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Social Networks and the Decision to Insure†

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Using data from a randomized experiment in rural China, we study the influence of social networks on weather insurance adoption and the mechanisms through which they operate. To quantify network effects, the experiment provides intensive information sessions about the 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 13 percent reduction in the insurance premium. By varying the information available about peers' decisions and randomizing default options, we show that the network effect is driven by the diffusion of insurance knowledge rather than purchase decisions. (*JEL* G22, O12, O16, P36, Q12, Q54, Z13)

Financial decisions involve complexities that individuals frequently have difficulty understanding based on their own education, information, and experience. Social networks can help people make these complex decisions: people can learn about product benefits from their friends, be influenced by their friends' choices, and/or learn from their friends' experiences with the product. This paper uses a novel experimental design to obtain clean measurements of the role and functioning of social networks in the decision to purchase a weather insurance product, which is typically hard for farmers to understand and has had a 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. Implemented jointly with PICC, the experiment involved 5,300 households across 185 villages of rural China. Our experimental design allows us to not only identify the causal effect of social networks on product adoption, but also test for the role of various channels through which social networks operate. Furthermore, using a household-level price randomization, we calculate the price equivalence of the social network effect on insurance take-up. Finally, taking advantage of the substantial variation in network

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structure across households, we measure the effect of network characteristics on the strength of social network effects.

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 by introducing 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 preexperiment survey) who were invited to an early round intensive session. We find that, while the intensive information session raised take-up by 40 percent in the first round, for second round participants, having one additional friend who participated in a first round intensive session increased take-up by almost half as much. The price randomization experiment shows that this spillover effect on take-up is equivalent to decreasing the average insurance premium by 13 percent.

We then ask what information conveyed by social networks drives this effect. Do networks matter because they diffuse knowledge among farmers about how insurance works and what are its expected benefits? Or is it because farmers learn about each other's decisions? We find that, in this context, social networks do not convey information about peers' purchase decisions, even though people would like to know about this when they make their own decisions, but that networks do effectively transfer information about the functions and benefits of insurance.

This result is obtained in the following manner. First, we show that the effect of an intensive session on insurance knowledge was smaller in the second round than in the first round, and that farmers understood insurance benefits better when they had a greater number of friends invited to a first round intensive session. These results evidence 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' decisions on individuals' choices. Surprisingly, however, when we told farmers about other villagers' decisions, these decisions strongly influenced their own take-up choices. 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 information on 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 social structure (Galeotti et al. 2010; Jackson and Yariv 2010; Banerjee et al. 2013). 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 that are less frequently named as friends by other people, less easily reached by others, or less important in the network are more influenced by other people.

This paper contributes to the social network literature by using randomized experimental methods to estimate the causal effect of social networks on weather insurance purchase and the monetary equivalence of this effect.[1] The main contribution is to identify different channels through which social networks affect behavior. Kremer and Miguel (2007) for the usage of deworming pills and Banerjee et al. (2013) for participation to microfinance programs find that acquiring product information from friends is the most important channel, while Maertens (2012) for Bt cotton finds that both acquiring knowledge and imitating others are important for adoption. Our results clearly support the role of knowledge acquisition over imitative behavior.

Furthermore, from a policy perspective, our paper sheds light on the challenge of how to improve weather insurance take-up. Despite its importance, evidence shows that adoption rates are low, even with heavy government subsidies.[2] Existing research has tested possible explanations for low take-up, such as lack of trust, financial illiteracy, credit constraints, or ambiguity aversion (Giné, Townsend, and Vickery 2008; Cole et al. 2013; Gaurav, Cole, and Tobacman 2011; Bryan 2013), but insurance demand remains low even after some of these barriers were removed in experimental treatments. We provide evidence that adoption can be enhanced by combining education on insurance offered to a subset of households in a community with reliance on social networks to amplify the effect, and combining subsidy or marketing strategies with social norms marketing in which information about the decisions of peers is disseminated to the full population of potential adopters.[3]

The rest of the paper is organized as follows. Section I describes the background for the study and the insurance product. Section II explains the experimental design. Section III presents the results, and Section IV concludes.

I. Background

Rice is the most important food crop in China, with nearly half 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

[1] Existing studies have linked social networks to a wide range of activities, including risk sharing, political outcomes, labor market and job satisfaction, building trust, technology adoption, criminal behavior, productivity, international trade, and skill accumulation. For a comprehensive review, see Jackson (2011). On the subject of financial decision making, see Duflo and Saez (2003); Hong, Kubic, and Stein (2004); Banerjee et al. (2013). To overcome the identification problem (Manski 1993), experimental approaches were used by Duflo and Saez (2003); Dupas (2014); Kling, Liebman; and Katz (2007); and Oster and Thornton (2012), etc. Nonexperimental methods were used notably by Arcidiacono and Nicholson (2005); Bandiera and Rasul (2006); Bertrand, Luttmer, and Mullainathan (2000); Conley and Udry (2010); Foster and Rosenzweig (1995); and Imberman, Kugler, and Sacerdote (2012).

[2] For example, Cole et al. (2013) find an adoption rate of only 5 to 10 percent for a similar insurance policy in two regions of India in 2006. Higher take-up levels with steep price elasticities were, however, found in two recent studies in India (Mobarak and Rosenzweig 2012) and in Ghana (Karlan et al. 2013).

[3] 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. 2014); Cai, Chen, and Fang (2009); Frey and Meier (2004); and Fellner, Sausgruber, and Traxler (2013). However, there is little evidence on how social norms marketing may affect choices in products such as insurance.

PICC to design and offer the first rice production insurance policy in selected pilot counties. The experimental sites for this study were randomly selected villages included in the 2010 expansion of insurance coverage, 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 such insurance was new, farmers, and even local government officials at the town or village level, had very limited understanding of the product. In 2011, the program expanded rapidly and reached all main rice producing counties of China.

The insurance contract is as follows. The actuarially fair price is 12 RMB per mu per season.[4] The government gives a 70 percent subsidy on the premium, so farmers only pay the remaining 3.6 RMB per mu. Such governmental subsidies to agricultural insurance are common in China and in 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.[5] The insurance covers natural disasters, including heavy rain, flood, windstorm, extremely high or low temperatures, and drought. If any of these disasters occurs and leads to a 30 percent 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 percent loss to a maximum payout of 200 RMB per mu for a total loss. The average loss rate in yield is assessed by a committee composed of insurance agents and agricultural experts. Since the average gross income from cultivating rice in the experimental sites is around 800 RMB per mu, and the production cost is around 400 RMB per mu, this insurance policy covers 25 percent of gross income or 50 percent of production costs.

The insurance product considered here differs from index-based weather insurance offered in other countries in several aspects. The product is actually a great deal for farmers, as the postsubsidy price is only around 1 percent of the production cost. Moreover, this product is more vulnerable to moral hazard as the payout is determined by loss in yield. However, the moral hazard problem should not be large here as the maximum payout (200 RMB) is much lower than the profit (800 RMB), and the product does require natural disasters to happen in order to trigger payouts.

II. Experimental Design and Data

A. *Experimental Design*

In rural China, standard methods to introduce and promote policy reforms (such as production subsidies, health insurance, and pensions) include holding village meetings to announce and explain the policy and publishing individual villagers' purchase decision and outcomes, such as payouts for health insurance. These actions have been used not only to induce support for policy reforms, but also to assess

[4] 1 RMB = 0.15 USD; 1 mu = 0.067 hectare.

[5] Starting in 2004, the Chinese government has given production subsidies to rice farmers in order to increase production incentives.

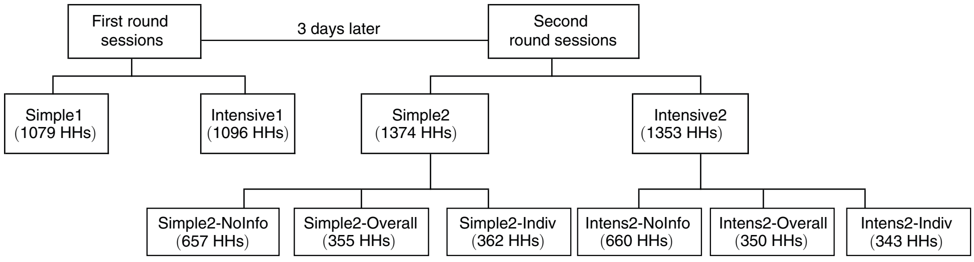

Figure 1.1. Experimental Design: Within-Village, Household-Level Randomization

farmers' responses and to let them monitor the fairness of policy implementation. We combined some of these methods in our experiment.

The experiment assumes that improving farmers' understanding of insurance reinforces take-up, a fact that we verify later. In order to generate household-level variation in the understanding of insurance products, two types of information sessions were offered: simple sessions that took around 20 minutes, during which PICC agents introduced the insurance contract;[6] and intensive sessions that took around 45 minutes and covered all information provided during simple sessions, plus an explanation of how insurance works and what its expected benefits are.[7]

In each village, two rounds of sessions were offered to introduce the insurance product. 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 was chosen to be sufficiently long that farmers have time to communicate with their friends, but not long enough that all the information from the first round sessions has diffused across the whole population through indirect links. 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 shown in Figure 1.1. First, all households in the sample were randomly assigned to one of the four sessions: first round simple (Simple1), first round intensive (Intensive1), second round simple

[6] A 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.

[7] Before designing the intensive session, we talked with many farmers to see which concepts they didn't understand. We then included the following main elements in the intensive session: first, how the insurance program differs from a government subsidy (the amount of payout is much larger than a government subsidy, which usually consists of some food relief after big disasters happen); second, the historical yield loss in the study region; third, the expected benefit or loss from purchasing insurance for five contiguous years depending on different disaster frequencies and levels. This last theme is extremely important because a key reason that many farmers do not buy insurance is that they believe that if they purchase the insurance this year and nothing happens next year, then the product makes them lose money. So in the intensive session, we used many concrete examples to explain that insurance is a type of product that you need to purchase repeatedly, and it is very likely that if you do so, even if disaster only happens in one year, you can get back all the premiums you paid.

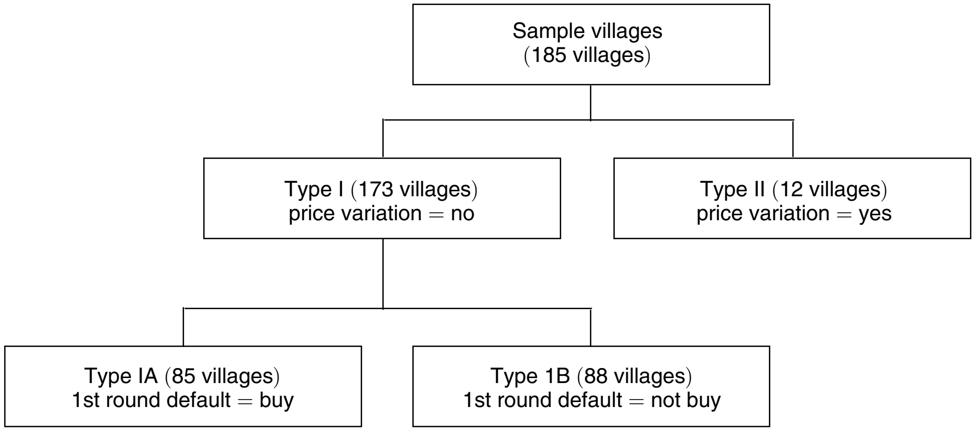

Figure 1.2. Experimental Design: Village-Level Randomization

Notes: Randomizations within Simple2 and Intensive2 treatments 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 second round sessions in type II villages.

(Simple2), or second round intensive (Intensive2).[8] This randomization generates exogenous variations among second round participants in the proportion of their group of friends exposed to first round intensive sessions. However, since this gives a within-village measure, it captures the effect of friends net of potential general diffusion in the village population, rather than the full spillover effect of the first round sessions. We discuss this in more detail in Section IIIA.

Second, for each second round session, after the presentation and before participants were asked to make their decisions, we randomly divided them into three groups and disseminated additional information. Farmers in groups Simple2-NoInfo and Intensive2-NoInfo received no additional information 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 (Simple1 and Intensive1). To farmers in groups Simple2-Overall and Intensive2-Overall, we told the overall attendance and take-up rate at the two first round sessions in their village. To farmers in groups Simple2-Indiv and Intensive2-Indiv, we showed the detailed list of purchase decisions made in the first round sessions, so that they knew nominally who had purchased the insurance and who had not. This part of the experiment was designed to help determine the main mechanisms that drive the social network effect.

The village-level randomizations are shown in Figure 1.2. First, we randomly divided villages into two types. In type I villages, all households face the same price of 3.6 RMB per mu. By contrast, in type II villages, we randomly assigned 1 of 7 different prices ranging from 1.8 to 7.2 RMB per mu to different participants.[9]

[8] For all household-level randomizations, we stratified the sample according to household size and area of rice production per capita. In order to guarantee a high attendance rate, we gave monetary incentives to village leaders and asked them to inform and invite household heads to attend these sessions.

[9] In all type II villages, farmers in second round sessions, Simple2 and Intensive2, received exactly the same information as households in first round sessions, Simple1 and Intensive1, respectively. No additional first round take-up information was provided.

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 did not want to purchase the insurance; if the default was "not buy," the farmer had to sign on if he decided to buy the insurance.[10] 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.

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

B. *Data and Summary Statistics*

The empirical analysis is based on the administrative data of insurance purchase from PICC, and data collected from two surveys: a social network survey carried out before the experiment, and a household survey completed after households had made their insurance purchase decisions. All rice-producing households were invited to one of the sessions, and almost 90 percent of them attended. Consequently, this provided us with a census of the population of these 185 villages. In total, 5,335 households were surveyed.

The household survey includes questions on demographics, rice production, income, natural disasters experienced and losses incurred, experience in purchasing any kind of insurance, risk attitudes, and perceptions about future disasters.[11] It also contains questions that test farmers' understanding of how insurance works and its potential benefits. These questions were based on materials presented in the intensive information sessions, in order to help us test the diffusion of insurance knowledge. Summary statistics of selected household characteristics are presented in panel A of Table 1. Household heads are almost exclusively male, and average education falls between primary and secondary school levels; rice production is the main source of household income, accounting, on average, for 74 percent of total income; 63 percent of households had experienced natural disasters in the most recent year, and the average yield loss rate was around 28 percent; sample households are risk loving, with an average risk aversion of 0.19 on a scale of 0 (risk loving) to 1 (risk averse).

[10] If default = "buy," after the presentation and 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." If 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."

[11] Risk attitudes were elicited by asking 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 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 percent loss in yield next year?"

TABLE 1—SUMMARY STATISTICS

	Mean	SD
Panel A. Household characteristics		
Gender of household head (1 = male, 0 = female)	0.914	0.280
Age	51.49	12.03
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)	13.63	19.51
Share of rice income in total income (percent)	74.12	27.68
Any disaster happened last year (1 = yes, 0 = no)	0.633	0.482
Loss in yield due to disasters last year (percent)	27.51	18.20
Risk aversion (0–1, 0 as risk loving and 1 as risk averse)	0.189	0.313
Perceived probability of future disasters (percent)	33.63	16.62
Post-session insurance knowledge score ([0,1])	0.46	0.30
Panel B. Social network measures		
Number of friends listed	4.918	0.434
General measure: friends invited to 1st round intensive session (rate)	0.165	0.190
Strong measure: mutually listed friends invited to 1st round intensive session (rate)	0.042	0.099
Weak measure: 2nd order friends invited to 1st round intensive session (rate)	0.168	0.117
Panel C. Social network structural characteristics		
In-degree (household level measure)	3.244	1.912
Path length (household level measure)	2.673	0.866
Eigenvector centrality (household level measure)	0.144	0.083
Panel D. Outcome variable		
Insurance take-up rate (percent), all sample	43.81	49.62
Insurance take-up rate (percent), 1st round simple session	35.22	47.79
Insurance take-up rate (percent), 1st round intensive session	50.36	50.02
Insurance take-up rate (percent), 2nd round simple session	44.29	49.71
Insurance take-up rate (percent), 2nd round intensive session	46.52	49.92
Number of households: 5,335		
Number of villages: 185		

Notes: In panel A, 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 percent loss in yield next year?" In panel C, in-degree indicates the number of persons that named a household as friend. Path length is defined by the mean of the shortest paths to a household from any other households. Eigenvector centrality measures a household's importance in the overall flow of information.

The social network survey asked household heads to list five close friends, either within or outside the village, with whom they most frequently discuss rice production or financial issues. Respondents were asked to rank these friends based on which one would be consulted first, second, etc. We chose to impose a fixed number of friends, so as to create an exogenous variable in the number or share of these friends that were assigned to a first round intensive session. The drawback of this specification is that the network characterization may be incomplete.[12] This concern is mitigated by the experience of the pilot test in two villages, where most farmers named 4 or 5 friends (82 percent five, 14 percent four, and 4 percent others) when the

[12] Most households listed 5 friends (on average 4.9, as reported in panel B). To account for these divergences, we control for the number of friends in all specifications.

number was not limited. We use these data to construct two types of variables: social network measures (panel B) and social network structural characteristics (panel C).

We use three types of household-level social network measures. The general measure is defined as the number of listed friends invited to a first round intensive session, divided by the network size. This measure 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. 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. 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 three social network structural characteristics as indicators for the importance of a given household in a network: (i) in-degree, which is the number of persons that named the household as a friend; (ii) path length, which is the mean of the shortest paths to this household from any other household; and (iii) eigenvector centrality, which measures a household's importance in the overall flow of information. This last indicator is a recursively defined concept where each household's centrality is proportional to the sum of its friends' centrality.[13] Average values for these variables are reported in panel C. Each household is, on average, cited as a friend by 3.2 other households. Average path-length is around 2.67, which means that a household can be connected to any other in the village by passing on average through two to three households. This short average path length reflects 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 in Type II villages is valid, we regress the five main household characteristics X_{ij} of household i in village j (gender, age, and literacy of household head, household size, and area of rice production) on the price $Price_{ij}$ at which the household was offered the insurance, and a set of village fixed effects η_j:

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

Results show that all the coefficient estimates are small in magnitude and none is statistically significant, suggesting that the price randomization is valid.

[13] Centrality captures the importance of a household in linking different subgroups within a village network. For example, one person that would be the only intermediary between two very interconnected subnetworks would have a very high centrality, while possibly having only two connections.

III. Estimation Results

A. *Social Network Effect on Insurance Adoption*

We first establish the effect of an intensive session on insurance take-up using the sample of first round participants by estimating:

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

where $Takeup_{ij}$ indicates whether the household decided to buy the insurance or not, $Intensive_{ij}$ is a dummy variable equal to one if the household was invited to an intensive session in village j, X_{ij} includes household characteristics, and η_j are village fixed effects.[14] 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, that is 40 percent above the base value of 35 percent take-up.[15]

To test the social network effect on insurance take-up, we focus on the sample of farmers assigned to second round groups who did not receive first round take-up information (Simple2-NoInfo and Intensive2-NoInfo) and estimate:

$$(3) \qquad Takeup_{ij} = \tau_0 + \tau_1 Network_{ij} + \tau_2 X_{ij} + \tau_3 NetSize_{ij} + \eta_j + \epsilon_{ij},$$

where $Network_{ij}$ is the fraction of friends named by a household in the network survey who have been invited to a first round intensive session, and $NetSize_{ij}$ is a set of five dummy variables indicating the number of friends listed.

Results reported in column 2 indicate a significantly positive effect of social networks on insurance take-up, with a magnitude of 29 percentage points. Thus, having 1 additional friend attend a first round intensive session, raising the network measure by 20 percent, increases a farmer's own take-up rate by $29 \times 0.2 = 5.8$ percentage points. This effect is equivalent to around 42 percent of the impact of attending an intensive session directly (column 1).

The other columns report complementary results: While farmers are influenced by their friends who attended intensive sessions, they are not significantly affected

[14] There are several reasons why attending an intensive session may increase insurance take-up, such as improving insurance knowledge, trust in the program, or through an endorsement effect. We show evidence for the knowledge argument in Section IIIC. We measured farmers' trust in the program but did not find a significant effect of attending an intensive session on it. As for an endorsement effect, it should be stronger for farmers who trust the insurance company more. The fact that the intensive session does not have a larger effect on farmers who purchased other insurance products and received payouts suggests that the endorsement effect is small (Table A3). These results indicate that the intensive session works mainly through improving farmers' insurance knowledge. In addition, in Table A3, we show no heterogeneity of effect with respect to the farmers' level of education, age, experience of receiving payouts from other insurance products, or risk aversion.

[15] As shown in panel D of Table 1, the take-up rate of second round intensive sessions (44 percent) is surprisingly lower than that of first round intensive sessions (50 percent). This is unlikely to be due to changing quality of sessions, as the trainers were the same PICC agents using standard materials, and we observe no difference over time in the intensive session effect (Table A3). A more likely explanation is that second-round participants paid less attention at their own sessions, relying instead on the information they learned from their friends. This is consistent with findings reported later that the effect of intensive sessions on insurance knowledge is also smaller in the second round, and that these reduced effects are not observed for farmers with no friends in first round intensive sessions.

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

Variables	Insurance Take-up (1 = Yes, 0 = No)					
	All 1st round (Simple1 & Intens1)	2nd round with no take-up information given (Simple2-NoInfo & Intens2-NoInfo)				All 1st round & 2nd round with no take-up info given and no friends in Intens1
Sample:	(1)	(2)	(3)	(4)	(5)	(6)
Intensive information session (1 = yes, 0 = no)	0.141*** (0.0260)	0.0298 (0.0332)	0.0256 (0.0331)	0.0809** (0.0397)	0.0936** (0.0419)	0.140*** (0.0259)
Network invited to 1st round simple session			−0.108 (0.0933)			
Network invited to 1st round intensive session (NET)		0.291*** (0.0820)	0.278*** (0.0845)	0.444*** (0.109)		
NET *intensive information session				−0.329** (0.161)		
Second round (SEC, 1 = yes, 0 = no)						0.0318 (0.0362)
SEC × intensive information session						−0.0525 (0.0468)
Number of friends invited to 1st round intensive session						
Equal to 1 (NETONE)					0.0970** (0.0425)	
Equal to 2 (NETTWO)					0.177 (0.111)	
Greater than 2 (NETMORE)					0.137 (0.0916)	
NETONE × intensive information session					−0.0869 (0.0551)	
NETTWO × intensive information session					−0.0908 (0.193)	
NETMORE × intensive Information Session					−0.141 (0.174)	
Observations	2,137	1,255	1,274	1,255	1,255	2,756
Administrative village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	No	Yes	Yes	Yes
R^2	0.125	0.119	0.091	0.123	0.129	0.107
p-value of joint-significance:						
Network invited to 1st round simple session				0.0003***		0.0000***
Intensive information session				0.0718*		

Notes: Robust standard errors clustered at the natural village level in parentheses. The subsample names (Simple1, Simple2-NoInfo, etc) as presented in Figure 1.1. Social network is measured by the fraction of the friends that a household listed who were assigned to a first round intensive session. Household characteristics controlled in some specifications include gender, age, education of household head, rice production area, risk aversion, and perceived probability of future disasters. A set of dummy variables indicating the number of friends and administrative village dummies are included in all estimations.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

by friends who attended first round simple sessions (column 3).[16] Moreover, people are less influenced by their friends when they have direct education about the insurance products (column 4). This linear specification even suggests that the intensive session has a negative effect on people who have all of their friends invited to the intensive session. However, using a nonparametric specification in column 5, where $Network_{ij}$ is replaced with 3 dummy variables (1 friend, 2 friends, and 3 or more friends) shows that this is an artifact of the linearity driven by the small number (4 percent) of farmers who have at least 3 friends in first round intensive session. Finally, to test for the presence of spillover effects through nonfriends, we compare the take-up of second round participants with no friends in a first round intensive session with the take-up of first round participants. Results in column 6 suggest no diffusion through nonfriends: there is no difference in take-up by participants in simple sessions (coefficient of 0.03, not significant), nor in intensive sessions (0.03–0.05$=-$0.02, not significant).

We next examine alternative measures of social network and a nonlinear specification of the network effect. Results from estimating equation (3) using the strong measure (bilateral links) and the weak measure (second-order links) of social networks are reported in Table 3: Having one additional strongly linked friend attending a first round intensive session improves a farmer's probability of taking the insurance policy by 8 percentage points (column 1), which is larger than the effect of the standard social links (5.8 percentage points). By contrast, friends with weak links are much less influential, at least over a short period of time (three days in the experiment) (column 2). In column 3, we test for a nonlinear effect of social networks on take-up: among second round participants, having 2 friends invited to a first round intensive session increases the take-up rate by 11.1 percentage points; this is about 6 percentage points higher than the 5.3 percentage points effect of having only 1 friend invited to a first round intensive session. However, having more than two friends invited to an intensive session does not have a higher effect on take-up than having two.

B. *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.

The underlying theory is that information may affect both the level and the price sensitivity of insurance demand. The intuition is as follows. Farmers' imperfect understanding of insurance can be modeled by adding an uncertain subjective term to the payout scheme of the insurance contract. Individual demand for insurance thus depends positively on the perceived benefit of insurance and negatively on its uncertainty. The aggregate demand is then a function of the distribution of perceived benefits in the population. Acquisition of information on the insurance product has

[16] Household characteristics are controlled for in all specifications (coefficients not reported here). These correlations 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.

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

Variables	Insurance take-up (1 = Yes, 0 = No)		
Sample: 2nd round with no take-up information given	Strength of ties		Nonlinear effects
(Simple2-NoInfo and Intens2-NoInfo)	(1)	(2)	(3)
Network invited to 1st round intensive session (net)			
Strong social network	0.400**		
	(0.173)		
Weak social network		0.190	
		(0.143)	
Number of friends invited to 1st round intensive session			
Equal to 1			0.0531*
			(0.0315)
Equal to 2			0.111
			(0.0818)
Greater than 2			0.0750
			(0.0708)
Observations	1,255	1,255	1,255
Administrative village fixed effects	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes
R^2	0.113	0.109	0.123

Notes: Robust standard errors clustered at the natural village level in parentheses. Results in this table are based on the sample of participants in second round sessions who did not receive first round take-up information from us (Simple2-NoInfo and Intens2-NoInfo in Figure 1.1). Columns 1–2 test the social network effect using two alternative measures: the strong social network is defined as the fraction of a household's friends who were mutually listed and were assigned to the first round intensive session; the weak social network is defined as the fraction of second-order friends (friends' friends) who were assigned to the first round intensive session. Column 3 tests the nonlinear effect 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 are controlled in all estimations. A set of dummy variables indicating the number of friends and administrative village dummies are included in all estimations.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

potentially three effects: it may change the average perceived benefits of insurance in the population either positively or negatively depending on the prior, reduce individual uncertainty about insurance benefits, and reduce the heterogeneity of perception across farmers, which unequivocally induces an increase in demand at any level of price. The effect on the slope of the demand curve depends on the shape of the density function of perceived benefits at the threshold of positive net benefits. In the case of a normal distribution, the value and slope of the probability distribution function are directly related to the baseline level of demand. An increase in expected benefits or a reduction in uncertainty induces the demand curve to be steeper (flatter) if the prior demand is less than (more than) half of the population. A reduction in the heterogeneity of perceived benefits induces the demand curve to be flatter if the density function is convex, i.e., the demand is either very low or very high, and steeper in the intermediate range.

Turning to the data, we compare in Figure 2 the insurance demand curves of households with an above-median (high) and below-median (low) proportion of friends in first round intensive sessions. The insurance demand curve with above-median

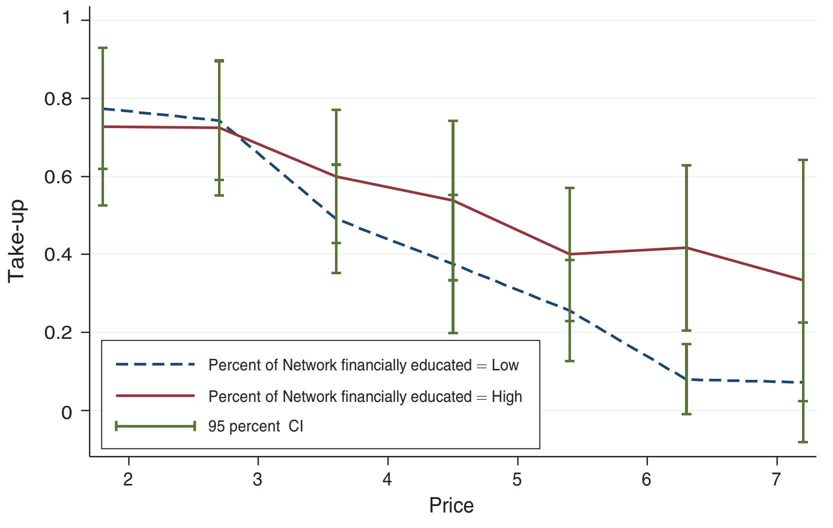

Figure 2. Effect of Having Friends Invited to a First Round Intensive Session on Insurance Demand

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

network is generally higher. It tends to be flatter both at very low prices (where the take-up rate is high) and at high prices (where the take-up rate is low). This result is consistent with the theory.

We formally estimate this relationship with the following equation:

$$(4) \qquad Takeup_{ij} = \gamma_0 + \gamma_1 Price_{ij} + \gamma_2 Network_{ij} + \gamma_3 Price_{ij} \times Network_{ij} + \gamma_4 X_{ijt} \gamma_5 NetSize_i + \eta_j + \epsilon_{ij},$$

where $Price_{ij}$ is the price assigned to household i in village j, which takes 1 of 7 different values ranging from 1.8 to 7.2 RMB per mu. Results presented in Table 4 show that increasing the price by 1RMB decreases take-up by 12.3 percentage points (column 1) and mitigates the price effect by $0.125 \times 0.2/0.151 = 16.6$ percent (column 2). To control for the potential effect of a perceived lack of fairness in pricing, we further include the share of friends with prices higher or lower than one's own price in the estimation. Results in column 3 show only a slight difference.

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

$$P = [\hat{\gamma}_2 + \hat{\gamma}_3 \times mean(Price)] \times 0.2/[\hat{\gamma}_1 + \hat{\gamma}_3 \times mean(Network)].$$

Using estimated coefficients from column 3, and the average values of Network (0.165, in Table 1) and assigned Price (4.31) in these villages, we find that having 1 additional friend is equivalent to a 13 percent decrease in the average insurance

Table 4—Monetary Value of the Social Network Effect on Insurance Take-Up

	Insurance take-up (1 = Yes, 0 = No)		
Variables	(1)	(2)	(3)
Sample: 2nd round participants in villages with household-level price randomization (type II villages)			
Price	−0.123***	−0.151***	−0.140***
	(0.0160)	(0.0191)	(0.0159)
Network invited to 1st round intensive session (NET)	0.353***	−0.178	−0.173
	(0.112)	(0.237)	(0.229)
NET × price		0.125**	0.121**
		(0.0489)	(0.0500)
Share of friends with higher prices ([0,1])			0.0916
			(0.0735)
Share of friends with lower prices ([0,1])			0.0314
			(0.0936)
Observations	433	433	433
Administrative village fixed effects	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes
R^2	0.265	0.270	0.273
p-value of joint-significance:			
Price		0.0000***	0.0000***
Network invited to 1st round intensive session		0.0069***	0.0131**

Notes: Robust standard errors clustered at the natural village level 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 at the household level. Social network is measured by the fraction of the friends that a household listed who were assigned to a first round intensive session. Household characteristics include gender, age and education of household head, household size, production area, risk aversion, and perceived probability of future disasters are controlled in all estimations. A set of dummy variables indicating the number of friends and administrative village dummies are included in all estimations.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

premium. This is a large effect, showing the importance of social networks in individual financial decision making.

C. *Identifying the Social Network Effect Mechanisms*

How do social networks operate? 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 for three reasons: (i) people gain knowledge from their friends about the value of the product (Conley and Udry 2010; Kremer and Miguel 2007); (ii) people learn from their friends how to use the product (Munshi and Myaux 2006; Oster and Thornton 2012); or (iii) people are influenced by other individuals' decisions (Bandiera and Rasul 2006; Banerjee 1992; Beshears et al. 2014; Bursztyn et al. 2014;[17] Ellison and Fudenberg 1993). In this last case, farmers could be influenced by their friends'

[17] There are different reasons why people are influenced by friends' decisions. While this is not the focus of our paper, Bursztyn et al. (2014) use a nice experimental design to separate between social learning and social utility effects.

decisions because of scale effects, a desire to imitate, or existence of informal risk-sharing arrangements (Bloch, Genicot, and Ray 2008).

With insurance, there is little to learn in terms of "how to use the product." We thus focus on the roles of the diffusion of insurance knowledge and purchase decisions, and explore each of them in turn.

Role of Social Networks in Diffusing Insurance Knowledge.—We test for evidence of a general diffusion of knowledge between the two rounds of sessions, by estimating

$$(5)\quad Knowledge_{ij} \;=\; \omega_0 + \omega_1 Intensive_{ij} + \omega_2 Sec_{ij} + \omega_3 Intensive_{ij} \times Sec_{ij} + \epsilon_{ij},$$

where Sec_{ij} indicates whether the household was assigned to a second round session, and $Knowledge_{ij}$ is the score that a household obtained on a ten-question insurance knowledge test. The sample is restricted to all first round participants, and second round session participants with no take-up information, so as to be comparable with the first round sessions. Results presented in Table 5, column 1, show that participating in an intensive session raises the test score significantly in the first round sessions (by 31 percentage points, over a first round simple session mean value of 0.25), but it has a much smaller effect in second round sessions, and that the knowledge score after the second round simple sessions is almost double that of the first round simple sessions.

Focusing then on the role of friends in diffusing insurance knowledge, we show that second round intensive sessions in fact raise the insurance knowledge of farmers with no friends invited to first round intensive session, but not that of farmers with such friends (column 2). Specifically, people who attended the simple session but had friends in a first round intensive session have basically the same level of knowledge score as those in the intensive session. We test whether farmers have a better understanding of insurance when they had more friends invited to a first round intensive sessions, by estimating

$$(6)\qquad Knowledge_{ij} \;=\; \lambda_0 + \lambda_1 Network_{ij} + \lambda_2 Intensive_{ij} + \lambda_3 X_{ij} + \eta_j + \epsilon_{ij}.$$

Column 3 in Table 5 shows that having 1 additional friend assigned to a first round intensive session improves one's score by 6 percentage points. We finally directly test whether a farmer's knowledge is affected by his friends' own knowledge, by estimating

$$(7)\quad Knowledge_{ij} \;=\; \lambda_0 + \lambda_1 Network_{ij} + \lambda_2 NetKnowledge_{ij} + \lambda_3 Network_{ij} \times NetKnowledge_{ij} + \lambda_4 Intensive_{ij} + \lambda_5 X_{ij} + \eta_j + \epsilon_{ij},$$

where $NetKnowledge_{ij}$ is the average test score received by household i's friends in the first round sessions in village j. To solve the endogeneity problem of $NetKnowledge_{ij}$, we use the fraction of friends in the first round intensive session as

Table 5—Did Social Networks Convey Insurance Knowledge?

Variables	Post-Session Insurance Knowledge Score ([0, 1])			
	All 1st round & 2nd round with no take-up info given (Simple1 + Intens1 + Simple2-NoInfo + Intens2-NoInfo)	2nd round with no take-up info given (Simple2-NoInfo & Intens2-NoInfo)		
Sample:	(1)	(2)	(3)	(4)
Intensive information session (1 = Yes, 0 = No)	0.315*** (0.0120)	0.197*** (0.0225)	0.0730*** (0.0167)	0.0404** (0.0192)
Second round (SEC, 1 = Yes, 0 = No)	0.224*** (0.0144)			
SEC × intensive information session	−0.250*** (0.0200)			
Having friends invited to 1st round intensive session (NET_YES)		0.190*** (0.0220)		
NET_YES × intensive information session		−0.231*** (0.0331)		
Network invited to 1st round intensive session			0.290*** (0.0488)	
Average network insurance knowledge				0.414*** (0.0797)
Observations	3,262	1,255	1,255	958
Administrative village fixed effects	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
R^2	0.241	0.154	0.130	0.052
p-value of joint-significance: Intensive information session	0.0000***	0.0000***		

Notes: Robust standard errors clustered at the natural village level in parentheses. This table tests the diffusion of insurance knowledge. Column 1 tests the diffusion of insurance knowledge by comparing the effect of intensive session on insurance knowledge between first and second round sessions, based on households who were assigned to first round sessions or those in second round session groups without additional information (Simple1, Intens1, Simple2-NoInfo, and Intens2-NoInfo in Figure 1.1). Columns 2–4 test the effect of social networks on insurance knowledge, based on households who were invited to second round sessions but did not receive any additonal take-up information (Simple2-NoInfo, and Intens2-NoInfo in Figure 1.1). In column 4, the fraction of friends in first round intensive session is used as the IV for average network insurance knowledge. Insurance knowledge is the score obtained on a test taken after the information session. The average insurance knowledge of second round participants with more than median share of friends in first round intensive session equals 0.52, while that of second round participants with below median share of friends in first round intensive session equals 0.47. The difference is significant at the 1 percent level. A set of administrative village dummies are included in all estimations.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

the IV. Results in column 4 show that a farmer does obtain a higher score when his friends themselves have higher scores.[18]

These results confirm that networks do transfer information that confer better knowledge and understanding of insurance.

[18] If a farmer has no friends in the first round, $NetKnowledge_{ij}$ is set as missing. Simply looking at summary statistics also supports estimation result of equation (7): the mean of insurance knowledge score equals 0.47 for farmers in Simple2-NoInfo and Intensive2-NoInfo whose friends in first-round sessions have a below-median knowledge test score, while it equals 0.52 when their friends in first-round sessions have an above-median knowledge score (the difference is significant at the 1 percent level).

Role of Social Networks in Diffusing Purchase Decisions.—To find out whether social networks affect adotpion by diffusing other villagers' purchase decisions, 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 the effect of the overall first round take-up rate:

$$(8)\ Takeup_{ij} \ = \ \gamma_0 + \gamma_1 TakeupRate_j + \gamma_2 Info_{ij} + \gamma_3 TakeupRate_j \times Info_{ij} + \epsilon_{ij}\,,$$

where $TakeupRate_j$ is the overall take-up rate in first round sessions in village j, a continuous variable ranging from 0 to 1, and $Info_{ij}$ is an indicator of whether we told second round participants this first round take-up rate. The hypothesis is that individuals are more likely to purchase insurance if they see higher take-up rates in previous sessions because of either a scale effect or imitation.

As unobservable variables such as social norms may affect both $TakeupRate_j$ and $Takeup_{ij}$, we use the randomized default options in an instrumental variables approach. We first verify in Table 6, column 1, that 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.[19]

OLS and IV estimation results are reported in columns 2 and 3. They show that farmers are more likely to buy insurance when the overall first round take-up rate is higher, although this effect is much smaller if we did not explicitly reveal this information. Breaking down the sample, 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 7). However, if we disseminate first round overall take-up rate during second round sessions, then a 10 percent higher take-up rate in the first session can raise the take-up rate in second round sessions by more than 7 percent (columns 5). Reduced form estimates give similar results, showing that first round default enrollment has no effect on the second round take-up unless we reveal the information on the overall take-up rate of first round participants (columns 4, 6, and 8).

We next analyze whether information about friends' decisions has similar effects 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 either did not receive any take-up information or received from us the first round

[19] Reasons why people follow the default option are discussed in Brown, Farrell, and Weisbenner (2011) and Beshears et al. (2010), including the complexity of decisions, an endorsement effect (this is what the government suggests), a social effect (everyone else is doing it), and procrastination. We explore these alternatives in Table A4 and A5. We find that (i) the magnitude of the default effect does not vary with the level of trust, suggesting that the endorsement effect cannot be the main explanation; (ii) the default option does not have a significant effect on the perception that people have of the overall take-up, ruling out the social effect explanation; and (iii) people are less likely to follow the default option in intensive sessions, and insurance knowledge is lower when the default is "buy," suggesting that the default option serves as a substitute for information. Together these results indicate that default is helping in taking a complex decision rather than transmitting an additional message (which may violate the exclusion restriction). We also verify that default treatment itself does not affect the effectiveness of information diffusion (Table A4) nor insurance knowledge (when we regress insurance knowledge on default treatment using the first round sample, the coefficient equals 0.004 and is insignificant).

TABLE 6—EFFECT OF THE OVERALL 1ST ROUND TAKE-UP RATE ON 2ND ROUND TAKE-UP

Variables	Insurance Take-up (1 = Yes, 0 = No)							
	All 1st round (Simple1 & Intens1)	All 2nd round (Simple2 & Intens2)			2nd round with overall/detailed info (Simple2-Overall+ Simple2-Indiv+Intens2-Overall+Intens2-Indiv)		2nd round with no take-up info given (Simple2-NoInfo & Intens2-NoInfo)	
		OLS	IV	RF-OLS	IV	RF-OLS	IV	RF-OLS
Sample:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Default (1= buy, 0 = not buy)	0.124***							
	(0.0328)							
1st round overall take-up rate		0.378***	0.719***		0.791***		0.0171	
		(0.0680)	(0.235)		(0.267)		(0.325)	
No 1st round take-up information revealed (NOINFO)		0.120***	0.273*	0.0413				
		(0.0412)	(0.141)	(0.0279)				
NOINFO × 1st round overall take-up rate		−0.285***	−0.643*					
		(0.0755)	(0.335)					
1st round default (1= buy, 0 = not buy)				0.0929***		0.0934***		0.00178
				(0.0301)		(0.0301)		(0.0345)
NOINFO × 1st round default				−0.0914**				
				(0.0446)				
Observations	2,137	2,674	2,674	2,674	1,378	1,378	1,296	1,296
Administrative village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.137	0.106	0.095	0.098	0.127	0.121	0.110	0.110
p-value of joint-significance: 1st round overall take-up rate		0.0000***	0.0096***					

Notes: Robust standard errors clustered at the natural village level in parentheses. Column 1 presents the effect of default options on insurance take-up among first round participants. Estimations in columns 2–4 test the effect of first round overall take-up rate on second round participants' take-up using OLS, IV (using default and default*no information revealed as the IV), and the reduced form estimation, respectively. In columns 5–6 and columns 7–8, we split the sample into the two subsamples of second round participants with overall or detailed individual take-up information given, and those with no take-up information given. The F-statistics for the excluded instruments is 10.85, which is above the conventional weak instrument threshold of 10. A set of administrative village dummies are included in all estimations.

decision list (Simple2-NoInfo, Intens2-NoInfo, Simple2-Indiv and Intens2-Indiv in Figure 1.1):

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

where $TakeupRateNetwork_{ij}$ represents the take-up rate among friends of household i who attended first round sessions in village j. Instruments for $TakeupRate_j$ and $TakeupRateNetwork_{ij}$ are first round default option, *Default*, and *Default* times the ratio of network in first round sessions (first round default options are more likely to influence friends' decisions if more friends are included in first round sessions).

Results are presented in Table 7. We report OLS, IV, and reduced form results in columns 1–3. Focusing on the subsample to whom we reveal detailed take-up information, column 4 shows that decisions made by friends in a farmer's social network have a large and significant influence on the farmer's own decision. However,

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

Variables	Insurance Take-up (1 = Yes, 0 = No)							
	2nd round with no take-up info or with detailed take-up info given (Simple2-NoInfo + Intens2-NoInfo + Simple2-Indiv + Intens2-Indiv)			2nd round with detailed take-up info (Simple2-Indiv & Intens2-Indiv)		2nd round with no take-up info given (Simple2-NoInfo & Intens2-NoInfo)		2nd round in Type II villages
	OLS	IV	RF-OLS	IV	RF-OLS	IV	RF-OLS	IV
Sample:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Default × network in 1st round session			0.323***		0.338***		0.0841	
			(0.0858)		(0.0876)		(0.0781)	
1st round overall take-up rate	0.448***	0.881		0.927		0.163		
	(0.117)	(0.726)		(0.735)		(0.695)		
1st round network's take-up rate	0.106**	0.556**		0.579***		0.0603		0.0990
	(0.0495)	(0.259)		(0.216)		(1.232)		(0.205)
No 1st round take-up information revealed (NOINFO)	0.135**	0.274	0.0284					
	(0.0587)	(0.329)	(0.0373)					
NOINFO × 1st round overall take-up rate	−0.343***	−0.736						
	(0.131)	(1.018)						
NOINFO × 1st round network's take-up rate	−0.0406	−0.0143						
	(0.0701)	(1.199)						
1st round default (1= buy, 0 = not buy)			0.0357		0.0393		−0.0170	
			(0.0587)		(0.0605)		(0.0433)	
NOINFO × 1st round default			−0.0466					
			(0.0694)					
NOINFO × 1st round default × Network in 1st round sessions			−0.246**					
			(0.114)					
Observations	1,500	1,500	1,930	613	675	887	1,255	405
Administrative village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.114		0.094		0.145	0.116	0.099	0.237
p-value of joint-significance:								
1st round overall take-up rate	0.0009***	0.4792						
1st round network take-up rate	0.0515*	0.1022						

Notes: Robust standard errors clustered at the natural village level in parentheses. Columns 1–3 test the effect of first round overall and network take-up rate on second round participants' take-up using OLS, IV, and reduced form estimation, respectively. Columns 4–5 and columns 6–7 tests the impact of first round overall and network take-up using the subsample to whom we revealed the first round individual take-up information (Simple2-Indiv and Intens2-Indiv in Figure 1.1) and those who received no extra information in addition to the presentation (Simple2-NoInfo and Intens2-NoInfo in Figure 1.1), respectively. Column 8 uses the sample of second round participants in Type II villages with price randomization to estimate the impact of friends' take-up rate, using friends' average price as the IV. A set of administrative village dummies are included in all estimations.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

for farmers who did not receive take-up information from us, neither first-round overall take-up nor friends' take-up has a significant effect on their own decision (columns 6). Reduced form estimates in columns 5 and 7 confirm this contrast in the transmission of first round default option on second round take-up. To provide additional support for this result, we estimate the model in the subsample of villages where household-level prices were randomized, using friends' average price as the IV for their take-up rate. Results reported in column 8 tell the same story: if we do not explicitly reveal other people's decisions, it does not significantly affect your own decision.

In addition, we directly asked people whether they knew each of their friends' decisions in the household survey. Only 9 percent of the households to whom we did

Table 8—Heterogeneity of the Social Network Effect: Who Is More Likely to Be Influenced and Who Is More Influential?

Variables Sample: 2nd round with no take-up info given (Simple2-NoInfo & Intens2-NoInfo)	Insurance Take-up (1 = Yes, 0 = No)			
	(1)	(2)	(3)	(4)
Network invited to 1st round intensive session	0.793***	0.795**	0.345**	1.132***
	(0.224)	(0.311)	(0.158)	(0.349)
Heterogeneity effects:				
Own in-degree (mean = 3.266)				
Direct effect	0.0214**			0.0216**
	(0.00957)			(0.0105)
Interaction with network	−0.0811**			−0.0936**
	(0.0401)			(0.0418)
Average network in-degree (mean = 3.266)				
Direct effect	0.0122			0.00885
	(0.0136)			(0.0317)
Interaction with network	−0.0952			−0.0350
	(0.0577)			(0.130)
Own path length (mean = 2.613)				
Direct effect		−0.0297*		−0.0247
		(0.0177)		(0.0182)
Interaction with network		−0.0703		−0.0824
		(0.0723)		(0.0710)
Average network path length (mean = 2.613)				
Direct effect		0.0125		−0.00127
		(0.0199)		(0.0420)
Interaction with network		−0.151*		−0.0574
		(0.0824)		(0.164)
Own eigenvector centrality (mean = 0.148)				
Direct effect			−0.0250	−0.214
			(0.273)	(0.287)
Interaction with network			0.103	1.052
			(1.116)	(1.171)
Average network eigenvector centrality (mean = 0.148)				
Direct effect			0.243	0.0450
			(0.292)	(0.714)
Interaction with network			−2.509*	−1.061
			(1.364)	(3.117)
Observations	1,255	1,255	1,255	1,255
Administrative village fixed effects	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
R^2	0.118	0.123	0.114	0.128
p-value of joint-significance:				
Network attending 1st round intensive session	0.005***	0.0092***	0.0112**	
Network structure (of friends)	0.1856	0.0848*	0.1201***	
Network structure (own)	0.0564*	0.0042***	0.995	

Notes: Robust standard errors clustered at the natural village level in parentheses. Results in this table are based on the sample of participants in second round sessions who did not receive first round take-up information from us (Simple-NoInfo and Intens-NoInfo in Figure 1.1). Social network is measured by the fraction of the friends that a household listed who were assigned to a first round intensive session. See definitions of social network characteristics in Section IIB. Household characteristics include gender, age and education of household head, household size, rice production area, risk aversion, and perceived probability of future disasters. A set of administrative village dummies are included in all estimations.

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

not inform friends' decisions 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: networks do not convey information on purchase decisions, although farmers actually care a great deal about that information, as indicated by its significant effect on decision making when explicitly revealed.

We thus conclude that the observed 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.

D. *Heterogeneity in Network Characteristics*

Given that social networks can improve insurance take-up by helping diffuse knowledge about the product, are there particular individuals who 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, Bimpikis, and Ozdaglar 2014; Allcott et al. 2007). We examine the heterogeneity of network effects across households with the following estimation:

$$\begin{aligned} (10) \qquad Takeup_{ij} = \eta_0 + \eta_1\, Network_{ij} + \eta_2\, OwnCharact_{ij} + \eta_3 Network_{ij} \\ \times\, OwnCharact_{ij} + \eta_4\, NetCharact_{ij} + \eta_5 Network_{ij} \\ \times\, NetCharact_{ij} + \epsilon_{ij}, \end{aligned}$$

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 influence is given by: $\eta_1 + \eta_3 OwnCharact_{ij} + \eta_5 NetCharact_{ij}$.

With the caveat that these network characteristics are endogenous, results in Table 8 (column 4) indicate that farmers who were named more often by others (higher in-degree) are less likely to be influenced by other people. Turning to the question of who is more influential, we see in column 4 that none of the network characteristics has a significant impact on the magnitude of influence. These results project a consistent image of greater autonomy in decision making by the more looked upon farmers.

IV. Conclusions

This paper uses a randomized field experiment conducted in China's main rice producing region 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 expected benefits of the product to a subset of farmers has a large and positive spillover effect on other farmers. This spillover effect is driven by the diffusion of knowledge about how insurance works and its expected benefits rather than by the diffusion of information on behavior. While people care a great deal about whether others in their social network have purchased the new insurance product or not, this information is not conveyed to them through these traditional social networks.

Several policy implications can be drawn from these results. First, our study suggests that providing intensive information sessions about insurance to a subset of farmers and relying on social networks to rapidly multiply their effect on knowledge by others can be an effective strategy to increase the adoption of new insurance products in similar contexts. Targeting this intervention on individuals who are more central in the village network can make a significant difference in the size of the multipliers achieved. Second, our finding that farmers in traditional villages typically do not tell others about their purchase decisions 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. However, 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 adoption rate of innovative products.

Appendix

Table A1—Randomization Check: Session Assignments

	First round		Second round		
	Simple session	Intensive session	Simple session	Intensive session	p-value
Gender of household head (1 = male, 0 = female)	0.908 (0.289)	0.923 (0.266)	0.91 (0.286)	0.915 (0.279)	0.5982
Age	51.489 (11.879)	51.091 (12.173)	51.724 (12.227)	51.592 (11.841)	0.6118
Household size	4.902 (2.122)	4.856 (2.094)	4.943 (2.203)	4.945 (2.103)	0.7084
Education (0 = illiteracy, 1 = primary, 2 = secondary, 3 = high school, 4 = college)	1.193 (0.859)	1.215 (0.85)	1.194 (0.866)	1.17 (0.839)	0.6471
Area of rice production (mu)	13.668 (14.85)	14.811 (25.653)	13.041 (13.982)	13.238 (21.68)	0.1216
Share of rice income in total income (percent)	75.477 (26.746)	74.767 (26.741)	73.051 (28.465)	73.577 (28.313)	0.1312
Any disasters happened last year (1 = yes, 0 = no)	0.626 (0.484)	0.635 (0.482)	0.638 (0.481)	0.632 (0.483)	0.9528 0.9208
Loss in yield last year (percent)	27.042 (18.498)	27.683 (18.116)	27.601 (18.374)	27.651 (17.861)	
Observations	1079	1096	1587	1570	

Notes: 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.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table A2—Randomization Check: Price Randomization

	OLS coefficient on price
Gender of household head (1 = male, 0 = female)	0.00206 (0.0122)
Age	0.404 (0.319)
Household size	−0.0135 (0.0485)
Literate (1 = yes, 0 = no)	−0.00656 (0.0136)
Area of rice production (mu)	−0.000545 (0.197)
Observations	433

Note: This table checks the validity of the price randomization.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table A3—Heterogeneity of the Intensive Session Effect

Variables	Insurance Take-up (1 = Yes, 0 = No)				
Sample: all first round (simple1 and intens1)	(1)	(2)	(3)	(4)	(5)
Intensive information session	0.136	0.151***	0.128***	0.131***	0.196***
(1 = yes, 0 = no)	(0.0965)	(0.0347)	(0.0328)	(0.0303)	(0.0576)
Heterogeneity effects:					
Age	0.00172	0.00185*	0.00175	0.00178*	0.00184*
	(0.00142)	(0.00104)	(0.00107)	(0.00106)	(0.00106)
Age × intensive	0.000100				
	(0.00188)				
Education		0.0939***			
(1 = above average, 0 = below average)		(0.0343)			
Education*intensive		−0.0210			
		(0.0480)			
Experience with insurance			0.0237		
(1 = yes, 0 = no)			(0.0327)		
Experience*intensive			0.0335		
			(0.0455)		
Risk aversion ([0,1])				−0.0218	
				(0.0483)	
Risk aversion*intensive				0.0482	
				(0.0702)	
Day of session (1–61)					−0.0139
					(0.0112)
Day of session × intensive					−0.00279
					(0.00234)
Male	0.0408	0.0439	0.0400	0.0409	0.0356
	(0.0476)	(0.0469)	(0.0472)	(0.0474)	(0.0475)
Household size	−0.00294	−0.00216	−0.00315	−0.00309	−0.00329
	(0.00519)	(0.00537)	(0.00519)	(0.00520)	(0.00519)
Rice production area (mu)	0.000789	0.000773	0.000756	0.000786	0.000812
	(0.000755)	(0.000767)	(0.000730)	(0.000754)	(0.000774)
Observations	2,137	2,161	2,137	2,137	2,137
Administrative village fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.125	0.128	0.127	0.125	0.127
p-value of joint-significance:					
Intensive information session	0.0000***	0.0000***	0.0000***	0.0000***	0.0000***

Notes: Robust standard errors clustered at the natural village level in parentheses. The estimation is based on the sample of participants in the two first-round sessions (Simple-NoInfo and Intens-NoInfo in Figure 1.1).

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

Table A4—Heterogeneity of the Default Effect

Variables	Insurance Take-up (1 = Yes, 0 = No)			Prediction on percent of farmers purchasing insurance (1 if >50 %, 0 if < 50 %)
Sample: All first round (Simple1 and Intens1)	(1)	(2)	(3)	(4)
Default (1 = buy, 0 = not buy)	0.00186	0.175***	0.112*	0.00964
	(0.0446)	(0.0425)	(0.0655)	(0.0201)
Heterogeneity effects:				
Network invited to first round intensive session (NET)	0.286**			
	(0.121)			
Net × default	0.0105			
	(0.158)			
Intensive information session	0.0298	0.191***	0.142***	
(1 = yes, 0 = no)	(0.0333)	(0.0360)	(0.0260)	
Intensive × default		−0.101*		
		(0.0521)		
Trust on government (0–1)			0.00888	
			(0.0407)	
Trust on government × default			0.0136	
			(0.0662)	
Observations	1,255	2,137	2,137	2,137
R^2	0.119	0.140	0.137	0.1
p-value of joint-significance:				
Default (1 = buy, 0 = not buy)		0.0002***	0.0001***	

Notes: Robust standard errors clustered at the natural village level in parentheses. The estimation is based on the sample of participants in the two first-round sessions (Simple-NoInfo and Intens-NoInfo in Figure 1.1).

***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

Table A5—Characteristics of Insurance Takers: By Default Option

Sample: All first round (Simple1 and Intens1)	Default = Not Buy	Default = Buy	Difference
Gender of household head (1 = male, 0 = female)	0.903	0.93	−0.027
	(0.297)	(0.256)	
Age	51.588	51.212	0.377
	(11.655)	(11.526)	
Household size	4.668	5.054	−0.386***
	(1.819)	(1.988)	
Area of rice production (mu)	15.1	14.913	0.187
	(22.768)	(16.438)	
Education (0 = illiteracy, 1 = primary or above)	0.825	0.797	0.028
	(0.381)	(0.403)	
Trust on government (0-1)	0.87	0.87	0.001
	(0.337)	(0.336)	
Post-session insurance knowledge score ([0, 1])	0.519	0.466	0.052**
	(0.294)	(0.309)	
Perceived probability of future disasters (percent)	32.99	34.519	−1.53
	(17.552)	(16.778)	
Revealed purchase decision to friends (1 = yes, 0 = no)	0.104	0.122	−0.018
	(0.306)	(0.328)	

Notes: This table compares first round insurance takers facing the default buy option with those facing the default not buy option. Standard deviations are in parentheses.

***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

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