in a network sense (they have higher eigenvector centrality). Moreover, households which are more frequently named as friends by other people (higher in-degree), which can more easily be reached by others (smaller length of in-path), or which are more central in the village network, are less 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 large effect. Do social networks matter in insurance adoption because they can diffuse knowledge among farmers about the 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? I find that there is something special about social networks in 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 reached in the following manner. First, I compare the effect of financial education on insurance take-up and knowledge between the two rounds. I 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, I 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 is found, but, surprisingly, when I told farmers about other villagers' decisions, it actually mattered a lot to them. This suggests that in this case the main mechanism of the social network effect is social learning about insurance benefits, as opposed to a scale effect (greater expected leverage over the insurance company), imitation, or informal risk sharing.

While improving the initial participation rate is crucial as it is a prerequisite for scaling up the program, identifying financially sustainable ways of maintaining high take-up rates over time is also essential. Social networks can be effective for this, because individuals use not only their own experience with the product, but also the experience of others in making purchase decisions. For this, I followed up one year later with a subsample of households from the first year experiment. The randomization in year two includes a household level insurance price. I find that households are not influenced by their friends' purchase behavior during the previous year. However, observing an above median share of friends receiving payouts improves second year take-up at all price levels (by 21.7 percentage points on average) and makes people less sensitive to price change (offsets the price effect by more than 50%). The effect is equivalent to reducing the average insurance premium by 35%. Comparing the effect of learning from others with learning from one's own experience, I show that the observation of friends receiving payouts has about 54% of the impact of a subject's receipt of an actual payout. This means that social networks affect insurance take-up over time through social learning about friends' experience with payouts.

The findings in this paper speak to the commonly used policy of providing a one-time subsidy to a subset of potential buyers with the expectation that this will affect the take-up of the others. My result suggests that such a policy alone cannot lead to indefinitely sustainable voluntary purchases over time. However, combining it with social norms marketing, which disseminates information about the actions of a population's peers, may improve take-up significantly. Moreover, providing financial education to a subset of households and relying on social networks to extend the effect, as well as disseminating payout information effectively, would be good ways of improving the sustained insurance demand.

This paper contributes to the existing literature in the following ways. First, it provides insights on the social network literature. The estimation of the causal effect of social networks is made challenging by the problem of correlated unobservables (Manski (1993); Manski (1995))[5]. Economists have used experimental approaches and other identification strategies to solve this issue, and the results vary greatly with the context and the product considered[6].

[5]For example, social norms, homophily, etc.

[6]Papers using a randomized experimental approach to identify the causal effect of social networks include Duflo and Saez (2003), Duflo et al. (2008), Dupas (2010), Kremer and Miguel (2007), Kremer and Levy (2008), and Oster and Thornton (Forthcoming). Examples that use non-experimental methods to identify the effect include: Bandiera and Rasul (2006), Banerjee et al. (2011), Conley and Udry (2010), Foster and Rosenzweig (1995), Munshi (2003) and Munshi (2004).

This paper uses randomized experimental methods to estimate the causal effect of social networks, and the monetary equivalence of this effect, in a previously unexplored field. Moreover, while the study of mechanisms through which social networks affect behavior is crucial from both theoretical and policy perspectives, only a few studies to date have shed light on this point[7]. This paper contributes by digging deeper into this question and using experimental designs to directly identify a comprehensive set of general channels of social network effects.

Second, the paper sheds light on the puzzle of how to improve weather insurance take-up. Although existing works have tested the possible explanations of trust, credit constraints, and ambiguity aversion (Giné et al. (2008); Cole et al. (2011); Bryan (2010)), insurance demand is still low even after some of the above treatments were implemented. I provide evidence that a previously unexplored determinant, social networks, can improve both initial participation rates and longer term insurance demand, and significantly reduce households' sensitivity to the removal of subsidies.

Third, this paper contributes to the literature on financial education. Although there is 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)), the experimental evidence on financial education is mixed[8]. In a context where insurance is new, and farmers have relatively low levels of general education, my results show that lack of financial education is a major constraint on the demand for insurance, and that modest financial training can improve take-up rates significantly.

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. Section 4 presents the results, and section 5 concludes.

[7]In general, the mechanisms through which social networks affect the adoption of new technology and financial products include social learning about product benefits, imitation, learning how to use the product, etc. The following two papers are examples which have worked on the mechanisms of social network effects. Kremer and Miguel (2007) find negative peer effects, which effectively rules out explanations such as imitation and learning how to use the product. Banerjee et al. (2011) take advantage of differences in predicted patterns of behavior as a function of the diffusion of basic information (awareness of microfinance) as compared to peer effects (influence of others' decisions). They find that the diffusion of information in microfinance participation is more in line with peer effects than with basic information diffusion.

[8]Some find small or no effects of financial education on individual decisions (Duflo and Saez (2003); Cole et al. (2011)), while others find positive and significant effects (Cai and Song (2011)); Cole et al. (Forthcoming); Gaurav et al. (2011).

2 Background

Rice is the most important food crop in China. Nearly 50% of the farmers produce rice, and more than 60% of the Chinese people use rice as their staple food. In order to maintain food security and shield farmers from negative weather shocks, in 2009 the Chinese government designated the People's Insurance Company of China (PICC) to design and offer the first rice production insurance program to rural households in 31 pilot counties[9]. The program was extended to 62 counties in 2010 and 99 counties in 2011. The experimental sites for this study are two rice production counties included in the second round pilots in Jiangxi province, which is one of China's major rice bowls[10]. In these two counties, rice production is the main source of income for most farmers. Since the product was new, no households had 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 level had very limited knowledge of weather insurance products and the insurance company as the provider.

The insurance contract is as follows. The actuarially fair price is 12 RMB per mu per season[11]. The government gives a 70% subsidy on the premium, so farmers only pay the remaining 3.6 RMB per mu. If a farmer decided to buy the insurance, the premium will be deducted from the agricultural card, no cash payment is needed[12]. The insurance covers natural disasters including heavy rain, flood, windstorm, extremely high or low temperature, and drought. If any of the above natural disasters happened and led to a 30% or more loss in yield, farmers were eligible to receive payouts from the insurance company. The indemnity rule is illustrated in Figure A2. The amount of payout increases linearly with the loss rate in yield, with a maximum payout of 200 RMB. The loss rate in yield is investigated and determined by a group of insurance agents and agricultural experts[13]. 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 provides partial insurance that covers 25% - 30% of the gross income or

[9]Although there was no insurance before 2009, if major natural disasters happened, governments issued subsidies to households whose production was seriously hurt. However, the level of subsidy was usually very limited and far from enough for farmers to restart production.

[10]The location and map of Jiangxi province is presented in Figure A1.

[11]1 RMB = 0.15 USD; 1 mu = 0.067 hectare. In the experimental sites, farmers produce two or three seasons of rice each year.

[12]Starting in 2004, the Chinese government has provided rice production subsides 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).

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

50% - 70% of the production cost.

It is also important to note that the post-subsidy price is below the actuarially fair price according to the following calculation. The profit of the insurance company equals revenue minus payouts and fixed cost:

$$\pi = N * Premium - N * P * Payout - FC$$

Where P is the probability of future disasters, and N is the number of households that buy the insurance. Based on communications with local government officials and farmers, the actual probability of disasters that can cause 30% or more loss in yield is estimated to be around 12%. Since N*3.6 < N*12%*(200*30%), the post-subsidy price is below fair price. This implies that, as the expected benefit of purchasing insurance is positive for farmers, it is optimal for all farmers who cultivate rice to purchase it. However, as the pre-subsidy price is higher than the fair price, the insurance company earns a profit if the fixed cost is not too large.

3 Experimental Design and Data

I use a two-year randomized experiment to identify the role of social networks in influencing insurance demand. The first year experiment was carried out in spring 2010, and includes 185 villages with around 5332 households[14]. The first year data is used to test how social networks affect insurance take-up in the short-run. The second year experiment was implemented in spring 2011; in that phase, I followed 1871 households that were covered in year one, in order to examine social network effects overtime.

3.1 Year One: Identify the Short-run Social Network Effect

The first year experiment is used to answer three questions: first, what is the causal effect of social networks on the initial year insurance demand? Second, what is the monetary equivalence of the social network effect? Third, what kind of information did social networks convey that is driving the effect?

In order to generate household level variation in the knowledge of insurance products, two types of information sessions were offered to different households in this year. The simple session took around 20 minutes, during which we only introduced the insurance contract[15].

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

[15] The simple session introduces terms in the contract including the insurance premium, the amount of

The intensive session took around 45 minutes and covered all information provided during simple sessions, plus financial education to help farmers understand how insurance works and the product benefits[16].

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 was finished, in order to allow late participants to communicate with early participants. Each household was invited to only one of these four sessions. The effect of social networks on insurance take-up is thus identified by looking at whether second round participants are more likely to buy insurance if they have more friends exposed to financial education in first round intensive sessions.

The experimental design in year one is illustrated in Figure 1.1 and 1.2. There are four randomizations in this experiment, two on the household level and two on the village level. The within-village randomization is 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)[17]. This randomization is used to account for exogenous variations among second round participants in the proportion 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 made final decisions, I randomly divided them into three groups and led different groups to separate rooms, and then disseminated different additional information to the different groups of participants. Specifically, I did not give farmers in groups U1 and U4 any additional information but directly asked them to make take-up decisions; thus, farmers in these two groups received exactly the same information from us as those in the two first round sessions (T1 and T2). For farmers in groups U2 and U5, I told them the overall take-up rate at the two first round sessions in the village that they belong to, so that they knew how many

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.

[16] Sample topics included in the financial education included: How does the insurance program differ from a government subsidy? How much payout can you get under different conditions? What is the expected benefit of purchasing insurance for five continuous years depending on different disaster frequencies and levels, in order to see whether you can gain or lose from buying insurance?

[17] Before doing randomizations, I first approached leaders of each village to obtain a household list that includes name of the household head and basic household characteristics. Households who did not grow rice were excluded. For all household level randomizations in this experiment, I stratified the sample within each village according to household size and area of rice production per capita, and random assignments of households to different treatment groups were made 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, I gave monetary incentives to village leaders and asked them to inform and invite household heads to attend these sessions.

people had attended previous sessions and how many of them had purchased the insurance. For groups U3 and U6, I showed farmers the detailed decision list made in the two first round sessions, so that they knew specifically who purchased the insurance and who did not. This randomization will help determine the main mechanism that drives the social network effect.

Above the within-village randomization, there are two village-level randomizations, which is shown in Figure 1.2. First, I randomly divided villages into two types. In type I villages, all households face the same final price 3.6 RMB, while in each type II village, I randomly assigned seven different final prices ranging from 1.8 RMB to 7.2 RMB to different participants in second round sessions[18]. Type II villages are used to measure the monetary value of the social network effect. The second village-level randomization is only within type I villages, where there was no price variation; in type I villages, I randomized the default option in first round sessions. If the default was BUY, then the farmer needed to sign off if he or she did not want to purchase the insurance; if the default was NOT BUY, then the farmer had to sign on if he or she decided to buy the insurance[19] . 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 will be used in some estimations as an instrumental variable for first round purchase decisions[20] .

In all cases, households make take-up decisions individually at the end of our visit. Moreover, all households were asked to respond to a household survey, which will be illustrated in detail later.

3.2 Year Two: Identify the Social Network Effect Over Time

One year after the first time provision of the rice insurance program, a follow-up experiment was conducted in a subset of villages (72 out of 185, around 2000 households) covered in year one. Both buyers and non-buyers in these villages who were surveyed in year one were

[18] In all type II villages, farmers in second round sessions T3 and T4 receive 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.

[19] 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."

[20] 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).

sampled for the follow-up experiment. Combining data for both years, I test the effect of social networks on the second year insurance demand curve.

In year two, I randomized the household level subsidy. The randomization strategy is similar as the design in Dupas (2010). In total, eight different prices were offered, with the level of subsidy ranging from 90% to 40%. However, within each village, only two or three prices were assigned[21]. To randomize price sets on the village level, the sample of villages was stratified according to village size (total number of households) and first year village-level payout ratio. For price randomization on the household level, the sample within each village was stratified according to rice production area. Except for the final price, everything else remained the same in the contract as in year one. With the price randomization, I can test the medium-run social network effect on both the level and the slope of the insurance demand curve.

The procedure is as follows. In each village, I gather households assigned with the same final price and hold meetings for different price groups simultaneously. Households make second year purchase decisions individually right after the meeting[22]. During the meeting, insurance agents briefly repeat items in the insurance contract and announce the list of people in the village who purchased insurance and have received a payout last year, so all households know who in the village received a payout and the amount of the payout[23]. This helps me test the effect of an important type of social network effect: social learning about friends' experiences. Specifically, I calculate the fraction of a group friends (listed in the year one social network survey) who purchased insurance and received a payout; I use that fraction as the measure of social learning about friends' experiences, and test its impact on the second year demand curve.

3.3 Data, Summary Statistics and Randomization Check

At the end of the visit in both years, a census was collected in all villages included in the experimental sites. In total, 5332 households were surveyed in year one and 1871 households were surveyed in year two. The survey consists of two components: a household survey and

[21] Price sets with either two or three different prices were randomly assigned on the village level. For villages assigned with two prices {P1, P2}, P1 $<=$ 3.6 and P2 $>$ 3.6; for villages with three prices {P1, P2, P3}, P1 $<$ 3.6, P2 $=$ {3.6, 4.5}, and P3 $>$ 4.5.

[22] Note that the price experiment is different between the first and second year experiment. In year one, I did price randomization in both first and second round sessions, so second round participants knew different households are facing different prices when they made take-up decisions. However, in year two, because meetings with households in different price groups were held simultaneously, and farmers made decisions at the end of the meeting, they did not know prices are different from household to household before making second year purchase decisions.

[23] After the insurance was offered in April 2010, a low temperature disaster happened in October 2010, just before the harvest of the late season rice, which lead to yield loss for most farmers.

a social network survey.

The household survey contains five parts. The first part asks about household characteristics including household size; age and education of the household head; area of rice production; yields and sales; household income from different sources; borrowing; etc.; The second part asks about types of natural disasters experienced, loss rate in rice yield in the past three years, and methods of coping with such losses. The third part covers experience in purchasing any kind of insurance, as well as payouts received in the past three years. The fourth part asks about risk attitudes and perceptions about future disasters[24]. The fifth part contains questions which test farmers' knowledge of how insurance works and its potential benefits; households' trust of the insurance company regarding loss checking and the payout issuing process; and willingness to pay for the insurance. Summary statistics of selected variables 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. Most households have experienced some types of natural disasters in the most recent year, and the average loss rate is around 28%. Households are risk averse on average, and they are more risk averse in the second year compared with in the first year, which can be due to experience of weather shocks during the first year.

The social network component of the survey asked the household head to list five friends, either within or outside the village, with whom the respondent most frequently discusses rice production and financial related problems[25]. 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. I use this data to construct an undirected measure of social links: two households have a link if at least one of them named the other. This measure is used in most of the following estimations and is henceforth called the general measure. In addition, another two measures of social links are defined. One is the strong measure where two households have a link if each of them named the other, and the weak measure where two farmers have a link if at least one of them were named by a friend of the other (second order links). A sample within-village social network map is presented in Figure A3[26]. In all cases, the social network

[24]Risk attitudes were elicited by asking sample households to choose between increasing amounts of certain money (riskless option A) and risky gambles (risky option B) in Table A1. 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?"

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

[26]In Figure A3, for household 11122066: household 11122076 is an undirected social link, household

variable is defined as the fraction of the group of friends with whom they have social links who were invited to a first round intensive session (where financial education was provided). According to Panel B in Table 1, the average number of friends listed by households is 4.9, which means only a small proportion of households listed less than five friends. On average, 16% of a household's friends named in the social network survey were invited to the first round financial education provided in the intensive session.

Since how well and how fast information can be diffused among households may depend on network structure such as village size, positions of households in the network, etc., I constructed several measures of village and household level social network characteristics. Summary statistics of these variables are listed in Panel C in Table 1 . The villages have an average of 32 households. Clustering rates are 0.18. This means that about 20% of the time that some household i has connections to some households j and k, j and k also have connections to each other. On average, a household has been named by about three other households. The average path length is about 3.5, which means a household can be connected to any others in the village by passing three households. Eigenvector centrality is a recursively defined notion of centrality: a household's centrality is defined to be proportional to the sum of its friends' centrality. The larger the centrality, the more important is the person's position in the village network.

The overall take-up rate in the first year is 44%, while that in the second year is higher, about 50%. According to Panel D and E in Table 1, around 56% households who purchased the rice insurance received some payouts during the first year, and the average amount of payout was about 86 RMB per mu.

Randomization checks are presented in Table A2.1 and A2.2. According to Table A2.1, most household characteristics are balanced across the four different sessions in the first year experiment. To check whether the price randomization is valid, I estimate the following regression in both of the type II villages where price variation was implemented in year one, and in all villages in year two:

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

Where X_{ij} is a set of characteristic of household i in village j, including gender, age, household size, education, and area of rice production. $Price_{ij}$ is the post-subsidy price faced by household i in village j, and η_j includes village dummies. Estimation results are listed in Table A2.2, showing that none of the coefficient are statistically significant. As a result, the price randomization was valid in both years.

11122098 is a strong social link, and household 11122103 is a weak social link.

4 Estimation Strategies and Results

4.1 Effect of Social Networks on Initial Year Insurance Demand

This section tests the effect of social networks on insurance demand when it was offered at the first time, and explains what types of information act as the mechanism driving the effect, using data collected in year one.

4.1.1 Estimation of the Social Network Effect

The average take-up rate in different information sessions is illustrated in Figure 2. It shows 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. The above evidence 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 of sessions, there was information diffusion from first round to second round participants.

To estimate the effect of social networks on insurance take-up, using the experimental design in Figure 1.2, I use only type I villages (those without price randomization). First, I estimate the financial education effect using the sample of first round participants (simple session T1 vs. intensive session T2) using the following equation:

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

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 household i was invited to one of the two intensive sessions in village j and zero otherwise. X_{ij} includes household characteristics such as gender, age, production size, etc., and η_j includes village dummies. According to results in Table 2, the take-up rate of first round intensive sessions (50%) is 15 percentage points higher than that of first round simple sessions (35%), suggesting a large and significantly positive financial education effect that increases take-up rate by 43% in the first round.

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

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

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 (the general social network measure)[27]. Since households are more likely to be exposed to the information provided during financial education (which improves insurance take-up as shown in Table 2) if more of their friends attended a financial education session, a positive social network effect is expected.

Estimation results are listed in Table 3.1. According to column (1), I find a significantly positive effect of social networks on insurance take-up, and the magnitude of that effect is around 33.7 percentage points. This suggests that having one additional friend attending a first round intensive session - in other words, raising the general network measure by 20% because each household lists five friends - increases a farmer's own take-up rate by 33.7 * 0.2 = 6.74 percentage points. This explains about 45% of the direct financial education effect (column (1) in Table 2). In column (2), some control variables were added into the regression[28]. This column shows that the magnitude of the social network effect does not change much with additional controls. In addition, it suggests that older people, farmers with larger production size, or those with more education are more likely to buy the insurance. Moreover, households who are more risk averse, or those who predict a higher probability of natural disasters in the following year, are more likely to purchase insurance. In column (3), I test whether the magnitude of social network effects depends on whether a farmer received financial education. The social network effect is larger in second round simple sessions, according to the significantly negative coefficient of the interaction term between the network measure and intensive session. This means 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[29]. To test this, I extend the framework to include different measures of social links: the strong measure (mutually named links) and the weak measure (second order links), and re-estimate equation (3) using these two measures. Results are listed in Table 3.2. According to column (2), having

[27]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.

[28]Because a small proportion of households named less than five friends in the social network survey, and these households might be different from other farmers in some aspects, I did a robustness check by excluding these households and re-estimating the social network effect. Results in Table A3 show that the significance and magnitude of the social network effect remained almost the same.

[29]There are various ways to measure the strength of a tie, and in some contexts, effect of weak ties on outcomes can be as important as that of strong ties Granovetter (1973).

one additional strongly linked friend attending first round financial education improves a farmer's own chance of taking the insurance by 8.5 percentage points, which is larger than the effect of undirected social links (6.7 percentage points). In contrast, friends with weak links are much less influential: according to column (4) in Table 3.2, 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 during a short period of time (three days in this case), households are not influenced much by friends' friends. In addition, I test whether the magnitude of social network effects varies according to the relationship between the farmer and the person he or she named in Table 3.3. The results show that government officials have the largest effect on influencing their friends' purchase decisions, followed by relatives and neighbors.

While having friends exposed to financial education improves a farmer's own take-up, the effect can be nonlinear. The question is whether having just one friend receiving financial education is enough, or having more friends receiving financial education generates larger effects. I 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 which equal one if household i has one, two, or more than two friends assigned to the first round intensive session (the session with financial education) in village j, and 0 otherwise. Results are presented in Table 4. According to column (1), 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 20.2 percentage points; this is about 14 percentage points higher than the effect of having only one friend financially educated in the first round, which is only 5.6 percentage points. However, having more than two friends financially educated has just a slightly higher effect on take-up (8 percentage points higher) than that of having two. The effect holds when additional controls are added (column (2)). As a result, the social network effect increases with the number of friends receiving financial education, but the marginal return is diminishing when the number is larger than two.

4.1.2 Social Network Effect, Network Characteristics, and Injection Points

How efficiently information can be diffused, and to what extent a farmer can be influenced by other farmers, may depend on network characteristics at both the village and individual level. First, the role of village-level network structure is obviously important in most diffusion models[30]: for example, the spread of information might be easier and faster in more clustered villages where households are more strongly connected with each other. Taking advantage of cross-village variations in network structure, I estimate how the magnitude of social network effect varies with a set of variables that capture village-level network structure, including: village size, clustering, segmentation, etc., 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 different measures of village-level network characteristics (detailed definitions in appendix B). According to the results in table 5.1, while characteristics such as village size, transitivity, etc. do not affect the magnitude of the social network effect, clustering does: according to column (2), in villages with a higher clustering coefficient (households are more strongly connected with each other), the effect of social networks on insurance take-up is larger, suggesting that, in these villages, information diffusion is more efficient.

Second, the "injection points" (the households that were included in the first round financial education) could affect diffusion in a social network[31]. The question I want to answer is: in a village with hundreds of people, if only a small group of households can be formally financially educated, will the strength of the social network effect depend on which individuals are initially contacted, as well as on the importance in the village network of farmers who make the take-up decision? I define a set of individual level network characteristics, including in-degree (how often is a farmer named by other households), path length (the average length of the path between a farmer and any other households), and eigenvector centrality, and answer this question by estimating the following equation[32]:

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

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

[30] See Chapter 7 in Jackson (2008) for detailed discussion and background.

[31] The idea that injection points may matter has been discussed in Katz and Lazarsfeld (1955), Ballester et al. (2006), and Banerjee et al. (2011). However, most of the previous literature has not tested that explicitly, with the exception of Banerjee et al. (2011).

[32] While Banerjee et al. (2011) studied the effect of group-level characteristics of initially treated households on village level microfinance participation, here I define injection point characteristics for each household's social links. I explain how the magnitude of social network effect depends on characteristics of friends who were financially educated first and on each farmer's own importance in the village network.

characteristics of household i. The coefficient η_3 tells us what types of person have more influence on others, while coefficient η_5 suggests who is more likely to be influenced by others. According to the results in Table 5.2, the average in-degree or out-path length of one's friends does not influence the magnitude of the social network effect, but their eigenvector centrality is. Referring to column (6), 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 of social networks (having one additional friend financially educated) on take-up is around 6.4 percentage points larger. Another noteworthy point is that what matters more is a farmer's own network characteristics: according to columns (2), (4) and (6), those who were named more often by other households (higher in-degree), who can be reached more easily (smaller in-path length), and who have a more important network position (higher eigenvector centrality), are less likely to be influenced by other people. However, these characteristics only affect the magnitude of the social network effect, and do not directly affect the take-up decisions.

Given that individual-level network characteristics are important, what are the determinants? I show this in Table A4. According to column (4) in Table A4, for example, households with higher centrality in the network are usually better educated and have larger production size. The reason that they are more influential may be that they better understand the benefits of purchasing insurance and can explain it better. A reason that they are less likely to be influenced by others may be that, as they are larger farmers, having insurance is more important for them, so they purchase it regardless of what other people say. I present the heterogeneity of social networks depending on these easily observable determinants in Table A5.

4.1.3 Monetary Equivalence of the Social Network Effect

In order to understand the importance of the social network effect better, I assess the price equivalence of it using type II villages, where price randomization was implemented. Specifically, I estimate the effect of removing subsidies on insurance demand, and test whether households are less sensitive to subsidy removal if they have more friends exposed to financial education. Then I calculate the price equivalence of the social network effect based on estimated coefficients. I write a simple theoretical model of insurance demand to explain why social networks can potentially influence both the level and slope of insurance demand curve; this is presented in Appendix C. The slope of the insurance demand curve can be influenced by household level perceptions of the expected benefit of the new insurance product, and the uncertainty about the expected benefit. The degree of concentration or dispersion in distribution of the expected product benefit can also influence the slope of the demand curve. All of these factors can be influenced by social networks. For example, when a farmer has friends receiving financial education in the first round, the farmer may be less uncertain about the product benefit after friends explained it; as a result, the farmer who learned insurance knowledge from friends may be less sensitive to a price increase than a farmer who did not learn insurance knowledge through any social channels.

In Figure 3, I compare the insurance demand curve between households who have an above-median proportion of friends receiving financial education and those who have a below-median proportion of friends who were financially educated. It is clear that the insurance demand curve is higher and flatter, especially under high prices, when a high proportion of friends is exposed to financial education in intensive sessions. To estimate this empirically, I use the following estimation 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 final price assigned to household i in village j, which ranges from 1.8 RMB to 7.2 RMB, with a total of seven different prices. The coefficient of the interaction term between $Price_{ij}$ and $Network_{ij}$ tells us whether the social network effect can substitute for part of the subsidy effect. Results are presented in Table 6. Column (1) shows that reducing subsidies by 10% (1.12 RMB) decreases take-up by around 10 percentage points. However, according to column (2), the interaction term between social network and price is significantly negative, which suggests that households are less sensitive to subsidy removal if they have more friends receiving financial education. Specifically, having one additional friend receiving financial education mitigates the price effect by 0.13*0.2/0.167 = 16%.

One concern of the above estimation is that, for households in the price experiment, some of their friends face lower prices than they do, while some of their friends face higher prices. How this "fairness" issue might bias the price elasticity of insurance demand is uncertain. To control for this, I included two additional variables when estimating equation (7): %friends with prices higher than one's own price and %friends with prices lower than one's own price. Referring to the results in column (3) of Table 6, the effect changed slightly: having one additional close friend receiving financial education mitigates the price effect by around 0.15*0.2/0.151 = 20%, and is equivalent as the effect of a 12% decrease in the average insurance premium[33].

[33] I calculate the price equivalence X of the social network effect by the following formula:

$$X = \frac{\frac{Coef(Network)[0.2*(1-Coef(Price*Network)*Mean(price))]}{Coef(Price)[1-Coef(price*Network)*Mean(Network)]}}{Mean(Price)}$$

In summary, the above results tell us that providing financial education about the product improves insurance 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 attending financial education has an effect equal to almost 45% of the first order education effect, and is as effective as reducing the average insurance premium by 12%.

4.1.4 Mechanisms of the Social Network Effect

A natural question is why social networks matter. What did people actually learned from their friends? 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 new technology or financial products because individuals care about other people's decisions (Bandiera and Rasul (2006); Banerjee (1992); Ellison and Fudenberg (1993); Rogers (1995)), or because people learn how to use the product from their friends (Duflo and Saez (2003); Munshi and Myaux (2006); Kremer and Miguel (2007); Oster and Thornton (Forthcoming)). Social networks could also matter if people learn the value or benefits of a product from their friends (Kremer and Miguel (2007); Koher et al. (2001)).

Because insurance is a financial product rather than a technology, people do not need to learn how to use it, and thus this paper does not consider the "learn to use" channel. I will focus instead on the importance of two types of information that can be conveyed by social networks and can influence people's behavior: 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, farmers could be influenced by their friends' behavior in deciding whether to buy insurance. The influence could occur because of scale effects (famers have greater leverage over the insurance company if more of them purchase together), imitation (farmers want to act like each other), or informal risk-sharing (a farmer's decision depends on the purchasing decision of households from which the farmer borrows or to which the farmer lends). If the network effect is driven by 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.

First, to test the "insurance knowledge" mechanism, I use the following two strategies. The first method is to compare 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, with no take-up information revealed in either U1 or U4). Intuitively, if late participants can obtain insurance knowledge from early participants during the time interval between the two rounds, then they have already been exposed to the information we provided during financial education before attending their own sessions, regardless of whether they were assigned to the simple or intensive session. As a result, we should see a smaller effect of financial education in the second round. 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 which equals one if a household is assigned to one of the two second-round sessions in his village, and $knowledge_{ij}$ is a measure of insurance knowledge, which is defined as the score that a household got in the ten questions that we asked during the household survey to test farmers' insurance knowledge. Results are presented in Table 7. Column (1) shows that while financial education raises the take-up rate significantly in the first round (14 percentage points), it makes almost no difference in the second round. Similar patterns regarding insurance knowledge can be found in columns (3). Moreover, while the levels of insurance take-up and insurance knowledge between the two second round sessions are very similar, they are significantly higher than that of first round simple sessions.

The second strategy to identify the insurance knowledge mechanism is to test whether households perform better in the insurance knowledge test when they have more friends attending first round financial education, by estimating the following equation:

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

According to column (4) of Table 7, having one additional friend assigned to first round intensive sessions improves the level of insurance knowledge by 7 percentage points. Furthermore, I test whether the effect is larger when one's friends better understand the materials provided during financial education, and as a result can better teach other people:

$$\begin{aligned} Knowledge_{ij} = \lambda'_0 + \lambda'_1 Network_{ij} + \lambda'_2 NetKnowledge_{ij} \\ + \lambda'_3 Network_{ij} * NetKnowledge_{ij} + \lambda'_4 X_{ij} + \eta_j + \epsilon_{ij} \end{aligned} \quad (11)$$

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 7 shows that a farmer can learn more insurance knowledge from friends who were financially educated when those friends better understand the information provided in financial education. These results support the argument that, during the three days between the two rounds of sessions, second round participants obtained insurance knowledge from the first set of people who were financially educated, and that such informal learning of insurance knowledge improved insurance take-up significantly.

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

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

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 a scale effect or imitation. However, OLS cannot provide a consistent estimates because unobservable variables such as social norms may affect both $TakeupRate_j$ and $Takeup_{ij}$.

As shown in column (1) of Table 8, 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. As a result, I can use the default option as the 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) of Table 8: 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. To see this more clearly, I break down the sample and re-estimate the influence of first round overall take-up rate in columns (4) - (5). According to column (4), second round participants are not influenced by decisions made by first round participants. However, they do care about what other farmers do: as suggested by columns (5), if we disseminated first round overall take-up information during second round sessions, then increasing the first round take-up rate by 10% can raise take-up rate by around 4.3%, which is almost half of the first-order effect.

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

$$Takeup_{ij} = \delta_0 + \delta_1 TakeupRate_j + \delta_2 TakeupRateNetwork_{ij} + \delta_3 Reveal_{ij} \\ + \delta_4 TakeupRate_j * Reveal_{ij} + \delta_5 TakeupRateNetwork_{ij} * Reveal_{ij} + \delta_6 X_{ij} + \epsilon_{ij} \quad (13)$$

where $TakeupRateNetwork_{ij}$ represents the take-up rate among friends of household i who attended first-round sessions in village j[34]. Similar to what has been discussed before, both $TakeupRate_j$ and $TakeupRateNetwork_{ij}$ are endogenous. While I still use first round default option as the IV for the overall first round take-up rate, I use two IVs for $TakeupRateNetwork_{ij}$: Default*%friends 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), and %friends who were in the first round and were assigned to the intensive session (because financial education has a positive effect on insurance take-up, friends' take-up rate in the first round should be higher if more of them were assigned to the intensive session[35]). According to results in Table 9, 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 such information.

The above results suggest that, while social networks are efficient in transmitting insurance knowledge, they do not convey purchase decisions. This is surprising, because farmers actually care a good deal about that type of information, which we know because of the significant effect if the information is explicitly revealed. I conclude that the short-run social network effect on insurance take-up is mainly driven by the diffusion of insurance knowledge, as opposed to mechanisms related to the behavior of other people, such as scale effect, imitation, or informal risk-sharing.

There are two potential explanations as to why farmers do not tell each other what they do. First, it is possible that it takes time for information about purchase decisions to be revealed and diffused, so it cannot be captured during the three days between the two

[34]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.

[35]If, among the five friends listed, three of them were invited to first-round sessions and two of them were assigned to first-round intensive sessions, then the "fraction of friends in first-round" = 2/5= 0.4, and the "fraction of first-round friends in intensive sessions" = 0.5.

rounds. I can check this possibility by testing whether farmers are influenced by their friends' decisions over time using second year take-up data. Second, because of cultural factors and the type of financial product they are considering, farmers may be reluctant to reveal their decisions, because they are not sure whether they have made the right decision[36].

Several policy implications can be drawn from the above 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. Second, these results cast some doubt on 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 sub-population may not be sufficient to achieve the expected outcomes, at least in some contexts. However, social norms marketing, in which we disseminate information to the full population about the behavior of peers, might be effective as a supplemental strategy. Because we do see increased take-up when farmers are explicitly informed about the behavior of others, combining either education or subsidies for a sub-population with social norms marketing may be an inexpensive way to expand the take-up rate for innovative products to a broader population[37].

4.2 Effect of Social Networks on Second Year Insurance Demand

My results so far show that social networks significantly improve the first year insurance demand through diffusing insurance knowledge. However, if we cannot maintain voluntary insurance purchase over time when subsidies are gradually removed, the insurance program cannot be financially sustainable or be effective on improving household welfare. As a result, it is important to estimate the social network effect on insurance demand over longer periods. In this section, I estimate the impact of social networks, especially social learning about friends' payout experience, on the second year insurance demand curve, using survey data from both years and payout data from the insurance company[38].

[36]Please note that while first round participants made purchase decisions directly after the meeting, second round participants did not know that. Therefore, even if they did not reveal the purchase decisions (they can simply say they have not decided yet), they will be not blamed by meant to do that.

[37]Field experiments have shown that social norms marketing which tries to exploit people's tendency to imitate peers, have mixed effect 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 fields such as insurance.

[38]According to Figure A4, the correlation between loss rate in yield and the probability of receiving payouts is consistent with what was stated in the contract.

4.2.1 Social Network Effect Over Time

In this part, I estimate the social network effect one year after the insurance was offered the first time. Specifically, I look at the effect of friends' take-up decisions in the previous year on a farmer's own insurance demand curve in the current year. The estimation equation is as follows:

$$\begin{aligned} Takeup_{ij2} = \sigma_0 + \sigma_1 Price_{ij2} + \sigma_2 NetworkTakeup_{ij1} \\ + \sigma_3 Price_{ij2} * NetworkTakeup_{ij1} + \sigma_4 X_{ij} + \eta_j + \epsilon_{ij} \end{aligned} \tag{14}$$

where $Takeup_{ij2}$ is a dummy equal to one if household i in village j bought the insurance in year two; $Price_{ij2}$ is the final price faced by household i in village j in year two, which ranges from 1.2 RMB to 7.2 RMB; $NetworkTakeup_{ij1}$ is the proportion of friends who have purchased insurance in year one[39]; X_{ij} includes household characteristics such as age, gender, education of household head, household size, rice production area, insurance knowledge, risk attitude, and perceived probability of future disasters in year two; and η_j includes village dummies.

However, OLS estimation cannot give a consistent estimation of the above equation because friends' decision in year one is endogenous. According to results reported in section 4.1, default options and first round financial education substantially influence first-year insurance take-up. As a result, here I use two IVs for $NetworkTakeup_{ij1}$: %friends in first round sessions * default option, and %friends in first round intensive sessions[40].

Table 10 presents the estimation results. First, raising prices (removing subsidies) has a significantly negative effect on insurance demand in year two: on average, removing subsidies by 10% decreases insurance demand by around 5.04 percentage points. Second, OLS estimation results in columns (1) and (2) show that farmers are slightly more likely to purchase insurance in year two if more friends purchased it in year one. Specifically, having one additional friend buy insurance in year one increases the probability of purchase in year two by around 2.3 percentage points; this result is barely significant. Turning to the IV result, the first-stage estimation result in column (3) shows that the two IVs affect friends' decisions in year one significantly. However, according to columns (4) and (5), the IV estimation result shows that friends' decisions in year one does not have a significant effect on a farmer's own

[39]For example, if a household listed five friends during the social network survey in year one, and three of them purchased insurance in year one, then the variable is defined as $3/5 = 0.6$.

[40]One concern of using %friends in first round intensive sessions as the IV is that this may affect both friends' financial knowledge and a farmer's own knowledge through information diffusion in networks, which will further affect a farmer's insurance demand curve in year two. To deal with this problem, I controlled for households' insurance knowledge in year two in this estimation.

decision in year two. Moreover, as presented in column (6), the interaction term between price and friends' decisions in year one is also not significant, which means decisions made by friends in year one do not influence either the level or the slope of the insurance demand curve in year two.

In summary, households do not copy their friends' decisions over time. However, this does not mean that farmers are not influenced by their friends at all, because what they observe over time is not only friends' purchase decisions, but also their experience. It is possible that some specific types of experience of their friends still influence their own decisions[41]. The most important type of experience that farmers care about in this context is receiving payouts from the insurance company: after the first year, if disasters happened, farmers can see whether anyone received a payout, whether loss checking and payout issuance are done fairly, etc., which can potentially affect their own long-run insurance demand. As a result, in the next part, I measure the effect of observing friends' payout experience on the second year insurance demand curve.

4.2.2 Learning from Own and Friends' Payout Experience

First, I study the effect of directly receiving payout in the first year on the insurance demand curve in the following year, using the sample of households who purchased insurance in the first year. In Figure 4, I compare the insurance demand curve of households that received payout to the insurance demand curve of households that did not. It shows that people are significantly more likely to renew the contract if they received some payouts in the first year. Furthermore, those who received payouts are less sensitive to subsidy removal in the second year; the insurance demand curve is almost flat for them. I then estimate whether these effects are statistically significant using the following regression:

$$Takeup_{ij2} = \phi_0 + \phi_1 Price_{ij2} + \phi_2 Payout_{ij1} + \phi_3 Price_{ij2} * Payout_{ij1} + \phi_4 X_{ij} + \eta_j + \epsilon_{ij} \quad (15)$$

where $Payout_{ij1}$ is a dummy equal to one if the household received payout last year. According to results in columns (1)-(3) in Table 11, receiving payouts improves second year take-up rate by around 40 percentage points, and mitigates the subsidy removal effect by around 70%. While this effect could be driven by "learning by doing", it could also be explained if people changed their risk altitudes or perceived probability of future disasters after experiencing some weather shocks in year one. In order to control for this effect, I use a regression discontinuity method to re-estimate the effect of receiving payouts on renewal

[41]Several papers have shown the importance of learning from own or friends' experience in the process of new product adoption (Besley and Case (1994); Conley and Udry (2010); Dupas (2010)).

behavior, using loss rate in yield during the first year as the running variable. According to the results in columns (4) and (5) in Table 11, the results stay almost the same, so the weather shock mechanism can be ruled out as a possible explanation.

Next, I compare the effect of "learning by doing" to that of social learning about friends' payout experience. By definition, a farmer who did not buy insurance in the first year could not directly receive a payout, so his or her second year behavior cannot be explained as "learning by doing". Regardless of whether a farmer purchased insurance in the first year, observing other people receiving payouts may affect the second year take-up decision, which is a specific social network mechanism which I describe as social learning about friends' payout experience.

In figure 5, I compare the second year insurance demand curve of households who have an above-median proportion of friends receiving payouts in the first year and that of those who have a below-median proportion of friends receiving payouts. We can see that, when a farmer has more friends who received payouts, the insurance demand curve is significantly higher and flatter. To estimate this empirically, I use the following regression:

$$\begin{aligned} Takeup_{ij2} = \psi_0 + \psi_1 Price_{ij2} + \psi_2 NetworkPayoutHigh_{ij1} + \psi_3 Price_{ij2} \\ * NetworkPayoutHigh_{ij1} + \psi_4 NetworkTakeup_{ij1} + \psi_5 X_{ij} + \eta_j + \epsilon_{ij} \quad (16) \end{aligned}$$

where $NetworkPayout_{ij1}$ is the proportion of friends in one's social network who have purchased insurance in the first year and received payout[42], and $NetworkPayoutHigh_{ij1}$ is a dummy which is defined as one if $NetworkPayout_{ij1}$ is higher than the sample median and zero otherwise. It is possible that households' insurance demand curve changes according to friends' payout experience because households may update their beliefs about the potential benefits of this product or the uncertainty about this program after observing friends' experience with it.

I estimate equation (16) using three different samples: the whole sample, only those who purchased insurance in the first year, and only those who did not purchase in the first year. According to columns (1), (3) and (5) in Table 12, overall, households who have an above-median proportion of friends receiving payouts are about 22 percentage points more likely to purchase insurance in year two. However, the effect is only significant for those who did not purchase insurance in the first year; those who bought insurance in year one do not care about whether other people received payout. Moreover, as shown in columns (2), (4) and (6) of Table 12, friends' payout experience affects price sensitivity for all households, regardless

[42]For example, if a household listed five friends in the social network survey, four of them purchased insurance in year one, and two of them received payouts, then the variable is defined as $2/4 = 0.5$.

of whether a household purchased insurance in the first year. Specifically, observing an above-median proportion of friends receiving payouts mitigates almost 50% of the negative subsidy removal effect, which is equivalent to the effect of reducing the average insurance premium by 35%[43].

As a result, the effect of learning from friends' experience on the level of insurance demand equals about half the effect of directly receiving payout; the effect of learning from friends' experience on the slope of the insurance demand curve equals about 70% of the learning by doing effect. Consequently, observing more friends receiving payouts can substantially influence a farmer's own insurance demand and price sensitivity in future periods.

5 Conclusions

This paper uses a two-year randomized field experiment in rural China to analyze social network effects in the adoption of a new weather insurance product. I find strong evidence that social networks play important roles in affecting insurance take-up through social learning mechanisms, in both the short and medium-run. In the first year, providing financial education to a subset of farmers has large and positive spillover effect on other farmers; this is driven by the diffusion of insurance knowledge through social networks, as opposed to diffusion of behavior, which in turn might reflect an effort to gain greater leverage over the insurance company (acquiring strength in numbers), imitation (acting like the others), or informal risk-sharing. One year later, through social learning of friends' payout experiences, social networks affect the insurance demand of households that did not purchase insurance previously. For all households, observing friends receiving payouts significantly reduces the negative effect of subsidy removal. These results suggest that policy interventions such as providing intensive financial education to a subset of households and relying on social networks to multiply its effect on others at the early stage, disseminating information on payouts when they are made, or combining subsidy policies with dissemination of peers' decisions, can remarkably improve the demand for weather insurance.

[43] I calculate the price equivalence of the social network effect X by the following formula:

$$X = \frac{\frac{Coef(NetworkPayoutHigh)[(1-Coef(Price*NetworkPayoutHigh))*Mean(price)]}{Coef(Price)[1-Coef(price*NetworkPayoutHigh)*Mean(NetworkPayoutHigh)]}}{Mean(Price)}$$

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Figure 1.1. Experimental Design in Year One: Within Village Randomization

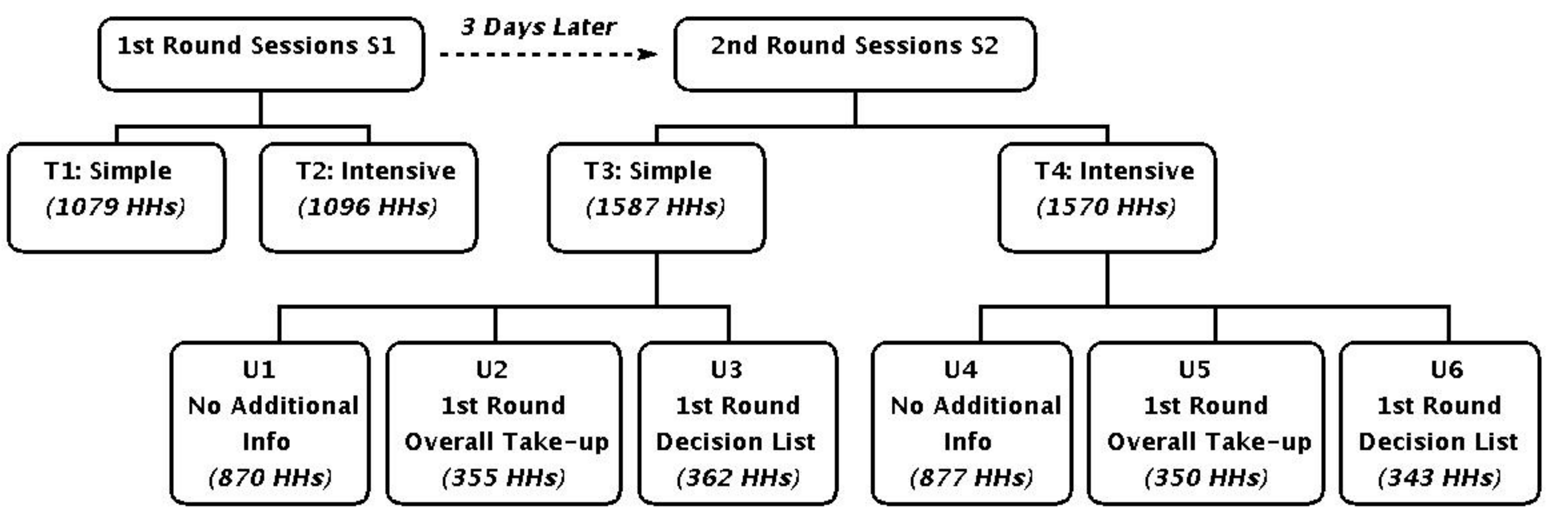
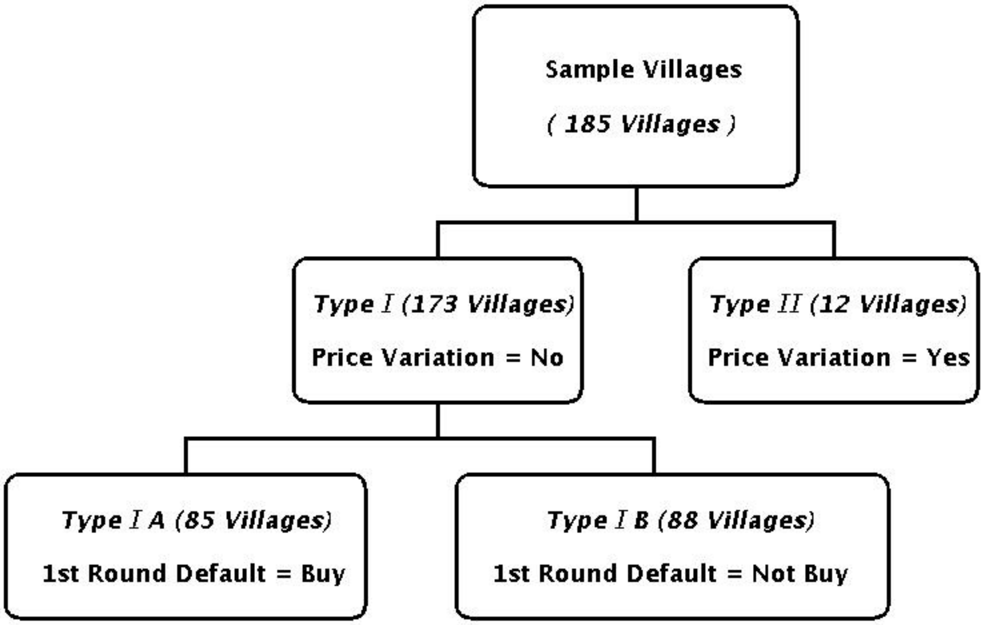


Figure 1.2. Experimental Design in Year One: Village Level Randomization



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. Average Take-up Rate in Different Sessions, Year One

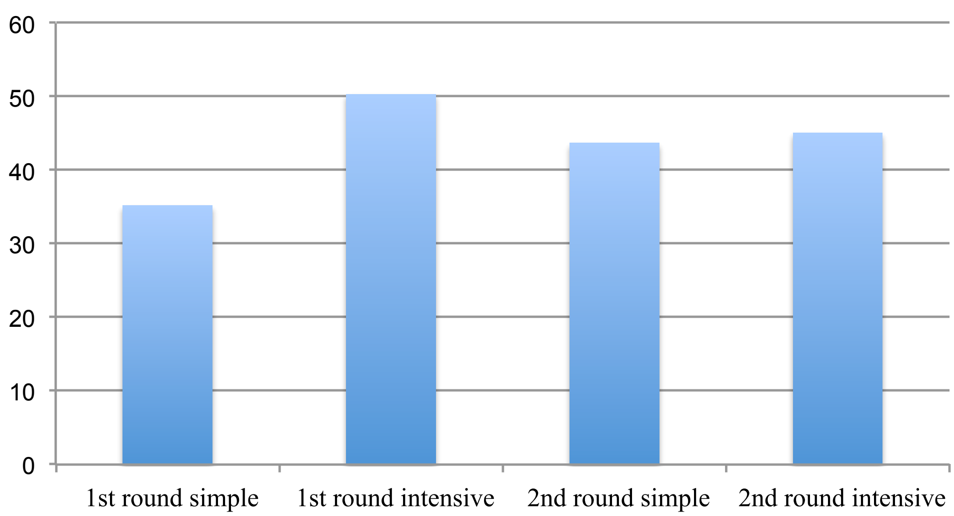
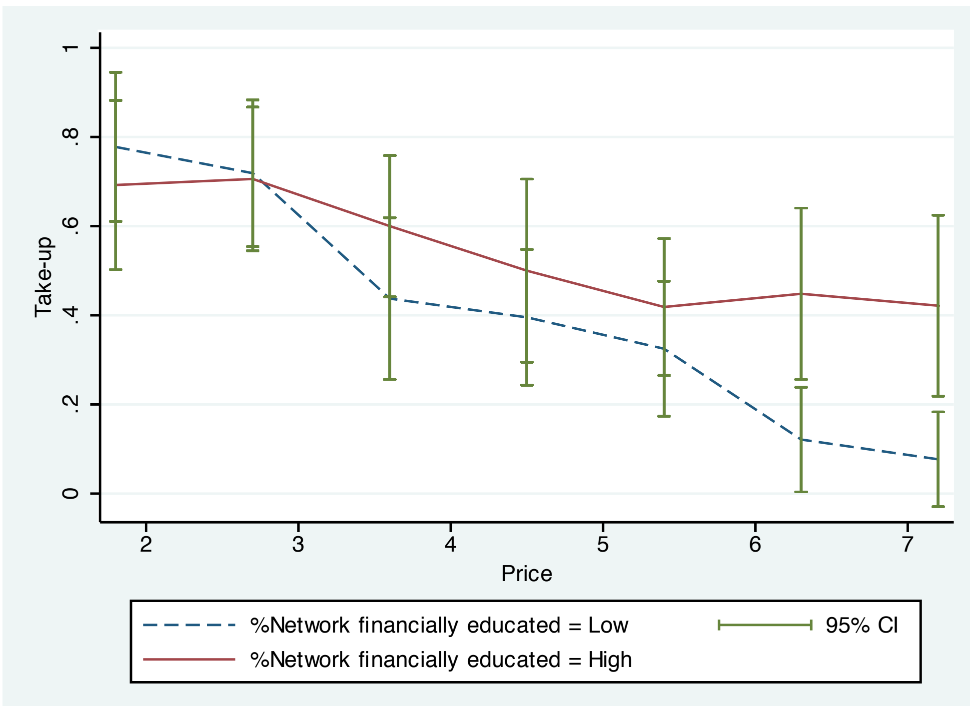
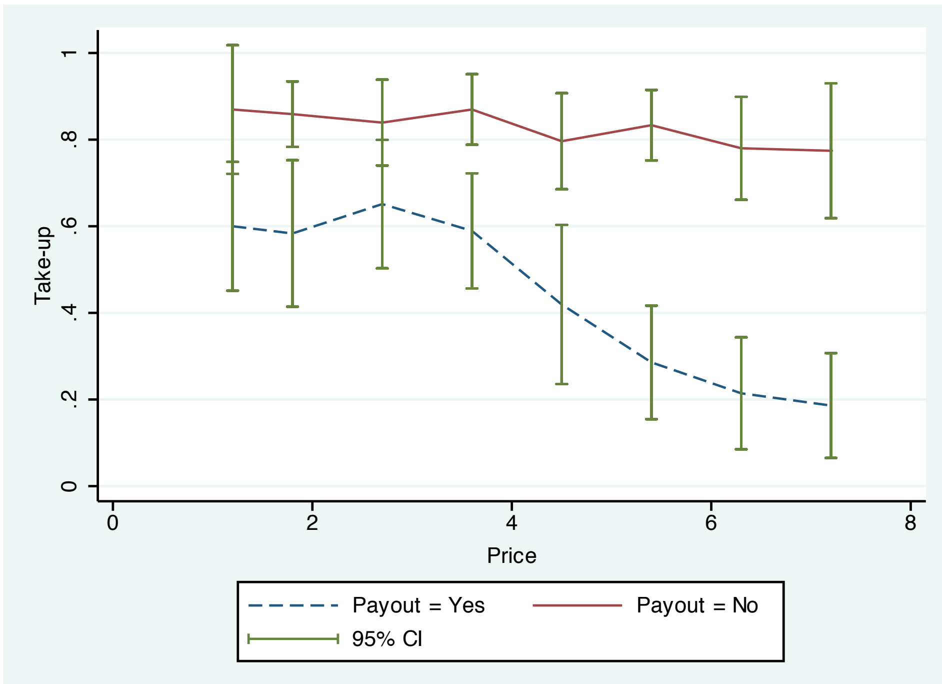


Figure 3. Effect of Having Friends Attending Financial Education on Insurance Demand, Year One



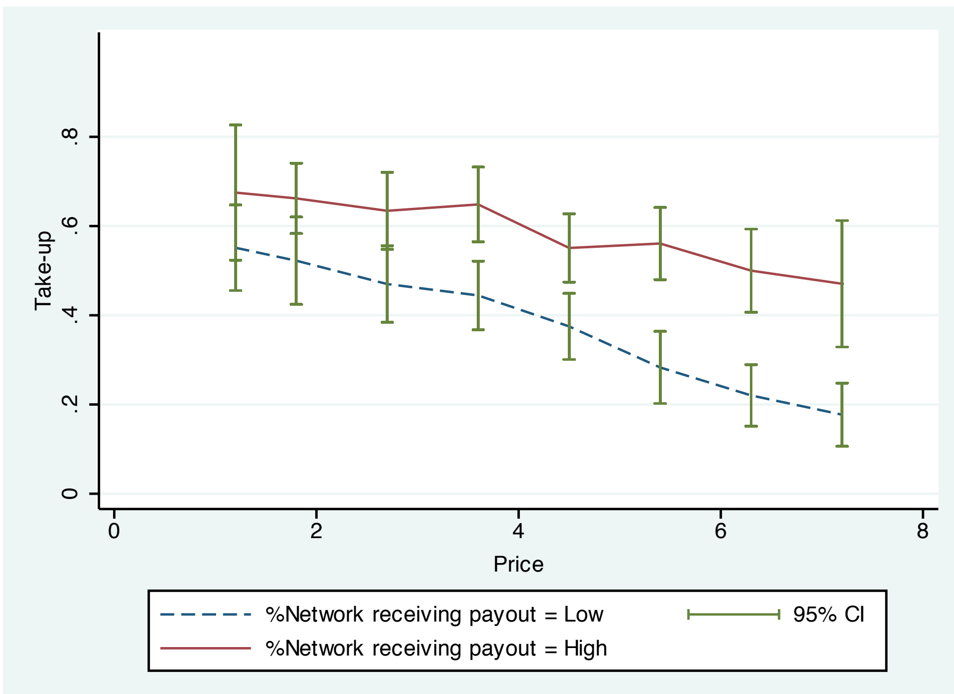
Notes: This figure is based on the sample of households in type II villages where price randomization was implemented in year one. The variable %Network financially educated is defined as "high" if it is above the sample median and is defined as "low" if it is below the sample median.

Figure 4. Effect of Receiving Payout on Insurance Demand, Year Two



Notes: This figure is based on the sample of households who purchased insurance in the first year.

Figure 5. Effect of Observing Friends Receiving Payout on Insurance Demand, Year Two



Notes: This figure is based on the sample of households who did not purchase insurance in the first year. The variable %Network receiving payout 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)	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), Year One	0.711	0.313
Perceived Probability of Future Disasters (%), Year One	33.633	16.619
Risk Aversion (0-1, 0 as risk loving and 1 as risk averse), Year Two	0.849	0.284
Perceived Probability of Future Disasters (%), Year Two	27.081	22.133
PANEL B: SOCIAL NETWORK 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: INSURANCE PAYOUT, YEAR ONE		
Payout Rate Among First Year Buyers (%)	56.710	49.580
Amount of Payout Received by First Year Buyers (RMB, per mu)	86.358	66.899
PANEL E: OUTCOME VARIABLE		
Insurance Take-up Rate (%), Year One	43.941	49.637
Insurance Take-up Rate (%), Year Two	49.920	50.013
No. of Households: 5332 in year one, 1871 in year two		
No. of Villages: 185 in year one, 72 in year two		

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

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)
Literacy (1 = Yes, 0 = No)		0.0823***
		(0.0269)
No. of Observation	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. Village dummies are included in all estimations. *** p<0.01, ** p<0.05, * p<0.1

Table 3.1. Effect of Social Networks (General Measure) On Insurance Take-up, Year One

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)		
	(1)	(2)	(3)
%Network Receiving 1st Round Financial Education	0.337***	0.348***	0.489***
	(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)
Literacy (1 = Yes, 0 = No)		0.0844***	0.0841***
		(0.0320)	(0.0319)
Risk Aversion		0.119**	0.114**
(0-1, 0 as risk loving and 1 as risk averse)		(0.0494)	(0.0492)
Perceived Probability of Disaster		0.00211**	0.00208**
		(0.000819)	(0.000819)
No. of Observation	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. 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

Table 3.2. Effect of Social Networks (Strong and Weak Ties) On Insurance Take-up, Year One

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)			
	(1)	(2)	(3)	(4)
%Network Receiving 1st Round Financial Education	0.447**	0.428**		
(Strong ties, mutually listed)	(0.183)	(0.182)		
%Network Receiving 1st Round Financial Education			0.0717	0.0843
(Weak Ties, second order links)			(0.148)	(0.149)
Male		0.0376		0.0397
		(0.0671)		(0.0680)
Age		0.00379***		0.00365***
		(0.00127)		(0.00127)
Household Size		-0.00838		-0.00836
		(0.00699)		(0.00694)
Rice Production Area (mu)		0.00281**		0.00288**
		(0.00120)		(0.00118)
Literacy (1 = Yes, 0 = No)		0.0778**		0.0808**
		(0.0320)		(0.0321)
Risk Aversion		0.121**		0.119**
(0-1, 0 as risk loving and 1 as risk averse)		(0.0492)		(0.0488)
Perceived Probability of Disaster		0.00220***		0.00217***
		(0.000829)		(0.000831)
Intensive Financial Education Session		0.000230		0.00305
(1 = Yes, 0 = No)		(0.0328)		(0.0330)
No. of Observation	1,274	1,255	1,274	1,255
Village Fixed Effects	Yes	Yes	Yes	Yes
R-Squared	0.077	0.101	0.073	0.097

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 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. Village dummies are included in all estimations. *** p<0.01, ** p<0.05, * p<0.1

Table 3.3. Effect of Social Networks (With Different Relationships) On Insurance Take-up, Year One

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)	
	(1)	(2)
%Network Receiving 1st Round Financial Education	0.339***	0.336***
(Relationship = Neighbors)	(0.109)	(0.105)
%Network Receiving 1st Round Financial Education	0.241*	0.291**
(Relationship = Relatives)	(0.131)	(0.134)
%Network Receiving 1st Round Financial Education	0.499*	0.528**
(Relationship = Government officials)	(0.274)	(0.258)
Intensive Financial Education Session		0.00704
(1 = Yes, 0 = No)		(0.0330)
Male		0.0397
		(0.0673)
Age		0.00380***
		(0.00125)
Household Size		-0.00875
		(0.00683)
Rice Production Area (mu)		0.00331***
		(0.00114)
Literacy (1 = Yes, 0 = No)		0.0828**
		(0.0319)
Risk Aversion		0.117**
(0-1, 0 as risk loving and 1 as risk averse)		(0.0497)
Perceived Probability of Disaster		0.00211**
		(0.000819)
No. of Observation	1,274	1,255
Village Fixed Effects	Yes	Yes
R-Squared	0.087	0.113

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 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

Table 4. Nonlinear Effect of Social Networks On Insurance Take-up, Year One

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)	
	(1)	(2)
No. of Friends Receiving 1st Round Financial Education = 1	0.0556*	0.0616*
(1 = Yes, 0 = No)	(0.0322)	(0.0319)
No. of Friends Receiving 1st Round Financial Education = 2	0.202***	0.206***
(1 = Yes, 0 = No)	(0.0418)	(0.0398)
No. of Friends Receiving 1st Round Financial Education > 2	0.282*	0.279*
(1 = Yes, 0 = No)	(0.146)	(0.156)
Male		0.0432
		(0.0667)
Age		0.00361***
		(0.00122)
Household Size		-0.00812
		(0.00669)
Rice Production Area (mu)		0.00339***
		(0.00113)
Literacy (1 = Yes, 0 = No)		0.0835***
		(0.0317)
Risk Aversion		0.116**
(0-1, 0 as risk loving and 1 as risk averse)		(0.0498)
Perceived Probability of Disaster		0.00202**
		(0.000818)
Intensive Financial Education Session		0.00467
(1 = Yes, 0 = No)		(0.0329)
No. of Observation	1,274	1,255
Village Fixed Effects	Yes	Yes
R-Squared	0.095	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 received 1st round take-up information from us. Social network is measured by the number of 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

Table 5.1. Heterogeneity on the Social Network Effect: Village Level Network Characteristics, Year One

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)				
	(1)	(2)	(3)	(4)	(5)
%Network Receiving 1st Round Financial Education	0.202	0.0578	-0.727	0.252	0.257
	(0.261)	(0.166)	(0.796)	(0.252)	(0.251)
Number of Households	-0.00480**	-0.00465**	-0.00403**	-0.00424**	-0.00425**
	(0.00241)	(0.00200)	(0.00184)	(0.00213)	(0.00196)
Number of Households	0.00433				
*%Network Receiving 1st Round Financial Education	(0.00745)				
Graph Clustering		-0.490**			
		(0.234)			
Graph Clustering		1.648**			
*%Network Receiving 1st Round Financial Education		(0.799)			
Fraction in Giant Component			-0.194		
			(0.325)		
Fraction in Giant Component			1.094		
*%Network Receiving 1st Round Financial Education			(0.812)		
Transtivity				-0.286	
				(0.361)	
Transitivity				0.437	
*%Network Receiving 1st Round Financial Education				(1.116)	
Reciprocity					-0.224
					(0.401)
Reciprocity					0.562
*%Network Receiving 1st Round Financial Education					(1.402)
Intensive Financial Education Session	0.0100	0.0140	0.00913	0.00644	0.0105
(1 = Yes, 0 = No)	(0.0325)	(0.0325)	(0.0326)	(0.0322)	(0.0325)
Observations	1,255	1,255	1,255	1,274	1,255
Household Characteristics	Yes	Yes	Yes	Yes	Yes
R-Squared	0.033	0.037	0.034	0.020	0.033
P-Value of Joint-significance:					
Village Level Network Characteristics	0.0868*	0.083*	0.382	0.6639	0.8471
%Network Receiving 1st Round Financial Education	0.0002***	0.0000***	0.0001***	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 received 1st round take-up information from us. Social network is measured by the fraction of five friends that a household listed who were assigned to a first round intensive session. Definitions of village level social network characteristics are in appendix B. Household characteristics include gender, age and education of household heads, household size, rice production area, risk aversion, and perceived probability of future disasters. Village dummies are included in all estimations. *** p<0.01, ** p<0.05, * p<0.1

Table 5.2. Heterogeneity on the Social Network Effect (Year One):
Who are More Influential and Who are More Likely to be Influenced?

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)					
	(1)	(2)	(3)	(4)	(5)	(6)
%Network Receiving 1st Round Financial Education	0.316***	0.544***	0.419***	0.834***	0.165*	0.273
	(0.101)	(0.189)	(0.107)	(0.213)	(0.0997)	(0.171)
Average in-degree	0.00409	0.00209				
(friends in 1st round financial education)	(0.00635)	(0.00850)				
Average in-degree		0.0186				
*%Network Receiving 1st Round Financial Education		(0.0415)				
In-degree (own)	0.00874	0.0235***				
	(0.00566)	(0.00885)				
Indegree (own)		-0.0860**				
*%Network Receiving 1st Round Financial Education		(0.0397)				
Average Out-path Length			-0.0150	-0.000249		
(friends in 1st round financial education)			(0.0124)	(0.0177)		
Average Out-path Length				-0.0666		
*%Network Receiving 1st Round Financial Education				(0.0995)		
In-Path Length (own)			-0.0128*	-0.00530		
			(0.00729)	(0.00631)		
In-Path Length (own)				-0.0680**		
*%Network Receiving 1st Round Financial Education				(0.0284)		
Average Eigenvector Centrality					0.492***	-0.0565
(friends in 1st round financial education)					(0.157)	(0.225)
Average Eigenvector Centrality						3.232***
*%Network Receiving 1st Round Financial Education						(0.948)
Eigenvector Centrality (own)					-0.0472	0.422*
					(0.174)	(0.235)
Eigenvector Centrality (own)						-2.836***
*%Network Receiving 1st Round Financial Education						(1.016)
Intensive Financial Education Session	0.00446	0.00821	0.0107	0.00926	0.00589	0.00908
(1 = Yes, 0 = No)	(0.0331)	(0.0330)	(0.0331)	(0.0328)	(0.0329)	(0.0328)
Observations	1,255	1,255	1,255	1,255	1,255	1,255
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.105	0.111	0.108	0.116	0.110	0.125
P-Value of Joint-significance:						
%Network Receiving 1st Round Financial Education		0.01***		0.0002***		0.0003***
Network Structure (friends in 1st round financial education)		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 received 1st round take-up information from us. Social network is measured by the fraction of five friends that a household listed who were assigned to a first round intensive session. Definitions of social network characteristics are in appendix B. Household characteristics include gender, age and education of household heads, household size, rice production area, risk aversion, and perceived probability of future disasters. Village dummies are included in all estimations. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Monetary Value of the Social Network Effect on Insurance Take-up, Year One

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	0.364***	-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)
Literacy (1 = Yes, 0 = No)	-0.0361	-0.0371	-0.0461
	(0.0830)	(0.0830)	(0.0933)
Risk Aversion	0.141*	0.144**	0.136*
(0-1, 0 as risk loving and 1 as risk averse)	(0.0697)	(0.0652)	(0.0672)
%Network Assigned with Higher Prices			0.0795
			(0.101)
%Network Assigned with Lower Prices			-0.0911
			(0.0770)
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 type II villages where seven different prices ranging from 1.8 RMB to 7.2 RMB were randomly assigned on the household level. Village dummies are included in both estimations. *** p<0.01, ** p<0.05, * p<0.1

Table 7. 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 (1 = Yes, 0 = No)	0.0901***		0.245***		
	(0.0309)		(0.0142)		
Intensive Financial Education Session *Second Round	-0.138***		-0.323***		
	(0.0422)		(0.0200)		
%Network Receiving 1st Round Financial Education		-0.106		0.356***	0.128
		(0.167)		(0.0475)	(0.103)
%Network Receiving 1st Round 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)
Literacy (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	0.0934***	0.108**	0.0827***	0.0495*	0.0441
(0-1, 0 as risk loving and 1 as risk averse)	(0.0265)	(0.0496)	(0.0139)	(0.0267)	(0.0269)
Perceived Probability of Disaster	0.000773	0.00209**	0.000553**	0.00145***	0.00144***
	(0.000521)	(0.000815)	(0.000277)	(0.000440)	(0.000441)
No. of Observation	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. Column (2), (4) and (5) are based on households who were invited to second round sessions but did not received any additonal take-up information. 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 8. Effect of the Overall 1st Round Take-up Rate on 2nd Round Decision, Year One

	First Stage: Overall 1st Round Take-up	Insurance Take-up (1 = Yes, 0 = No)			
VARIABLES		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*
(Village level)		(0.0710)	(0.215)	(0.338)	(0.237)
No 1st Round Take-up Information Revealed		0.128***	0.181		
(1 = Yes, 0 = No)		(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)
Literacy (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		0.122***	0.133***	0.131***	0.114***
(0-1, 0 as risk loving and 1 as risk averse)		(0.0163)	(0.0162)	(0.0271)	(0.0261)
Perceived Probability of Disaster		0.00183***	0.00189***	0.00175*	0.00193**
		(0.000564)	(0.000572)	(0.000890)	(0.000805)
No. of Observation	2,137	2,674	2,709	1,296	1,378
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 Sessions' 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 onthe 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 receive no extra information in addition to the presentation; Column (5) is based on the subgroup of households to whom we desseminate the first round take-up information. In IV estimations, Default options are used as the instrumental variable for the first round take-up rate. *** p<0.01, ** p<0.05, * p<0.1

Table 9. Effect of Friends' Decisions in 1st Round Sessions on 2nd Round Take-up, Year One

	First Stage: Network 1st round take-up%	Insurance Take-up (1 = Yes, 0 = No)			
VARIABLES		All Sample		No Information Revealed	Revealed 1st Round Decision List
		OLS	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
1st Round Overall Take-up Rate		0.608***	0.104	0.0711	0.460
(Village level)		(0.109)	(0.732)	(0.430)	(0.790)
1st Round Network's Take-up Rate		-0.0152	0.961**	0.0996	0.969**
		(0.0528)	(0.377)	(0.252)	(0.383)
Not Revealed 1st Round Decision List		0.256***	0.441**		
(1 = Yes, 0 = No)		(0.0554)	(0.203)		
1st Round Overall Take-up Rate		-0.544***	0.0584		
*Not Revealed 1st Round Decision List		(0.124)	(0.753)		
1st Round Network's Take-up Rate		0.0192	-0.853*		
*Not Revealed 1st Round Decision List		(0.0732)	(0.464)		
Default * % Network in 1st Round Sessions	0.2829***				
	(0.0614)				
%1st Round Network in Intensive Session	0.112***				
	(0.0372)				
Male	-0.0177	0.0554	0.0479	0.0169	0.0293
	(0.041)	(0.0569)	(0.0600)	(0.0922)	(0.0732)
Age	-0.0004	0.00483***	0.00582***	0.00466***	0.00652***
	(0.0009)	(0.00106)	(0.00129)	(0.00133)	(0.00244)
Household Size	0.0028	-0.00409	-0.0116*	-0.00991	-0.00793
	(0.005)	(0.00629)	(0.00651)	(0.00791)	(0.0108)
Rice Production Area (mu)	0.0006	0.000819	0.00302***	0.00406***	0.00178
	(0.0007)	(0.00119)	(0.00102)	(0.00126)	(0.00162)
Literacy (1 = Yes, 0 = No)	0.0077	0.0858***	0.0943***	0.0943**	0.102
	(0.0276)	(0.0307)	(0.0338)	(0.0366)	(0.0628)
Intensive Financial Education Session	-0.0007	0.0237	0.0210	0.000123	0.0556
(1 =Yes, 0 = No)	(0.02)	(0.0240)	(0.0288)	(0.0359)	(0.0511)
No. of Observation	1530	1,643	1,530	920	610
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-Squared	0.1648	0.088		0.115	
P-value of Joint-significance:					
1st Round Sessions' 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 the whole second round sample. Column (4) is based on a sub-sample of the second round participants who did not received any additional information except for the presentation, while column (5) is based on households who were provided with the decision list of 1st round session. Column (1) verifies whether variables Default * network% in 1st round and fraction of friends in the 1st round who were assigned to the intensive sessions can work as valid IVs for the 1st round take-up rate among social network. *** p<0.01, ** p<0.05, * p<0.1

Table 10. Effect of Friends' Take-up Decisions in Year One on Second Year Insurance Demand Curve

VARIABLES	OLS Estimation		IV Estimation			
			1st Stage:	2nd Stage:		
	Insurance Take-up (Year two, 1 = Yes, 0 = No)		%Network Take-up (Year one)	Insurance Take-up (Year two, 1 = Yes, 0 = No)		
	(1)	(2)	(3)	(4)	(5)	(6)
% Network in 1st Round Sessions * Default			0.148***			
(Year One)			(0.0346)			
%Network Receiving 1st Round Financial Education			0.241***			
(Year One)			(0.0623)			
Price	-0.0504***	-0.0539***		-0.0502***	-0.0539***	-0.00487
	(0.00832)	(0.00766)		(0.00843)	(0.00765)	(0.0295)
%Network Take-up in Year One	0.118*	0.100		0.150	0.125	0.636*
	(0.0560)	(0.0649)		(0.157)	(0.165)	(0.299)
Price * %Network Take-up in Year One						-0.135
						(0.0797)
Male		-0.0171			-0.0160	-0.0228
		(0.0852)			(0.0862)	(0.0871)
Age		0.00267*			0.00265*	0.00295*
		(0.00142)			(0.00143)	(0.00148)
Household Size		0.00992			0.00986	0.0101
		(0.00709)			(0.00708)	(0.00696)
Rice Production Area (mu)		0.00373***			0.00372***	0.00399***
		(0.000922)			(0.000935)	(0.000920)
Literacy (1 = Yes, 0 = No)		0.0726**			0.0728**	0.0706**
(1 = Yes, 0 = No)		(0.0315)			(0.0310)	(0.0282)
Insurance Knowledge		0.0828**		0.0998**	0.0796*	0.0979**
		(0.0371)		(0.0393)	(0.0389)	(0.0417)
Risk Aversion		0.124***			0.123**	0.130***
(0-1, 0 as risk loving and 1 as risk averse)		(0.0386)			(0.0389)	(0.0398)
Perceived Probability of Disaster		0.00322***			0.00322***	0.00328***
		(0.000308)			(0.000313)	(0.000320)
Observations	1,782	1,741	1,783	1,782	1,741	1,741
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.084	0.13	0.142	0.087	0.130	0.120
P-value of Joint-significance: Price and Price*Network Take-up						0.0001***
Network Take-up and Price*Network take-up						0.1526

Notes: Robust clustered standard errors in parentheses. Columns (1) ~ (2) are OLS estimation results, columns (3) ~ (6) are IV estmation results with first stage results in column (3) and second stage results in columns (4) ~ (6), using %friends in 1st round sessions * Default and %friends in first round financial education as the IV for %network take-up. Variables are year two values without special comments. *** p<0.01, ** p<0.05, * p<0.1

Table 11. Effect of Receiving Payouts on Second Year Insurance Demand Curve

VARIABLES	Insurance Take-up (Year two, 1 = Yes, 0 = No)				
	OLS			Regression Discontinuity	
	(1)	(2)	(3)	(4)	(5)
Price	-0.0506***	-0.0831***	-0.0793***	-0.0516***	-0.0800***
	(0.0111)	(0.0127)	(0.0124)	(0.0103)	(0.0123)
Payout (1 = Yes, 0 = No)	0.402***	0.144	0.173*	0.422***	0.204*
	(0.0350)	(0.0904)	(0.0942)	(0.0529)	(0.111)
Price * Payout		0.0618***	0.0538**		0.0543**
		(0.0171)	(0.0183)		(0.0180)
Age			0.00130	0.00149	0.00124
			(0.00158)	(0.00159)	(0.00164)
Male			-0.0211	-0.0247	-0.0164
(1 = Yes, 0 = No)			(0.0796)	(0.0852)	(0.0818)
Household Size			0.00751	0.00778	0.00761
			(0.00781)	(0.00785)	(0.00772)
Rice Production Area (mu)			0.00108*	0.00129**	0.00106**
			(0.000507)	(0.000487)	(0.000460)
Literacy (1 = Yes, 0 = No)			0.0437	0.0518	0.0445
			(0.0475)	(0.0497)	(0.0469)
%Loss in Yield_history			0.000581	0.00107	0.000965
			(0.000911)	(0.00119)	(0.00120)
%Loss in Yield				-0.000728	-0.00127
				(0.00380)	(0.00360)
%Loss in Yield (square)				-1.47e-06	3.30e-06
				(3.29e-05)	(3.12e-05)
Insurance Knowledge	0.0198	0.00309	0.0109	0.0227	0.00813
	(0.0370)	(0.0380)	(0.0436)	(0.0399)	(0.0427)
Risk Aversion	0.108*	0.108*	0.0954*	0.0952*	0.0953*
(0-1, 0 as risk loving and 1 as risk averse)	(0.0518)	(0.0502)	(0.0503)	(0.0514)	(0.0497)
Perceived Probability of Disaster	0.00195***	0.00186***	0.00150***	0.00155***	0.00151***
	(0.000435)	(0.000424)	(0.000452)	(0.000462)	(0.000454)
%Network Take-up in Year One	-0.0316	-0.0231	-0.0396	-0.0467	-0.0410
	(0.0971)	(0.0835)	(0.0731)	(0.0778)	(0.0725)
Observations	735	735	718	718	718
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-Squared	0.269	0.284	0.290	0.280	0.291
P-value of Joint-significance: Price and					
Price*Payout		0.0002***	0.0002***		0.0003***
Payout and Price*Payout		0.0000***	0.0000***		0.0000***

Note: Robust clustered standard errors in parentheses. Results in this table is based on the sample of households who purchased insurance in the first year. Columns (1)-(3) report OLS estimation results, and columns (4) and (5) report regression discontinuity estimation results. Variables are year two values without special comments. %Loss in yield_history is defined as the average loss rate in yield in the past three years. *** p<0.01, ** p<0.05, * p<0.1

Table 12. Effect of Observing Friends Receiving Payouts on Second Year Insurance Demand Curve

VARIABLES	Insurance Take-up (Year two, 1 = Yes, 0 = No)					
	All Sample		1st Year Take-up = Yes		1st Year Take-up = No	
	(1)	(2)	(3)	(4)	(5)	(6)
Price	-0.0499***	-0.0660***	-0.0512***	-0.0699***	-0.0464***	-0.0686***
	(0.00815)	(0.0106)	(0.0111)	(0.00999)	(0.0115)	(0.0179)
%NetworkPayout_High	0.217***	0.0816	0.0476	-0.109	0.224***	0.0407
(= 1 if % > median, and 0 otherwise)	(0.0266)	(0.0589)	(0.0317)	(0.0793)	(0.0400)	(0.0937)
Price * %NetworkPayout_High		0.0300**		0.0368*		0.0425**
		(0.0107)		(0.0177)		(0.0179)
Age		0.00231		0.00177		0.000878
		(0.00164)		(0.00191)		(0.00193)
Male		-0.0229		-0.0310		-0.0225
(1 = Yes, 0 = No)		(0.0813)		(0.0852)		(0.109)
Household Size		0.0111		0.0108		0.00902
		(0.00721)		(0.00838)		(0.00780)
Rice Production Area (mu)		0.00330**		0.00177**		0.00184
		(0.00123)		(0.000594)		(0.00127)
Literacy (1 = Yes, 0 = No)		0.0728**		0.0533		0.0564*
		(0.0310)		(0.0542)		(0.0263)
%Loss in Yield_history		0.00207**		0.000633		0.00121
		(0.000713)		(0.000924)		(0.00132)
Insurance Knowledge	0.0868**	0.0886**	0.0321	0.0366	-0.0146	-0.0148
	(0.0342)	(0.0346)	(0.0409)	(0.0536)	(0.0744)	(0.0755)
Risk Aversion	0.138***	0.121***	0.127**	0.111*	0.0974**	0.0808**
(0-1, 0 as risk loving and 1 as risk averse)	(0.0342)	(0.0363)	(0.0560)	(0.0574)	(0.0351)	(0.0354)
Perceived Probability of Disaster	0.00304***	0.00277***	0.00190***	0.00148**	0.00262***	0.00244***
	(0.000316)	(0.000295)	(0.000409)	(0.000475)	(0.000537)	(0.000509)
%Network Take-up in Year One	0.170	0.0739	0.00186	-0.0473	0.0551	-0.0177
	(0.164)	(0.156)	(0.136)	(0.102)	(0.341)	(0.346)
Payout (1 = Yes, 0 = No)			0.403***	0.396***		
			(0.0367)	(0.0354)		
Observations	1,642	1,603	671	654	971	949
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.158	0.177	0.297	0.313	0.148	0.161
P-value of Joint-significance: Price and Price*%NetworkPayout_High		0.0001***		0.0001**		0.0032***
%NetworkPayout_high and Price*%NetworkPayout_High		0.0000***		0.0723*		0.0001***

Notes: Robust clustered standard errors in parentheses. Columns (1) ~ (2) are based on the whole sample, columns (3) ~ (4) are based on the group of households who purchased insurance in the 1st year, and columns (5) ~ (6) are based on households who did not purchased in the 1st year. Variables are year two values without special comments. %NetworkPayout_high is a measure of experience of a household's social networks. Consider the fraction of a household's friends who received payou in the total number of his friends who purchased insurance in the 1st year, if it is higher than the sample median of that vairiable, %NetworkPayout_high is defined as 1, and otherwise it is defined as 0. %Loss in yield_history is defined as the average loss rate in yield in the past three years. *** p<0.01, ** p<0.05, * p<0.1

Appendices

A Supplementary Figures and Tables

Figure A1. Geographic Location of the Experimental Sites

Figure A2. The Insurance Indemnity Rule

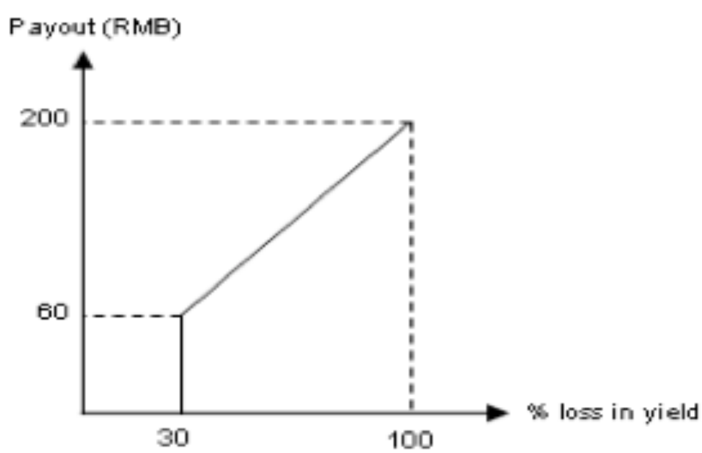


Figure A3. A Sample Social Network Map Within Beilian Village (ID = 1023)

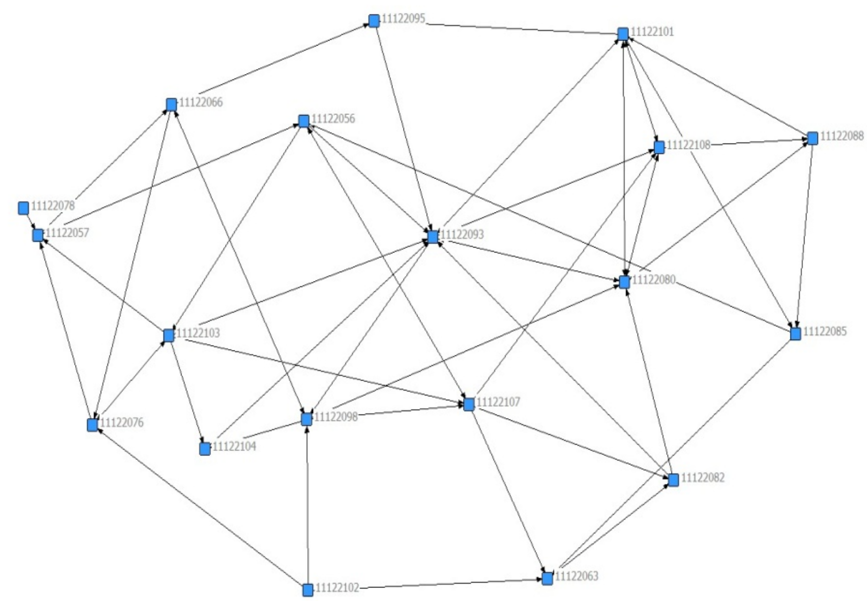


Figure A4. Probability of Receiving Payouts

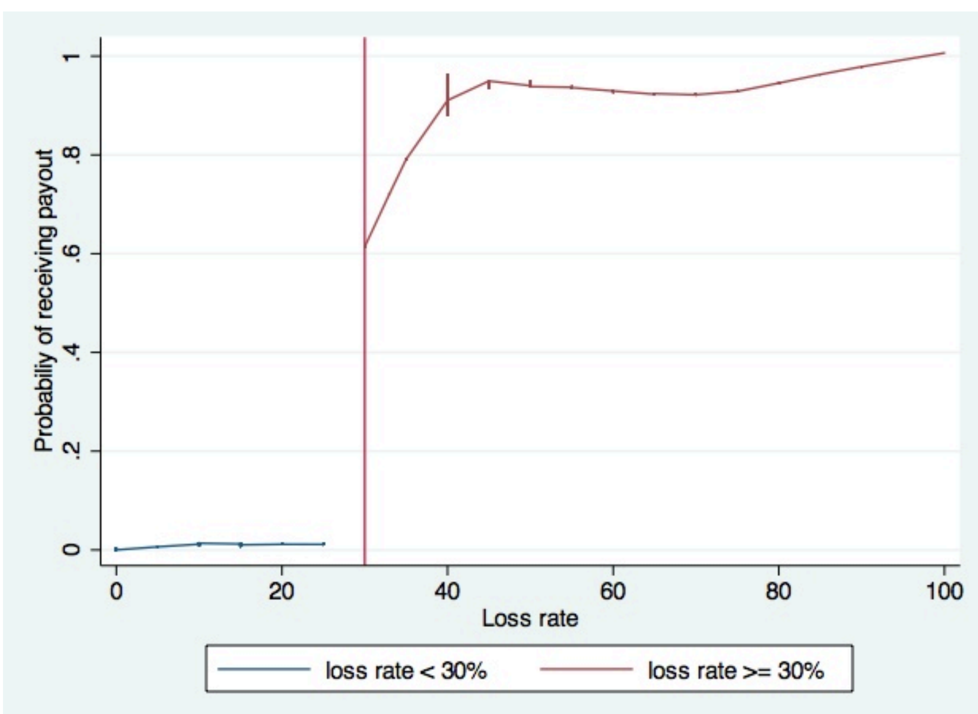


Table A1. Risk Attitude Questions

	Option A	Option B
1	50 RMB	Toss a coin. If it is heads, you get 200 RMB; if it is tails, you get nothing.
2	80 RMB	Toss a coin. If it is heads, you get 200 RMB; if it is tails, you get nothing.
3	100 RMB	Toss a coin. If it is heads, you get 200 RMB; if it is tails, you get nothing.
4	120 RMB	Toss a coin. If it is heads, you get 200 RMB; if it is tails, you get nothing.
5	150 RMB	Toss a coin. If it is heads, you get 200 RMB; if it is tails, you get nothing.

Note: The risk aversion measure ranges from 0 to 1 and is defined as the fraction of option A choices.

Table A2.1 Randomization Check: Session Assignments, Year One

	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 validity of 1st year session randomization. Standard deviations are in parentheses. P-values reported are F-test of equal means of the four session groups. *** p<0.01, ** p<0.05, * p<0.1.

Table A2.2 Randomization Check: Price, Year One and Year Two

	Year One			Year Two		
	OLS Coeff on Price	OLS Coeff on Price Squared	P-Value Joint Test (Price and Price Squared)	OLS Coeff on Price	OLS Coeff on Price Squared	P-Value Joint Test (Price and Price Squared)
	(1)	(2)	(3)	(4)	(5)	(6)
Gender of Household Head	0.007	0.001	0.4374	-0.0006	-0.00004	0.7919
(1 = Male, 0 = Female)	(0.072)	(0.008)		(0.011)	(0.001)	
Age	-0.331	0.096	0.2317	-0.919	0.092	0.3993
	(1.961)	(0.209)		(0.898)	(0.107)	
Household Size	0.105	-0.013	0.8798	-0.099	0.012	0.8028
	(0.236)	(0.026)		(0.228)	(0.023)	
Literacy	0.0113	-0.001	0.9845	0.036	-0.004	0.3782
(1 = Yes, 0 = No)	(0.07)	(0.008)		(0.03)	(0.003)	
Area of Rice Production (mu)	1.085	-0.123	0.7783	1.176	-0.138	0.3922
	(1.574)	(0.185)		(1.199)	(0.118)	
Number of Households	431			1871		

Note: This table checks validity of price randomization in both year one and year two. *** p<0.01, ** p<0.05, * p<0.1.

Table A3. Effect of Social Networks On Insurance Take-up, Year One: Excluding Households with Less Than Five Friends

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)	
	(1)	(2)
%Network Receiving 1st Round Financial Education	0.324***	0.335***
	(0.0876)	(0.0841)
Intensive Financial Education Session		-0.00444
(1 = Yes, 0 = No)		(0.0337)
Male		0.0124
		(0.0686)
Age		0.00362***
		(0.00127)
Household Size		-0.00970
		(0.00704)
Rice Production Area (mu)		0.00319**
		(0.00124)
Literacy (1 = Yes, 0 = No)		0.0840**
		(0.0332)
Risk Aversion		0.122**
(0-1, 0 as risk loving and 1 as risk averse)		(0.0510)
Perceived Probability of Disaster		0.00213**
		(0.000839)
No. of Observation	1,222	1,204
Village Fixed Effects	Yes	Yes
R-squared	0.089	0.114

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 received 1st round take-up information from us. Households who listed less than five friends are exluded from the estimation. Social network is measured by the fraction of 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

Table A4. Determinants of Household Level Social Network Characteristics, Year One

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)
Literacy (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. Definitions of social network characteristics are in appendix. Village dummies are included in all estimations. *** p<0.01, ** p<0.05, * p<0.1

Table A5. Heterogeneity on the Social Network Effect: Household Characteristics, Year One

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***
	(0.113)	(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	0.117**	0.116**	0.121**	0.122**	0.123**	0.122**	0.120**	0.130***
(0-1, 0 as risk loving and 1 as risk averse)	(0.0494)	(0.0491)	(0.0500)	(0.0500)	(0.0495)	(0.0496)	(0.0492)	(0.0494)
Perceived Probability of Disaster	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
	(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 received 1st round take-up information from us. Social network is measured by the fraction of 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 Glossary of Network Terminology

In this section, I provide brief definitions of measures of social network characteristics studied in Section 4.1.2. More detailed descriptions can be found in Jackson (2008).

- **Clustering Coefficient:**

  Village level. It equals the fraction of pairs of a household's neighbors that are neighbor of each other. This is a measure of how interwoven a household's neighborhood is.

- **Transitivity:**

  Village level. It is defined as the fraction of transitive triads (A-B, B-C, A-C) in total number of triads.

- **Reciprocity:**

  Village level. It equals the fraction of mutually linked pairs in the total number of pairs. There is an equilibrium tendency toward dyadic relationships to be either null or reciprocated, and that asymmetric ties may be unstable. A network that has a predominance of null or reciprocated ties over asymmetric connections may be a more equal or stable network than one with a predominance of asymmetric connections (more of a hierarchy).

- **Fraction of nodes in the giant component:**

  Village level. The share of households in the graph that are in the largest connected component. This is a measure of how interwoven the underlying network is.

- **Degree:**

  Household level.

  1. Out-degree: The number of ties from a household to other households. Households who have unusually high out-degree are those who are able to exchange with many others, or make many others aware of their views (more influential actors);
  2. In-degree: The number of ties received by each household. If a household receives many ties (many others seek advice from them), they are often said to be prominent, or to have high prestige.

- **Average path length:**

  Household level. The average out-path (in-path) length equals the mean of the shortest path to (from) a household from (to) any other households. Shorter out-path (in-path) length means information has to travel less to reach (from) other households from (to) a household.

- **Eigenvector centrality:**

  A recursively defined notion of importance. A household's importance is defined to be proportional to the sum of its neighbors' importance. It corresponds to the ith entry of the eigenvector corresponding to the maximal eigenvalue of the adjacency matrix. This is a measure of how important a node is, in the sense of information flow.

C An Insurance Demand Model

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

C.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

$$\mathbb{E}\left(U(\omega - P + \epsilon_i)\right) \geq \mathbb{E}\left(U(\omega - Z)\right) \tag{17}$$

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

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

Plugging these back into condition (17), we have

$$
\begin{aligned}
& -e^{-A_i(\omega-P+\mu_{\epsilon_i})+\frac{1}{2}A_i^2\sigma^2_{\epsilon_{i}i}} \geq -e^{-A_i(\omega-\mu_z)+\frac{1}{2}A_i^2\sigma_z^2} \\
\Longleftrightarrow\ & \omega - P + \mu_{\epsilon_i} - \frac{1}{2}A_i\sigma^2_{\epsilon_i} \geq \omega - \mu_z - \frac{1}{2}A_i\sigma_z^2 \\
\Longleftrightarrow\ & P \leq \mu_z + \mu_{\epsilon_i} + \frac{1}{2}A_i\left(\sigma_z^2 - \sigma^2_{\epsilon_i}\right) \qquad (18) \\
\Longleftrightarrow\ & \mu_{\epsilon_i} \geq P - \mu_z - \frac{1}{2}A_i(\sigma_z^2 - \sigma^2_{\epsilon_i}) \qquad (19)
\end{aligned}
$$

As a result, on 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 either formal financial education or informal information diffusion, or observing friends purchasing insurance or receiving payouts, can all influence households' expectation of the product benefits and the uncertainty about it, I expect that these factors have significant effect on individual insurance demand. Besides, individuals who are more risk averse are more likely to buy the insurance.

C.2 Aggregate Insurance Demand

To study determinants of the level and slope of the insurance demand curve, I 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, I can aggregate (19) to obtain the insurance demand curve:

$$
Q(P) = 1 - F\left(P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2)\right) \qquad (20)
$$

and the slope of the demand curve

$$
\frac{\partial Q}{\partial P} = -f\left(P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2)\right) \qquad (21)
$$

where $f(.)$ is the pdf. From equation (21), the perceived product benefits, the uncertainty about insurance benefits, and the dispersion on the valuation of the product, could potentially affect the slope of the demand curve.

To give a specific example, let's look at Figure C1. 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 C2. 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 C1, 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 C2. The demand reduces 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 year two, during the household survey, we asked households' willingness to pay for the insurance. Using that as a proxy for the expected benefits of the product, I draw the distribution of it and compare the distribution between group of households who have a high proportion of friends receiving payouts (higher than the sample median) and those who have a low proportion (lower than the sample median) in Figure C3. It shows that the distribution of WTP of households who have more friends receiving payout has a higher pivotal value and is less dispersed.

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, I 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 (20) becomes

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

and the slope of the demand curve is

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

- Mean of perceived insurance benefit (η):

$$\frac{\partial Q}{\partial \eta}(P) = \frac{1}{\psi}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \tag{24}$$

$$\frac{\partial S}{\partial \eta}(P) = -\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi^3}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \tag{25}$$

From equation (24) and (25), 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):

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

$$\begin{aligned}\frac{\partial S}{\partial \psi}(P) =& \frac{1}{\psi^2}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \\ &- \frac{(P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta)^2}{\psi^4}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \\ =& \frac{\psi^2 - (P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta)^2}{\psi^4}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right)\end{aligned} \tag{27}$$

From equation (26) and (27), 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):

$$\frac{\partial Q}{\partial \sigma_\epsilon^2}(P) = -\frac{A}{2\psi}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \tag{28}$$

$$\frac{\partial S}{\partial \sigma_\epsilon^2}(P) = \frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi^3} 2A\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \tag{29}$$

From (28) and (29), 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 C1. An Example of the Distribution of the Perceived Insurance Benefits

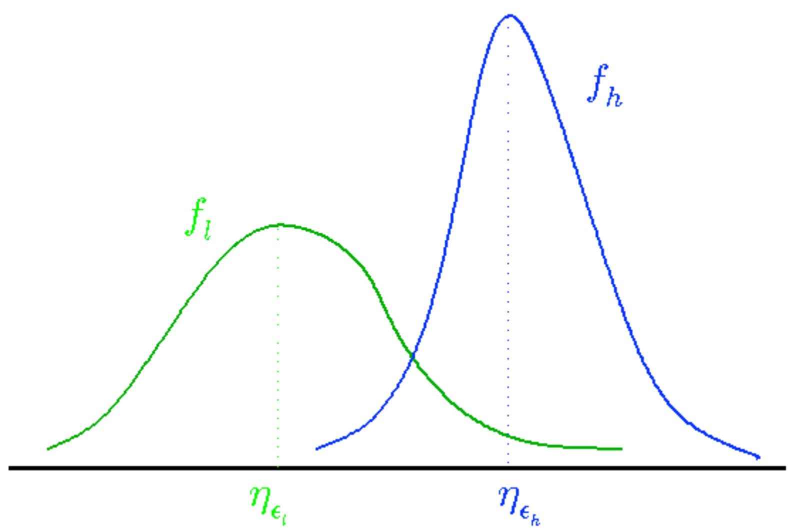


Figure C2. An Example of Insurance Demand Curve

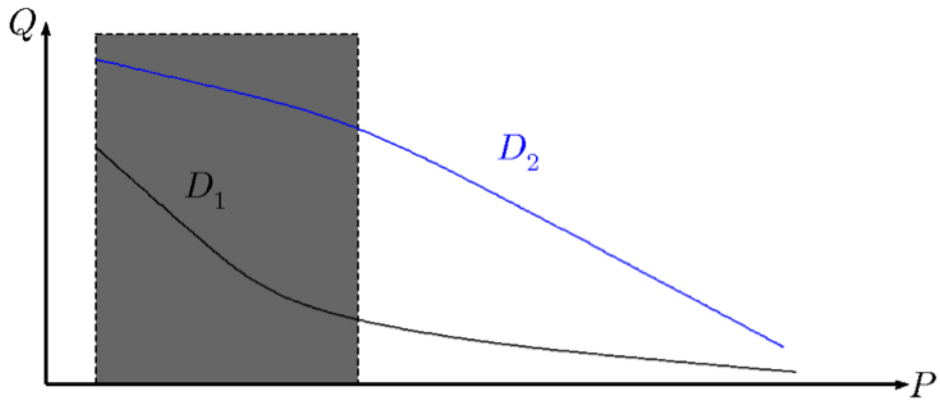


Figure C3. Distribution of Willingness To Pay for Insurance, Year Two