Subsidy Policies with Learning from Stochastic Experiences*

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Abstract

Many new products presumed to be privately beneficial to the poor have a high price elasticity of demand and ultimately zero uptake at market prices. This has led governments and donors to provide subsidies to increase the take-up rate, with the hope of reducing the subsidies once the value of the product is known. In this study, we use data from a two-year field experiment in rural China to define the optimum subsidy scheme that can insure a given uptake for a new weather insurance product for rice producers. We estimate a structural model of learning from stochastic experience, which we use to conduct policy simulations. Our results show that the optimum current subsidy necessary to achieve a desired level of take-up rate depends on both past subsidy levels and past payout rates, implying that subsidy levels should vary locally year-to-year.

Keywords: Subsidy, Insurance, Take-up, Stochastic Learning
JEL Classification Numbers: D12, D83, H20, G22, O12, Q12

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1 Introduction

The issue of whether to subsidize a beneficial product is a thorny one for governments and policymakers. On the one hand, there is reluctance to subsidize for fear of creating a cycle of subsidization by increasing preferences for leisure (Maestas, Mullen, and Strand (2013)) or crowding out other unsubsidized products (Cutler and Gruber (1996)). On the other hand, subsidies can be critical in achieving both product learning and economies of scale. To address this challenge, policymakers have sought to design "smart" subsidies that can fulfill their immediate purpose of enhancing take-up while offering an exit option when demand objectives have been met (Cohen and Dupas (2010)).

In this paper, we study the impact of subsidies on demand for a new weather insurance product for rice farmers in China. Uninsured weather risks are known to be a major source of welfare loss for farmers and to distort behavior in allocating resources (Rosenzweig and Binswanger (1993), Dercon and Christiaensen (2011)). However, weather insurance products typically face low take-up rates.[1] To boost adoption, governments frequently choose to subsidize the insurance.[2] Subsidies can be successful in inducing immediate take-up if demand for the insurance product is price elastic (Karlan et al. (2014), Mobarak and Rosenzweig (2014)). If take-up in turn induces learning, the hope is that future subsidies can be reduced and eventually eliminated. However, this learning process can be challenging, as learning about the value of an insurance product is a stochastic process. That is, people learn about its benefits only when an insured shock triggers a payout to themselves (direct learning) or to those in their social network (social learning, see Foster and Rosenzweig (1995), Conley and Udry (2010), Cole, Stein, and Tobacman (2014), and Karlan et al. (2014)).

In our study, we follow the framework of Sutton and Barto (1998) to construct a model of learning from stochastic experiences in which individuals update their valuation of the insurance product based on a combination of their past valuation

[1] For example, Cole et al. (2013) find an adoption rate of only 5%-10% for a similar insurance policy in two regions of India in 2006. Higher take-up at market prices was observed in Ghana, but only following a year of extensive payouts (Karlan et al. (2014)).

[2] For example in Mexico, CADENA provides index-based drought insurance to 2 million smallholder farmers at a cost fully assumed by the state and federal governments. In India, the Weather Based Crop Insurance Scheme covers 9.3 million farmers with an index-based scheme, where insurance purchase is compulsory for farmers that want to borrow from public financial institutions. For farmers who grow food crops, the cost to the farmers themselves is less than 2% of the commercial premium.

of the product and their prediction error relative to the recent realization. In our model, we specify three channels through which learning takes place: (1) a direct learning effect from one's own payout experiences, with an expected positive effect on take-up if there has been an insured shock and a payout has been received, and a negative erosion effect if a premium has been paid and either no shock occurs or a shock occurs without a corresponding payout, (2) a social learning effect from network payout experiences, which follows the same process of positive and negative effects in relation to stochastic payouts, and (3) a habit forming effect, with past use of the product influencing current demand. We then model how these learning channels would be impacted by subsidies through three separate effects: (1) a scope effect where subsidies enhance take-up and hence the opportunity to witness payouts, (2) an attention effect where a lower insurance cost for the individual leads to lower attention given to information generated by payout experiences, and (3) a price anchoring effect, where low past prices reduce current willingness to pay.

After specifying the model, we test its predictions through a two-year randomized field experiment that includes 134 villages with some 3,500 households in rural China. In the first year, we randomize subsidy policies at the village level by offering either a partial subsidy of 70% of the actuarially fair price or a full subsidy. In the second year, we randomly assign eight prices to the product at the household level, with subsidies ranging from 40% to 90%.

Results show that those households receiving a full subsidy in the first year exhibit greater demand for insurance in the second year, but that this demand is not differentially price elastic compared to that of households receiving a partial subsidy in the first year. Exploring the channels, we show that, first, receiving a payout has a positive effect on second year demand, and makes demand for the insurance product less price elastic. This effect is stronger for those households that paid for their insurance, supporting the presence of an attention effect. Symmetrically, the reduction in demand when there was no payout is stronger when households had to pay for the insurance, showing evidence of an erosion effect. Second, we find that observing payouts in their network increases second-year demand for those not insured in the first year. For those that receive insurance for free, we see a mild effect of observing payouts in their network if they did not receive a payout themselves. To explain why the learning effect is smaller under the full subsidy policy, we show that people paid less attention to the payout information if they received the insurance for free. Third, we find no evidence of price anchoring: restricting the sample to households who purchased (non-free villages) or were willing to purchase (free villages) the insurance at a 70% subsidy in the first year and facing higher subsidies in the second year, the second year take-up rate is not lower among households who got fully subsidized. Finally, we find that holding insurance in the first year does not influence either the level or the slope of the demand curve in the following year. This finding suggests that enlarging the coverage rate is not enough to secure persistence in insurance take-up.

Reduced form results help us validate the empirical relevance of the channels at work in the structural model of learning from stochastic experiences. We then estimate the structural model and use it to simulate policy options. We find that current subsidies can be reduced when the previous year's subsidy level and payout rates were higher. This finding suggests that subsidies need to be continuously adjusted to achieve the desired take-up rate at the minimum cost. We provide a way to design a simple policy rule that governments can use to determine the optimum level of subsidy in a particular location and time to achieve the desired level of take-up.

A number of studies have examined the impact of providing subsidies on the take-up of products where learning is non-stochastic. For example, Dupas (2014) finds that a one-time subsidy for insecticide-treated bednets has a positive effect on take-up the following year, a result which is mainly driven by a large positive learning effect. In another study, Fischer et al. (2014) find that positive learning can offset price anchoring in the long term adoption of health products. Finally, Carter, Laajaj, and Yang (2014) find that subsidies in Mozambique induce both short-term take-up and long-term persistence in the demand for fertilizer and improved seeds, which they attribute to both direct and social learning effects. Our results contribute to this literature by showing that products with stochastic learning processes may need to have continuously adjusted subsidy rates based on both past subsidy levels and payout rates.

Our study also provides insight into why products such as weather index insurance face low adoption rates.[3] Existing research has elicited factors influencing take-up such as liquidity constraints, a lack of financial literacy, present bias, and a lack of

[3]To protect farmers from weather shocks, many governments have introduced comprehensive financial strategies that allow the transfer of risk through disaster insurance (Cummins and Mahul (2009)). In these cases, index-based insurance is often selected over standard insurance as it avoids adverse selection and moral hazard concerns. It also sharply reduces implementation transaction costs (Chantarat et al. (2013)).

trust in the insurance provider (Gaurav, Cole, and Tobacman (2011), Giné, Townsend, and Vickery (2008), Cole et al. (2013), Cai, de Janvry, and Sadoulet (2015)). However, even when these barriers are removed in an experimental setting, studies have found that insurance take-up remains low. Our insight regarding the stochastic nature of the learning process related to insurance benefits contributes to the overall understanding of the reasons behind the low take-up phenomenon, in particular by showing that subsidies need to be carefully calibrated to past policies and events to be effective in enhancing take-up while holding costs low.

Finally, our study contributes to the literature on the optimal design of financial strategies for disaster risk financing and insurance. Countries typically use a combination of financial reserves, contingent credit, index insurance, and post-disaster budget reallocations and borrowing in forming their disaster risk financing plans. The design of such strategies has been explored through both actuarial cost-minimization (Clarke et al. (2015)) and Probabilistic Catastrophe Risk Models (CAPRA (2015)). We extend this analysis by formalizing a rule for how subsidy use can be optimized when learning from stochastic experiences determines private take-up.

The paper proceeds as follows. In section 2, we explain the background for the insurance product in China. In section 3, we present the experimental design and discuss the data collected. In section 4, we develop a structural model of dynamic learning, conceptualizing the different channels that impact subsequent insurance take-up. In section 5, we outline the reduced form estimation strategy and present both the aggregate and channel-level results of our analysis. Section 6 reports on the estimation of the structural model and the policy simulation. Section 7 concludes with a discussion of policy implications.

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 asked 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.[4] The program was expanded to 62 counties in 2010 and then to 99 in 2011. The experiment was conducted in 2010 and 2011 in a set of randomly selected villages in Jiangxi province, one of China's major rice producing areas.[5] In the selected villages, rice production is the main source of income for most farmers. Given the new nature of the insurance product, farmers and government officials had limited understanding of weather insurance and no previous interaction with the PICC.

The product in our study is an area-index based insurance policy that covers natural disasters, including heavy rains, floods, windstorms, extremely high or low temperatures, and droughts. If any of these natural disasters occurs and leads to a 30% or more average 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 full yield loss.[6] Areas for indexing are typically fields that include the plots of 5 to 10 farmers. 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 production costs around 400 RMB per mu, the insurance policy covers 25% of gross income or 50% of production costs. The actuarially fair price for the policy is 12 RMB per mu, or 3% of production costs, per season.[7] If a farmer decides to buy the insurance, the premium is deducted from a rice production subsidy deposited annually in each farmer's bank account, with no cash payment needed.[8]

Like any area-yield insurance product, it is possible that insured farmers may collude. However, given that the maximum payout (200 RMB/mu) is much lower

[4] Although there was no insurance before 2009, if major natural disasters occurred, the government made payments to households whose production had been seriously hurt by the disaster. However, the level of transfer was usually far from sufficient to help farmers resume normal levels of production the following year.

[5] These refer to natural villages, whereas "administrative villages" refer to bureaucratic entities that typically contain several natural villages.

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

[7] 1 RMB = 0.15 USD; 1 mu = 0.165 acre. Farmers produce two or three seasons of rice each year. The annual gross income per capita in the study region is around 5000 RMB.

[8] Starting in 2004, the Chinese government provided production subsidies to rice farmers in order to increase production incentives. Each year, subsidies are deposited directly in the farmers' accounts at the Rural Credit Cooperative, China's main rural bank.

than the expected profit (800 RMB/mu), as well as the verifiable nature of natural disasters, it is unlikely that the insurance is subject to moral hazard concerns.

3 Experimental Design and Data

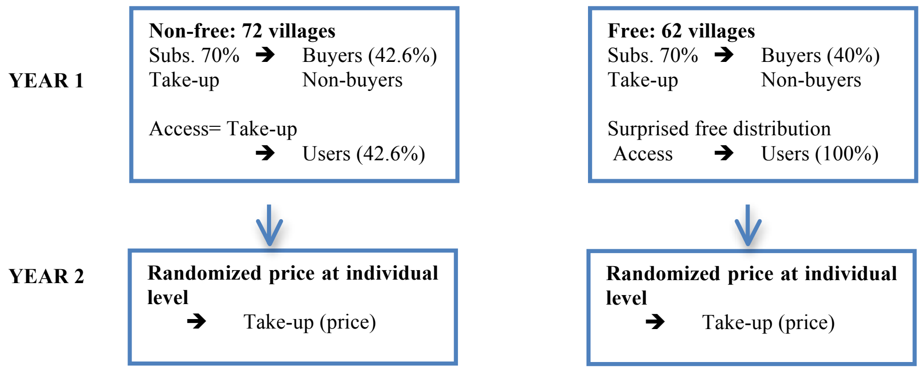
3.1 Experimental Design

The experimental site consists in 134 randomly selected villages in Jiangxi Province with around 3500 households. We carried out a two-year randomized experiment in Spring 2010 and 2011.

The experimental design is presented in Figure 1. The treatment involves randomization of the subsidy level in each year of the study. In the first year, we randomize the subsidy policy at the village level. The insurance product is first offered at 3.6 RMB/mu, i.e. with a 70% subsidy on the fair price, to all households in order to observe take-up at that price. Two days after this initial sale, households from 62 randomly selected villages were surprised with an announcement that the insurance will be offered for free to all, regardless of whether they had agreed to buy it or not at the initial price. These villages are referred to as the "free sample" while the remaining 72 villages as the "non-free sample". This design allows us to distinguish "buyers" of insurance who agree to pay the offer price of 3.6 RMB/mu from "users" of insurance who include all buyers from the non-free sample group as well as all households from the free sample group. As reported in Figure 1, the insurance take-up rate at the 3.6 RMB/mu price is similar in the two samples at around 40-43%.

For the first year village randomization, we stratify villages by their total number of households. In order to generate exogenous variation in individual insurance take-up decisions, we also randomize a default option in 80% of the villages. We assign half the households in a given village with a default "BUY" option, meaning the farmer must sign off if he does not want to purchase the insurance. We assign the other half with a default "NOT BUY" option, meaning the farmer must sign on if he decides to buy the insurance. Both groups otherwise receive the same pitch for the product. The randomized default option will be used in some estimation as an IV for the first year insurance purchase decisions together with the randomized subsidy policy. Note that the first year of our study coincided with a fairly large occurrence of adverse weather events that triggered insurance payouts, with almost 60% of the insured receiving a payout from the insurance company.

Figure 1. Experimental Design



In the second year of our study, we randomize the subsidy level from 90 to 40% of the fair price for each household. This creates eight different price treatment subgroups. Except for the price, everything else remained the same in the insurance contract as in the first year. Similar to the design in Dupas (2014), only two or three prices are assigned within each village.[9] For example, if one village is assigned a price set (1.8, 3.6, 5.4), each household in that village is randomly assigned to one of these three prices. To randomize price sets at the village level, we stratify villages by size (total number of households) and first year village-level insurance payout rate. To randomize prices within the set, we stratify households by rice production area.

In both years, we offer information sessions about the insurance policy to farmers, in which we explain the insurance premium, the amount of government subsidy, the responsibility of the insurance company, the maximum payout, the period of coverage, the rules for loss verification, and the procedures for making payouts. Households make their insurance purchase decision immediately after the information session. In the second-year information session, we also inform farmers of the list of people in the village who were insured and of the payouts made during the first year at both the household and village level.

[9] Price sets with either two or three different prices are randomly assigned at the village level. For villages assigned with two prices $(P_1, P_2), P_1 <= 3.6$ and $P_2 > 3.6$; for villages with three prices $(P_1, P_2, P_3), P_1 < 3.6, P_2 \in (3.6, 4.5)$, and $P_3 > 4.5$.

3.2 Data and Summary Statistics

The empirical analysis is based on the administrative data of insurance purchase and payout from the insurance company, and on household surveys conducted after the insurance information session each year. Since all rice-producing households were invited to the information session, and almost 90% of them attended, this provides us with a quasi census of the population of these 134 villages. In total, 3474 households were surveyed.

We present the summary statistics of selected variables in Table 1. The statistics in Panel A show that household heads are almost exclusively male and cultivate on average 12 mu (0.80 ha) of rice per year. Rice production is the main source of household income, accounting on average for almost 70% of total income. Households indicate an average risk aversion of 0.2 on a scale of zero to one (risk averse).[10] In Panel B, we summarize the payouts issued during the year following the first insurance offer. With a windstorm hitting some sample villages, 59% of all insured households received some payout in the first year of our study, with an average payout size of around 90 RMB. The payout rate was not significantly different between households in free vs. non-free villages, at 61% and 57%, respectively. For the non-free villages, this corresponds to 24% of all households. All households, regardless of whether they purchased the insurance or not, could also observe their friends' experiences. Identification of friends come from a social network census conducted before the experiment in year one. In that survey, we 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.[11] In the sample of non-free villages, 68% of households had at least one friend receiving a payout, while in free villages, 81% of households observed at least one of their friends receiving a payout. As a result, since more households were covered by insurance in villages with full subsidies, most households were able to enjoy the benefits of insurance by themselves, or could observe their friends' positive experiences with the product. Lastly, Panel C shows that the first year take-up rate is 41% while the second year take-up rate is 53%, with this increase coming a 7.3

[10] Risk attitudes are 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 a risky gamble of (200 RMB, 0) with probability (0.5, 0.5) (risky option B). The proportion of riskless options chosen is then used as a measure of risk aversion, which ranges from 0 to 1.

[11] For a detailed description of the network data, please refer to Cai, de Janvry, and Sadoulet (2015).

(16.3) percentage point increase in the non-free (free) villages.

Table 1. Summary Statistics

	Sample Mean			
	All	Non-free	Free	Difference
PANEL A: HOUSEHOLD CHARACTERISTICS				
Household Head is Male	0.969	0.973	0.965	0.009
	(0.003)	(0.004)	(0.005)	(0.006)
Household Head Age	53.074	52.855	53.330	-0.475
	(0.200)	(0.268)	(0.301)	(0.401)
Household Size	5.231	5.170	5.301	-0.131
	(0.041)	(0.054)	(0.061)	(0.082)
Household Head is Literate	0.718	0.716	0.720	-0.003
	(0.008)	(0.010)	(0.011)	(0.015)
Area of Rice Production (mu)	11.774	11.962	11.556	0.405
	(0.202)	(0.294)	(0.272)	(0.405)
Share of Rice Income in Total Income (%)	69.692	68.984	70.494	-1.51
	(0.494)	(0.643)	(0.760)	(0.989)
Risk Aversion (0-1, 0 as risk loving and 1 as risk averse)	0.204	0.200	0.209	-0.009
	(0.006)	(0.008)	(0.008)	(0.011)
Perceived Probability of Future Disasters (%)	33.030	32.831	33.263	-0.432
	(0.269)	(0.397)	(0.352)	(0.539)
PANEL B: INSURANCE PAYOUT				
Payout Rate (% of all households)	40.82	24.18	60.19	-0.36***
	(0.83)	(0.99)	(1.22)	(0.016)
Payout Rate Among First Year Insured (%)	58.58	56.71	60.91	-0.042
	(1.3)	(1.76)	(1.93)	(0.026)
Amount of Payout Received by First Year Insured (RMB, per mu)	93.34	98.04	87.47	10.57
	(4.91)	(7.29)	(6.22)	(0.01)
Having at Least One Friend Receiving Payout (1 = Yes, 0 = No)	0.74	0.68	0.81	-0.125***
	(0.01)	(0.01)	(0.01)	(0.015)
%Friends Receiving Payout (among insured friends)	54.51	56.58	52.33	0.043***
	(0.7)	(1.07)	(0.89)	(0.014)
PANEL C: OUTCOME VARIABLE				
Insurance Take-up Rate (%), Year One	41.39	42.64	39.91	0.027
	(0.84)	(1.14)	(1.23)	(0.017)
Insurance Take-up Rate (%), Year Two	52.85	49.92	56.26	-0.063***
	(0.85)	(1.16)	(1.24)	(0.017)
No. of Households: 3474				
No. of Villages: 134				

Note: Standard errors are in brackets. 1 mu=1/15 hectare; 1 RMB=0.16 USD. Risk attitudes were elicited by playing five rounds of games with households, in which they were asked to choose between increasing amounts of certain money (riskless option A) and risky gambles (risky option B). The number of riskless options was then used as a measure of risk aversion. The perceived probability of future disasters was elicited by asking "what do you think is the probability of a disaster that leads to more than 30% loss in yield next year?". In Panel B, payout rate (% of all households) indicates the rate of payout among all sample households, regardless of whether they purchased insurance; Payout rate among first year insured (%) is defined as the payout rate among households who purchased insurance (nonfree sample) or households who were willing to purchase the insurance (free sample). *** p<0.01, ** p<0.05, * p<0.1.

To verify the price randomization, we regress the five main household characteristics (gender, age, household size, education, and area of rice production) on a quadratic function in the insurance price and a set of village fixed effects:

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

where X_{ij} represents a characteristic of household i in village j, $Price_{ij}$ is the post-subsidy price faced by household i in village j, and η_j a village fixed effect. Table 2 reports the coefficient estimates and standard errors for α_1 (column (1)) and α_2 (column (2)). All of the coefficient estimates are small in magnitude and none is statistically significant, confirming the validity of the price randomization.

Table 2. Price Randomization Check

Sample: All	OLS Coeff on Price (1)	OLS Coeff on Price Squared (2)	P-Value Joint Test (Price and Price Squared) (3)
Household Head is Male	0.0089	-0.0011	0.6224
(Number of obs: 3474)	(0.0093)	(0.0012)	
Household Head Age	0.3191	-0.0354	0.8653
(Number of obs: 3471)	(0.6006)	(0.0694)	
Household Size	-0.01	0.0022	0.9117
(Number of obs: 3471)	(0.128)	(0.0147)	
Household Head is Literate	0.0196	-0.002	0.6038
(Number of obs: 3450)	(0.0232)	(0.0027)	
Area of Rice Production (mu)	0.6467	-0.071	0.5745
(Number of obs: 3471)	(0.7086)	(0.0864)	

Note: Each row represents a regression of the characteristic noted in the first column on the price and its square, and column 3 reports the p-value for the joint test of significance of the two coefficients. Robust clustered (to village level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4 Theoretical Framework

4.1 Set-up

The net utility of buying insurance is posited to be additive in gains and costs. We assume that there are two states of nature, and let p^L be the probability of a negative weather shock, and $p^H = 1 - p^L$. The benefit V^L of having insurance in a negative weather shock state is the utility gain of receiving a payout at the low realization of income y^L, $V^L = U(y^L + payout) - U(y^L))$, while the utility gain in the absence of a shock is $V^H = 0$. Without other information, the expected utility gain of having insurance at the onset of the first year is:

$$EV_1 = p^L V^L + p^H V^H.$$

In the context of insurance products, any learning from one period is contingent on the realization of the state of nature. We assume a simple learning model, the temporal difference reinforcement learning (TDRL in Sutton and Barto (1998)), which incorporates recency effects. In this model, individuals update their valuations based on the realization in the previous period:

$$EV_t = EV_{t-1} + \lambda \left(V^*_{t-1} - EV_{t-1} \right) \tag{2}$$

where V^*_{t-1} is the experienced benefit in year $t-1$. This experienced benefit results from either your own realization V_{t-1} or observing your network realization $NetV_{t-1}$ in the previous year. It also depends on I_{t-1}, an indicator of whether an individual is insured at the time of the realization. Without specifying further, the functional form is $V^*_{t-1} = g(V_{t-1}, NetV_{t-1}, I_{t-1})$.

Note that the term $V^*_{t-1} - EV_{t-1}$ represents a *prediction error*. If this term is positive (negative), then the realized value of the insurance is higher (lower) than its expected value. In this specification, λ controls the rate at which information from past observations is discounted. When $\lambda = 1$, the expected value of insurance is the previous year's realization; when $\lambda = 0$, there is no updating in the expected benefits from insurance. The higher the parameter, the more responsive individuals are to the recent realizations. The model thus captures "recency bias". We further specify λ to be a function of the price paid for the insurance: $\lambda_t = \lambda(p_{t-1})$. In this way, our model is similar to a Bayesian learning model that allows for incomplete information or poor recall related to past events Gallagher (2014). However, in our model, a belief is updated regarding the value of the insurance, as it is really the payout experience and not the weather event that influences subsequent take-up decisions, as we will see it later.

The costs of insurance include three terms: the price at which the insurance is offered p_t, a gain-loss in utility which we assume to be a linear function of the difference between the offered price and a reference price, $\gamma(p_t - p_{rt})$, and a transaction cost Îťt. Transaction costs are assumed to depend on past experience, i.e., $\delta_t = \delta(I_{t-1})$. Adding a preference shock ϵ_t, the overall utility of purchasing insurance for an individual then becomes:

$$W_t - \epsilon_t \equiv EV_{t-1} + \lambda_t \left(g(V_{t-1}, NetV_{t-1}, I_{t-1}) - EV_{t-1} \right) + \beta p_t + \gamma \left(p_t - p_{rt} \right) I_{t-1} + \delta_t - \epsilon_t \tag{3}$$

4.2 Link with the Experiment

In the experiment, we analyze the purchase of insurance in years 1 and 2 such that:

$$\begin{aligned} Buy_1 &= 1 \quad \text{if } \epsilon_1 < W_1 \equiv EV_1 + \beta p_1^* \\ &= 0 \quad \text{otherwise} \\ Buy_2 &= 1 \quad \text{if } \epsilon_2 < W_2 \equiv EV_1 + \lambda(p_1) \left(g(V_1, NetV_1, I_1) - EV_1 \right) + \beta p_2 + \gamma \left(p_2 - p_1 \right) I_1 + \delta(I_1) \\ &= 0 \quad \text{otherwise} \end{aligned} \tag{4}$$

Note that there are two prices for period 1: the price p_1^* is the unique price at which the insurance was first offered to all farmers in order to elicit their demand for insurance. Then, in a random sample of villages, farmers were "surprised" by a government decision to give out the insurance for free. The reference price that enters the second year decision, p_1, is thus either the initial price offer p_1^* or 0. This design allows us to separate the insurance purchase Buy_1 (at p_1^*) from access I1, which also includes farmers that receive the insurance in year 1 for free after choosing not to buy it originally.

These two preference shocks are correlated. We further assume that they are jointly distributed Normal: $\epsilon_1, \epsilon_2 \sim \mathbb{N}(0, 0, 1, 1, \rho)$. The probability of observing a given purchase behavior over the two years is thus:

$$\begin{aligned} Pr(Buy_1 = b_1, Buy_2 = b_2) &= \Phi(b_1 W_1 + (1 - b_1)(1 - W_1), \\ &\quad\; b_2 W_2 + (1 - b_2)(1 - W_2), \rho), \quad \text{for } b_1, b_2 \in (0, 1) \end{aligned}$$

which can also be written as:

$$Pr(Buy_1 = b_1, Buy_2 = b_2) = \Phi(q_1 W_1, q_2 W_2, q_1 q_2 \rho) \tag{5}$$

with $q_t = 2b_t - 1, t = 1, 2$.

Note that we have distinguished purchase and access in year 1 to accommodate the experimental design. In the policy simulation, however, access is determined endogenously by the first year purchase decision.

The different mechanisms that may influence the purchase of insurance in the second year are readily seen in the W_2 expression:

- *Direct learning from own payouts*: This mechanism enters the equation through the realized V_1 in expression (4), creating a recency bias in demand. Neglecting any network effect, for those insured in year 1, the term $g(V_1, NetV_1, I_1) - EV_1$ is equal to $V_1 - EV_1$. If these households experience a weather shock and subsequent payout, this term is positive and their demand increases. By contrast, with no weather shock, $V_1 - EV_1$ is negative and insurance demand drops, revealing an erosion effect. Since the updating parameter is a function of the price in year 1, $\lambda(p_1)$, the rate of updating can be sharper under a partial subsidy than when insurance is provided for free, due to an attention effect.

- *Social learning from network payouts*: This mechanism enters the equation through $NetV_1$ in $g(V_1, NetV_1, I_1)$. The effect is qualitatively similar to that of receiving a payout.

- *Habit formation and transactions costs* enter the equation through the term $\delta(I_1)$

The respective effects of any first year price subsidy on second year take-up can also be identified in equation (4):

- A *scope* effect or potential for experience through its determination of access I_1 in year 1.

- An *attention* effect with its influence on the rate of adjustment in expectation through $\lambda(p_1)$.

- A *price anchoring* effect with the term $\gamma\,(p_2 - p_1)$.

5 Reduced Form Results

In this section, we estimate the reduced form relationship between the first year subsidy level and the second year insurance take-up rate. We first compare the overall second year insurance take-up in villages that either received the insurance for free or paid a base price of 3.6 RMB/mu in the first year. We then explore potential channels leading to the aggregate effect, including learning (direct and social learning, as well as discouragement and attention effects), price anchoring, and habit formation.

5.1 The Aggregate Effect of First-Year Subsidies on Second-Year Take-up

To evaluate the aggregate effect of providing insurance for free in the first year, we estimate the following equation:

$$Takeup_{ij2} = \alpha_1 Price_{ij2} + \alpha_2 Free_{ij1} + \alpha_3 Price_{ij2} * Free_{ij1} + \alpha_4 X_{ij} + \eta_j + \epsilon_{ij} \quad (6)$$

where $Takeup_{ij2}$ is an indicator for the purchase decision made by household i in village j in year two, $Price_{ij2}$ the price that it faced, $Free_{ij1}$ an indicator for being under full subsidy in the first year, X_{ij} are household characteristics such as gender, age, production size, etc., and η_j are village dummies.

Results in Table 3, column (1), show that the second year take-up rate among households offered a full subsidy policy in the first year is higher than that of households offered a partial subsidy (5.97 percentage points, about a 10% increase, significant at the 10% level). The results in column (2) show that adding controls does not impact our findings. The results in column (3) show that households with different first year subsidies do not differ in the slope of their demand curve. The slope parameter of -0.49 translates into a price elasticity of -0.44 for the price level of 3.6 RMB/mu and the corresponding take-up rate of 40%. This is lower than the [-1.04, -1.16] range for the price elasticity found in Gujarat by Cole et al. (2013), but of the same order of magnitude as the U.S. price elasticities they cite (in the [-.32, -.73] range).

5.2 Mechanisms Driving the Subsidy Effect on Insurance Take-Up

While the observed aggregate effect may seem small, it is the result of a number of opposing forces and heterogeneous effects that we now explore. In particular, we

Table 3. Effect of First Year Subsidy Policies on Second Year Insurance Demand

VARIABLES	Insurance Take-up Year 2 (1 = Yes, 0 = No)		
Sample: All	(1)	(2)	(3)
Price (RMB/mu)	-0.0487***	-0.0492***	-0.0526***
	(0.00545)	(0.00525)	(0.00736)
Free year 1 (1 = Yes, 0 = No)	0.0597*	0.0544*	0.0240
	(0.0304)	(0.0295)	(0.0503)
Price * Free year 1			0.00749
			(0.0104)
Household head is male		-0.0132	-0.0120
		(0.0491)	(0.0493)
Household head age		0.00326***	0.00325***
		(0.000835)	(0.000836)
Household size		0.0117***	0.0116***
		(0.00373)	(0.00373)
Household head is literate		0.0610***	0.0608***
		(0.0202)	(0.0202)
Area of rice production (mu)		0.00195**	0.00196**
		(0.000763)	(0.000765)
Risk aversion (0-1)		0.176***	0.178***
		(0.0305)	(0.0306)
Perceived probability of future disasters (%)		0.00255***	0.00255***
		(0.000373)	(0.000374)
Observations	3,474	3,442	3,442
R-squared	0.036	0.069	0.1552
P-value of joint significance test:			
Price and Price*Free			0.0000***
Free and Price*Free			0.0000***

Notes: 1 mu=1/15 hectare; 1 RMB=0.16 USD. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

analyze three potential channels of causation between subsidy policies and subsequent demand for insurance: learning, price anchoring, and habit formation.

5.2.1 Direct and Social Learning, and the Attention Effect

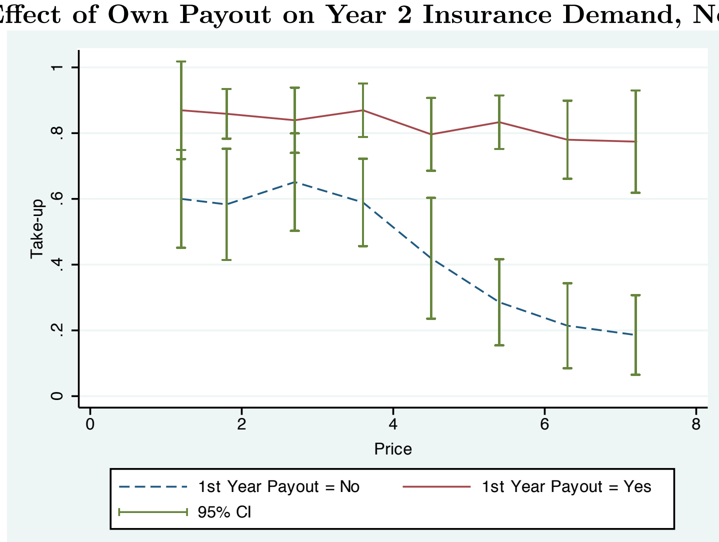
Households learn about the value of insurance by receiving or observing insurance payouts. However, the impact of subsidy levels on this learning is unclear. On the one hand, a subsidy may increase initial take-up rates, meaning more people may receive or observe payouts. On the other hand, if a household has not contributed to paying for its own insurance, there may be less attention or intensity dedicated to learning about the value of the insurance product.[12]

To explore the impact of payout experience on subsequent take-up, we first examine the effect of directly receiving a payout in the first year on second year insurance demand. To maintain sample comparability, we restrict this analysis to those households that pay for insurance (in the non-free villages) or are willing to do so (in the free villages) in the first year. Figures 2.1 and 2.2 compare the free and non-free group insurance demand curves for households that receive a payout to those for households that do not receive a payout. These figures show that receiving a payout induces a higher level of renewal of the insurance contract, making the insurance less price elastic. The corresponding estimating equation is:

$$Takeup_{ij2} = \alpha_1 Price_{ij2} + \alpha_2 Payout_{ij1} + \alpha_3 Price_{ij2} * Payout_{ij1} + \alpha_4 X_{ij} + \eta_j + \epsilon_{ij} \quad (7)$$

where $Payout_{ij1}$ is a dummy variable equal to one if the household received a payout in year 1.

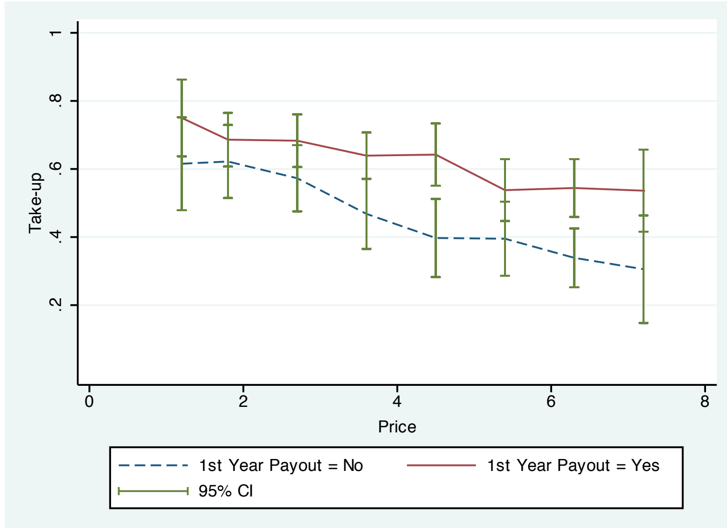
Figure 2.1. Effect of Own Payout on Year 2 Insurance Demand, Non-free Year 1



We report the estimation results in Table 4. For households that receive a partial subsidy in the first year (columns (1) and (2)), receiving a payout improves their

[12]For experience-based goods, two arguments have been given for why the learning effect could be lower when people pay less: the "screening effect" of prices could be lower (Ashraf, Berry, and Shapiro (2010)) or people who pay more for a product may feel more obliged to use it; thus, the "sunk cost" effect is higher with lower subsidies.

Figure 2.2. Effect of Own Payout on Year 2 Insurance Demand, Free Year 1



second year take-up rate by 35 percentage points, and mitigates the subsidy removal (price) effect by around 80%.[13] To control for any potential confounding effect related to the fact that experiencing a bad weather shock could affect people's risk attitudes or perceived probability of future disasters, we include these variables in the vector of household characteristics X_{ij}. To further control for any direct effect due to the severity of a weather-related loss, we use a regression discontinuity method, with the loss rate as the running variable and instrumenting payout with a threshold in loss of 30%. The results of this analysis, in column (3), show that the payout effect is still large and significant, suggesting that the weather shock event does not explain the payout effect. For households that receive a full subsidy in the first year (columns (4)-(6)), the magnitude of the payout effect is only about half of that observed for households that paid some amount for their insurance. The effect of a payout on the slope of the second year demand curve is similar in size but is less significant.

To further characterize the learning process, note in Figures 2.1.and 2.2 that absent a payout, there is a very substantial decline in take-up rate at 3.6 RMB/mu from 100% in year 1 to 45-60% in year 2, depending on whether the insurance was free or not in year 1, while the demand after a payout is higher among those that paid for the insurance in the first year. Column (7) of Table 4 confirms this: in absence of

[13]We also test the impact of the amount of payout received in the first year on second year take-up rates (Table A1). The effect pattern is similar to that indicated in Table 4.

Table 4. Effect of Receiving Payouts on Second Year Insurance Demand

VARIABLES	Insurance Take-up Year 2 (1 = Yes, 0 = No)						
Sample: Insurance Take-up Year 1=Yes	*Non-free Year 1*			*Free Year 1*			*All*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price	-0.0452***	-0.078***	-0.0717***	-0.0458***	-0.0651***	-0.0731***	-0.0466***
	(0.0086)	(0.0135)	(0.0133)	(0.01)	(0.0188)	(0.0210)	(0.00652)
Payout (1 = Yes, 0 = No)	0.35***	0.0901	0.206*	0.1658***	0.0346	0.0243	0.356***
	(0.0351)	(0.0798)	(0.108)	(0.0403)	(0.083)	(0.128)	(0.0349)
Price * Payout		0.0633***	0.0520***		0.0333	0.0473*	
		(0.0164)	(0.0177)		(0.0216)	(0.0258)	
Free year 1							0.0996**
							(0.0465)
Payout*Free year 1							-0.166***
							(0.0557)
Loss rate in yield			-0.00334			0.00364	
			(0.00295)			(0.00502)	
Square of loss rate in yield			3.48e-05			-5.64e-05	
			(2.97e-05)			(5.01e-05)	
Mean value of dependent variable	0.499	0.499	0.499	0.563	0.563	0.563	0.528
Observations	790	790	790	632	632	608	1,422
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.2581	0.2736	0.26	0.130	0.1344	0.138	0.183
P-value of joint significance test:							
Price and Price*Payout		0.0000***	0.0000***		0.0001***	0.0002***	
Payout and Price*Payout		0.0000***	0.0000***		0.0004***	0.012**	
Payout and Payout*Free							0.0000***
Free and Payout*Free							0.0119**

Note: This table is based on the sample of households who purchased insurance (nonfree) or agreed to purchase insurance (free) with 70% government subsidies in Year 1. In columns (3) and (6), payout is instrumented by the cutoff of yield loss to receive payout. Household characteristics include gender, age, level of education of the household head, rice production area, housheold size, risk attitude, and the perceived probability of future disasters. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

payout, the demand for insurance is higher after a year of free experience than it is if households have paid some amount for their insurance. However, the opposite holds if a payout if received. These results suggest that providing a full subsidy mitigates any payout reaction, with less of a decline in demand when there is no payout but also a smaller positive effect when there is a payout.

We next examine the effect of observing payouts in your network on subsequent insurance take-up rates. To do so, we include the network payout variable, $NetPayHigh$. This is a dummy variable that indicates whether more than half of the insured members within a farmer's personal network receive a payout in the first year. The results in Table 5, column (1) indicates that the effect of observing payouts in your network on subsequent insurance take-up is smaller among households that receive a full subsidy.

To better understand the interaction between learning from one's own experience and learning from others' experiences, we look at the results for three groups sepa-

Table 5. Effect of Observing Friends Receiving Payouts on Second Year Insurance Demand

VARIABLES	Insurance Take-up Year 2 (1 = Yes, 0 = No)			
Sample:	All	Not insured in Year 1	Insured (not free) in Year 1	Insured (for free) in Year 1
	(1)	(2)	(3)	(4)
Price	-0.0466***	-0.0464***	-0.0468***	-0.0413***
	(0.00546)	(0.0107)	(0.0085)	(0.0074)
High network payout rate (NetPayHigh)	0.218***	0.226***	0.0492	0.1205***
	(0.0318)	(0.0394)	(0.066)	(0.0456)
Payout			0.3813***	0.1959***
			(0.0426)	(0.0423)
NetPayHigh*Payout			-0.0066	-0.1258**
			(0.0793)	(0.0536)
Free year 1	0.119***			
	(0.0370)			
NetPayHigh*Free year 1	-0.102**			
	(0.0475)			
Mean value of dependent variable	0.530	0.390	0.645	0.567
Observations	3,179	962	665	1,552
Village fixed effects	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
R-squared	0.120	0.148	0.314	0.107
P-value of joint significance test:				
NetPayHigh and NetPayHigh*Free	0.0000***			
Free and NetPayHigh*Free	0.0069***			

Note: High network payout rate is defined as equal to 1 if network payout rate ≥ 0.5 and 0 otherwise. Household characteristics include gender, age, level of education of the household head, rice production area, household size, risk attitude, and the perceived probability of future disasters. Regressions in columns (2) and (3) also control for the proportion of friends in one's social network who have purchased the insurance in the first year, instrumented with the network members average default option and education. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

rately: households not insured in the first year, households that pay for the insurance, and households that receive a full subsidy. The estimating equation is as follows:

$$\begin{aligned} Takeup_{ij2} =& \alpha_1 Price_{ij2} + \alpha_2 NetPayHigh_{ij1} + \alpha_3 Payout_{ij1} \\ &+ \alpha_4 NetPayHigh_{ij1} * Payout_{ij1} + \alpha_5 NetTakeup_{ij1} + \eta_j + \epsilon_{ij} \end{aligned} \tag{8}$$

where $NetTakeup_{ij1}$ is the proportion of friends in one's social network who purchased the insurance in the first year, instrumented by the household head's education and the default first-year insurance option.

Column (2) of Table 5 shows that households not insured in year 1 (and hence without any direct experience) are strongly influenced by their network experience. In contrast those that purchased the insurance are solely affected by their own experience (column (3)). Among households that received a full subsidy, observing payouts to their network influences subsequent take-up only for those that have not received any payout themselves (column(4)).[14] This effect is half of what is observed for those that were not insured (column (2)).[15] In conclusion, households that had a tangible experience with the insurance (either because they purchased it or because they received it for free but benefited from a payout) rely on their own experience to update their valuation of the insurance, while those that either were not insured or insured for free and had no payout are influenced in their decision by the experience of their network.

It is possible that the results could be driven by either an improvement in trust in the insurance company or by an income effect. In additional tests, we consider these possibilities. In the first test, we construct a trust index based on household responses to a question on the second year survey as to whether they trust the insurance company regarding loss assessment and the payout issuing process. The findings in Table A4 indicate that regressing this trust index on receiving or observing a payout shows no effect, in either non-free or free villages. Furthermore, we find that adding the trust index in the regressions of insurance take-up in year 2 on payout does not change the payout coefficients. In the second test, we looked at heterogeneity in the effect of one's own payout on take-up in year 2 by year 1 household income level, and find no significant effect (Table A5). As a result, we conclude that the payout effect is mainly driven by learning about the value of insurance.

We also further explore the finding that those who receive a full subsidy exhibit less learning about the value of insurance, as measured by the effect of payout on subsequent take-up rates. We interpret this result as evidence of an attention effect. To verify this interpretation, we examine household information session attendance and performance on a short knowledge quiz. We find no significant difference in the attendance rate between villages with different first year subsidy policies (both at 86%). However, on a question testing a household's knowledge of the payout rate in their village, 55% of respondents in the non-free villages answer correctly, but only 36% in free villages do so (Table A6). We use this finding as evidence that households

[14] We also examine the effect of peer experience among those not willing to buy the insurance initially but then receiving it as part of the "free" treatment condition and find a similar impact magnitude.

[15] We also use two other indicators of network payouts to estimate equation (8): a dummy variable indicating whether a household has at least one friend receiving payout and the average amount of payout received by friends. The results are reported in Tables A2 and A3, respectively. These results show that while people care about whether their friends receive any payout (Table A2), they do not pay much attention to the amount of the payout (Table A3).

that receive a full subsidy pay less attention to payout information.

5.2.2 Price Anchoring

We next consider whether there is a price anchoring effect (which would make the price subsidy less attractive to the policy makers). To assess the possibility of an anchoring effect, we examine the set of households that were willing to purchase the insurance at 3.6 RMB/mu in the first year and that are assigned a price lower or equal to 3.6 RMB/mu in the second year. For this group, the second year price is an increase for those that receive a full subsidy in the first year, a decrease or no change for those that received a partial subsidy. If there is an anchoring effect, we should see a lower second-year take-up rate among the households with full subsidy the first year. However, regression results in Table 6 show that the difference between those who are fully subsidized and those who are not is small and insignificant. As a result, we do not find evidence for a price anchoring effect in this context.

Table 6. Test of Price Anchoring Effect

VARIABLES	Insurance Take-up Year 2 (1 = Yes, 0 = No)	
	(1)	(2)
Price	-0.0111	0.00609
	(0.0240)	(0.0329)
Free year 1	0.0184	0.120
	(0.0378)	(0.0799)
Price * Free year 1		-0.0406
		(0.0357)
Observations	745	745
Household characteristics	Yes	Yes
R-squared	0.018	0.019
P-value of joint significance test:		
Price and Price*Free		0.3138
Free and Price*Free		0.305

Note: The sample consists in households that either purchased or were willing to purchase the insurance at 3.6 RMB/mu the first year, and were offered the insurance at a price less or equal to 3.6 RMB/mu the second year. Household characteristics include gender, age, level of education of the household head, rice production area, housheold size, risk attitude, and the perceived probability of future disasters. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2.3 Habit formation

Finally, to assess the existence of habit formation, we test whether households are more likely to buy insurance in the second year if they are insured in the first year with the following regression:

$$Takeup_{ij2} = \alpha_1 Price_{ij2} + \alpha_2 Insured_{ij1} + \alpha_3 Price_{ij2} * Insured_{ij1} + \alpha_4 X_{ij} + \eta_j + \epsilon_{ij} \quad (9)$$

where $Insured_{ij1}$ is an indicator for being insured for household i in village j in the first year. Since being insured in the first year is endogenous to the second year purchase behavior, we use first year subsidy policies (free or non-free) and the randomized default options as instruments for $Insured_{ij1}$.

The estimation results in column (1) of Table 7 show that these two instruments have a significant effect on first year take-up decisions. Furthermore, the IV results in columns (4) and (5) suggest that having insurance for one year does not influence either the level or the slope of the demand curve in the following year. As a result, we conclude that simply enlarging the coverage rate in the initial year is not sufficient to improve the second year take-up rate.

Overall, we conclude that the regression results validate the empirical relevance of the channels we examine as mechanisms in our model of learning from stochastic experiences.

Table 7. Effect of Having Insurance on Second Year Demand Curve

VARIABLES	Insured Year 1 (1 = Yes, 0 = No)	Insurance Take-up Year 2 (1 = Yes, 0 = No)			
Sample: Subsample with Randomized Default Options in the 1st Year		OLS		IV	
	(1)	(2)	(3)	(4)	(5)
Price		-0.0517***	-0.0504***	-0.0532***	-0.0472***
		(0.0059)	(0.0096)	(0.006)	(0.0154)
Insured year 1		0.1956***	0.2043***	0.0368	0.0802
		(0.0258)	(0.0567)	(0.0631)	(0.1113)
Price * Insured year 1			-0.0021		-0.0099
			(0.0118)		(0.0232)
Free year 1	0.5853***				
	(0.0213)				
Buy as default year 1	0.0574*				
	(0.0302)				
Observations	2701	2701	2701	2701	2701
Village fixed effects	No	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes
R-squared	0.3101	0.4732	0.1073	0.0837	0.0843
P-value of joint significance test:					
Price and Price*Insured			0.0000***		0.0000***
Access and Price*Insured			0.0000***		0.7375

Notes: This table is based on the subsample of villages in which default options were randomized in the first year. Column (1) reports the first stage results. Columns (2)-(3) are OLS estimation results, and columns (4)-(5) are IV results, using free distribution and default in the first year as the IVs for access to insurance in the first year. Household characteristics include gender, age, level of education of the household head, rice production area, housheold size, risk attitude, and the perceived probability of future disasters. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6 Model Estimation and Policy Simulation

In this section, we estimate the structural model of Section 4. The empirical specification that we estimate is the following:

$$Pr(Buy_{ij1} = b_{ij1}, Buy_{ij2} = b_{ij2}) = \Phi(q_{ij1}W_{ij1}, q_{ij2}W_{ij2}, q_{ij1}q_{ij2}\rho) \tag{10}$$

with $q_{ijt} = 2b_{ijt} - 1, t = 1, 2$

$$W_{ij1} = \mu_j + \beta p_1^* \tag{11}$$
$$\begin{aligned} W_{ij2} = {} & \mu_j + \eta + \beta p_{i2} \\ & + I_{i1}[\lambda_1 p_{i1} + (\lambda_2 + \lambda_3 p_{i1})Payout_i + (\lambda_4 + \lambda_5 p_{i1})NetPayHigh_i + (\lambda_6 + \lambda_7 p_{i1}) \\ & Payout_i NetPayHigh_i] + (1 - I_{i1})\lambda_8 NetPayHigh_i + \gamma(p_{i2} - p_{i1})I_{i1} + \delta I_{i1} \end{aligned} \tag{12}$$

where μ_j are village fixed effects and η is a second year fixed effect. The interaction effect between $Payout$ and $NetPayHigh$ is notably suggested by the reduced form estimation. In the above expression, δ combines the negative effect of no-payout when the insurance is fully subsidized and the benefit from reduced transaction costs from previous experience. Its sign depends on the relative strength of these two forces. The parameter λ_1 shows the differential (negative) effect of no-payout when a household paid for the insurance.

Estimating this structural model allows us to exploit the first- and second-year decisions jointly controlling for selection through correlated unobservable factors.

6.1 ML Estimation Results

We report the results from the Maximum Likelihood estimation in Table 8.[16] Specifically, we estimate village fixed effects μ_j, year fixed effect η, price response β, response to payouts $(\lambda_1 - \lambda_8)$, anchoring effect γ, and habit formation effect δ.

Column (3) reports conditional marginal effects for the take-up in year 2,

$$\frac{\partial Pr(Buy_2 = 1|I_1)}{\partial x} = \phi(W_2)\frac{\partial W_2}{\partial x}$$

[16] The estimated parameters are robust to including individual covariates. However, given the absence of covariates for non-sample network members, only a model without covariates can be used for simulations.

These effects can be compared with the results from the reduced form estimations in section 5. In general, we find that marginal effects are similar to the reduced form values, with the exception of a higher habit formation effect. The structural model also allows estimating a year 2 fixed effect. It is negative but not statistically significant. The similar results across these two estimations provide informal validation for the two approaches.

Table 8. Structural Model Estimation and Comparison with Reduced Form Parameters

		Structural model			Reduced form models	
Effects	Parameter	Estimate (1)	St. Err. (2)	Marginal effect on prob. of uptake in year 2 (3)	Estimate (4)	Reference (5)
Price	β	-0.121***	0.023	-0.044	[-0.047,-0.049]	T3, T5
Learning effects for insured in year 1						
Year 1 price	λ_1	-0.142***	0.041	-0.051	[-0.033,-0.027]	T5-c4, T4-c5
Payout	λ_2	0.470***	0.098	0.169	[0.166, 0.196]	T4-c3, T5-c3
Payout*Year 1 price	λ_3	0.191***	0.053	0.069	0.051	T4-c1&3, T5-c2&3
Network payout	λ_4	0.260*	0.117	0.093	0.121	T5-c3
Network payout*Year 1 price	λ_5	-0.032	0.056	-0.012	[-0.023, -0.020]	T5-c4; T5-c2&3
Payout*Network payout	λ_6	-0.234	0.149	-0.084	-0.126	T5-c3
Payout*Network payout*Year 1 price	λ_7	0.070	0.077	0.025	0.028	T5-c2&3
Learning effect for not insured in year 1						
Network payout	λ_8	0.622***	0.083	0.223	0.226	T5-c1
Anchoring effect	γ	-0.005	0.028	-0.002	~ 0	T6
Habit forming	δ	0.268*	0.143	0.096	0.037	T7-c4
Year 2	η	-0.093	0.072	-0.033		
Correlation between unobservables	ρ	0.342***	0.043	0.123		

Notes: Marginal effects are unconditional marginal effects, equal to the coefficient multiplied by the average of the predicted pdf (0.359). The estimation include villages fixed effects.*** p<0.01, ** p<0.05, * p<0.1.

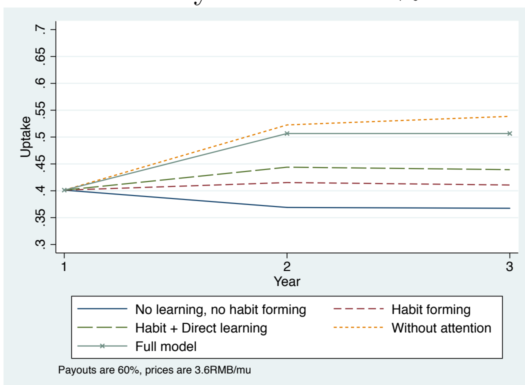
The results from the structural model estimation confirm the negative price response of insurance demand, with a 4.4% reduction per additional RMB/mu. In addition, using a non-parametric estimation for each of the nine assigned prices, we find no evidence of non-linearity for W_2. We confirm the importance of receiving a payout for those insured, equivalent to a reduction in price by 3 RMB/mu (or 25% of the fair price) and of observing payouts in the network for those not insured (equivalent to a reduction of 5 RMB/mu if more than half of the network has received a payout). We also find an important habit forming effect: having had access to insurance in the first with a full subsidy is equivalent to a 2.5 RMB/mu price reduction. Finally, the role of the price in influencing learning is clear from these results: λ_3 is positive, indicating that individuals who pay for their insurance value any payout received more than those who receive a full subsidy. λ_1 is negative, indicating that this group is also more discouraged by the absence of any payout.

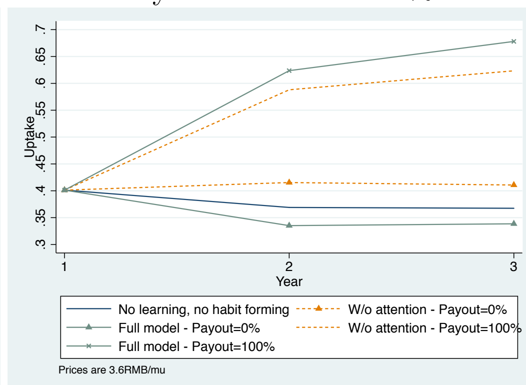
To illustrate the tradeoff between coverage and learning intensity as a function of the first year subsidy rate, we consider two payout extremes. At the one extreme, we suppose that there is no weather incident in the first year and thus no one receives a payout. In this case, the second year take-up rate is a function of $I_1(\delta + \lambda_1 p_1) = I_1(0.268 - 0.142p_1)$, where $\delta > 0$ embeds the habit formation effect, and $\lambda_1 < 0$ is the differential negative effect of not receiving a payout when one pays for the insurance. Here, a higher subsidy level (lower p_1) both increases the coverage I_1 in the first year and reduces the negative effect of no payout, leading to the second year take-up being a negative function of the price paid in year 1. At the other extreme, if everyone receives a payout in the first year, the second year take-up rate is a function of $I_1(\delta + \lambda_2 + \lambda_4 + \lambda_6 + (\lambda_1 + \lambda_3 + \lambda_5 + \lambda_7)p_1) = I_1(0.764 + 0.087p_1)$. Here, both the intercept and the coefficient on the price are positive. Hence, while a higher subsidy level increases coverage, it also reduces the learning from experiencing a payout.

Figure 3 provides an illustration of the overall learning model into its elements. Panel 3a report simulations for a price at 3.6 RMB/mu and a payout rate of 60%. Take-up in the first year is, as in the experiment, 40.1%. Ignoring all learning and habit formation effects, take-up over the next two years exhibits a small negative time trend (parameter η). When we add the positive habit formation effect (δ), the take-up rate stabilizes at just above 40%. When we add the direct learning effect ($\lambda_1 - \lambda_3$), those that did purchase the insurance update their valuation of the insurance product from their own experience. In this simulation 60% of the farmers updated it positively but 40% updated it negatively. The net is positive and the overall take-up increases to 44%. Allowing for learning from others ($\lambda_4 - \lambda_8$) further increases the take-up as the 60% that had not purchased the insurance in year 1 can now observe the relatively large payout rate. With this full model, take-up reaches 51%. Finally, if we do not allow for differential attention due to having paid for the insurance ($\lambda_1 = \lambda_3 = \lambda_5 = \lambda_7 = 0$), the take-up would be slightly higher, due to a mix of greater take-up by those that did not receive a payout but lower take-up by those that did receive a payout. With a universal 100% payout, represented in panel 3b, attention only has a positive effect and there is indeed a higher take-up with attention. We also show results for the case where there would be no payout in panel 3b. With no attention effect, the absence of payout does not affect take-up, and hence take-up is the same as with habit forming. Adding the attention effect makes take-up fall by eight percentage points to 33%.

Figure 3. Decomposing the learning model into its components

3a. Payout rate of 60%   3b. Payout rates of 0-100%





a: No learning nor habit forming, i.e., setting $\hat{\lambda}_1 - \hat{\lambda}_8 = 0, \hat{\delta} = 0$
b: Habit forming but no learning, i.e., setting $\hat{\lambda}_1 - \hat{\lambda}_8 = 0$
c: Habit forming and direct learning, i.e., setting $\hat{\lambda}_4 - \hat{\lambda}_8 = 0$
d: Full model without attention enhanced by paying for insurance, i.e., setting $\hat{\lambda}_1 = \hat{\lambda}_3 = \hat{\lambda}_5 = \hat{\lambda}_7 = 0$
e: Full model

This decomposition shows how each component of the learning model is important in determining the final take- up. With a 60% payout rate, the individual components of learning (habit formation and own experience) and social learning have effects of similar order of magnitude on overall take-up and attention has little aggregate effect. However, when payout rates are either very low or very high, the attention effect becomes large (negative with no payout and positive with universal payout).

6.2 Policy Simulation

Based on the estimated parameters in Table 8, we next conduct policy simulations. To validate the model, we simulate the take-up behavior over the years 2012-2014, using the insurance company's price policy and the aggregate yearly payout rate. We also confirm with a simulation exercise that initial subsidy levels have no lasting effect, because the subsidy effect strongly depends on the payout experience. We then examine how a 40% take-up rate could be achieved. This rate reflects the level at which the insurance company would find the insurance to be financially sustainable.

This is an important consideration given the Chinese government's goal of moving to an ex-ante insurance program to replace informal weather-related compensation schemes. Such insurance schemes are viable for the insurance company and beneficial for the farm sector only if there is a sufficient take-up rate.

The simulations are done on the sub-sample of households for which we have information on their network and on the network of their network. It includes 3,255 of the 3,474 households used in the estimation.

Validation of the model and simulation of long-run effect of short-term subsidies

We simulate the take-up pattern over five consecutive years using different subsidy policies. We take as given the annual average payout rate observed in 2010-2014. While the 2010 year was exceptional with a payout rate of 58.6%, it was followed by lower rates of 6.1, 15.6, 7, and 31.3% in 2011-2014, respectively.

The steps for the simulation are as follows:

(a)We generate a vector of T random variables ($\epsilon_{it}, t = 1, T$) from a multivariate normal distribution with correlation $\hat{\rho}$ for each individual i from the population.

(b) We infer the first year take-up decision for each household i in village j by comparing the value of $\hat{W}_{ij1} = \hat{\mu_j} + \hat{\beta} p_1$ to ϵ_{i1}.

(c) We apply the same expected payout rate to the whole sample, and define the payout outcome for each insured household by comparing a random number with uniform distribution to the expected payout rate. We then use this simulated payout data to calculate the network payout variable for each household. This is a dummy variable equal to one if the share of insured network households receiving payout is larger than 50%, and zero otherwise.

(d) Given the first year take-up rate, individual payout, and network payout variables, we then calculate the value of $\hat{W}_{ij2}$ as defined in equation (12), and infer the second year take-up decision by comparing the value of $\hat{W}_{ij2}$ to ϵ_{i2}.

(e) We repeat steps $(c) - (d)$ over the desired number of years.

Figure 4 reports the take-up rates corresponding to four price policies over 5 years:

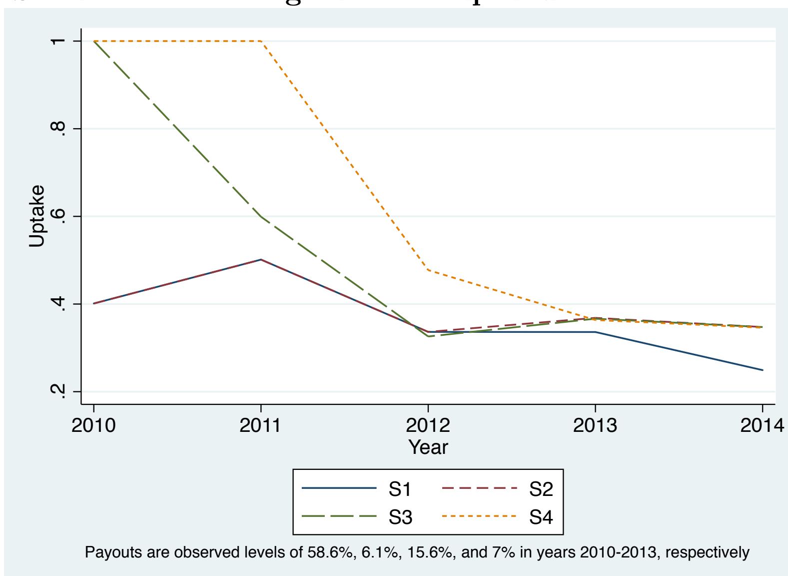
$S1$: The actual policy with observed prices equal to (3.6, 3.6, 3.6, 4.2, 5.7) RMB/mu

$S2$: A constant subsidy policy, with prices equal to 3.6 RMB/mu every year

$S3$: A one-year-free insurance policy, with prices equal to (0, 3.6, 3.6, 3.6, 3.6) RMB/mu

$S4$: A two-years-free insurance policy, with prices equal to (0, 0, 3.6, 3.6, 3.6) RMB/mu

Figure 4. Simulations of Long-run Take-up under Different Price Policies



$S1$: The actual policy with observed prices equal to (3.6, 3.6, 3.6, 4.2, 5.7) RMB/mu
$S2$: A constant subsidy policy, with prices equal to 3.6 RMB/mu every year
$S3$: Free insurance the first year, with prices equal to (0, 3.6, 3.6, 3.6, 3.6) RMB/mu
$S4$: Free insurance the first two years, with prices equal to (0, 0, 3.6, 3.6, 3.6) RMB/mu

To validate the simulation model, we compare the simulated and actual take-up rates out of sample for the years 2012- 2014. The simulation yields yearly take-up rates of 32.8%, 34.7%, and 25.0%, which are similar to the actual aggregate rates of 30%, 35%, and 25-30%, respectively.[17] This remarkable similarity in take-up rates helps validate the model.

Using the observed payout rates, we present the results of simulations $S2$, $S3$ and $S4$ in Figure 4. These results show that a full subsidy does not affect the take-up rate beyond the year immediately following the subsidy. This finding is in line with the earlier finding that the larger base effect is counteracted by a lower payout-based learning.

Defining the subsidy policy that ensures a given take-up rate

An important finding from the previous simulations is that, under a constant subsidy (at

[17] While we could not obtain the exact take-up from the sample of households that we observed in 2010 and 2011 for this study, the insurance company gave us an aggregate take-up rate for the region.

3.6 RMB/mu in $S2$) take-up rates fluctuate with previous year payout experiences. This suggests that subsidies need not be very high to ensure a good take-up if the previous year shows a good payout rate, but may need to be higher if previous payouts are low. Hence a variable subsidy policy would be appropriate if a government's goal is to maintain a certain take-up rate. In order to design such a policy tool, we first establish by simulation the price policy that would ensure the given take-up rate for a large number of potential payout sequences, and then show that a reduced form function of lagged variables satisfactorily approximates the policy.

We consider three potential first year price $p_1 = 0, 1.8, \text{or } 3.6$ RMB/mu, and four potential levels of payout rate for each year, $Payrate_t = 0, 30, 60, \text{or } 100\%$ for $t = 1, ...4$. For each of these 768 combinations, we then compute individual take-up and payout in year 1. From this information, we find by trial and error the price p_2 that leads to a 40% aggregate take-up in year 2. We repeat this process to obtain $p_3, p_4, \text{and } p_5$.

To extract a policy rule from this exercise, we then regress the obtained price in each year on the previous year's payout rates and prices:

$$p_{kt} = \beta_0 + \beta_1 * p_{k,t-1} + \beta_2 * Payrate_{k,t-1} + \beta_3 * p_{k,t-1} * Payrate_{k,t-1} + \epsilon_{kt} \qquad (13)$$

where k indicates one of the 768 $(p_1, Payrate_t, t = 1, ...4)$ combinations. Beginning with year 3, we find similar parameters across years. Consequently, we consider the model stable from year 3 on and regroup these years.

The results in column (1) of Table 9 show that the price and payout rate from the previous year are sufficient for predicting 98% of the price variance for a given year. Adding one more lag (column (2)) does not improve the prediction accuracy. Column (3) shows some significant differences across years, but these are always small in magnitude, and don't show any particular pattern. Based on these findings, we conclude that simulation results can be confidently approximated by the simple relationship to the previous year price and payout, thus providing an easily implementable policy instrument.

The policy rule given by column (1) is represented on Figure 5, using again the observed payout rates. Prices fluctuate, climbing up to 6.2 RMB/mu in year 2 (or 52% of the fair price) after the very large payout rate of the first year, down to only 1.7 RMB/mu in year 3 after the very low payout rate of the second year. We contrast it with the constant price policy that would insure the same average take-up during this period. With stable price, it is the take-up that fluctuates in response to past year payout. We compute the annual budget cost as the product of the implied subsidy (the fair-price 12 RMB/mu less the price charged to the buyers) and the take-up. The budgets of the two policies are mirror images

Table 9. Price Policy that Ensures a 40% Take-up Rate

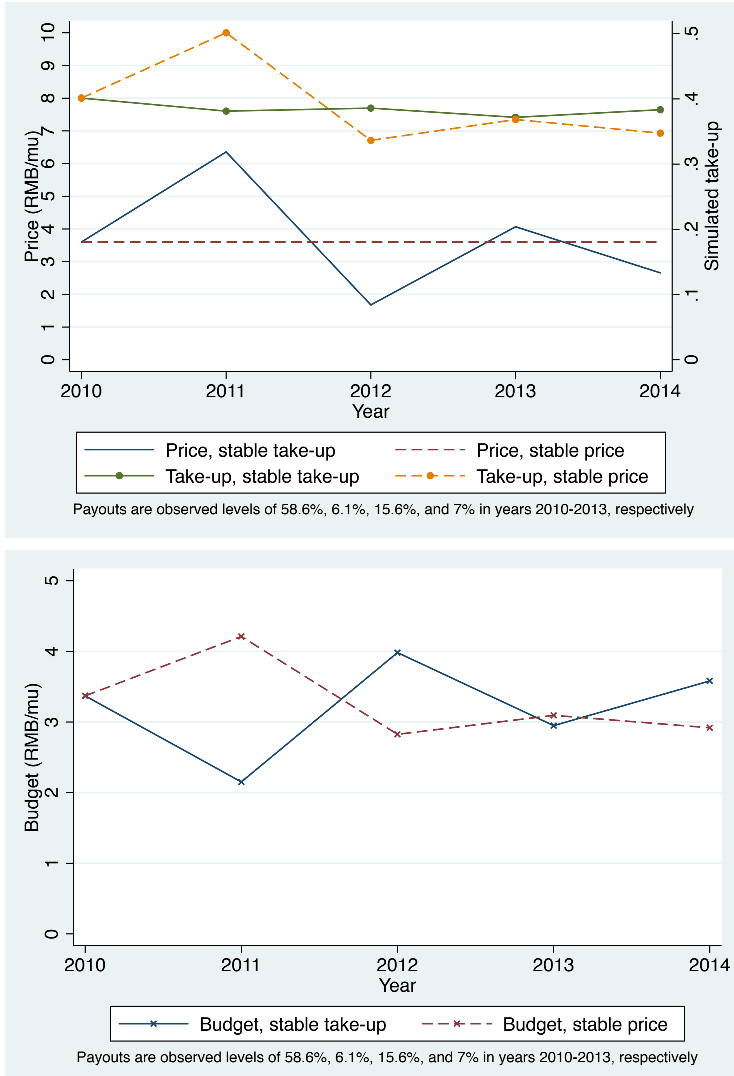
VARIABLES	Price (in RMB/mu)		
	(1)	(2)	(3)
Price (*t* -1)	-0.443***	-0.480***	-0.415***
	(0.005)	(0.011)	(0.010)
Payout Rate (t -1)	0.0420***	0.0420***	0.0440***
	(0.0005)	(0.0005)	(0.0011)
Price (t -1) * Payout Rate (t -1)	0.00712***	0.00712***	0.00681***
	(0.0001)	(0.0001)	(0.0002)
Year 4 *			
Price (*t* -1)			-0.0399***
			(0.0119)
Payout Rate (t -1)			-0.00492***
			(0.0013)
Price (t -1) * Payout Rate (t -1)			0.000347*
			(0.0002)
1			0.133*
			(0.076)
Year 5 *			
Price (*t* -1)			-0.0235*
			(0.0123)
Payout Rate (t -1)			-0.000342
			(0.0013)
Price (t -1) * Payout Rate (t -1)			0.000477**
			(0.0002)
1			0.368***
			(0.077)
Payout Rate (*t* -2)		0.00309***	
		(0.0008)	
Price (*t* -2)		-0.00505	
		(0.0036)	
Constant	3.822***	3.901***	3.611***
	(0.033)	(0.043)	(0.063)
Observations	2,304	2,304	2,304
R-squared	0.979	0.979	0.985

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

of each other. Under a stable take-up policy, budgets are high when prices are low, i.e, the year after a low payout rate. Under a stable price policy, budgets are high when take-up is high, i.e., after a year of high payout rate.

The purpose of the simulation was to demonstrate how one could design a subsidy policy that insures a steady take-up rate for the insurance, through variable subsidy levels that respond to the payout rate of the previous year. While this policy seems quite effective in insuring a sufficient coverage against weather risk, it may face some resistance in its implementation because of the year-to-year change in prices charged to potential customers. There could also be variation in the composition of insurance takers from year to year, if there is heterogeneity among the population in the sensitivity to price and payout experience. This rule provides however a benchmark that could be used in the design of a subsidy policy.

Figure 5. Stable Price vs. Stable Take-up Policies



7 Conclusions

In this paper, we examine the use of subsidies in influencing insurance take-up when individual learning about the value of insurance is affected by stochastic experiences. Learning under these conditions is particularly complex as there are many channels at play, with both positive and negative effects on the ultimate choice of whether to purchase insurance in the future. This paper integrates these channels into a comprehensive structural model that we use to design an optimum subsidy scheme based on the goal of achieving a desired stable take-up rate over time.

Specifically, we examine a number of mechanisms through which households learn about the value of insurance: (1) a direct learning effect from receiving a payout, with both recency effects from payouts in response to insured shocks and erosion effects from paying premiums with no payouts; (2) a social learning effect from observing payouts made to insured members of one's social network; (3) an attention effect where greater salience is attributed to payout events when an individual pays some amount for the insurance; (4) a price anchoring effect whereby past prices paid impact current willingness to pay for the product; and (5) a habit formation effect where having held the insurance product in the past may reduce future transaction costs.

We test the model through a two-year study of the adoption of weather insurance by rice farmers in China. We use an RCT design to measure the impact of different subsidy levels on take-up rates, examining the role of the above learning channels in the take-up decision process. The reduced form estimates show that subsidies are effective in boosting demand, with take-up increasing from 28% to 60% as the subsidy rate increases from 40% to 90%. The results also show that participants who pay for their insurance react to receiving a payout more strongly than those who receive their insurance for free, showing the importance of price in eliciting attention. We further find that there is a strong discouragement effect when insurance has been paid for and there is no payout, and that this effect is attenuated by subsidies. Finally, we find that observing payouts in your network has an effect on take-up for those who are uninsured and, to a lesser extent, for those who obtained their insurance for free but did not receive a payout. We find no evidence of price anchoring and only a limited effect of habit formation on take-up rates.

In addition, we estimate a structural model that we use to simulate the outcomes of alternative subsidy schemes. The simulation suggests that subsidies may need to be continuously adapted based on local recent events. For example, a policymaker may choose to price insurance at 51% of the fair price if the past subsidy and payout rates are 70% and 58.6%, respectively, but to price the insurance at only 15% of the fair price if the past price and payout rate change to 30% and 6.1%, respectively. In short, a policymaker interested in achieving a desired threshold in take-up rates should locally differentiate its subsidy levels and carefully customize these subsidies based on past price policy and past stochastic events.

Since learning about new technologies and institutions is frequently affected by stochastic experiences, the approach we proposed here to the design of smart subsidies can have wide applicability.

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Appendix - Supplementary Tables

Table A1. Compare the Effect of the Amount of Payouts under Different Subsidy Policies, Insurance Takeup Year 1 = 1

VARIABLES	Insurance take-up Year 2 (1 = Yes, 0 = No)				
Sample: Insurance Takeup Year 1 = 1	*Nonfree Year 1*		*Free Year 1*		*All Sample*
	(1)	(2)	(3)	(4)	(5)
Price	-0.0457***	-0.0576***	-0.0448***	-0.0515***	-0.0460***
	(0.00903)	(0.0105)	(0.00976)	(0.0129)	(0.00681)
Amount of Payout (1000 RMB)	0.409***	-0.227	0.352***	0.0548	0.379***
	(0.113)	(0.234)	(0.0945)	(0.194)	(0.100)
Price * Amount of Payout		0.158***		0.0794	
		(0.0499)		(0.0648)	
Free Year 1					0.0118
(1 = Yes, 0 = No)					(0.0364)
Payout*Free Year 1					-0.0163
					(0.135)
Observations	790	790	632	632	1,422
Village fixed effects	Yes	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes	Yes
R-squared	0.145	0.151	0.120	0.122	0.114
P-value of joint significance test:					
Price and Price*Payout		0.0000***		0.0001***	
Payout and Price*Payout		0.0000***		0.0033***	
Payout and Payout*Free					0.0000***
Free and Payout*Free					0.9474

Note: This table is based on the sample of households who purchased insurance (nonfree) or agreed to purchase insurance (free) in Year 1. Columns (1)-(2) tests the effect of receiving payout using the sample households who received partial subsidy in the first year; columns (3)-(4) tests that using households who received full subsidy in the first year. Column (5) is based on the whole sample of those households. Robust clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A2. Effect of Observing Friends Receiving Payouts on Second Year Insurance Demand

VARIABLES	Insurance Take-up Year 2 (1 = Yes, 0 = No)			
Sample:	Not insured in Year 1	Insured (not free) in Year 1	Insured (for free) in Year 1	All
	(1)	(2)	(3)	(4)
Price	-0.0447***	-0.0646***	-0.0463***	-0.0460***
	(0.0103)	(0.0148)	(0.0114)	(0.00533)
Network Payout	0.286***	-0.00936	0.0313	0.253***
(1=Yes, 0=No)	(0.0469)	(0.0977)	(0.0647)	(0.0347)
Payout		0.393***	0.140***	
		(0.0441)	(0.0353)	
Network Payout*Payout		0.0243	0.00686	
		(0.0173)	(0.0137)	
Free year 1				0.145***
				(0.0498)
Network Payout*Free year 1				-0.142**
				(0.0587)
Mean value of dependent variable	0.390	0.645	0.567	0.530
Observations	962	665	1,552	3,179
Village fixed effects	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
R-squared	0.182	0.315	0.105	0.115
P-value of joint significance test:				
Payout*Free				0.0000***
Free and Network Payout*Free				0.0159**

Note: Network payout is defined as equal to 1 if network payout rate > 0 and 0 otherwise. Household characteristics include gender, age, level of education of the household head, rice production area, household size, risk attitude, and the perceived probability of future disasters. Regressions in column (2) also control for the proportion of friends in one's social network who have purchased the insurance in the first year, instrumented with the network members average default option and education. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3. Effect of Observing Friends Receiving Payouts on Second Year Insurance Demand

VARIABLES	Insurance Take-up Year 2 (1 = Yes, 0 = No)			
	Not insured	Insured (not free)	Insured (for free)	
Sample:	in Year 1	in Year 1	in Year 1	All
	(1)	(2)	(3)	(4)
Price	-0.0486***	-0.0433***	-0.0459***	-0.0479***
	(0.0106)	(0.0103)	(0.00918)	(0.00539)
Amount of Network Payout (NetAmount)	0.0807	0.135	-0.0932	0.0560
(1=Yes, 0=No)	(0.0749)	(0.152)	(0.0639)	(0.0351)
Payout		0.387***	0.161***	
		(0.0380)	(0.0332)	
NetAmount*Payout		-0.0193	0.0157	
		(0.0267)	(0.0128)	
Free year 1				0.0736**
				(0.0321)
NetAmount*Free year 1				-0.0426
				(0.0523)
Mean value of dependent variable	0.390	0.645	0.567	0.530
Observations	953	665	1,552	3,170
Village fixed effects	Yes	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes	Yes
R-squared	0.120	0.312	0.104	0.086
P-value of joint significance test:				
NetAmount and NetAmount*Free				0.267
Free and NetAmount*Free				0.0744*

Note: Household characteristics include gender, age, level of education of the household head, rice production area, household size, risk attitude, and the perceived probability of future disasters. Regressions in column (2) also control for the proportion of friends in one's social network who have purchased the insurance in the first year, instrumented with the network members average default option and education. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4. Effect of Receiving or Observing Payouts on Trust

VARIABLES	Trust on the Insurance Company Year 2 (0-1)		
Sample:	All	Year 1 Take-up = Yes	Year 1 Take-up = No
	(1)	(2)	(5)
Free Year 1	0.0134	0.0272	-0.00926
(1 = Yes, 0 = No)	(0.0198)	(0.0449)	(0.0274)
Payout		-0.0527	
(1 = Yes, 0 = No)		(0.0390)	
Free Year 1 * Payout		0.0120	
		(0.0591)	
High Network Payout			0.0105
(= 1 if % > median, and 0 otherwise)			(0.0275)
Free Year 1 * High Network Payout			0.0145
			(0.0407)
Observations	3,442	1,422	1,880
Village fixed effects	Yes	Yes	Yes
Household characteristics	Yes	Yes	Yes
R-squared	0.037	0.048	0.048
P-value of joint significance test:			
Payout and Free Year 1*payout		0.2495	
High Network Payout and Free Year 1*High Network Payout			0.6701
Free Year 1		0.4815	0.9248

Note: Robust clustered (to village level) standard errors in parentheses. Household characteristics including gender, age, level of education of the household head, rice production area, housheold size, risk attitude, and the perceived probability of future disasters are controlled in all regressions. *** p<0.01, ** p<0.05, * p<0.1.

Table A5. Heterogeneity of the Payout Effect, Insurance Take-up Year 1 = 1

VARIABLES	Insurance take-up Year 2 (1 = Yes, 0 = No)	
Sample: Year 1 Takeup = Yes	Non-free Year 1	Free Year 1
	(1)	(3)
Price	-0.0431***	-0.0455***
	(0.00856)	(0.0106)
Payout	0.392***	0.161***
(1 = Yes, 0 = No)	(0.0533)	(0.0494)
Income (1000 RMB)	0.00763	0.000786
	(0.00599)	(0.00325)
Payout*Income	-0.00252	0.000492
	(0.00520)	(0.00290)
Observations	699	618
Village fixed effects	Yes	Yes
Household characteristics	Yes	Yes
R-squared	0.26	0.134
P-value of joint significance test:		
Payout and Payout*Income	0.0000***	0.0002***
Income and Payout*Income	0.0000***	0.0006***

Note: Robust clustered (to village level) standard errors in parentheses. Household characteristics including gender, age, level of education of the household head, rice production area, housheold size, risk attitude, and the perceived probability of future disasters are controlled in all regressions. *** p<0.01, ** p<0.05, * p<0.1.

Table A6. Effect of Subsidy Policies on Attention to the Session

VARIABLES	Answer to payout question (1 = Right, 0 = Wrong)	Attendance (0-1)
Sample: All	(1)	(2)
Free Year 1	-0.197***	-0.0133
(1 = Yes, 0 = No)	(0.0386)	(0.0129)
Observations	3,442	3,442
Village fixed effects	Yes	Yes
Household characteristics	Yes	Yes
R-squared	0.145	0.233

Note: In the second year survey we asked each farmer the share of households received insurance payout last year. The dependent variable of column (1) is a dummy variable equal to one if a farmer answered that question correctly, and zero otherwise. Household characteristics including gender, age, level of education of the household head, rice production area, housheold size, risk attitude, and the perceived probability of future disasters are controlled in all regressions. Robust clustered (to village level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.