Subsidy Policies and Insurance Demand*

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Abstract

Using data from a two-year randomized pricing experiment in China, we study the impact and design of subsidy policies for weather insurance. Results show that subsidies are effective in boosting demand in the short-run but not in the longer term. Exploring the channels, we show that while subsidies increase the direct and social effects of payout experiences by enlarging coverage, they also dampen these effects by reducing attention to payouts. We estimate a demand model for policy simulations. Results suggest that the optimum subsidy scheme should be continuously adjusted based on the policy objective and on past subsidies and payouts.

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1 Introduction

Whether to subsidize or not a privately beneficial product is a thorny issue for policymakers. On the one hand, there is reluctance to subsidize for fear of creating a spiral of subsidization by increasing preference 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 or minimizing costs if they have to be sustained (Cohen and Dupas (2010)).

In this paper, we study the case of a new weather insurance for rice farmers in China. Uninsured weather risks are known to be a major source of welfare loss for farmers (Rosenzweig and Binswanger (1993), Dercon and Christiaensen (2011)) and to distort resource allocation (Rosenzweig and Wolpin (1993)). 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 insurance demand is price elastic (Karlan et al. (2014), Mobarak and Rosenzweig (2014)). If take-up in turn induces learning, future subsidies could be reduced and eventually eliminated. However, experience with insurance consists in sharply contrasted outcomes as it maps continuous production losses into either receiving or not receiving a payout. Although these outcomes should be no surprise, as it is in the nature of insurance to cover certain events and not others, it has been shown that demand for insurance is very sensitive to the salience of short-term realizations of payouts (Karlan et al. (2014), Gallagher (2014), Cole, Stein, and Tobacman (2014)). This

[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, while the cost to the farmers themselves is less than 2% of the commercial premium.

suggests that a subsidy policy that aims, for instance, at ensuring a given take-up at minimum cost should be adjusted to the past realizations of payouts. This is the essence of our proposition.

We propose a theoretical framework of response to stochastic experiences in which individuals adjust their valuation of the insurance product with their recent experience. In the framework, we specify three recognized channels through which recent experience can affect demand: (1) the effect of experiencing payout, 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 occurred or a shock occurred without a corresponding payout, (2) the effect of observing 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.[3] We model how these channels would be impacted by subsidies through three separate effects: (1) a scope effect where subsidies enhance take-up and hence the opportunity of witnessing payouts, (2) an attention effect where a lower insurance cost for the individual leads to lower attention given to information generated by payout experiences (as evidenced for health products in Ashraf, Berry, and Shapiro (2010)), and (3) a price anchoring effect, where low past prices reduce current willingness to pay (evidenced in Cohen and Dupas (2010)).

We estimate the impact of subsidy policies on insurance take-up and the underlying mechanisms using a two-year randomized field experiment, which includes 134 villages with about 3,500 households in rural China. In the first year, we randomized 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 assigned eight prices to the product at the household level, with subsidies ranging from 40% to 90%.

Results show that households receiving a full subsidy in the first year exhibit greater demand for insurance in the second year, but that the price elasticity of

[3]The influence of own and network payout experiences have been identified by Cole, Stein, and Tobacman (2014), Gallagher (2014), and Karlan et al. (2014). Persistence in adoption has been shown for insurance by Hill, Robles, and Ceballos (2016), and for agricultural inputs by Carter, Laajaj, and Yang (2014)

demand is not statistically different compared to that of households receiving a partial subsidy. Exploring the channels driving the result, we show that, first, directly receiving a payout has a positive effect on second year take-up, and makes insurance demand less price elastic. This effect is stronger for households that paid for insurance, supporting the presence of an attention effect. Second, we find that observing payouts in their network increases second-year demand for those not insured in the first year. However, the effect is much smaller for households who received insurance for free. To explain why the payout 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 (in non-free villages) or were willing to purchase (in 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 a full subsidy. Finally, we find that holding insurance for one year does not influence either the level or the slope of the following year demand curve. This finding suggests that enlarging the coverage rate is not enough to secure persistence in insurance take-up.

We then estimate an insurance demand model, allowing for interactions between price, own payout, and network payout experiences revealed in the reduced form estimations. We validate the model predictions by comparing them to the observed take-up over the 3 years beyond sample period. Results show no evidence of weakening of the payout effect over time. The model is used to simulate policy options. We show that to maintain a minimum insurance take-up rate or government subsidy budget, current subsidies can be reduced when the previous year's subsidy level and payout rates were high. This finding suggests that subsidies need to be continuously adjusted. We provide a way of designing a simple policy rule that a budget-constrained government can use to determine the optimum level of subsidy.

A number of studies have examined the impact of providing subsidies on the take-up of products where the product experience is non-stochastic. For example, Dupas (2014) finds that a one-time subsidy for insecticide-treated bednets has a positive effect on take-up in the following year, a result which is mainly driven by a 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 benefits may need to have a continuously adjusted subsidy rate based on both past subsidy levels and payout rates.

Our study provides insight into why weather insurance faces low adoption rates. Existing research has elicited factors influencing take-up such as liquidity constraints, a lack of financial literacy, present bias, and a lack of trust in the insurance provider (Giné, Townsend, and Vickery (2008), Gaurav, Cole, and Tobacman (2011), Cole et al. (2013), and Cai, de Janvry, and Sadoulet (2015)). However, even when these barriers are removed in experimental settings, insurance take-up remains low. Our insight regarding the stochastic nature of the payout which influences the salience of insurance benefits contributes to the understanding of the low take-up phenomenon, and we show that subsidies need to be carefully calibrated to past policies and events to be effective in enhancing take-up while holding cost low.

Our study also 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 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 subsidies can be optimized when stochastic experiences influence 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 model of insurance demand. In section 5, we present the reduced form estimation results. Section 6 reports the model estimation and 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 randomly selected villages included in the 2010 expansion in Jiangxi province, one of China's major rice producing areas. In the selected villages, rice production is the main source of income for most farmers. Given that the product was new, farmers and government officials had limited understanding of it 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 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. 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.[5] 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

[4] 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.

[5] One concern of the contract design is that good farmers might have less incentive to purchase insurance as the payout is based on the fields average. We estimated the impact of baseline yield on take-up but did not find a significant impact.

policy covers 25% of the 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.[6] 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, removing any liquidity constraint problem, identified for example by Giné, Townsend, and Vickery (2008) and Cole et al. (2013) in India.[7]

Like with 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 than the expected profit (800 RMB/mu), and the verifiable nature of natural disasters, the product is not subject to moral hazard concerns.[8]

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 I. The treatment involves randomization of the subsidy level in each year of the study. In the first year, we randomized the subsidy policy at the village level. The insurance product was 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

[6] 1 RMB = 0.15 USD; 1 mu = 0.165 acre. Farmers produce three seasons of rice each year.

[7] Starting in 2004, the Chinese government provided production subsidies to rice farmers in order to increase production incentives.

[8] If there were moral hazard problems, the likelihood of collusion should increase with the price paid by farmers. We tested the impact of price on the payout probability and found a small and insignificant effect.

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 I, 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 stratified villages by their total number of households. In order to generate exogenous variation in individual insurance take-up decisions, we also randomized a default option in 80% of the villages. We assigned 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 assigned 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 received 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 59% of the insured receiving a payout from the insurance company.

In the second year of the study, we randomized the subsidy level from 90 to 40% of the fair price for every 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.[9] Similar to the design in Dupas (2014), only two or three prices are assigned within each village.[10] 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 stratified villages by size (total number of households) and first year village-level insurance payout rate. To randomize prices within the set, we stratified households by rice production area.

[9] This two-year price randomization scheme is similar to Karlan et al. (2014). But by eliciting demand before surprising people with free offer in the first year, we can look at price effect absent of selection.

[10] 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 $P_3 > 4.5$.

In both years, we offered information sessions about the insurance policy to farmers, in which we explain the insurance contract, the amount of government subsidy, the responsibility of the insurance company, the rules for loss verification, and the procedures for making payouts. Households made their insurance purchase decision immediately after the information session. In the second-year information session, we also informed 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.

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 almost all households have rice production, and all rice producers were invited to the information session with a more than 90% attendance rate, this provides us with a quasi census of the population of these 134 villages, a representative sample of rice-producers in Jiangxi. In total, 3474 households were surveyed.

We present the summary statistics of selected variables in Table I. 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).[11] 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 a 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

[11]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.

households. All households, regardless of whether they purchased the insurance or not, could also observe their friends' experiences. Identification of friends comes 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.[12] 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, 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.[13] Lastly, Panel C shows that the first year take-up rate was 41% while the second year take-up rate was 53%, with this increase corresponding to a 7.3 (16.3) percentage point increase in the non-free (free) villages.

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:

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

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 II 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.

[12] About 92% of the network connections are within villages, suggesting that inter-village spillover effects should be small. For a detailed description of the network data, please refer to Cai, de Janvry, and Sadoulet (2015).

[13] The correlation between self and network payout is about 0.37, meaning that there's substantial heterogeneity of yield loss within villages. This is because the disaster happened in the first year was wind storms, and the yield loss depends on the location of the plot.

4 Theoretical Framework

4.1 Set-up

The net utility of buying insurance is posited to be additive in perceived benefits and costs. Perceived benefits in year t is a function of three factors: own experience with the insurance in the previous year V_{t-1}, network experience $NetV_{t-1}$, and I_{t-1}, an indicator of whether the individual was insured the previous year. Without specifying further, we write this function as $g(V_{t-1}, NetV_{t-1}, I_{t-1})$, and the perceive benefits as $EV + \lambda_t g(V_{t-1}, NetV_{t-1}, I_{t-1})$, where EV is the objective expected benefit of the insurance contract, and λ controls the rate at which information from past observations is taken into account. When $\lambda = 0$, there is no updating in the expected benefits from insurance experience. The higher the parameter, the more responsive individuals are to the recent realizations. The model can thus capture either a standard Bayesian updating or "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 cost of insurance includes 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 δ_t. 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:

$$W_t - \epsilon_t \equiv EV + \lambda_t g(V_{t-1}, NetV_{t-1}, I_{t-1}) + \beta p_t + \gamma\left(p_t - p_{rt}\right) I_{t-1} + \delta_t - \epsilon_t \quad (2)$$

4.2 Link with the Experiment

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

$$\begin{aligned}
Buy_1 &= 1 \quad \text{if } \epsilon_1 < W_1 \equiv \alpha + \beta p_1^* \\
&= 0 \quad \text{otherwise} \\
Buy_2 &= 1 \quad \text{if } \epsilon_2 < W_2 \equiv \alpha + \lambda(p_1) g(V_1, NetV_1, I_1) + \beta p_2 + \gamma\,(p_2 - p_1)\, I_1 + \delta(I_1) \\
&= 0 \quad \text{otherwise} \qquad (3)
\end{aligned}$$

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 I_1, which also includes farmers that receive the insurance in year 1 for free after choosing not to buy it originally.

We further assume that the two preference shocks 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:

$$Pr(Buy_1 = b_1, Buy_2 = b_2) = \Phi(q_1 W_1, q_2 W_2, q_1 q_2 \rho) \qquad (4)$$

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

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

- *Effect of own payout experience*: This mechanism enters through the realized V_1 in expression (3), creating a recency bias in demand. Neglecting any network effect, for those insured in year 1, if households experienced a weather shock and subsequent payout, we expect this term to be positive and their demand to increase. By contrast, with no weather shock, we expect the term to be negative and insurance demand to drop. 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.

- *Effect of observing network payouts*: This mechanism is qualitatively similar to that of receiving a payout and enters through $NetV_1$ in $g(V_1, NetV_1, I_1)$.
- *Habit formation and transaction costs* enter through the term $\delta(I_1)$.

The effects of first year price subsidy on second year take-up can also be identified in equation (3):

- A *scope* effect or potential for experience through its determination of I_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 impact of the first year subsidy on the second year insurance demand. We first compare the second year insurance take-up in villages that either received the insurance for free or paid a price of 3.6 RMB/mu in the first year. We then identify channels leading to the aggregate effect, including the effect of experiencing payouts, price anchoring, and habit formation.

5.1 The 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:

$$Takeup_{ij2} = \alpha_1 Price_{ij2} + \alpha_2 Free_{ij1} + \alpha_3 Price_{ij2} * Free_{ij1} + \alpha_4 X_{ij} + \eta_j + \epsilon_{ij} \quad (5)$$

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 region dummies.

Results in Table III, column (1), show that the second year take-up rate among households offered a full subsidy in the first year is higher than that of households offered a partial subsidy (by 5.97 percentage points, about a 10% increase, significant at the 10% level). Adding controls does not affect the result (column (2)). 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 that in the U.S. (in the [-.32, -.73] range).

5.2 Mechanisms

The small aggregate effect might be driven by a number of opposing forces and heterogeneous effects. In this section, we analyze three mechanisms of the subsidy effect: the effect of experiencing payouts, price anchoring, and habit formation.

5.2.1 Effect of Experiencing Payouts - Direct and Social Effects

The impact of subsidy levels on the payout experience effect is ambiguous. 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 paid for the insurance, less attention may be paid to the payout outcomes.[14]

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. Figure II compares the insurance demand curves for households that receive a payout to those for households that do not receive a payout. The figure shows that receiving a payout induces a higher level of renewal of the insurance contract and makes the insurance less price elastic. The corresponding estimating equation is:

$$Takeup_{ij2} = \alpha_1 Price_{ij2} + \alpha_2 Payout_{ij1} + \alpha_3 Price_{ij2} * Payout_{ij1} + \alpha_4 X_{ij} + \eta_j + \epsilon_{ij} \tag{6}$$

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

We report the estimation results in Table IV. For households that received a partial subsidy in the first year (columns (1) and (2)), receiving a payout improves their second year take-up rate by 35 percentage points, and mitigates the subsidy removal (price) effect by around 80%.[15] 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 the 30% loss rate threshold. 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.[16]

[14] For experience-based goods, two arguments have been given for why the 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.

[15] 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 IV.

[16] Allowing different functions on both sides of the discontinuity does not change the result.

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 payout effect, note in Figure II that absent a payout, there is a substantial decline in take-up rate at 3.6 RMB/mu in year 2, especially for those who paid for insurance. The demand after a payout is higher among those that paid for the insurance in the first year. Column (7) of Table IV confirms this: in absence of 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 true if a payout has been received. These results suggest that providing a full subsidy mitigates 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. 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 received a payout in the first year. The results in Table V, column (1) indicates that the effect of observing payouts in your network on subsequent insurance take-up is smaller among households that received a full subsidy.

To better understand the interaction between the direct and social effects of payouts, we look at the results for three groups separately: households not insured in the first year, households that paid for the insurance, and households that received insurance for free. The estimating equation is as follows:

$$\begin{aligned} Takeup_{ij2} = &\alpha_1 Price_{ij2} + \alpha_2 NetPayHigh_{ij1} + \alpha_3 Payout_{ij1} \\ &+ \alpha_4 NetPayHigh_{ij1} * Payout_{ij1} + \alpha_5 NetTakeup_{ij1} + \eta_j + \epsilon_{ij} \end{aligned} \tag{7}$$

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 financial education and the default first-year insurance option.[17]

Column (2) of Table V 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)).[18] This effect is half of what is observed for those that were not insured (column (2)).[19] 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.

What factors are driving the impact of self or friends payout experience on long-term insurance demand? First, it could be that experiencing payouts change farmers' perceived probability of future disasters or risk aversion. However, results in Table IV suggest that we observe large and significant payout effects even when those two variables are controlled. Second, the results can be induced by either an improvement in trust in the insurance company or by a wealth effect.[20] We test and reject the trust and wealth effects as follows. We construct a trust index based on household responses to a question in the second year survey as

[17]Financial education about insurance products was offered to randomly selected 50% households in year 1. Cai, de Janvry, and Sadoulet (2015) shows that participating in education sessions substaintially improved insurance take-up. One problem of using Default as the IV is that it might influence people's understanding of the insurance and the level of trust on the insurance company (as the product is heavily subsidized). We tested the impact of Default on knowledge of the insurance product and trust in year 1, the effects are small and not significant.

[18]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 and find a similar impact.

[19]We use two other indicators of network payouts for robustness check: 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).

[20]Cole, Gine, and Vickery (2014) show that being insured improve trust in the insurance company and that this effect is larger (although not significantly) for those receiving a payout.

to whether they trust the insurance company regarding loss assessment and the payout issuing process. Regressing this trust index on receiving or observing a payout shows no effect, in either non-free or free villages (Table A4). 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. For the wealth effect, we looked at heterogeneity in the effect of one's own payout on take-up in year 2 by year 1 household income, and find no significant effect (Table A5). Third, since this was the first time farmers experienced a weather insurance, observing how it works (you do receive a payout when you have a large loss) may have provided confirmation in farmers' understanding of the insurance product. If this was the main reason for the second year take-up patterns, it should be a one time learning, with stabilization after the first year. With a two-year experiment, we cannot rigorously dismiss this argument. However, indirectly we reject this channel through the simulation exercise in section 6.2.

As a result, we conclude that the direct and social effect of experience is mainly driven by the salience of either the benefits or the costs of insurance from observing payouts or absence of payouts. To further support this argument, 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 answered correctly, but only 36% in free villages did so (Table A6). This suggests that households that receive a full subsidy pay less attention to payout information, reducing the salience effect.

5.2.2 Price Anchoring

We next consider whether there is a price anchoring effect, by examining the set of households that were willing to purchase the insurance at 3.6 RMB/mu in the first year and that were assigned a price lower than 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, and 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 in the first year. However, regression results in Table VI 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.

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:

$$Takeup_{ij2} = \alpha_1 Price_{ij2} + \alpha_2 Insured_{ij1} + \alpha_3 Price_{ij2} * Insured_{ij1} + \alpha_4 X_{ij} + \eta_j + \epsilon_{ij} \tag{8}$$

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 VII 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 response to stochastic experiences.

6 Model Estimation and Policy Simulation

In this section, we jointly estimate the two demand equations of the model in Section 4.2. The empirical specification that we estimate is the following:

$$Pr(Buy_{ij1} = b_{ij1}, Buy_{ij2} = b_{ij2}) = \Phi(q_{ij1} W_{ij1}, q_{ij2} W_{ij2}, q_{ij1} q_{ij2} \rho) \tag{9}$$

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

$$W_{ij1} = \mu_j + \beta p_1^* \tag{10}$$

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

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 due to previous experience. Its sign depends on the relative strength of these two forces. The parameter λ_1 shows the additional (negative) effect of no-payout when a household paid for the insurance.

Estimating the system allows us to exploit the first- and second-year decisions jointly in the whole sample, controlling for selection through correlated unobservable factors.

6.1 ML Estimation Results

We report the Maximum Likelihood estimation results in Table VIII.[21] 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,

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

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

[21]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.

form values, with the exception of a higher habit formation effect. The joint estimation 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. The advantage of the joint estimation is that it yields one consistent set of parameters for the whole sample, while the reduced form estimates use the randomization on corresponding sub-samples.

Results from the joint 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 price reduction by 3.9 or 9.6 RMB/mu[22] depending on whether they have received it for free or not (or 32 or 80% of the fair price) and of observing network payouts for those not insured (equivalent to a reduction of 5.2 RMB/mu if more than half of the network has received a payout). We also find an important habit forming effect: receiving the insurance in the first year for free is equivalent to a 2.2 RMB/mu price reduction. Finally, the role of the price in influencing the attention to payout is clear from these results: λ_3 is positive, indicating that individuals who paid for their insurance value payout more than those who received a full subsidy. λ_1 is negative, indicating that this group is also more discouraged by the absence of payout.

To illustrate the tradeoff between coverage and attention as a function of the first year subsidy rate, we consider two payout extremes. At 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 paid 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

[22]This is for farmers with less than half of their network having received a payout, and is computed as λ_2/β or $(\lambda_2 + \lambda_3)/\beta$.

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 attention to payout experience.

Figure III provides a decomposition of the overall model into its elements. Panel III.a reports 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 payout 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 payout effect ($\lambda_1 - \lambda_3$), those that did purchase the insurance update their valuation of the product from their own experience. In this simulation 60% of the insured farmers (i.e., 24% of the population) updated it positively but 40% (16% of the population) updated it negatively. The net is positive and the overall take-up increases to 44%. Allowing the influence of payouts to 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 III.b, increased 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 III.b. The differential attention effect makes take-up fall by eight percentage points to 33%.

This decomposition shows how each component of the model is important in determining the final take-up. With a 60% payout rate, payout experiences increased take-up by 10.9 percentage points or 27% of the base rate. The network payout effect represents 64% of these 10.9 percentage points, larger than the direct payout effect. This is because the direct effect applies to 40% of the population and for 40% of them the effect of not receiving a payout is negative. On the other hand, the differential attention effect due to paying for the insurance is small. However, when payout rates are either very low or very high, this differential attention effect becomes large (negative with no payout and positive with a universal payout).

6.2 Validation of the model

Our objective in estimating the joint model is to use the estimated parameters to conduct policy simulations. The model however was estimated with data from 2 years of insurance purchase, i.e., only one year to infer how observing payouts affect take-up. Can we apply the model over several years? It could be that observing payouts only once is important to confirm the understanding of insurance, and then demand stabilizes to this level. Or that successive observations of payouts and absence of payouts build the correct evaluation of the insurance through a Bayesian process. In both cases, the contrasted effects of either payouts or absence of payouts would decrease over time. To validate our model over a longer period than 2 years, we simulate the take-up behavior over five consecutive years and compare these with the observed uptake, using the insurance company's price policy and the aggregate yearly payout rate. While we do not have observations at the individual level, we verify in this section that our model reproduces the observed aggregate take-up, while either reducing or increasing the previous period payout effects leads to worse fit.

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.

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 (11), 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.

We use the observed payout rate 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. We also use the actual subsidy policy, denoted $S1$, with observed prices equal to (3.6, 3.6, 3.6, 4.2, 5.7) RMB/mu.

Validation comes from the comparison of 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. This remarkable similarity in take-up rates helps validate the model.

Year	2010	2011	2012	2013	2014
Observed payout rate	58.6%	6.1%	15.6%	7%	31.3%
Observed prices $S1$	3.6	3.6	3.6	4.2	5.7
Observed uptake	41.4%	49.9%	30%	35%	25-30%
Simulated uptake	40.1%	50.1%	32.8%	34.7 %	25.0 %

6.3 Policy Simulation

In a series of simulations, we confirm that initial subsidy levels have no lasting effect. Figure IV reports the simulation of three price policies over 5 years:

$S2$: 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

These results show that a full subsidy does not affect the take-up rate beyond the year immediately following the subsidy. Two years after the free offer, take-up is back to where it would have been without this short-run exceptional subsidy. This finding is in line with the earlier result that the larger base effect is counteracted by a lower payout-based learning.

We now use the model to simulate policies. We look at two policies: (i) the subsidy policy that ensures a given take-up rate as desired by the insurance company, and (ii) the subsidy policy that ensures a constant budget outlay as preferred by the government. We compare these policies to the default option of a constant subsidy as would be the normal practice. As a practical example, we anchor these policies on the realization of the first year: the price was set at 3.6 RMB/mu, which corresponds to a 70% subsidy on the fair price, and take-up reached 40%, leading to a subsidy cost for the government of 3.36 RMB per mu. The three policies that we compare will thus be maintaining a constant price at 3.6 RMB/mu, maintaining a constant take-up rate of 40%, and maintaining a constant subsidy budget of 3.36 RMB per mu.

The justification for a policy that ensures a given take-up rate comes from the objective that the insurance company had set for itself in agreement with the government. The company announced that it would not provide the product if the take-up rate were lower than 40%. Given large fixed costs, this rate reflects the level at which the insurance company considered the product to be financially sustainable.

The constant budget outlay objective is the ideal option for the government that wants to shift to an ex-ante financing scheme that will avoid the deeply erratic budget outlays associated with relief expenditures. Instability has a high opportunity cost as liquidity would typically be obtained by holding large idle reserves, or by reallocating public expenditures to relief away from normal appropriations to such categories as health, education, and infrastructure. Desire for a stable annual budget appropriation for relief from stochastic natural disasters is illustrated by Mexico's Natural Disaster Fund (FONDEN). The program has a fixed budget appropriation equal to 0.4% of the annual federal budget (equal to $800 million in 2011). Volatility of demands for emergency expenditures is managed through risk transfer instruments such as index insurance and catastrophe bonds (World Bank, 2012).

In order to establish these policies we proceed in two steps. We first establish by simulation the price policy that would ensure the objective (constant take-up rate or constant budget) for a large number of potential payout sequences. We then show that a simple 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 the given take-up or the given budget in year 2. We repeat this process to obtain $p_3, p_4, \text{and } p_5$, the prices in years 3 to 5..

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

$$p_{kt} = \beta_0 + \beta_1 * p_{k,t-1} + \beta_2 * Payrate_{k,t-1} + \beta_3 * p_{k,t-1} * Payrate_{k,t-1} + \epsilon_{kt} \qquad (12)$$

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 are reported in Table IX, columns (1-3) for a constant take-up, and (4-6) for a constant budget. The results in column (1) and (4) show that the price and payout rate from the previous year are sufficient to predict 98% and 99% of the price variance for a given year. Adding one more lag (columns (2) and (5)) does not improve the prediction accuracy. Columns (3) and (6) show 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 columns (1) and (4) are represented in Figure V together with the constant price policy. We report in the first panel the payout rates that are used for determining the price policies. Under a constant price policy, take-up widely fluctuate in response to payout rates in the previous years, and budgetary costs follow the same pattern. Stabilizing take-up requires price policies that counteract these payout effects, i.e., high prices after a high payout rate and low prices after a low payout rate. Budgetary costs are the mirror image of the prices, and hence widely fluctuates. The price policy that stabilizes the budgetary cost is intermediate between the constant price and the constant uptake policy. It does adjust the price in response to past payout rate, but not so much as to stabilize the uptake. So price fluctuates some, reducing the fluctuation in uptake.

The purpose of the simulation was to demonstrate how one can design a subsidy policy that insures an objective (steady take-up rate for the insurance or steady subsidy budget for the government) through variable subsidy levels that respond to the payout rate of the previous year. While such policies would be quite effective in achieving their objective, they may face some resistance in 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. These rules provide benchmarks that can be used in the design of a subsidy policy, in particular in seeking a compromise between insurance company and government objectives.

7 Conclusions

In this paper, we examine the impact of offering subsidies on insurance take-up when subjective valuation of insurance is affected by stochastic experiences. We integrate multiple channels of the subsidy effect into a comprehensive model that we use to design optimum subsidy schemes.

Specifically, we combine a number of mechanisms through which households update their belief about the value of insurance: (1) a direct effect from receiving a payout; (2) a social 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 paid 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 use a randomized experiment to measure the impact of different subsidy levels on the take-up of a new weather insurance product in rural China, examining the role of each of the above 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.

We use the estimated simultaneous demand model that combines the various channels at play to simulate the outcomes of alternative subsidy schemes. The result suggests that subsidies need to be continuously adapted based on local recent events to achieve the desired take-up. For example, a policymaker interested in meeting the insurance company's demand for a 40% take-up rate may choose to price insurance at 51% of the fair price if the past subsidy and payout rates were 70% and 58.6%, respectively, but to price the insurance at only 6% of the fair price if the past subsidy and payout rates were 30% and 6.1%, respectively. A government interested in keeping a constant budget would act differently, pricing the insurance at 38% and 12% in these two cases, respectively. In short, a policymaker interested in achieving one or the other of these policy objectives should locally differentiate its subsidy levels and carefully customize these subsidies based on past price policy and past stochastic events.

Since valuation of new technologies and institutions is frequently affected by stochastic experiences and recency bias, the approach we propose here to the design of smart subsidies can have wide applicability.

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Figure I. Experimental Design

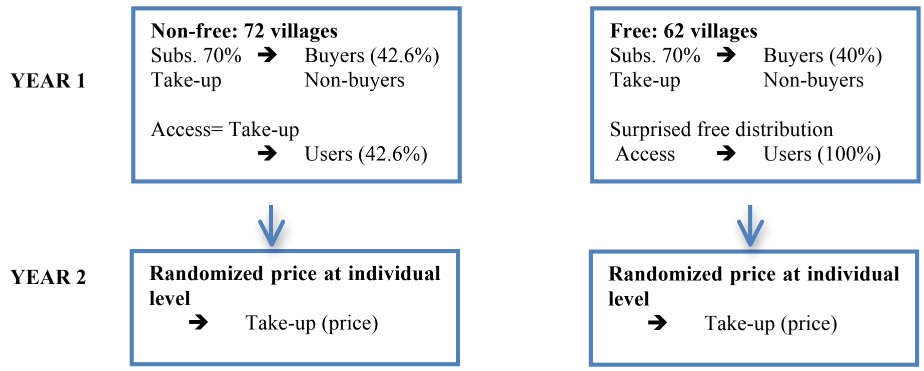


Figure II. Effect of Own Payout on Year 2 Insurance Demand

Non-free Villages Free Villages

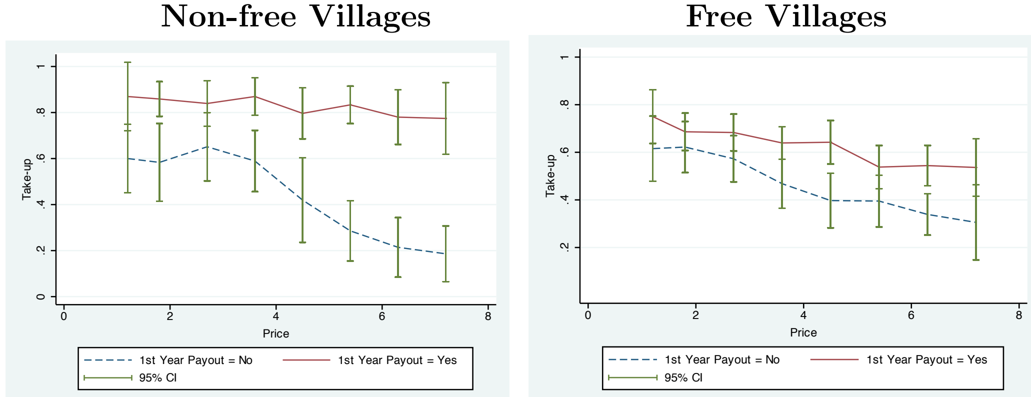
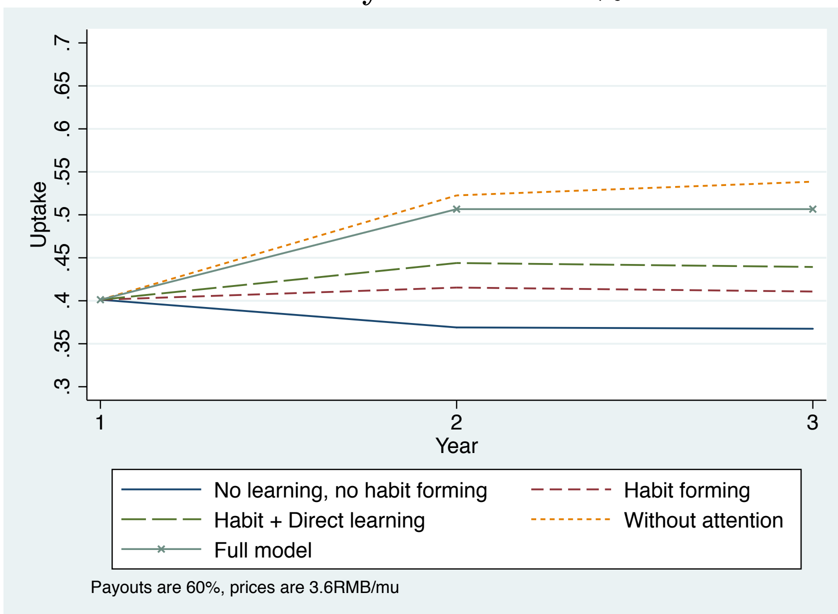
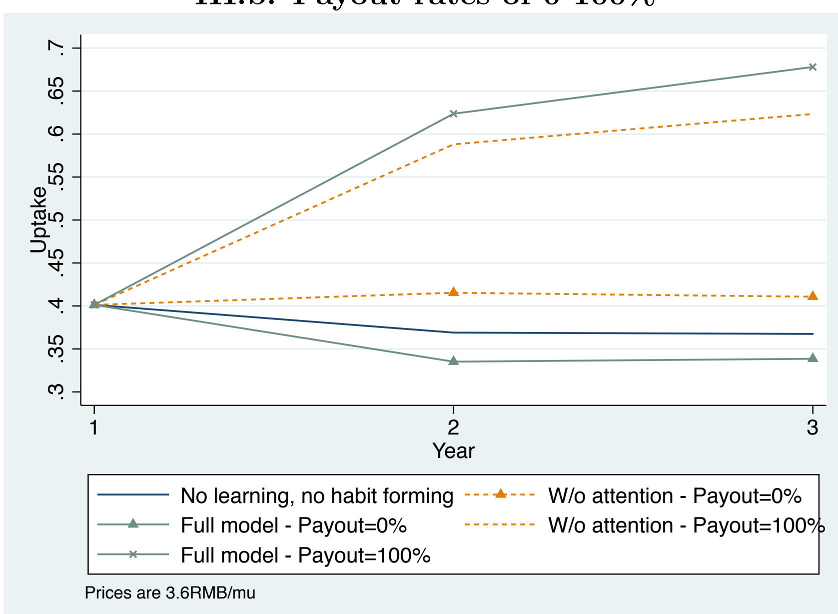


Figure III. Decomposing the learning model into its components

III.a. Payout rate of 60%

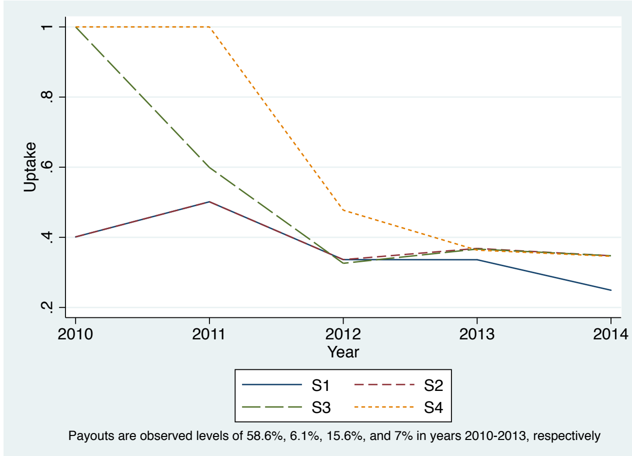


III.b. Payout rates of 0-100%



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

Figure IV. 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

Figure V. Price Policy Simulations

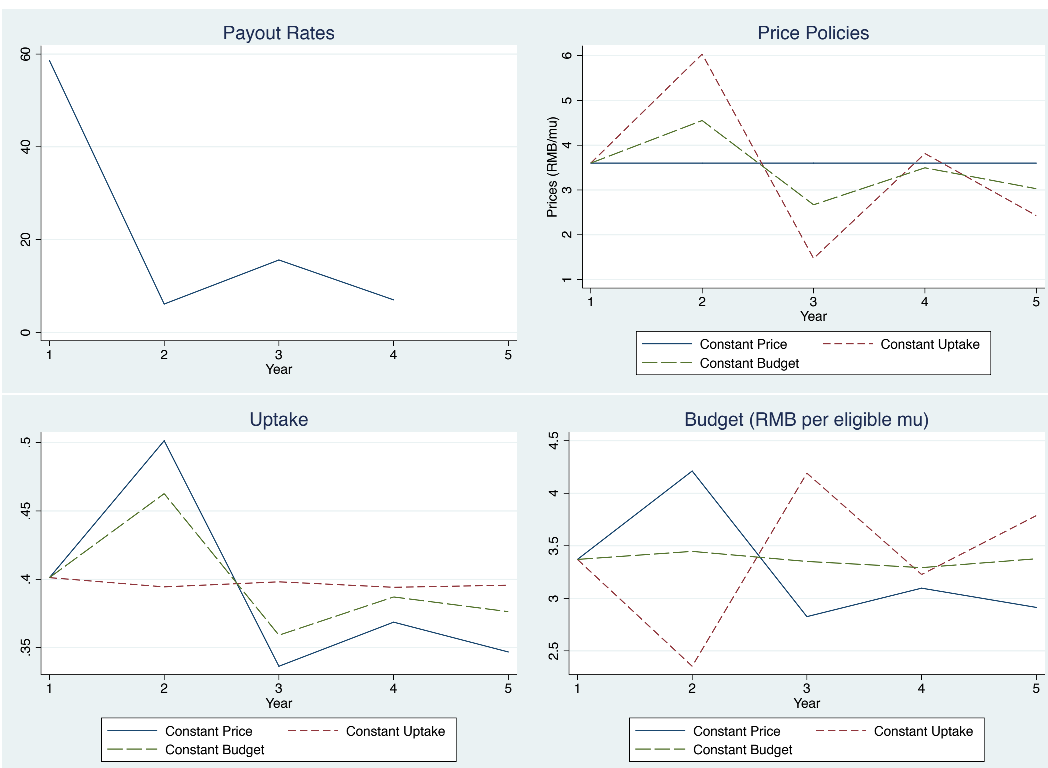


Table I. Summary Statistics

	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)	(9.87)
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. 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.

Table II. 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: This table checks the validity of price randomization. Each row represents a regression of the characteristic noted in the first column on the price and its square. Column (3) reports the p-value for the joint test of significance of the two coefficients. Robust clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table III. Effect of First Year Subsidy 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	0.069
P-value of joint significance test:			0.0000***
Price and Price*Free			0.0000***
Free and Price*Free			0.1552

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

Table IV. 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 Sample*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Price	-0.0441***	-0.0779***	-0.0717***	-0.0469***	-0.0651***	-0.0731***	-0.0466***
	(0.00868)	(0.0135)	(0.0133)	(0.00998)	(0.0188)	(0.0210)	(0.00652)
Payout (1 = Yes, 0 = No)	0.368***	0.0901	0.206*	0.168***	0.0346	0.0243	0.356***
	(0.0355)	(0.0798)	(0.108)	(0.0406)	(0.0830)	(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 (1 = Yes, 0 = No)							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	0.230	0.260	0.26	0.130	0.137	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, household size, risk attitude, and the perceived probability of future disasters. Robust clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table V. 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 (1 = Yes, 0 = No)			0.3813***	0.1959***
			(0.0426)	(0.0423)
NetPayHigh*Payout			-0.0066	-0.1258**
			(0.0793)	(0.0536)
Free Year 1 (1 = Yes, 0 = No)	0.119***			
	(0.0370)			
NetPayHigh*Free Year 1	-0.102**			
	(0.0475)			
Mean value of dependent variable	0.53	0.39	0.645	0.567
Observations	3,179	962	665	1552
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:				
HighNet and HighNet*Free	0.0000***			
Free and HighNet*Free	0.0069***			

Note: This table tests the effect of observing a high share of friends receiving payout on the second year insurance take-up. 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 financial education. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table VI. Test for Price Anchoring Effect

VARIABLES	Insurance take-up Year 2 (1 = Yes, 0 = No)	
Sample: all price <= 3.6	(1)	(2)
Price	-0.0111	0.00609
	(0.0240)	(0.0329)
Free Year 1 (1 = Yes, 0 = No)	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 in the first year, and were offered the insurance at a price less or equal to 3.6 RMB/mu in the second year. 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. Robust standard errors clustered at the village level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table VII. 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 Randomzied 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 (1 = Yes, 0 = No)		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 (1 = Yes, 0 = No)	0.5853***				
	(0.0213)				
Buy as Default Year 1 (1 = Yes, 0 = No)	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*Access			0.0000***		0.0000***
Access and Price*Access			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, household 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.

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

Effects	Parameter	Structural model Estimate	St. Err.	Marginal effect on prob. of take-up in year 2	Reduced form models Estimate	Reference
		(1)	(2)	(3)	(4)	(5)
Price	β	-0.121***	0.023	-0.044	-0.049	T.3, col.1
Payout effects for insured in year 1						
Year 1 price	λ_1	-0.152***	0.039	-0.054	-0.033	(b)
Payout	λ_2	0.369***	0.074	0.132	0.172	T.5, col.5
Payout*Year 1 price	λ_3	0.222***	0.039	0.080	0.057	T.5, col.2&5
Network payout	λ_4	0.118	0.073	0.042	0.058	T.6, col. 6&8
Network payout*Year 1 price	λ_5	0.010	0.038	0.004	0.005	T.6, col. 2
Payout effect for not insured in year 1						
Network payout	λ_6	0.622***	0.083	0.223	0.222	T.6, col. 4
Anchoring effect	γ	-0.004	0.028	-0.002	~ 0	T.10
Habit forming	δ	0.301**	0.142	0.108	0.075	(a)
Year 2	η	-0.093	0.072	-0.033		
Correlation between unobservables	ρ	0.330***	0.038	0.118		

Note: 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.

Table IX. Price Policy that Ensures a Constant Take-up Rate or a Constant Subsidy Budget

VARIABLES	Price (in RMB/mu) Constant take-up rate			Price (in RMB/mu) Constant subsidy budget		
	(1)	(2)	(3)	(4)	(5)	(6)
Price (*t* -1)	-0.443***	-0.480***	-0.415***	-0.351***	-0.374***	-0.358***
	(0.005)	(0.011)	(0.010)	(0.00333)	(0.00741)	(0.00607)
Payout Rate (t -1)	0.0420***	0.0420***	0.0440***	0.00857***	0.00857***	0.00668***
	(0.0005)	(0.0005)	(0.0011)	(0.00025)	(0.00024)	(0.00047)
Price (t -1) * Payout Rate (t -1)	0.00712***	0.00712***	0.00681***	0.00598***	0.00598***	0.00613***
	(0.0001)	(0.0001)	(0.0002)	(0.00006)	(0.00005)	(0.00010)
Year 4 *						
Price (*t* -1)			-0.0399***			-0.0378***
			(0.0119)			(0.00754)
Payout Rate (t -1)			-0.00492***			0.000333
			(0.0013)			(0.00057)
Price (t -1) * Payout Rate (t -1)			0.000347*			0.000388***
			(0.0002)			(0.00013)
1			0.133*			-0.0313
			(0.076)			(0.03420)
Year 5 *						
Price (*t* -1)			-0.0235*			0.0391***
			(0.0123)			(0.00750)
Payout Rate (t -1)			-0.000342			0.00380***
			(0.0013)			(0.00056)
Price (t -1) * Payout Rate (t -1)			0.000477**			-0.000482***
			(0.0002)			(0.00013)
1			0.368***			-0.221***
			(0.077)			(0.03390)
Payout Rate (*t* -2)		0.00309***			0.000643***	
		(0.0008)			(0.00022)	
Price (*t* -2)		-0.00505			-0.0137***	
		(0.0036)			(0.00175)	
Constant	3.822***	3.901***	3.611***	4.050***	4.163***	4.163***
	(0.033)	(0.043)	(0.063)	(0.01480)	(0.02670)	(0.02800)
Observations	2,304	2,304	2,304	2,304	2,304	2,304
R-squared	0.979	0.979	0.985	0.992	0.992	0.994

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Prices are those that ensure a 40% take-up rate (in columns 1-3) or a constant budget (in columns 4-6) for three potential first year price (0, 1.8, or 3.6 RMB/mu), and four levels of payout rate for each year (0, 30, 60, or 100%). These prices were obtained by trial and error using simulations with the estimated structural model.

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)			
Sample:	Not insured in Year 1	Insured (not free) in Year 1	Insured (for free) in Year 1	All
	(1)	(2)	(3)	(4)
Price	-0.0486***	-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	-0.0462***	-0.0452***
	(0.0081)	(0.0099)
Payout	0.422***	0.113*
(1 = Yes, 0 = No)	(0.0472)	(0.066)
Area of Rice Production (mu)	0.00343	0.002
	(0.0027)	(0.0028)
Payout*Area of Rice Production	-0.00369	0.0046
	(0.00322)	(0.0041)
Observations	729	632
Village fixed effects	Yes	Yes
Household characteristics	Yes	Yes
R-squared	0.29	0.134
P-value of joint significance test:		
Payout and Payout*Income	0.0000***	0.0001***
Income and Payout*Income	0.0000***	0.0002***

Note: Robust clustered standard errors in parentheses. *** 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.