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SOCIAL NETWORKS AND THE DECISION TO INSURE*

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Abstract

Using data from a randomized experiment in rural China, this paper studies the influence of social networks on weather insurance adoption and the mechanisms through which social networks operate. To quantify network effects, the experiment offers intensive information sessions about the insurance product to a random subset of farmers. For untreated farmers, the effect of having an additional treated friend on take-up is equivalent to granting a 15% reduction in the insurance premium. By varying the information available about peers' decisions and using randomized default options, the experiment shows that the network effect is driven by the diffusion of insurance knowledge rather than purchase decisions.

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1 Introduction

Financial decisions often involve complexities that individuals have difficulty understanding based on their own education, information, and experience. Social networks can help ordinary individuals make these complex decisions: people can acquire knowledge about financial product benefits from their friends, be influenced by their friends' choices, and/or learn from their experiences with a product. This paper uses a novel experimental design to obtain clean measurements of the role and functioning of social networks in the decision to adopt purchase a weather insurance product, which is typically hard for farmers to understand and has had particularly low spontaneous take-up in most countries.

We designed a randomized experiment based on the introduction of a new weather insurance policy for rice farmers, offered by the People's Insurance Company of China (PICC), China's largest insurance provider. Together with PICC, we conducted the experiment which covered 5,300 households across 185 villages of rural China. Our experimental design allows us to not only identify and measure the causal effect of social networks on product adoption, but also to test for the role of various channels through which social networks operate, including learning from peers about the function and benefits of insurance and learning from peers' decisions. Furthermore, taking advantage of the substantial variation in network structures across households, we are able to measure the effects of social structures and initial conditions on the strength of social network effects and mechanisms. Finally, using household level price randomization, we calculate the price equivalence of the social network effect.

To estimate the value of social networks for insurance take-up, we measure the spillover effect of providing intensive information sessions about the product to a subset of farmers on the rest of the farmers in the village. Causality is established in the following way: we introduced the insurance product through four sessions in each village, in two rounds three days apart, with one simple session and one intensive session in each round, randomly assigning households to one of these sessions. For each household, the social network variable is defined as the fraction of a group of friends (whose names were identified in a pre-experiment survey) who were invited to an early round intensive session. We find that, while the intensive information session raised take-up by 43% in the first round, for second-round participants, having one additional friend who participate in a first-round intensive session increased take-up by almost half as much. The household level price randomization experiment shows that this spillover effect is equivalent to decreasing the average insurance premium by 15%.

After observing a large and significant effect of social networks, it is natural to ask what information conveyed by social networks drives this effect. Do networks matter because they diffuse knowledge among farmers about the product? Or is it because farmers learn about each other's decisions? We find that in this context, social networks do not convey information about what other people do, even though others would like to obtain this information, but they do effectively convey information about what other people know.

This result is obtained in the following manner. First, we compare the effect of the intensive information session on insurance knowledge between the two rounds. We find that, in the second round, the effect of the intensive session is smaller than in the first round, and that farmers understand insurance benefits better when they have a greater number of friends who were invited to a first round intensive session. These results show a diffusion of insurance knowledge from first-round intensive session participants to second-round participants.

Second, we exploit the exogenous variation in both the overall and individual take-up decisions generated by randomized default options to determine whether or not subjects are affected by their friends' decisions. Our findings indicate no significant effect of friends' behavior on individuals' decisions. Surprisingly, however, when we told farmers about other villagers' decisions, these decisions actually mattered a lot to them. This suggests that, in this case, the main mechanism through which social networks affect decision-making is social learning about insurance benefits, as opposed to the influence of friends' purchase decisions which are not transmitted in social networks. At the same time, it also suggests that if other villagers' decisions can be revealed in complement to the performance of the network, it can have a large impact on adoption decisions.

Under what circumstances can social networks diffuse information more effectively? Existing studies suggest that the magnitude of social network effects depends on the social structure (Galeotti et al. (2010); Jackson and Yariv (2010); Banerjee et al. (2012)). By exploiting variations in household level network characteristics, we show that the network effect is larger when participants in the first round intensive information session are more central in the village network. We also find that households which are less frequently named as friends by other people, less easily reached by others, or less important in the network are more likely to be influenced by other people.

This paper contributes to the social network literature on two fronts.[1] First, estimating the causal effect of social networks is challenging due to the problem of correlated unobservables such as social norms and homophily (Manski (1993)). To overcome this difficulty, both experimental and non-experimental approaches have been used.[2] Results vary greatly with both the product and the context considered. This paper is the first to use randomized experimental methods to estimate the causal effect of social networks on weather insurance purchase decisions and to estimate the monetary equivalence of this effect.

Second, as its main contribution, the paper provides evidence on the mechanisms through which social networks affect behavior. While the study of social network mechanisms is crucial from both theoretical and policy perspectives, only a few studies to date have shed light on this. For example, Kremer and Miguel (2007) find negative peer effects on the uptake of deworming pills, which effectively rules out explanations such as imitation and learning how to use the product. Banerjee et al. (2012), based on the estimation of a structural model, find that acquiring information from friends is the most important channel to decide on microfinance participation. By contrast, Maertens (2012) uses a survey design to study the adoption of Bt cotton and finds that both acquiring knowledge from others about product profitability and imitating others' behavior contribute to individual adoption rates. This paper extends the existing literature by using an experimental design to directly identify a comprehensive set of generic channels through which social networks operate.

In addition to furthering our understanding of social networks, this paper adds

[1]Existing studies have linked social networks to a wide range of activities, including risk sharing (Ambrus et al. (2010)), political outcomes (Galeotti and Mattozzi (2011)), labor market and job satisfaction (Beaman (2011); Fogli and Veldkamp (2011); Pistaferri (1999); Munshi (2012); Card et al. (2012)), building trust (Karlan et al. (2009)), financial decision-making (Duflo and Saez (2003); Hong et al. (2004); Banerjee et al. (2012)), technology adoption (Conley and Udry (2010); Goolsbee and Klenow (2002); Henkel and Maurer (2010); Maertens (2012)), criminal behavior (Bayer et al. (2009); Glaeser et al. (1996)), productivity (Bandiera et al. (2010); Mas and Moretti (2009), Waldinger (2012)), international trade (Chaney (2011)) and skill accumulation (Mookherjee et al. (2010)). For a comprehensive review, see Jackson (2010).

[2]Experimental approaches were used by Duflo and Saez (2003), Dupas (2010), Kling et al. (2007), and Oster and Thornton (Forthcoming), etc. Non-experimental methods were used notably by Arcidiacono and Nicholson (2005), Bandiera and Rasul (2006), Bertrand et al. (2000), Conley and Udry (2010), Foster and Rosenzweig (1995), and Imberman et al. (2012).

insight to the literature on financial education. Although correlational evidence indicates that individuals with low levels of financial literacy are less likely to participate in financial markets (Lusardi and Mitchell (2007); Stango and Zinman (2009)), experimental research on the value of financial education provides mixed results. For example, Duflo and Saez (2003) and Cole et al. (2011) find small or no effects of financial education on individual decisions. By contrast, Cai and Song (2012) and Gaurav et al. (2011) find positive and significant effects. In a context where insurance is new, and farmers have low levels of formal education, our results show that lack of knowledge of insurance is a major constraint on the demand for insurance, and that improving farmers' understanding of insurance products can significantly improve take-up rates.

Finally, from a policy perspective, our paper sheds light on the challenge of how to improve weather insurance take-up. This type of insurance is important for farm households, whose production is exposed to substantial weather shocks.[3] Yet evidence from several countries shows that participation rates are low, even with heavy government subsidies.[4] Existing research has tested possible explanations for low take-up such as lack of trust, credit constraints, or ambiguity aversion (Giné et al. (2008); Cole et al. (2011); Bryan (2010)), but insurance demand remains low even after some of these barriers were removed in experimental treatments. We provide evidence on the role of scalable instruments in improving adoption, such as combining intensive insurance knowledge provision to a subset of households with reliance on social networks to amplify the effect and boost uptake rates, and combining subsidy or marketing strategies with social norms marketing in which information is disseminated to the full population about the behavior of peers.[5]

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.

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

[4]For example, Cole et al. (2011) find an adoption rate of only 5%-10% for a similar insurance policy in two regions of India in 2006.

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

Section 4 presents the results, and Section 5 concludes.

2 Background

Rice is the most important food crop in China, with nearly 50% of the country's farmers engaged in its production. In order to maintain food security and shield farmers from negative weather shocks, in 2009 the Chinese government requested the People's Insurance Company of China (PICC) to design and offer the first rice production insurance policy to rural households in 31 pilot counties.[6] The program was expanded to 62 counties in 2010 and to 99 in 2011. The experimental sites for this study were 185 randomly selected rice production villages included in the 2010 expansion of the insurance program, located in Jiangxi province, one of China's major rice bowls. In these villages, rice production is the main source of income for most farmers. Because the product was new, farmers, and even local government officials at the town or village level, had very limited understanding of weather insurance products.

The insurance contract is as follows. The actuarially fair price is 12 RMB per mu per season.[7] The government gives a 70% subsidy on the premium, so farmers only pay the remaining 3.6 RMB per mu.[8] Such governmental subsidies for agricultural insurance are common in both China and other countries. If a farmer decides to buy the insurance, the premium is deducted from the rice production subsidy deposited annually in each farmer's bank account, with no cash payment needed.[9] The insurance covers natural disasters, including heavy rain, flood, windstorm, extremely high or low temperatures, and drought. If any of these natural disasters occurs and leads to a 30% or more loss in yield, farmers are eligible to receive payouts from the insurance company. The amount of the payout increases linearly with the loss rate in yield, from 60 RMB per mu for a 30% loss to a maximum payout of 200 RMB per mu for a total loss. The loss rate in yield is determined by a committee composed of insurance

[6] Before 2009, if disasters occurred, the government made payments to households whose production had been seriously hurt. However, the level of transfer was usually very low.

[7] 1 RMB = 0.15 USD; 1 mu = 0.067 hectare

[8] According to our price experiment, the take-up rate is close to zero when the post-subsidy price is larger than 8 RMB. As a result, subsidies were essential to do the network study as otherwise the extremely low take-up rate would have made the analysis difficult.

[9] Starting in 2004, the Chinese government has provided production subsidies to rice farmers in order to give them more production incentives.

agents and agricultural experts. Since 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, this insurance policy covers 25 to 30% of the gross income or 50 to 70% of the production cost.

3 Experimental Design and Data

3.1 Experimental Design

In rural China, standard methods to introduce and promote policy reforms (in recent years, notable reforms concerned production subsidies, health insurance, and pensions) include holding village meetings to announce and explain the policy and publishing individual villagers' purchase information and outcomes, such as the payouts for health insurance.[10] We combined some of these methods to design a randomized control experiment that could identify the role and functioning of social networks in influencing insurance demand. The experiment was carried out in the Spring of 2010, and includes 185 villages with a total of 5,332 households.[11]

The experiment assumes that improving farmers' understanding of insurance products reinforces insurance take-up, a fact that we verify later. In order to generate household level variation in the knowledge and understanding of insurance products, two types of information sessions were offered to different households: simple sessions that took around 20 minutes, during which the PICC agents introduced the insurance contract;[12] and intensive sessions that took around 45 minutes and covered all information provided during simple sessions plus an education about insurance products to help farmers understand how insurance works and what are its expected benefits.[13]

In each village, two rounds of sessions were offered to introduce the insurance

[10]These actions have been used not only to induce support for policy reforms, but also to confirm farmers' responses and to let them monitor the fairness of policy implementation.

[11]In this experiment, "villages" refers to the "natural villages" in rural China, which is a smaller unit (30-40 households) than "administrative villages." (5-10 natural villages)

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

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

program. During each round, there were two sessions held simultaneously, one simple and one intensive. To allow time for information sharing by first round participants, we held the second round sessions three days after the first round. The effect of social networks on insurance take-up is identified by looking at whether second round participants are more likely to buy insurance if they have more friends who were invited to first round intensive sessions. The delay between the two sessions has been chosen to be both sufficiently long that friends have time to communicate among themselves, and yet not long enough that all the information from the first round sessions has diffused across the whole population through indirect links.

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

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

[14]For all household-level randomizations, we stratified the sample according to household size and area of rice production per capita, and randomly assigned households to different treatment groups in each stratum. Only household heads were invited to attend one of the four sessions. No one could attend more than one session. In order to guarantee a high session attendance rate, we gave monetary incentives to village leaders and asked them to inform and invite household heads to attend these sessions.

mechanisms that drive the social network effect.

In this experiment, we chose to randomize the information treatment within village in order to test for network mechanisms. Since this is a within village measure, it captures the effect of friends net of the potential general diffusion in the village population, rather than the full spillover effect of the first round sessions.[15]

The village level randomizations are shown in Figure 1.2. First, we randomly divided villages into two types. In type I villages, all households face the same price of 3.6 RMB per mu. By contrast, in type II villages, we randomly assigned one of seven different prices ranging from 1.8 to 7.2 RMB per mu to different participants.[16] The price randomization in Type II villages allows us to measure the monetary value of the social network effect. The second village-level randomization was only within type I villages. We randomized the default option to buy in first round sessions. If the default was BUY, the farmer needed to sign off if he or she did not want to purchase the insurance; if the default was NOT BUY, the farmer had to sign on if he or she decided to buy the insurance.[17] Both groups otherwise received exactly the same pitch for the product. Default options were the same in the two first round sessions within each village. The objective of offering different default options was to generate exogenous variations in the first round insurance take-up across villages which could be used in some estimations as an instrumental variable for first round purchase decisions.[18]

In all cases, households had to decide whether to purchase the insurance individ-

[15]We conducted another experiment to estimate the full spillover, with a standard cluster design on 52 villages, with control villages and control households within treatment villages. Although the information sessions are not fully comparable to this experiment, we will compare the two results later in section 4.1.

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

[17]During sessions where default = BUY, before farmers 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. 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." During sessions where default = NOT BUY, farmers were told: "We think that this is a very good insurance product, and we believe that most farmers will choose to buy it. If you have decided to buy the insurance, please come here and sign, then the premium will be deducted from your agricultural card; if you do not want to buy it, there's nothing you need to do."

[18]According to Beshears et al. (2010), default options can influence pension decisions significantly. A fuller discussion of reasons for compliance is provided in Section 4.3.2.

ually at the end of the information session.

3.2 Data, Summary Statistics, and Randomization Check

The empirical analysis is based on data obtained from two surveys: a social network survey which was carried out before the experiment, and a household survey filled out after households made their insurance purchase decision. All rice-producing households were invited to one of the sessions, and more than 90% of them attended. Consequently, this provided us with a detailed census of the population of these 185 villages. In total, 5,332 households were surveyed.

The household survey includes questions on demographics, rice production, income, borrowing experience, natural disasters experienced and losses incurred, experience in purchasing any kind of insurance, risk attitudes, and perceptions about future disasters.[19] It also contains questions that test farmers' understanding of how insurance works and its potential benefits. Those questions are based on materials presented in the intensive information session, in order to help us test one important mechanism of social network effect: the diffusion of knowledge about insurance. The summary statistics of selected household characteristics are presented in Panel A of Table 1: household heads are almost exclusively male, and the average education falls between a primary and secondary school level; rice production is the main source of household income, accounting for 73% of total income on average; 63% of the households had experienced some types of natural disaster in the most recent year, and the average yield loss rate was around 28%; sample households are risk averse, with an average risk aversion of 0.71 on a scale of zero (risk loving) to one (risk averse).

The social network survey asks the household head to list five close friends, either within or outside the village, with whom he/she most frequently discusses rice production or financially-related issues.[20] The respondent is asked to rank these friends based on which one would be consulted first, second, etc. Questions on relationships with each person named, commonly discussed topics, and contact frequency are also

[19]Risk attitudes were elicited by asking sample households to choose between a certain amount with increasing values of 50, 80, 100, 120, and 150 RMB (riskless option A), and risky gambles of (200RMB, 0) with probability (0.5, 0.5) (risky option B). The proportion of riskless options chosen by a household was then used as a measure of risk aversion, which ranges from 0 to 1. 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?"

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

included in the survey. We chose to impose a fixed number of friends, so as to create an exogenous variable with the number or share of these friends that were assigned to the first round intensive information session. The drawback of this specification is that the network characterization maybe incomplete. This concern is mitigated by the experience of the pilot test with two villages, where most farmers named four or five friends (82% five, 14% four, and 4% others) when the number was not limited. Having the village network census, we can characterize each village's social network. We use these data to construct two types of variables: social network measures (Panel B in Table 1) and social network structural characteristics (Panel C in Table 1).

We use three types of household-level social network measures. The general measure is defined as the number of socially-linked households invited to a first round intensive session, divided by five, the household's network size. Household A is said to be socially linked to B if A named B or B named A in the social network survey.[21] As can be seen in Panel B of Table 1, most households listed five friends (average 4.9). The general measure of social network varies between 0 and 1, with an average of 0.16. We construct two other social network variables based on the strength of the link between households (Granovetter (1973)). The strong measure is defined as the number of bilaterally-linked households invited to a first round intensive session, divided by network size. Household A and B are defined as bilaterally linked if they named each other as friends. The weak measure is defined as the number of second-order linked households invited to a first round intensive session, divided by the sum of friends' network sizes (25 in most cases). A second-order linked household is one that is named as a friend by a given household's friends. These three measures represent the main independent variables used to estimate the social network effect.

We also construct indicators of the household-level network characteristics, with the idea that these network features may provide sources of heterogeneity of the network effect on insurance adoption. We retain three indicators for the importance of a given household in a network: (i) in-degree, which is the number of persons that named it as friend;[22] (ii) path length, which is the mean of the shortest paths to/from this household from/to any other household; and (iii) Eigenvector centrality,

[21] As in Banerjee et al. (2012), we consider an undirected graph for most estimations in the paper. This seems appropriate for information which can flow in either direction as long as one farmer communicates with the other frequently.

[22] Only the in-degree measure is considered here because the out-degree measure is defined as network size, which equals five for most households.

which measures a household's importance in the overall flow of information. This last indicator is a recursively-defined concept where each household's centrality is proportional to the sum of its neighbors' centrality.[23] Average values for these variables are reported in Panel C of Table 1. Each household is on average cited as a friend by three other households. The average path-length is around 2.5, which means that a household can be connected to any other in the village by passing through two to three households, on average. These relatively short average paths reflect the intensity of network links in these small villages.

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

$$X_{ij} = \alpha_0 + \alpha_1 Price_{ij} + \eta_j + \epsilon_{ij}, \tag{1}$$

where X_{ij} represents 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 price at which the household was offered the insurance, and η_j represents village fixed effects. Results show that all the coefficient estimates are small in magnitude and none is statistically significant, suggesting that the price randomization is valid.

4 Estimation Results

4.1 Social Network Effect on Insurance Adoption

In this section, we present the results for the estimation of the social network effect on farmers' insurance purchase decisions. The average insurance take-up rates in different information sessions are reported in Table 1, Panel D. They show that,

[23] While measures such as degree are intuitive notions of graphical importance, they miss the key feature that a node's ability to propagate information through a graph depends not only on the sheer number of connections it has, but also on how important these connections are, which can be captured by the centrality measure. For example, one person that would be the only intermediary between two very interconnected subnetworks would have a very high centrality while only two connections (Figure A1(b)).

while the difference between the two first round sessions is substantial, there is a much smaller difference between the two second round sessions. Moreover, the take-up rate of second round sessions is much higher than that of first round simple sessions. This finding suggests that the knowledge about insurance products provided at first round intensive sessions improved farmers' take-up rates, and that, during the three days between the two rounds, there was substantial information diffusion from first round to second round participants.

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

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

where $Takeup_{ij}$ is a dummy variable which takes a value of one if the household decided to buy the insurance and zero otherwise. $Intensive_{ij}$ is a dummy variable equal to one if the household was invited to an intensive session in village j and zero otherwise. X_{ij} includes household characteristics such as gender, age, education of the household head, rice production area, etc., and η_j are village fixed effects. Results in Table 2 (Column (1)) show that the take-up rate in first round intensive sessions is 14 percentage points higher than in simple sessions (at 35%),[24] suggesting a large and significantly positive intensive session effect that increases the take-up rate by 43% in the first round.[25]

We next estimate the social network effect on insurance take-up, i.e., the spillover effect of first round intensive sessions on second round participants. To do so, we focus on the sample of households assigned to second round groups U1 and U4 (where no first round take-up information was revealed).[26] We test whether participants are

[24] We show the heterogeneity of the intensive session effect in Table A3. Better educated farmers are more influenced by attending the intensive session (Column (2)). The reason could be that well educated farmers can learn better and more rapidly.

[25] There are several reasons why attending an intensive session may increase insurance take-up, such as improving farmers' understanding of the product, trust in the program, etc. We show in section 4.3.1 that participating in an intensive session significantly improves farmers' understanding of how insurance works and the benefits of such products. We tested farmers' trust in this program but did not find a significant effect of attending an intensive session on it. This suggests that the intensive session works mainly through improving farmers' insurance knowledge rather than through a trust channel.

[26] Only second round groups U1 and U4 are included in the estimation of social network effects

more likely to buy insurance if they have more friends who were invited to the first round intensive session by estimating:

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

where $Network_{ij}$ is defined as the fraction of the group of friends named by a household in the social network survey who have been invited to a first round intensive session.[27] Because households are more likely to be exposed to information provided during intensive sessions if more of their friends were invited to an intensive session, we expect a positive social network effect.

Estimation results are reported in Table 2. Results in Column (2) indicate a significantly positive effect of social networks on insurance take-up, with a magnitude of 33.7 percentage points. This finding suggests that having one additional close friend attend a first round intensive session - raising the general network measure by 20% - increases a farmer's own take-up rate by $33.7 * 0.2 = 6.74$ percentage points. This effect is equivalent to more than 45% of the impact of attending an intensive session directly (Column (1)). The result is robust to the addition of control variables (Column (3)).[28] Note that correlations with control variables are interesting in themselves: older farmers, farmers with a larger production area, or those with more education are more likely to buy the insurance. Households who are more risk averse or those who predict a higher probability of natural disasters in the following year, are also more likely to purchase insurance. We test whether the magnitude of the social network effect depends on whether a farmer directly participated in an intensive session. The results in Column (4) show that the social network effect is smaller in second round intensive sessions, indicating that people are less influenced by their friends when they have direct education about the insurance products.

As we noted above, we are measuring spillover effects of the first round intensive sessions through friends, rather than the spillover effects through all villagers. We

because those are the participants who received exactly the same treatment as first round sessions T1 and T2.

[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 fewer than 5 friends in the social network survey, and these households might be different from other farmers in some aspects, we conduct a robustness check by excluding these households and find that the magnitude and significance of the social network effect remain almost the same.

test for the presence of spillover effects through non-friends by comparing the take-up of second-round participants with no friends in the first round intensive session with the take-up of first round participants. Results shown in Column (5) suggest no difference in take-up by participants in simple sessions (coefficient of 0.019, not significant), nor in intensive sessions (0.019-0.0478=-0.029, not significant). This network effect we measured is also comparable to the overall network effect measured in another experiment with a standard cluster randomization design.[29]

We next examine alternative measures of social network and a non-linear specification of the role of the network size. First, we re-estimate equation (3) using the strong measure (bilateral links) and the weak measure (second-order links) of social networks. Results are reported in Columns (1) and (2) of Table 3, respectively. The result suggests that having one additional strongly linked friend attending first round intensive session improves a farmer's probability of taking the insurance policy by 8.5 percentage points, which is larger than the effect of the standard social links (6.7 percentage points). By contrast, friends with weak links are much less influential (Column (2)). This means that households are not significantly influenced by their friends' friends during a short period of time (three days in this case). Second, we test for a non-linear effect of social networks on take-up in Column (3). Among second round participants, having two friends invited to a first round intensive session increases the take-up rate by 20.6 percentage points; this is about 14 percentage points higher than the 6.2 percentage points effect of having only one friend invited to a first round intensive session. However, having more than two friends invited to an intensive session has only a slightly higher effect on take-up (7 percentage points) than having two.

In summary, these results indicate that offering intensive information session about insurance products when introducing the product improves take-up significantly. Importantly, it has a large and significant spillover effect on insurance adoption by other

[29]The design of this other experiment was as follows: From a sample of 52 villages, we randomly selected 30 treatment villages within which we randomly invited a subset of households (group A) to attend an information session about the insurance program. The content of the information session was intermediate between those of the simple and intensive sessions of this experiment. Three days after the session, we visited the remaining households (group B) individually. In control villages, all households (group C) were visited individually. We then measured the social network effect by comparing uptakes in groups B and C. Having one additional listed friend attending the information session increases one's own take-up by 4%, which equates to around 33% of the direct session effect. Although the design is not fully comparable to this experiment, the order of magnitude of the network effect is similar.

farmers: among second round participants, having one more friend invited to a first round intensive session transmits 45% of the first order session effect.

4.2 Monetary Equivalence of the Social Network Effect

In this section, we assess the importance of the social network effect by measuring its price equivalence through price randomization in type II villages (Figure 1.2). Specifically, we estimate whether households are less sensitive to price if they have more friends invited to an intensive session. We then use estimated coefficients to calculate the monetary equivalence of the social network effect, i.e., the amount by which the premium should be reduced in order to achieve the same effect on insurance take-up as the social network.[30]

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

$$\begin{aligned} Takeup_{ij} = \gamma_0 + \gamma_1 Price_{ij} + \gamma_2 Network_{ij} \\ + \gamma_3 Price_{ij} * Network_{ij} + \gamma_4 X_{ij} + \eta_j + \epsilon_{ij}, \end{aligned} \tag{4}$$

where $Price_{ij}$ is the price assigned to household i in village j, which takes one of seven different values ranging from 1.8 to 7.2 RMB per mu. The results presented in Table 4 show that increasing the price by 1RMB decreases take-up by 11.2 percentage points (Column (1)). The interaction term between price and social network is significantly positive (Column (2)), suggesting that households with more friends invited to intensive sessions are less sensitive to price. Specifically, having one additional friend invited to an intensive session mitigates the price effect by $0.13 * 0.2/0.167 = 16\%$.

A concern with this estimation is that, for households in the price experiment, some friends face lower prices than they do, while others face higher prices. A "fairness" concern may thus occur and affect the price elasticity of insurance demand. To control for the potential impact of a perceived lack of fairness in pricing, we include two additional variables when estimating equation 4: the share of friends with prices

[30] A simple theoretical model is presented in appendix B that explains why social networks can potentially influence both the level and the slope of the insurance demand curve.

higher or lower than one's own price. Results in Column (3) show only a slight change when controlling for fairness.

We can now calculate the price equivalence P of the social network effect using the following formula:

$$P = \frac{\hat{\gamma}_2 + \hat{\gamma}_3 * mean(Price)}{\hat{\gamma}_1 + \hat{\gamma}_3 * mean(Network)} * 0.2$$

Using estimated coefficients from Columns (2) and (3), and the average values of Network (0.161) and Price (4.34) in these villages, we find that having one additional friend is equivalent to a 15% decrease in the average insurance premium. This is a large effect, showing the importance of social networks in individual financial decision-making.

4.3 Identifying the Social Network Effect Mechanisms

A natural question to ask is why do social networks matter. What is it that farmers have learned from their informed friends that influenced their take-up decisions? Generally speaking, social networks may influence the adoption of a new technology or a financial product because of three reasons: (i) people gain knowledge from their friends about the value or the benefits of a product (Conley and Udry (2010); Kremer and Miguel (2007); Koher et al. (2001)); (ii) people learn from their friends how to use the product (Munshi and Myaux (2006); Kremer and Miguel (2007); Oster and Thornton (Forthcoming)); or (iii) individuals are influenced by other people's decisions (Bandiera and Rasul (2006); Banerjee (1992); Beshears et al. (2011); Bursztyn et al. (2012);[31] Çelen et al. (2010); Ellison and Fudenberg (1993); Rogers (1995)). In this last case, farmers could be influenced by their friends' decisions because of scale effects (farmers believe that they have greater leverage over the insurance company if more of them purchase the product together), a desire to imitate (farmers want to act like each other), or the existence of informal risk-sharing arrangements (a farmer's decision depends on the purchase decision of households from whom the farmer borrows or to whom he lends (Bloch et al. (2008)).

With insurance, there is little to learn in terms of "how to use the product".

[31] There are different reasons of why people are influenced by friends' decisions. While this is not the focus of our paper, Bursztyn et al. (2012) uses a very nice experimental design to separate between social learning and social utility effects.

We thus focus on the role of the other two types of information that can be usefully conveyed by social networks, insurance knowledge and purchase decisions, and explore each of them in turn. Specifically, if the reason why farmers are affected by their friends' exposure to the intensive session is that their understanding of insurance benefits is improved by learning from them, this means that insufficient knowledge of insurance impairs adoption; in that case, providing more information about the insurance product would be crucial. On the other hand, if the network effect is driven by the influence of friends' purchase decisions, then using marketing strategies to guarantee a high adoption rate by pilot clients could significantly improve the take-up rate by follow-up customers.

4.3.1 Role of social networks in diffusing knowledge of insurance

To test the insurance knowledge mechanism, we follow two approaches. The first consists of comparing the magnitude of the intensive session effect on post-session insurance knowledge test scores, between the first round (simple session T1 vs. intensive session T2) and second round sessions (simple session U1 vs. intensive session U4).[32] Intuitively, if second round participants can acquire sufficient insurance knowledge from first round participants during the time interval between the two rounds, then second round intensive session should make no difference relative to the simple session on either take-up or post-session knowledge of insurance. The estimation is as follows:

$$Knowledge_{ij} = \omega_0 + \omega_1 Intensive_{ij} + \omega_2 Sec_{ij} + \omega_3 Intensive_{ij} * Sec_{ij} + \epsilon_{ij} \tag{5}$$

where Sec_{ij} is a dummy variable indicating whether the household was assigned to one of the two second-round sessions, and $Knowledge_{ij}$ is a measure of insurance knowledge, which is defined as the score that a household obtained on a ten-question insurance knowledge test.

The results presented in Table 5, Column (1), show that, while participating in intensive session raises the insurance knowledge test score significantly in the first round (by 31 percentage points), it has a much smaller effect in second round sessions. Specifically, being invited to a second round intensive session improves insurance

[32] This is because only U1 and U4 received exactly the same treatment as T1 and T2 and are thus comparable with each other.

knowledge by farmers with no friends attending first round intensive session, but it has no effect on farmers who have at least one friend assigned to first round intensive session (Column (2)). As a result, intensive sessions in the second round improve insurance knowledge only for those farmers with no friends in first round intensive sessions.

The second approach tests whether households perform better on the insurance knowledge test when they had more friends invited to first round intensive sessions, by estimating the following equation:

$$Knowledge_{ij} = \lambda_0 + \lambda_1 Network_{ij} + \lambda_2 X_{ij} + \eta_j + \epsilon_{ij} \tag{6}$$

Results in Column (3) show that having one additional friend assigned to a first round intensive session improves the level of insurance knowledge by 6 percentage points (the mean of baseline knowledge score equals 0.25). Furthermore, we test whether this effect is larger when one's friend better understands the materials provided during the intensive session, and as a result can better teach other people, by estimating:

$$\begin{aligned} Knowledge_{ij} = \lambda_0 &+ \lambda_1 Network_{ij} + \lambda_2 NetKnowledge_{ij} \\ &+ \lambda_3 Network_{ij} * NetKnowledge_{ij} + \lambda_4 X_{ij} + \eta_j + \epsilon_{ij} \end{aligned} \tag{7}$$

where $NetKnowledge_{ij}$ is the average insurance knowledge test score received by household i's friends in the first round intensive session in village j. The results from this estimation (Column (4)) show that a farmer learns more from friends who demonstrate a better understanding of the information provided at the intensive session.

4.3.2 Role of social networks in diffusing purchase decisions

To understand whether social networks affect adoption by conveying information on participants' purchase decisions, we directly test the effect of other people's decisions on insurance take-up. To do so, we first look at the role of the overall take-up rate in first round sessions in influencing second round participants' behavior. We then look at the role of friends' take-up rate in first round sessions. Consider first the effect of the overall first round take-up rate:

$$Takeup_{ij} = \gamma_0 + \gamma_1 TakeupRate_j + \gamma_2 Info_{ij} + \gamma_3 TakeupRate_j * Info_{ij} + \epsilon_{ij} \tag{8}$$

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

First, we see that randomized default options in first-round sessions yield significant and substantial variations in the overall first round take-up rates: the average take-up rate of "default = BUY" sessions is around 12 percentage points higher than that of "default = NOT BUY" sessions (Table 6, Column (1)).[33] As a result, we can use the default option as an IV for first-round overall take-up rates. OLS and IV estimation results are presented in Columns (2) and (3). From these results, we find that farmers are more likely to buy insurance when the overall first round take-up rate is higher. However, this effect is much smaller if we did not explicitly reveal purchase information, becoming not statistically significant in IV estimation.

To see this more clearly, we break down the sample and re-estimate the influence of first round overall take-up rate (Columns (4) and (5)). We find that second round participants are not influenced by decisions made by first round participants when this information is not revealed to them (Column (4)). However, if we disseminate first round overall take-up information during second round sessions, we find that a 10% higher take-up rate in the first session can raise the take-up rate in second-round sessions by 4.3%.

We next analyze whether information about friends' decisions has similar effects

[33]Reasons why people follow the default option have been discussed in Brown et al. (2011) and Beshears et al. (2010), including the complexity of decisions, an endorsement effect (this is what government suggests), a social effect (everyone else is doing it), and procrastination. We explain the large default effect as follows in Table A4. First, we find that people are less likely to follow the default option when they receive better information about the product: the default effect is smaller in intensive sessions than in simple sessions (Column (1)). Second, the magnitude of the default effect does not vary whether a farmer trusts the government more or less (Column (3)), which means that the endorsement effect cannot be the main explanation here. Third, we asked farmers, "Do you think that more than 50% of the households in your village will purchase this insurance?" (Yes or No). The default option does not have a significant effect on the answer, and as a result rules out the social effect explanation. These pieces of evidence together suggest that the main reason why people follow the default option in our setting is that making the decision is too complex for them.

on farmers' decisions as information about the overall take-up rate. For this, we estimate the following equation using the sample of second round participants who did not receive take-up information and those who received from us the first-round decision list (U1, U3, U4, and U6 in Figure 1.1):

$$Takeup_{ij} = \delta_0 + \delta_1 TakeupRate_j + \delta_2 TakeupRateNetwork_{ij} + \delta_3 Info_{ij} \\ + \delta_4 TakeupRate_j * Info_{ij} + \delta_5 TakeupRateNetwork_{ij} * Info_{ij} + \epsilon_{ij} \quad (9)$$

where $TakeupRateNetwork_{ij}$ represents the take-up rate among friends of household i who attended first-round sessions in village j. Similar to what has been discussed before, both $TakeupRate_j$ and $TakeupRateNetwork_{ij}$ are endogenous. While we still use the first round default option as IV for the overall first round take-up rate, we use Default times the ratio of network in first-round sessions (first round default options are more likely to influence the number of friends who purchase insurance if more friends are included in first round sessions) as an IV for $TakeupRateNetwork_{ij}$.

Results are presented in Table 7. These results show that decisions made by friends in a farmer's social network do not influence the farmer's own decision (Column (4)). This is not because farmers do not care about other villagers' decisions, as this information has a large and significant influence if we explicitly revealed it (Columns (5)), but because, at least in this context, social networks did not convey this information. A qualitative analysis confirms this argument. In the household survey, we directly asked people whether they knew each of their friends' decisions. Only 9% of the households responded that they knew at least one of their friends' decisions. These results suggest an interesting regularity about the performance of social networks in rural villages in our study: while networks are efficient in transmitting knowledge, they do not generally convey information on purchase decisions. This is surprising, because farmers actually care a great deal about that information, as indicated by its significant effect on decision-making when explicitly revealed.

Direct interviews with farmers, as well as behavioral studies (Qian et al. (2007)), provide a possible interpretation for this apparent contradiction. The villages in our sample are likely characterized by a strongly ingrained cultural factor in traditional environments which can explain the limited diffusion of information on take-up decisions: Chinese people care a lot about "face" (i.e., their public image), and disclosing purchase decisions carries the risk of "losing face." Specifically, farmers are reluctant to reveal their decisions because they are unsure of whether they have made the right choice and do not want to expose their potential lack of judgment or be liable for having influenced someone in making a bad decision. This interpretation is consistent with the finding that 76% of those friends who revealed their decision are village leaders or opinion leaders within the village. These people should be more confident in their choices and as a result less worried about the risk of "losing face". Social networks in Chinese villages are thus useful instruments for the diffusion of knowledge from informed to uninformed individuals. However, these networks suffer from the drawback that the deep-rooted concern with not losing face limits the circulation of information on an essential determinant of decision-making, namely knowing what peers have decided regarding adoption of the innovation.[34]

Based on the above results and discussion, we conclude that the observed short-term social network effect on insurance take-up is mainly driven by the diffusion of insurance knowledge, as opposed to the diffusion of information regarding others' purchase decisions that may influence decision-making through scale effects, imitation, or informal risk-sharing.

4.4 Heterogeneity in Network Characteristics

Given that social networks can help improve insurance take-up by diffusing insurance knowledge, are there particular individuals which are more effective as entry points to receive intensive information about the product for the diffusion of information? This will depend on both individual and village network characteristics (Jackson (2010); Acemoglu et al. (2010); Allcott et al. (2007)). We examine the heterogeneity of network effects across households by the following estimation:

$$\begin{aligned} Takeup_{ij} = \eta_0 + \eta_1 Network_{ij} + \eta_2 OwnCharact_{ij} + \eta_3 Network_{ij} * \\ OwnCharact_{ij} + \eta_4 NetCharact_{ij} + \eta_5 Network_{ij} * NetCharact_{ij} + \epsilon_{ij} \end{aligned} \tag{10}$$

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

[34]It is unlikely that three days will be insufficient to convey purchasing decisions while it is sufficient for knowledge information to diffuse. Preliminary results from a follow-up survey one year later confirm that farmers are still not influenced by their friends' decisions.

fluence is given by: $\eta_1 + \eta_3 OwnCharact_{ij} + \eta_5 NetCharact_{ij}$, which is a function of both a farmer's own characteristics and those of the farmer's network. A natural interpretation of this expression is that a farmer's own characteristics measure how likely the farmer is to be influenced conditional on his/her network characteristics, while the characteristics of the network measure how much the network influences the farmer conditional on his/her own characteristics.

A concern about the above estimation is that these characteristics are endogenous. With this caveat in mind, results in Table 8 indicate that a farmer's own characteristics are important: those who were named more often by others (higher in-degree), who can be reached more easily (smaller path length[35]), and who have a more important network position (higher eigenvector centrality), are less likely to be influenced by other people (as seen in interaction terms in Columns (2), (4) and (6)). These characteristics not only affect the magnitude of the network effect, but also directly affect the take-up. Those who were named more often by others, who can be reached less easily, and who have a less important network position are more likely to buy insurance (Column (7)).

Turning to the question of who are more influential, we see in Column (8) that, even though the average in-degree and path length of one's friends do not influence the magnitude of the social network effect, their eigenvector centrality does. If the eigenvector centrality of the set of friends in first round intensive session is one standard deviation larger (0.1), second round overall take-up is around 5 percentage points larger, and the effect on take-up of social networks is around 6.8 percentage points larger.

5 Conclusions

This paper uses a randomized field experiment conducted in China's main rice producing area to analyze the role of social networks in the adoption of a new weather insurance product and the mechanisms through which networks operate. We find that providing intensive information about how insurance works and the benefit of the product to a subset of farmers has large and positive spillover effects on other farmers. This spillover effect is driven by the diffusion of insurance knowledge through social networks rather than the diffusion of information on behavior. While people

[35]The own path length means the average length of path for other farmers to reach me.

care a great deal about whether others in their social network have decided to purchase the new insurance product or not, this information is not conveyed through social networks.

Several policy implications can be drawn from these results. First, our study suggests that providing intensive information session about insurance to a subset of farmers and relying on social networks to rapidly multiply its effect on others, can be an effective strategy for increasing adoption of a new insurance product in similar contexts. Targeting individuals who are more central in the village network for this intervention can make a significant difference in the size of the multipliers achieved. Second, our finding that farmers typically do not convey their purchase decisions to others suggests that the common practice of providing heavy subsidies for innovative products to a subset of potential customers in order to encourage take-up with the hope that others will follow their behavior, may not be sufficient to achieve expected outcomes. Consequently, combining either information or subsidies for a targeted subpopulation together with social norms marketing, which disseminates information to the full population about the behavior of peers, may be an inexpensive way of expanding the take-up rate for innovative products.

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

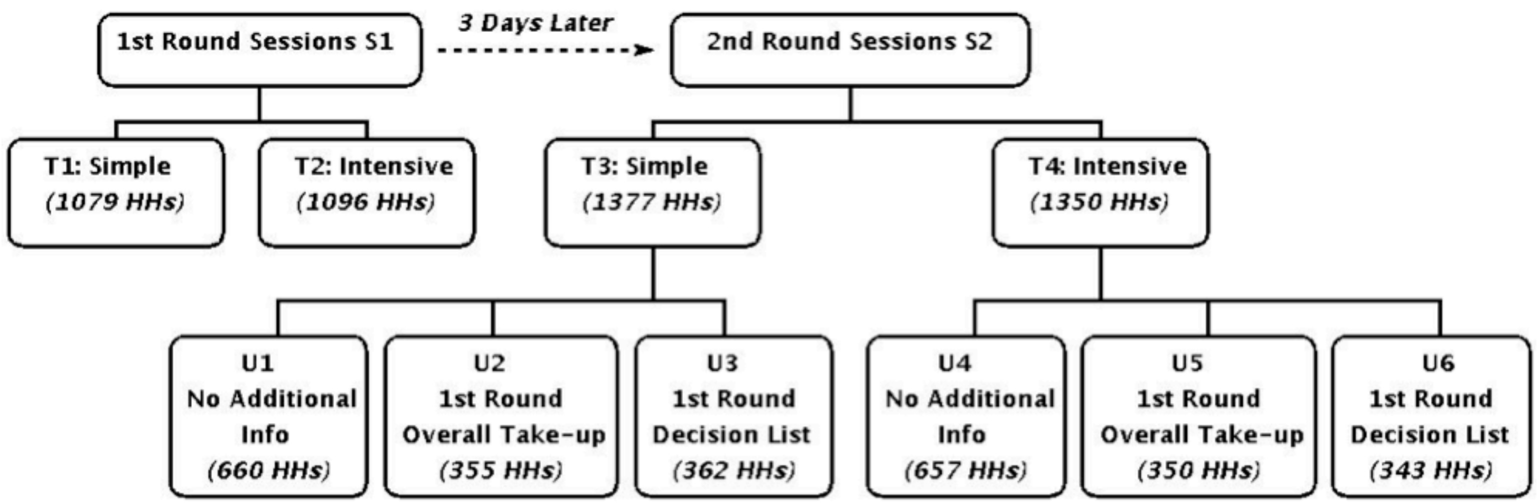
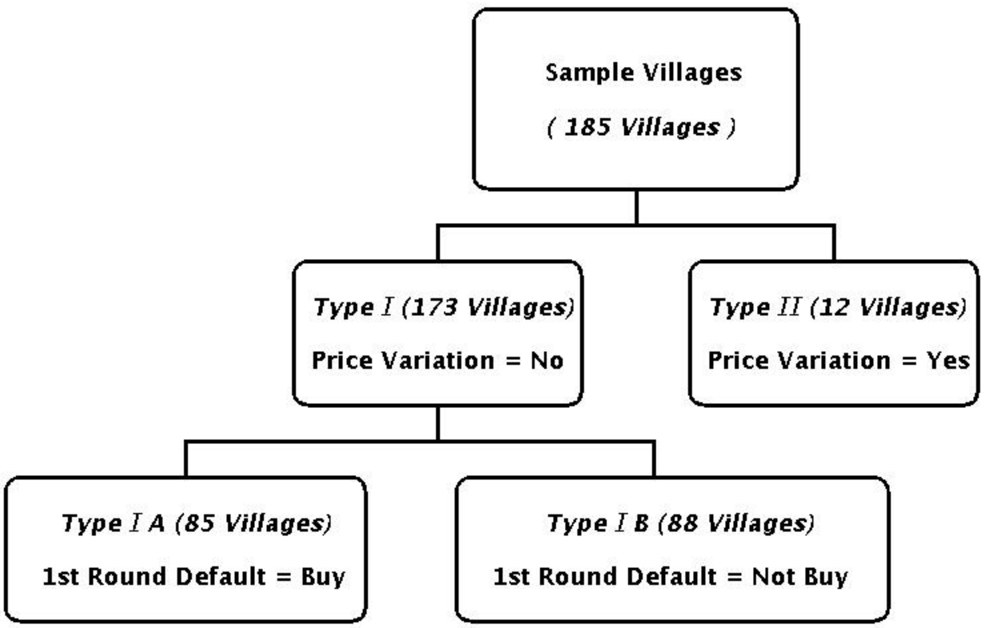
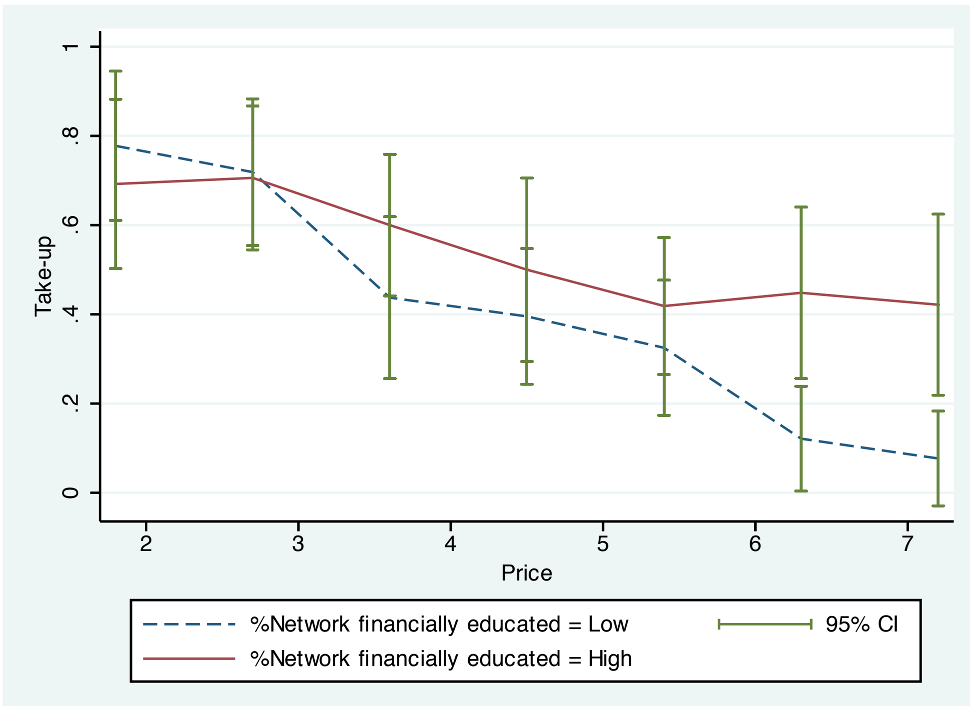


Figure 1.2. Experimental Design: Village Level Randomization



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

Figure 2. Effect of Having Friends Invited to 1st Round Intensive Session on Insurance Demand



Notes: This figure is based on the sample of households in type II villages where price randomization was implemented. The variable %Network financially educated is defined as "high" if a household has above median share of friends invited to 1st round intensive session and is defined as "low" otherwise.

Table 1. Summary Statistics

	Sample Mean	Sample Std. Dev
PANEL A: HOUSEHOLD CHARACTERISTICS		
Gender of Household Head (1 = Male, 0 = Female)	0.914	0.280
Age	51.494	12.032
Household Size	4.915	2.133
Education (0 = illiteracy, 1 = primary, 2 = secondary, 3 = high school, 4 = college)	1.192	0.853
Area of Rice Production (mu, 1 mu = 1/15 hectare)	12.635	19.921
Share of Rice Income in Total Income (%)	73.258	34.841
Any Disasters Happened Last Year (1 = Yes, 0 = No)	0.631	0.483
Loss in Yield Last Year (%)	27.507	18.199
Risk Aversion (0-1, 0 as risk loving and 1 as risk averse)	0.711	0.313
Perceived Probability of Future Disasters (%)	33.633	16.619
PANEL B: SOCIAL NETWORK MEASURES		
Number of Friends Listed	4.893	0.510
General Measure: %Friends Invited to 1st Round Intensive Session	0.161	0.189
Strong Measure: %Mutually Listed Friends Invited to 1st Round Intensive Session	0.043	0.100
Weak Measure: %2nd order Friends Invited to 1st Round Intensive Session	0.154	0.114
PANEL C: SOCIAL NETWORK STRUCTURAL CHARACTERISTICS		
In-Degree (Household level measure)	3.266	2.496
Path Length (Household level measure)	2.578	1.941
Eigenvector Centrality (Household level measure)	0.148	0.098
PANEL D: OUTCOME VARIABLE		
Insurance Take-up Rate (%), all sample	44.084	49.654
Insurance Take-up Rate (%), 1st round simple session	35.218	47.787
Insurance Take-up Rate (%), 1st round intensive session	50.365	50.021
Insurance Take-up Rate (%), 2nd round simple session	44.178	49.678
Insurance Take-up Rate (%), 2nd round intensive session	45.972	49.856
No. of Households: 5332		
No. of Villages: 185		

Table 2. Effect of Social Networks (General Measure) on Insurance Take-up

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)				
Sample:	*1st round session participants*	*2nd round session participants in U1 and U4*			*1st round (all) & 2nd round (U1 and U4, no friends in T2)*
	(1)	(2)	(3)	(4)	(5)
Intensive Information Session	0.140***		0.00643	0.0539	0.1396***
(1 = Yes, 0 = No)	(0.0259)		(0.0329)	(0.0397)	(0.0258)
Network Invited to 1st Round Intensive Session		0.337***	0.348***	0.489***	
([0, 1])		(0.0810)	(0.0779)	(0.105)	
Network Invited to 1st Round Intensive Session				-0.301*	
*Intensive Information Session				(0.162)	
Second round					0.019
(1 = Yes, 0 = No)					(0.0367)
Intensive Information Session * Second Round					-0.0478
					(0.0472)
Male	0.0393		0.0374	0.0408	0.0454
	(0.0476)		(0.0673)	(0.0672)	(0.0414)
Age	0.00205*		0.00374***	0.00384***	0.0026***
	(0.00108)		(0.00123)	(0.00122)	(0.001)
Household Size	-0.00381		-0.00878	-0.00901	-0.0047
	(0.00514)		(0.00677)	(0.00674)	(0.0049)
Rice Production Area (mu)	0.00161		0.00323***	0.00330***	0.0016*
	(0.000993)		(0.00115)	(0.00114)	(0.0009)
Literate (1 = Yes, 0 = No)	0.0821***		0.0844***	0.0841***	0.0617***
	(0.0269)		(0.0320)	(0.0319)	(0.0222)
Risk Aversion ([0, 1])			0.119**	0.114**	0.0793***
			(0.0494)	(0.0492)	(0.03)
Perceived Probability of Disaster ([0, 1])			0.00211**	0.00208**	0.00013
			(0.000819)	(0.000819)	(0.0006)
No. of Observations	2,137	1,274	1,255	1,255	2756
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-Squared	0.129	0.087	0.112	0.115	0.1067

Notes: Robust clustered (to village level) standard errors in parentheses. Column (1) in this table is based on the sample of first round session participants (T1 and T2). Columns (2) to (4) in this table are based on the sample of participants in 2nd round sessions who did not receive 1st round take-up information from us (U1, U4) in type I villages. Social network is measured by the fraction of the five friends that a household listed who were assigned to a first round intensive session. *** p<0.01, ** p<0.05, * p<0.1

Table 3. Effect of Social Networks on Insurance Take-up: Alternative Measures and Functional Form

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)		
	Strength of Ties		Nonlinear Effects
Sample: Second round session participants in U1 and U4	(1)	(2)	(3)
Network Invited to 1st Round Intensive Session ([0, 1])			
- Strong social network	0.428**		
	(0.182)		
- Weak social network		0.0843	
		(0.149)	
Number of Friends Invited to 1st Round Intensive Session			
- Equal to 1			0.0616*
			(0.0319)
- Equal to 2			0.206***
			(0.0398)
- Greater than 2			0.279*
			(0.156)
No. of Observations	1,255	1,255	1,255
Village Fixed Effects	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes
R-Squared	0.101	0.097	0.120

Notes: Robust clustered (to village level) standard errors in parentheses. Results in this table are based on the sample of participants in 2nd round sessions who did not receive 1st round take-up information from us (U1 and U4 in Figure 1.1). Columns (1) and (2) report heterogenous effect of social networks depending on the strength of ties, where social network is measured in two ways: the strong social network is defined as the fraction of the five friends who were mutually listed and were assigned to the first round intensive session; the weak social network is defined as the fraction of second-order friends (friends' friends) who were assigned to the first round intensive session. P-value of significance in difference between Strong and Weak network effect equals 0.004 (significant at 1% level). Column (3) shows nonlinear effects of social networks. Household characteristics include gender, age and education of household head, household size, rice production area, risk aversion, and perceived probability of future disasters. *** p<0.01, ** p<0.05, * p<0.1

Table 4. Monetary Value of the Social Network Effect on Insurance Take-up

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)		
Sample: Second round participants in Type II villages	(1)	(2)	(3)
Price	-0.112***	-0.167***	-0.151***
	(0.0162)	(0.0273)	(0.0306)
Network Invited to 1st Round Intensive Session ([0, 1])	0.364***	-0.199	-0.241
	(0.0979)	(0.230)	(0.243)
Price * Network Invited to 1st Round Intensive Session		0.130**	0.151**
		(0.0524)	(0.0520)
Share of Friends with Higher Prices ([0,1])			0.0795
			(0.101)
Share of Friends with Lower Prices ([0,1])			-0.0911
			(0.0770)
No. of Observations	429	429	429
Village Fixed Effects	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes
R-Squared	0.239	0.249	0.260
P-value of Joint-significance:			
Price		0.0000***	0.0013***
Network Invited to 1st Round Intensive Session		0.0057***	0.0018***

Notes: Robust clustered (to village level) standard errors in parentheses. This table is based on the sample of second round participants in type II villages where different prices ranging from 1.8 RMB to 7.2 RMB were randomly assigned on the household level. Household characteristics include gender, age and education of household head, household size, production area, risk aversion, and perceived probability of future disasters. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Did Social Networks Convey Insurance Knowledge?

VARIABLES	Post-Session Insurance Knowledge Score ([0, 1])			
Sample:	*T1 T2 U1 U4*		*U1 and U4*	
	(1)	(2)	(3)	(4)
Intensive Information Session	0.314***	0.196***	0.0731***	0.0765***
(1 = Yes, 0 = No)	(0.0120)	(0.0223)	(0.0167)	(0.0165)
Second round	0.224***			
(1 = Yes, 0 = No)	(0.0143)			
Intensive Information Session	-0.25***			
*Second Round	(0.0200)			
Having friends invited to 1st Round Intensive Session		0.189***		
(1= Yes, 0 = No)		(0.022)		
Intensive Information Session		-0.229***		
*Having friends invited to 1st Round Intensive Session		(0.033)		
Network Invited to 1st Round Intensive Session			0.30***	-0.01
([0, 1])			(0..048)	(0.106)
Network Invited to 1st Round Intensive Session				0.415***
*Average Network Insurance Knowledge				(0.127)
No. of Observations	3,259	1255	1,255	1,255
Village Fixed Effects	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes
R-Squared	0.241	0.2735	0.1345	0.1324
P-value of Joint-significance:				
Intensive Information Session	0.0000***	0.0000***		
Network Invited to 1st Round Intensive Session				0.0000***

Notes: Robust clustered (to village level) standard errors in parentheses. Estimation results in columns (1)and (2) are based on households who were assigned to first round sessions or those in second round session groups without additional information (T1, T2, U1, and U4 in Figure 1.1). Columns (3) and (4) are based on households who were invited to second round sessions but did not receive any additonal take-up information (U1 and U4 in Figure 1.1). Insurance knowledge is the score that a household got in ten questions that we asked during household survey to test their knowledge of insurance after taking the information session. The mean of insurance knowledge test score equals 0.254. *** p<0.01, ** p<0.05, * p<0.1

Table 6. Effect of the Overall 1st Round Take-up Rate on 2nd Round Take-up

	First Stage: Overall 1st Round Take-up	Second Stage: Insurance Take-up (1 = Yes, 0 = No)			
Sample:	*T1 and T2*	*T3 and T4*		*No Information Revealed (U1 U4)*	*Revealed 1st Round Overall Take-up (U2 U3 U5 U6)*
		OLS	IV	IV	IV
VARIABLES	(1)	(2)	(3)	(4)	(5)
Default (1 = Buy, 0 = Not Buy)	0.121***				
	(0.0326)				
1st Round Overall Take-up Rate		0.387***	0.370*	-0.00290	0.427*
		(0.0712)	(0.223)	(0.0856)	(0.237)
No 1st Round Take-up Information Revealed		0.137***	0.168		
		(0.0407)	(0.133)		
1st Round Overall Take-up Rate		-0.316***	-0.389		
*No 1st Round Take-up Information Revealed		(0.0757)	(0.314)		
No. of Observations	2,137	2,674	2,674	1,296	1,296
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes	Yes
R-Squared	0.120	0.098	0.098	0.095	0.135
P-value of Joint-significance:					
1st Round Overall Take-up Rate		0.0000***	0.2159		

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

Table 7. Effect of Friends' Decisions in 1st Round Sessions on 2nd Round Take-up

	First Stage: Network 1st Round Take-up Rate	Second Stage: Insurance Take-up (1 = Yes, 0 = No)			
Sample:	*U1U3 U4 U6*	*U1 U3 U4 U6*		*No Information Revealed (U1 U4)*	*Revealed 1st Round Overall Take-up (U3 U6)*
		OLS	IV	IV	IV
VARIABLES	(1)	(2)	(3)	(4)	(5)
1st Round Overall Take-up Rate		0.610***	0.436	0.0225	0.691
		(0.108)	(0.602)	(1.452)	(0.664)
1st Round Network's Take-up Rate		-0.0174	0.555**	-0.0891	0.589**
		(0.0528)	(0.274)	(1.456)	(0.280)
No Information Revealed		0.261***	0.412**		
(1 =Yes, 0 = No)		(0.0555)	(0.194)		
1st Round Overall Take-up Rate		-0.545***	-0.723		
* No Information Revealed		(0.123)	(1.181)		
1st Round Network's Take-up Rate		0.0169	-0.0950		
* No Information Revealed		(0.0730)	(1.030)		
Default	0.308***				
* Network in 1st Round Sessions	(0.0593)				
No. of Observation	1,643	1,643	1,643	983	660
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes	Yes
R-Squared	0.163	0.089		0.074	
P-value of Joint-significance:					
1st Round Overall Take-up Rate		0.0000***	0.7072		
1st Round Network's Take-up Rate		0.9466	0.1248		

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

Table 8. Heterogeneity of the Social Network Effect:
Who is More Likely to be influenced and Who is More Influential?

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)							
Sample: Second round participants in U1 and U4	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Network Invited to 1st Round Intensive Session	0.316***	0.544***	0.419***	0.834***	0.165*	0.273	0.247**	0.462
([0, 1])	(0.101)	(0.189)	(0.107)	(0.213)	(0.0997)	(0.171)	(0.116)	(0.335)
Intensive Information Session	0.00446	0.00821	0.0107	0.00926	0.00589	0.00908	0.00642	0.00613
(1 = Yes, 0 = No)	(0.0331)	(0.0330)	(0.0331)	(0.0328)	(0.0329)	(0.0328)	(0.0331)	(0.0327)
Heterogeneity Effects:								
Own in-degree (mean = 3.266)								
Direct effect	0.00874	0.0235***					0.0207***	0.0244**
	(0.00566)	(0.00885)					(0.00772)	(0.0119)
Interaction with Network		-0.0860**						-0.0218
		(0.0397)						(0.0466)
Average in-degree (mean = 3.266)								
Direct effect	0.00409	0.00209					-0.0214**	0.00538
	(0.00635)	(0.00850)					(0.00977)	(0.0208)
Interaction with Network		0.0186						-0.0770
		(0.0415)						(0.0768)
Own Path Length (mean = 2.578)								
Direct effect			-0.0128*	-0.00530			-0.0120*	-0.00363
			(0.00729)	(0.00631)			(0.00714)	(0.00693)
Interaction with Network				-0.0680**				-0.0669**
				(0.0284)				(0.0333)
Average Path Length (mean = 2.578)								
Direct effect			-0.0150	-0.000249			-0.0155	-0.0284
			(0.0124)	(0.0177)			(0.0129)	(0.0267)
Interaction with Network				-0.0666				0.165
				(0.0995)				(0.122)
Own Eigenvector Centrality (mean = 0.148)								
Direct effect					-0.0472	0.422*	-0.497**	0.000288
					(0.174)	(0.235)	(0.234)	(0.335)
Interaction with Network						-2.836***		-2.427*
						(1.016)		(1.418)
Average Eigenvector Centrality (mean = 0.148)								
Direct effect					0.492***	-0.0565	0.992***	0.177
					(0.157)	(0.225)	(0.244)	(0.515)
Interaction with Network						3.232***		3.416*
						(0.948)		(1.886)
No. of Observations	1,255	1,255	1,255	1,255	1,255	1,255	1,255	1,255
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-Squared	0.105	0.111	0.108	0.116	0.110	0.125	0.125	0.140
P-Value of Joint-significance:								
Network Attending 1st Round Intensive Session		0.01***		0.0002***		0.0003***		
Network Structure (of friends)		0.669		0.6202		0.0001***		
Network Structure (own)		0.0302**		0.0313**		0.0222**		

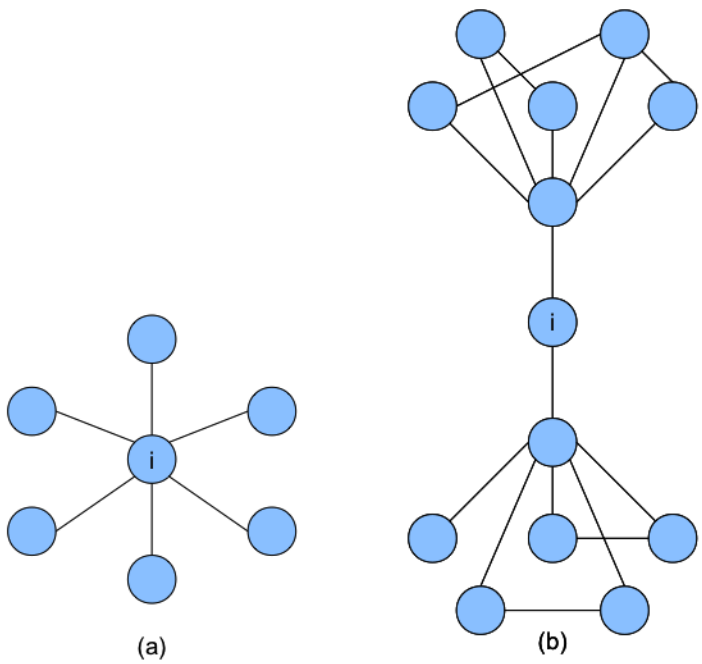
Notes: Robust clustered (to village level) standard errors in parentheses. Results in this table are based on the sample of participants in 2nd round sessions who did not receive 1st round take-up information from us (U1 and U4 in Figure 1.1). Social network is measured by the fraction of the five friends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

Appendices

*For online publication

A Supplementary Figures and Tables

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



Source: Breza et al. (2012), Figure 11

Table A1. Randomization Check: Session Assignments

	First Round		Second Round		P-Value
	Simple Session	Intensive Session	Simple Session	Intensive Session	
Gender of Household Head (1 = Male, 0 = Female)	0.908	0.923	0.91	0.915	0.5982
	(0.289)	(0.266)	(0.286)	(0.279)	
Age	51.489	51.091	51.724	51.592	0.6118
	(11.879)	(12.173)	(12.227)	(11.841)	
Household Size	4.902	4.856	4.943	4.945	0.7084
	(2.122)	(2.094)	(2.203)	(2.103)	
Education (0 = illiteracy, 1 = primary, 2 = secondary,	1.193	1.215	1.194	1.17	0.6471
3 = high school, 4 = college)	(0.859)	(0.85)	(0.866)	(0.839)	
Area of Rice Production (mu)	12.965	12.965	11.978	12.247	0.6263
	(15.25)	(26.307)	(14.397)	(21.882)	
Share of Rice Income in Total Income (%)	74.377	74.1	71.887	73.054	0.2812
	(33.878)	(33.553)	(36.015)	(35.414)	
Any Disasters Happened Last Year (1 = Yes, 0 = No)	0.624	0.633	0.634	0.632	0.9627
	(0.485)	(0.482)	(0.482)	(0.483)	
Loss in Yield Last Year (%)	27.042	27.683	27.601	27.651	0.9208
	(18.498)	(18.116)	(18.374)	(17.861)	
Attendance Rate (%)	88.31	88.87	87.08	86.03	0.1114
	(32.15)	(31.47)	(33.55)	(34.68)	
Number of Households	1079	1096	1587	1570	

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

Table A2. Randomization Check: Price Randomization

	OLS Coeff on Price
	(1)
Gender of Household Head	0.0165
(1 = Male, 0 = Female)	(0.0124)
Age	0.499
	(0.339)
Household Size	-0.0057
	(0.0521)
Literate	0.0233
(1 = Yes, 0 = No)	(0.1796)
Area of Rice Production (mu)	-0.0007
	(0.0127)
Number of Households	431

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

Table A3. Heterogeneity of the Intensive Session Effect

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)				
Sample: First round session participants	(1)	(2)	(3)	(4)	(5)
Intensive Information Session	0.131	0.150***	0.128***	0.130***	0.195***
(1 = Yes, 0 = No)	(0.0962)	(0.0346)	(0.0328)	(0.0303)	(0.0574)
Heterogeneity Effects:					
Age	0.00196	0.00214**	0.00204*	0.00208*	0.00212**
	(0.00142)	(0.00106)	(0.00109)	(0.00107)	(0.00107)
Age*Intensive	0.000181				
	(0.00188)				
Education		-0.0219			
(1 = Above average, 0 = Below average)		(0.0479)			
Education*Intensive		0.0932***			
		(0.0341)			
Experience With Insurance			0.0249		
(1 = Yes, 0 = No)			(0.0326)		
Experience*Intensive			0.0311		
			(0.0459)		
Risk Aversion ([0,1])				-0.0179	
				(0.0480)	
Risk Aversion*Intensive				0.0460	
				(0.0702)	
Day of Session (1-61)					-0.0141
					(0.0110)
Day of Session*Intensive					-0.00279
					(0.00233)
Male	0.0394	0.0425	0.0386	0.0394	0.0341
	(0.0477)	(0.0471)	(0.0473)	(0.0476)	(0.0477)
Household Size	-0.00381	-0.00301	-0.00402	-0.00394	-0.00415
	(0.00514)	(0.00533)	(0.00515)	(0.00516)	(0.00515)
Rice Production Area (mu)	0.00161	0.00161	0.00159	0.00161	0.00163
	(0.000995)	(0.00101)	(0.000974)	(0.000987)	(0.00101)
No. of Observations	2,137	2,161	2,137	2,137	2,137
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.129	0.131	0.130	0.129	0.131
P-value of Joint-significance:					
Intensive Information Session	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***

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

Table A4. Heterogeneity of the Default Effect

VARIABLES	Insurance Take-up (1 = Yes, 0 = No)				
Sample: First round session participants	(1)	(2)	(3)	(4)	(5)
Default (1 = Buy, 0 = Not Buy)	0.208***	0.169***	0.13	0.194***	0.148
	(0.0437)	(0.0374)	(0.086)	(0.0393)	(0.112)
Heterogeneity Effects:					
Intensive Information Session	0.194***	0.146***	0.144***	0.143***	0.146***
(1 = Yes, 0 = No)	(0.0348)	(0.0258)	(0.0257)	(0.0256)	(0.0258)
Intensive*Default	-0.102**				
	(0.0512)				
Education		0.123***			
(1 = Above average, 0 = Below average)		(0.0339)			
Education*Default		-0.0419			
		(0.0454)			
Trust on Government (0-1)			-0.026		
			(0.0426)		
Trust on Government*Default			0.0232		
			(0.066)		
Rice Production Area (mu)				0.00326***	
				(0.000810)	
Rice production Area*Default				-0.00285**	
				(0.00110)	
Age					0.00221
					(0.00139)
Age*Default					0.000103
					(0.00204)
Male	-0.0381	-0.0362	-0.0399	-0.0437	-0.0358
	(0.0478)	(0.0471)	(0.0476)	(0.0473)	(0.0470)
Household Size	-0.00212	-0.000811	-0.00158	-0.00150	-0.000811
	(0.00555)	(0.00565)	(0.00556)	(0.00553)	(0.00565)
Observations	2,137	2,161	2,137	2,137	2,161
Village Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.057	0.060	0.054	0.058	0.059
P-value of Joint-significance:					
Default (1 = Buy, 0 = Not Buy)	0.0001***	0.0001***	0.0001***	0.0001***	0.0000***

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

B An Insurance Demand Model

In this section, we present an insurance demand model to explain why social networks can influence both the level and the slope of the insurance demand curve. The intuition is as follows. Since the farmers in our study are largely unfamiliar with the benefits of insurance, these benefits have a subjective expected value. As a result, the level and slope of the insurance demand curve are determined by farmers' perceptions and uncertainty about the expected benefits of the product, and by the distribution of the expected benefits at an aggregate level. For an individual farmer, the certainty and level of his value for the insurance product depend on his understanding of the product. This understanding can be influenced by formal training, through learning about the product from knowledgeable friends, or by experiencing the value of the product directly or indirectly. Moreover, the effectiveness of information diffusion through the social network determines the level of concentration in the distribution of the farmer's expected product benefits. As a consequence, we expect that the diffusion of information through social networks can affect both the level and the slope of the insurance demand curve.

B.1 Individual Insurance Demand

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

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

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

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

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

$$\mathbb{E}\left(U(\omega - P + \epsilon_i)\right) \geq \mathbb{E}\left(U(\omega - Z)\right) \tag{11}$$

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

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

Replacing these in condition (11), we have

$$- e^{-A_i(\omega - P + \mu_{\epsilon_i}) + \frac{1}{2}A_i^2\sigma_{\epsilon_i i}^2} \geq -e^{-A_i(\omega - \mu_z) + \frac{1}{2}A_i^2\sigma_z^2}$$

$$\Longleftrightarrow \mu_{\epsilon_i} \geq P - \mu_z - \frac{1}{2}A_i(\sigma_z^2 - \sigma_{\epsilon_i}^2) \tag{12}$$

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

B.2 Aggregate Insurance Demand

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

$$Q(P) = 1 - F\left(P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2)\right) \tag{13}$$

and the slope of the demand curve

$$\frac{\partial Q}{\partial P} = -f\left(P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2)\right) \tag{14}$$

where $f(.)$ is the pdf. Equation (14) tells us that the perceived product benefits, the uncertainty about insurance benefits, and the dispersion on the valuation of the product, can affect the slope of the demand curve.

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

In order to derive the impact on the insurance demand curve of perceived benefits, dispersion on the product valuation, and the uncertainty about the benefits, we need to specify the distribution of μ_{ϵ_i}. Let $F(.)$ be the CDF of a Normal distribution with mean η and variance ψ^2, and $\Phi(.)/\phi(.)$ be the CDF/PDF of a standard normal distribution. Then $F(x) = \Phi\left(\frac{x-\eta}{\psi}\right)$ and $f(x) = \frac{1}{\psi}\phi\left(\frac{x-\eta}{\psi}\right)$. The demand curve in equation (13) becomes:

$$Q(P) = 1 - \Phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \tag{15}$$

and the slope of the demand curve is

$$S(P) \equiv \frac{\partial Q}{\partial P} = -\frac{1}{\psi}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \tag{16}$$

- Mean of perceived insurance benefit (η):

$$\frac{\partial Q}{\partial \eta}(P) = \frac{1}{\psi}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \tag{17}$$

$$\frac{\partial S}{\partial \eta}(P) = -\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi^3}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \tag{18}$$

  From equation (17) and (18), 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):

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

$$\begin{aligned}\frac{\partial S}{\partial \psi}(P) =& \frac{1}{\psi^2}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \\ &- \frac{(P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta)^2}{\psi^4}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right) \\ =& \frac{\psi^2 - (P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta)^2}{\psi^4}\phi\left(\frac{P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta}{\psi}\right)\end{aligned} \tag{20}$$

From equation (19) and (20), 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):

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

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

From (21) and (22), the uncertainty about insurance benefits has a negative effect on the level of demand curve. However, the impact on the slope of demand curve depends on the sign of $P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta$. The impact is positive if $P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta > 0$, and it is negative if $P - \mu_z - \frac{1}{2}A(\sigma_z^2 - \sigma_\epsilon^2) - \eta < 0$.

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

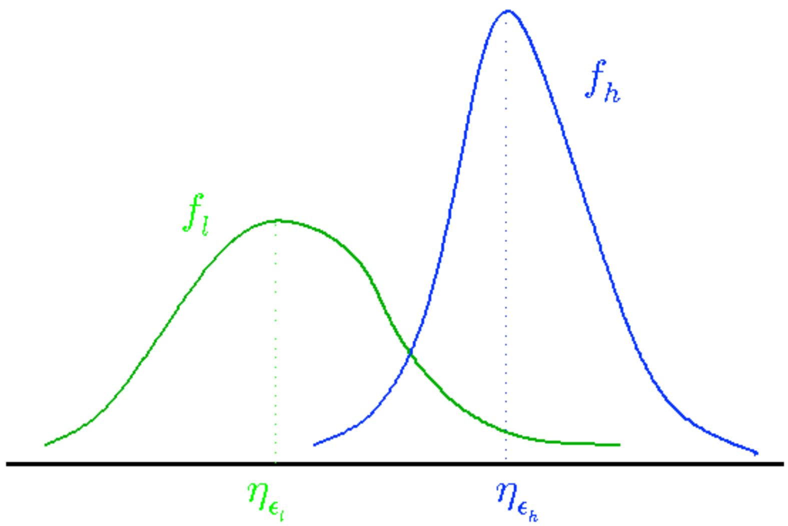


Figure B2. An Example of Insurance Demand Curve