Barriers to Household Risk Management: Evidence from India[1]

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ABSTRACT

Financial engineering offers the potential to significantly ameliorate income fluctuations faced by individuals, households, and firms. Yet, to date, much of this promise remains unrealized. In this paper, we study household participation in an innovative rainfall insurance product offered to low-income rural Indian households. Farmers are exposed to substantial income risk from rainfall variation during the growing season; the insurance contract compensates farmers in case of deficient rainfall. We first document relatively low levels of adoption of risk management: for example, households tend to purchase only one unit of insurance, no matter how large their risk exposure. We then conduct a series of field experiments to test theoretical predictions of why adoption may be low. These experiments demonstrate that price and credit constraints are important determinants of insurance adoption. However, we also find evidence that non-standard factors affect take-up: while an education module is not important, endorsement from a trusted third party is. We find some evidence that subtle psychological manipulations affect take-up.

A key insight of financial theory is that a household should hold a diversified market portfolio that minimizes non-systematic risk. In practice however, many idiosyncratic risks are not pooled, even when the source of risk is publicly observable and verifiable, and thus not subject to informational problems like moral hazard and adverse selection. For example, households often remain exposed to movements in local weather, regional house prices, occupation income and employment, local and national income growth, and so on. In many cases, financial contracts simply do not exist to hedge these exposures, while in other cases, contracts exist, but their use is not widespread. These facts suggest a puzzle, emphasized by Shiller (1993, p. 3): "It is odd that there appear to have been no practical proposals for establishing a set of markets to hedge the biggest risks to standards of living."

Why don't financial markets develop to help households to hedge these risks? Why don't more households participate when markets are available? This paper attempts to shed light on these questions by studying participation in a rainfall risk-management product offered in recent years to rural Indian households. The product is purchased at the start of the monsoon, and provides a payoff based on monsoon rainfall measured at a local weather station. Policies are sold in unit sizes as small as 46 rupees ($1.10 US), making the product accessible even to relatively poor households.

This is a setting where the benefits of risk diversification appear especially high. While 89% of the households in our sample report that variation in local rainfall is the most important risk they face, rainfall in our survey areas is close to uncorrelated with systematic risk factors, such as stock market returns, that are relevant for determining required risk premia for a diversified investor (Gine, Townsend and Vickery, 2007). Despite these attractive features, the rainfall insurance product, still in its infancy, has yet to receive widespread acceptance. Most households in the villages where it is offered do not purchase it, and those that do, typically purchase little coverage.

In this paper, we test competing theories of household insurance demand and draw conclusions about the barriers to widespread household participation in the rainfall risk management product. We do so through a set of randomized experiments. We conduct individual household marketing experiments in rural areas of two Indian states, Andhra Pradesh and Gujarat, in which farmers are given information about the risk management product, and have an opportunity to purchase policies. Various aspects of the visit are randomized across households. We estimate the price elasticity of demand for insurance by randomly varying the price of the policy. To understand the role of liquidity, we randomly assign certain households positive liquidity shocks. To measure the importance of trust, we vary whether the household receives a product endorsement by a trusted local agent. To understand whether limited financial education about the product limits adoption, we provide additional education to a subset of households relating the unfamiliar concept of rainfall in milimetres to the familiar concept of soil moisture. Finally, to understand whether product framing influences take-up, we vary the presentation of information on probability and the tone of the product marketing.

These randomized experiments allow us to estimate the causal effect on insurance participation of key factors suggested by neoclassical theory and the behavioral economics literature. To our knowledge, this study represents the first randomized evaluation of an insurance product. In addition to compelling internal validity, the paper combines experiments from two disparate regions, using very different rural populations, allowing a test of external validity as well. In most respects, we find similar results in these two different contexts, suggesting that the results are driven by predictable human behavior, rather than the idiosyncrasies of the environment.

Our main results are as follows. First, we document relatively low participation in the insurance product. In both survey areas, around 25% of households in our sample purchase the risk management product. The majority of those households purchase only a single policy.

Second, we find a pair of results that closely support neoclassical theories of insurance demand. Insurance demand is sensitive to price, with a price elasticity of demand between -0.66 and -0.88. And liquidity constraints bind: farmers who are surprised with a positive liquidity shock at the time of marketing are more than twice as likely to purchase rainfall insurance. Consistent with this finding, 64% of farmers in the Andhra Pradesh sample cite “insufficient funds to buy” as the primary reason for not purchasing insurance.

Third, we find evidence that non-standard factors such as trust and financial literacy influence takeup to an economically significant degree. A product endorsement from a trusted third party increases the probability of purchase by 40%. The simple act of conducting a household insurance marketing visit, even not combined with other treatments, significantly increases insurance purchase, even though the rainfall insurance is readily available to all households in our survey villages. Finally, we find some evidence that subtle psychological manipulations at the time of insurance marketing affect take-up.

These findings have broad implications for assessing the prospects for household risk management markets. These markets are nascent but growing. In the United States, for example, Case-Shiller housing futures allow households to hedge movements in city residentail property prices (Shiller, 2008). Prediction markets allow households to take positions on macroeconomic events such as recessions or election outcomes (Wolfers and Zitzewitz, 2004). Innovations in mortgage contracts, such as adjustable-rate mortgages and negative amortization contracts provide households the opportunity to customize their exposure to interest rate risk.

Insurance markets are also growing especially rapidly in developing countries. For example, a recent World Bank volume (World Bank, 2005) discusses ten case studies of index insurance (i.e. insurance contracts where payouts are linked to a publicly observable index like rainfall or commodity prices) in countries as diverse as Nicaragua, the Ukraine, Malawi and India.

Despite the promise of these markets, adoption to date has been relatively slow. While no formal estimates of household adoption are available, trading in Case-Shiller housing futures has been very sparse. Few, if any, private insurance options are available to cover idiosyncratic income loss for non-health related reasons.[2]

Our findings also contribute to a growing literature on household financial decision-making. Perhaps most advanced is work studying low levels of household participation in equity markets. Guiso, Sapienza, and Zingales (2007) find that trust is an important determinant of stock market participation. We find similar evidence for insurance market participation, using exogenous variation in trust generated by our experimental design. Hong, Kubik and Stein (2004) find that social interaction influences the stock market participation of individual households, while Hong and Stein (2005) find that social networks influence money manager investment decisions. Cole and Shastry (2007) find that household education plays an even larger role.

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[2] In a follow-up paper, we study the causal effect of insurance purchase on other margins of household investment and risk-taking. It is often argued that households in developing countries engage in costly risk-mitigation strategies to reduce income fluctuations. For example, Morduch (1995) finds that Indian farmers near subsistence level spatially diversify their plots, and devote a larger share of land to low-yield, traditional varieties of rice and castor. These income-smoothing activities reduce the variability of agricultural revenues, but at the expense of lower average income. This suggests an increase in the availability of insurance will have the opposite effect, increasing household investment in fertilizer, high-yield seed varieties, child education and so on.

A smaller literature studies household risk management. Campbell and Cocco (2003) and Koijen, Van Hemert and Van Nieuwerburgh (2008) examine risk management in the context of choosing an optimal residential mortgage. Also related, the home bias literature explores explanations for why household portfolios are not sufficiently diversified internationally (Coval and Moskowitz, 1999; van Nieuwerburgh and Veldkamp, 2007).

Finally, this paper contributes to the literature on financial innovation, risk management and risk sharing (Allen and Gale, 1994). Athanasoulis and Shiller (2000) discuss issues associated with creating securities linked to global aggregate asset returns. Athanasoulis and Shiller (2001) find substantial unexploited scope for international risk sharing. Townsend (1994) finds significant although incomplete risk sharing amongst households within Indian villages.

The rest of this paper proceeds as follows. Section I reviews the theoretical motivation for the hypotheses tested in the paper. Section II provides a description of the insurance products. Section III presents summary statistics for the households receiving randomized insurance marketing. Sections IV and V describe the design of the randomized trials in Andhra Pradesh and Gujarat respectively. Sections VI and VII present results for field experiments in these two states. Section VIII compares the experimental results to non-experimental evidence. Section IX concludes.

I. Determinants of insurance participation

A standard neoclassical model makes several predictions about demand for insurance. For example, Gine, Townsend and Vickery (2007) present a simple static model of insurance market participation under credit constraints. The model predicts that insurance demand is increasing in: (i) risk aversion; (ii) the expected payoff relative to the price of the policy inclusive of any additional transaction costs to the consumer; (iii) liquidity (i.e. willingness-to-pay is decreasing in the degree of credit constraints at the time insurance is purchased); (iv) the size of the risk exposure; and (v) the correlation between losses and insurance payouts (i.e. willingness-to-pay for insurance is decreasing in basis risk).

Many of these predictions have indeed been found to hold in insurance markets in the United States and other developed countries, typically through observational studies. Our experimental design allows us to directly estimate the causal effect of price and liquidity constraints on the probability of insurance purchase. We find that insurance demand is sensitive to both these factors.

However, other authors point to a variety of insurance puzzles inconsistent with neoclassical theory. Cutler and Zeckhauser (2004) write "we believe that there is an increasing divergence between the theory of and practice of insurance," and argue that "insurance purchases do not match theoretical predictions," and that "financial markets, despite their vast resources and wide participation, are not a major bearer of large private risks." (p. 2-3). For example, many consumers pay high premia for insurance on consumer durables, yet remain uninsured against disability and other catastrophic health events.

One potential explanation for insurance puzzles is that consumers may not fully understand or trust the product. Guiso, Sapienza and Zingales (2007) present a simple theoretical model of how trust influences stock market participation. Mistrust in their framework represents the consumer's subjective probability that they will be cheated, and will not receive a return for reasons that are orthogonal to the real returns produced by the firm. Their model predicts that less trusting investors are less likely to participate in the stock market.

We provide what we believe is the first experimental evidence for the role of trust in financial market participation, by varying whether the marketing visit to households includes an endorsement from a trusted third party, namely a customer service agent with whom the client is familiar. We also vary the amount of financial education provided to the household, to test the role of financial literacy in insurance market participation.

Insights from the economics and psychology literature provide additional guidance as to the source of observed insurance puzzles. For example, laboratory experiments support the idea that the framing of a choice can affect individuals' willingness to pay for insurance. Johnson, Hershey, Meszaros and Kunrether (1993) conduct a survey in which the maximum willingness to pay for flight insurance (covering a single airline flight) is elicited. The mean willingness to pay for a policy covering "*any act of terrorism*" is $14.12, compared to $12.03 for a policy covering an accident for "*any reason.*" In a standard model, the willingness to pay for the first policy must be weakly smaller than that for the second policy.

Similarly, psychological research (e.g., Mittal and Rose, 1998), finds that framing can also affect an individual's willingness to take risk. Even subtle, apparently arbitrary frames can have significant economic impacts. Bertrand, Karland, Mullainathan, Shafir and Zinman (2005) find subtle marketing cues matter. For example, including the picture of a man rather than a woman on an advertising flyer for a consumer loan has the same effect on demand for credit as a change of up to 2.2 percentage points in the *monthly* interest rate.

We therefore test several framing hypotheses. We first test one of the oldest framing effects, the "Asian Disease" preference reversal puzzle described in Tversky and Kahneman (1981), by describing the policy in terms of losses versus gains. Some prospective customers are told the policy "would have paid in 2 of the past 10 years," while others are told that it "would not have paid money in 8 of the past 10 years." Further tests of the framing effect are described in Section V.

Finally, a large theoretical and empirical literature analyzes how asymmetric information influences insurance demand (e.g. Abbring, Chiappori and Pinquet, 2003; Cawley and Philipson, 1996; Rothschild and Stiglitz, 1976). Such models are however of limited applicability to the rainfall insurance product studied here, since it is unlikely that households have significant private information about a public event like monsoon rainfall, especially given the availability of a long span of publicly available historical rainfall data.

II. Product description

Rainfall insurance is one of a range of innovative financial products made available to households in developing countries in recent years. Two factors led to its development in India, the first developing country in which it was introduced. First, India has dramatically liberalized financial markets in the past decade, enabling significant new entry. Insurance companies, like banks, face government pressure to serve (i.e., generate revenue) in rural areas. This has led to development of various micro-insurance products, including health, life, property, and livestock insurance. Second, around the year 2000 the International Task Force on Commodity Risk Management in Developing Countries was conceived, and began to work out, the technical details for offering rainfall insurance.[3]

In all cases, the basic structure of each contract is relatively simple. Contracts covering the growing season specify a threshold amount of rainfall, often the minimum needed to ensure successful growth of a given crop. If, during a pre-specified period of time (e.g. the entire growing season, or part thereof), cumulative rainfall is lower than this threshold, the policyholder is eligible to receive a payment. This payment typically increases

[3] Because financial products are difficult to copyright, the fixed cost of their development may limit financial innovation (Tufano, 2003). In this instance, the World Bank subsidized the development of the first product, providing substantial technical expertise and assistance.

with the size of the rainfall deficit relative to the threshold, reaching a maximum payout at a second threshold meant to approximate total crop failure.

A representative example is presented in Figure 1. Thresholds in the figure come from a contract offered in 2004 to households in one of our Andhra Pradesh study mandals (a mandal is roughly equivalent to a U.S. county). In the example, the product pays zero when cumulative rainfall during a particular 45 day period exceeds 100mm. Payouts are then linear in the rainfall deficit relative to this 100mm threshold, jumping to Rs. 2000 when cumulative rainfall is below 40mm. This second threshold is intended to correspond to total crop failure. Policies covering the harvest phase of the monsoon have a similar structure, except that the policy pays off when rainfall is particularly high, the mirror image of Figure 1.

[INSERT FIGURE 1 HERE]

For all policies, payments are promised automatically as a function of accumulated rainfall. Thus, beneficiaries do not need to file paperwork to collect payouts, an important benefit of the policy design that substantially reduces transaction costs.

Rainfall insurance was first offered in Andhra Pradesh in 2003, originally on a pilot basis, by the general insurer ICICI Lombard. ICICI Lombard partners with BASIX, a microfinance institution that markets the product to individual households through a network of local agents. These agents have close relationships with rural villages, and also sell other financial services like microfinance loans.

ICICI Lombard rainfall insurance policies divide the monsoon season into three contiguous phases, corresponding to sowing, podding/flowering and harvest. The length of each phase varies across policies, but is generally 35-45 days. Since the start of the monsoon varies from year to year, the start date of the first phase is not set in advance but instead is defined as the day in June when accumulated rainfall exceeded 50mm. (If less than 50mm of rain falls in June, the first policy phase begins automatically on July 1st.) Payoffs are based on measured rainfall at a local mandal (county) rain gauge.

Further information and institutional details about the Andhra Pradesh contracts is presented in Gine et. al. (2007) and Gine et. al (2008). Gine et. al. (2007) also estimate the distribution of returns on ICICI Lombard rainfall insurance contracts offered to Andhra Pradesh households in 2006, based on three decades of historical rainfall data. The distribution of insurance returns is found to be highly skewed. Policies produce a positive return in only 11% of phases. However, the maximum return, observed in about 1% of phases, is extremely high, around 900%. The estimated expected value of payoffs is on average about 30% of the policy premium.

Rainfall insurance contracts were first marketed in Gujarat in 2006 by SEWA, a large NGO serving women. SEWA marketed ICICI Lombard policies in the Ahmedabad, Anand, and Patan districts in Gujarat that share many features of the Andhra Pradesh contracts. In Anand and Ahmedabad, two district-specific policies were offered: one for crops requiring higher levels of rainfall, such as cotton, and one for crops requiring lower levels of rainfall (e.g., sorghum), which was naturally cheaper.

In response to feedback from the insurance sales team, SEWA streamlined their product offering in 2007, opting for a simpler policy from a different insurance provider, IFFCO-TOKIO. Further details are presented in Cole et. al. (2008).

A. Contract details

In this section we summarize contract details for insurance contracts offered to farmers in our survey areas in 2006, the year of the policy interventions. In both Andhra Pradesh and Gujarat, the 2006 insurance contracts divide the growing season into three phases, roughly corresponding to the timing of sowing, podding/flowering and harvesting of crops. Contract details are described in Table 1. The first two phases provided coverage against insufficient (deficit) rainfall, while the third phase paid in the event of excess rainfall. Originally, farmers were required to purchase coverage for all three phases each phase together in a single policy. However, for our interventions in 2006, farmers are allowed to purchase policies phase-by-phase, allowing customized coverage across different parts of the monsoon.[4]

[INSERT TABLE 1 HERE]

For example, consider the Gujarat policy labeled “Ahmedabad high” for 2006. The amount of payout is determined as follows: in Phase I, if rainfall is above the “strike” of 100mm, no payout is made. For each mm of deficit below 100mm, the policyholder is paid Rs. 5 per mm of deficit. If total rainfall is below 10 mm, the policy holder receives a single

[4] When the contracts were originally introduced in Andhra Pradesh, separate policies were designed for castor and groundnut, the two main cash crops in the region. These crops are on average, more profitable than food crops, such as grains and pulses, they are more sensitive to drought. From 2006 onwards, based on client feedback, the Andhra Pradesh product was streamlined to a single generic contract. In addition, the computation of the accumulated rainfall index was modified so that if rainfall on a given day was less than 2 mm, it was not counted towards the index, and in addition, if rainfall on a given day was greater than 60mm, the amount above 60mm did not count towards the index. These modifications reflect the fact that small amounts of rain are likely to evaporate before they affect soil moisture, and that very large amounts of rain are less beneficial for soil moisture and crop yields than smaller amounts of rain spread over a number of days.

payment of Rs. 500. In financial terms, the contract may be replicated by buying 5 puts on rainfall at a strike price of 100, selling 5 puts at a strike price of 10, and buying a digital option that pays Rs. 500 if rainfall falls below 10mm.

We note that the size of these policies is quite small, particularly in Gujarat. SEWA's members are among the poorest households in the state, and SEWA was committed to designing a product that was accessible to all. Purchasers were, however, not limited in the number of policies, and could purchase as many as they desired. As a point of reference, the Rs. 72 represents about two hours of labor for an agricultural worker.

In 2007 in Gujarat, to ensure the price was low, SEWA specified a policy size with a maximum payout of Rs. 1000, though of course households were free to purchase multiple policies. This policy was comprised of a single phase, from June 1 to August 31. Policy design specified a notional "normal" level of rainfall, roughly equal to the historic average in that district. Payout would occur if measured rainfall were 40% below this normal level of rainfall, with the amount of payout increasing (non-linearly) in the size of the rainfall deficit. The schedule of these payouts is given in Table 1. For example, the price of a policy in Patan was Rs. 85.51; if rain fell 80% short of the normal target of 389.9, the policy would pay Rs.400.

The actual realized rainfall amount led to a limited number of payouts. In Gujarat, rainfall was sufficiently high in both 2006 and 2007 so that no payout was triggered. However, in Andhra Pradesh, three policies out of five paid out. In the district of Mahbubnagar, Atmakur policies paid Rs. 214 in 2006, Rs.40 in 2005 and Rs. 613.33 in 2004 on average. Policies indexed to the Mahabubnagar station only had a payout in 2004 averaging Rs. 575. In Anantapur rainfall station, the policy paid Rs. 113 in 2006 and Rs. 4 in 2005. In Hindupur, also in Anantapur district, the policy paid Rs. 126 in 2006, Rs. 24 in 2005 but there was no payout in 2004. The Kondagal policy did not payout in any of the three years.

III. Summary statistics

In this section, we present summary statistics for households who received randomized insurance marketing interventions. These summary statistics are based on household surveys conducted in Andhra Pradesh and Gujarat in 2006. For Andhra Pradesh, the statistics below relate to exactly the set of households who received insurance interventions. For Gujarat, interventions were conducted both on survey households, and additional SEWA members in villages where insurance was offered. However, the statistics presented below are representative of SEWA members in villages where rainfall insurance is offered and interventions are conducted.

A. Sample selection: Andhra Pradesh

The 2006 household sample is the same (except for attrition) as an earlier, 2004 household survey. (Regressions in Gine, Townsend and Vickery, 2008, are based on this earlier survey). The sampling frame for the 2004 survey is a census of approximately 7000 landowner households across 37 villages in Mahboobnagar and Ananthapur. Amongst this population, a stratified random sample is selected. The strata are: households who purchased rainfall insurance in 2004 (267 households), households who attended an insurance marketing meeting but did not purchase insurance (233 households), households in villages where insurance was offered but did not attend a marketing meeting (252 households), and households in villages where insurance was not offered in 2004 (308 households). The total sample size is thus 1060. A random sample of households was selected within each of these strata. Between 2004 and 2006 there is attrition of 10.2%, due primarily to death and household migration. The sample for the 2006 field experiments is thus 952 households.

B. Sample selection: Gujarat

In 2006, prior to any interventions, 100 villages were selected for inclusion in the study, based on two criteria: (i) they are located within 30 km of a rainfall station, and (ii) SEWA has a presence in the village. (Subsequently, two of the 100 villages were deemed to be so close that it would not be possible to treat one and not the other, so they were grouped together, and assigned the same treatment status.) The villages are divided roughly evenly across three districts: Ahmedabad, Anand, and Patan.

We survey 15 households in each of these 100 villages. While SEWA intended to make the product available to any interested party, their main goal was to make it available to their members; hence, our sampling frame is the set of SEWA membership lists for the 100 survey villages. Of the 15 households, five are selected at random from the list of village SEWA members. An additional five are randomly selected from the subset of village SEWA members who also have a positive savings account balance. (This is because SEWA households are poor, and we were concerned liquidity may have limited take-up.) The final five households are selected (non-randomly) based on suggestions from a local SEWA employee that they would be likely to purchase rainfall insurance. This yields a total sample size of 1,500 households across 100 villages.[5]

A baseline survey of this sample was conducted in May 2006 by a professional survey team. Following the survey, treatment status was assigned, and rainfall insurance was offered to 30 of the 100 villages, selected randomly. A follow-up survey was conducted in October of 2006. In 2007, SEWA elected to continue to phase in the insurance product, offering it to an additional 20 villages, selected randomly from villages that were not offered insurance in 2006. Thus, in 2007, the year of our marketing experiments, insurance is made available in half the 100 villages.

In Andhra Pradesh, field experiments are confined to this sample of households for which demographic information is available through the household surveys. In Gujarat, experiments are based on a larger subset of households in villages where insurance was offered in 2007. Further details of the randomized interventions in Andhra Pradesh and Gujarat are discussed in sections V and VI.

C. Sample demographic characteristics

Table 2 presents summary statistics for surveyed households in both states. Because the surveys for Andhra Pradesh and Gujarat were developed independently, the set of variables is not identical. To the extent possible, we attempt to harmonize definitions and present consistent summary statistics.

[INSERT TABLE 2 HERE]

Agriculture is the primary income source in both areas. In Andhra Pradesh, agriculture is the main source of income for 65% of the households, mainly from own cultivation (64.1%) rather than agricultural labor (1.9%) In Gujarat, 72% of the households report agriculture as the main source of income. Many more households report agricultural labor (45%) as their primary source of income, relative to own cultivation (19%).

Household size is roughly similar in both areas, with a mean of 6.26 in Andhra Pradesh, and 5.94 in Gujarat. The fraction of historically disadvantaged minorities is low (10% of household are scheduled caste) in Andhra Pradesh, but relatively high in Gujarat: 35% of households are ‘scheduled caste,’ or former ‘untouchables’ reflecting SEWA’s membership of poor, self-employer women.

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[5] Because the same selection methodology was used in each village, and treatment status was assigned after the sample was selected, any causal estimates of the effect of rainfall insurance on household behavior will be an unbiased estimate, though the sample is of course not representative of the entire population.

The remainder of Table 2 describes household wealth and income. Gujarat is a substantially richer state than AP, with more productive soil. However, the Gujarati survey targeted the poor (SEWA members), while the Andhra Pradesh survey is representative of landowner households.

We ask households to report annual household income, and to list various assets to derive a measure of household wealth. By these measures, the Gujarati households appear to be better off, reporting an average annual income of Rs. 27,800, as against Rs. 17,000 in Andhra Pradesh. Reported consumption expenditures also suggest Gujarati households are richer, as the mean monthly per capita expenditure in Andhra Pradesh is Rs. 560, half of the Gujarati level.

However, comparing absolute levels of self-reported income may be unreliable. As an alternative measure, we calculate a wealth index based on a count of the type of assets or durable goods a household owns. We measure whether each household has a tractor, thresher, bullock cart, furniture, bicycle, motorcycle, sewing machine, electrical goods (television, radio, and fan) and a telephone (mobile or fixed). The mean number of assets held is 2.71 in Andhra Pradesh, but only 2.30 in Gujarat. The AP households were significantly more likely to have nearly all of these goods. To render these measures comparable for both samples, we extract the first principal component of assets held by each household.

D. Education and Financial Literacy

Table 3 presents information on the financial literacy of our sample, as well as attitudes towards risk. The rainfall insurance contracts offered to households are relatively complex, and household characteristics may affect how individuals value the product. While only a small fraction of the sample report being illiterate (17% in Gujarat), general levels of education are relatively low. 67% of sample households in Andhra Pradesh, and 42% in Gujarat, have at most a primary school education.

In Andhra Pradesh, insurance skill is measured by asking individuals a set of questions about whether a hypothetical insurance policy would pay out. Households generally answered these questions correctly (about 80% of households correctly answered each of them).

Since years of schooling may be a poor proxy for education, for the Gujarat sample, we ask a number of questions to directly measure numeracy and financial literacy. Respondents are offered Rs. 1 for each question answered correctly, paid immediately, providing some motivation to answer correctly.

First we administer a math test. The average math score is 64%. Almost all respondents correctly answer the simplest question ("what is 4+3") while many more had difficulty with multiplication ("3 times 6") and division ("one-tenth of 400"). Since respondents are not allowed to consult with friends or neighbors when answering, it is reasonable to think that in the real world, they may perform better when answering these questions.

To understand how households process information about index-based insurance products, we read a brief description of a sample insurance product (temperature insurance), and test household comprehension. After reading this description once, households are asked several hypothetical questions about whether the policy would pay out. Our sample did relatively well on this exam. 80% of the Andhra Pradesh sample and 68% of the Gujarat sample correctly answered questions testing knowledge of the putative product.

To measure general financial literacy, we adapt three questions used by Lusardi and Mitchell (2006). The questions were: (i) “Suppose you borrow Rs. 100 at a money lender at a rate of 2 percent per month, with no repayment for three months. After three months, do you owe less than Rs.102, exactly Rs. 102, or more than Rs. 102?” (ii) “If you have Rs. 100 in a savings account earning 1% interest per annum, and prices for goods and services rise 2% over a one-year period, can you buy more, less, or the same amount of goods in one year, as you could today?” (iii) “Is it riskier to plant multiple crops or one crop?” We also ask an additional question: (iv) “Suppose you need to borrow Rs. 500. Two people offer you a loan. One loan requires you to pay back Rs. 600 in one month. The second loan requires you pay back in one month Rs. 500 plus 15% interest. Which loan represents a better deal for you?”

Measured financial literacy is very low: the average score is 34%, or one correct answer from the three questions asked. If respondents guess randomly, we would expect a score of 44%, since two questions asked are multiple choices with two answers, while the other is a multiple choice with three answers.

The ability to evaluate an insurance policy depends critically on a respondent’s understanding of probability. We evaluate this skill graphically, showing respondents a set of diagrams. Each diagram depicts a pair of bags, in which a number of black and white balls were placed. We ask households to identify the bag in which a black ball was more likely to be drawn. Respondents perform much better on these questions, answering on average 72% of the questions correctly.

[INSERT TABLE 3 HERE]

E. Risk Attitudes, Discount Rates, and Expectations

Individuals' attitudes towards risk may be important when deciding whether to purchase insurance. Since the expected return of an insurance product is negative, the product has value only to the extent that households place a higher value on money in times of drought than in times of good rainfall. Risk aversion is difficult to measure, because people often do not make the same decisions in reality as they do when answering hypothetical questions.

We follow Binswanger (1980) and measure risk aversion using actual lotteries, for real (and substantial) amounts of money. We give individuals a choice of a set of lotteries, ranging from a perfectly safe lottery paying Rs. 50 for sure, to a lottery that pays Rs. 110 in Andhra Pradesh (Rs. 100 in Gujarat) with probability ½ and Rs. 0 with probability ½. The lottery and selection results are presented in Appendix A. Only 10% and 14% of the sample select the safe option in Andhra Pradesh and Gujarat respectively, while only 10% percent in both samples select the riskiest lottery (which would only be selected by a household that is locally risk-neutral or risk-seeking).

Rainfall insurance represents an investment made at the beginning of the growing season, for a (potential) payout that will be paid two to four months in the future. Higher discount rates will therefore make the insurance less attractive. Household discount rates are proxied by eliciting the minimum amount a household would be willing to accept in lieu of a Rs. 10 payment in one month.[6] Consistent with other evidence, respondents reported relatively high discount rates: the average elicited discount rate is 99% in Andhra Pradesh, and 59% in Gujarat.[7]

F. Sample insurance participation rates

We now turn to the household decision to purchase insurance. Because of the large fixed costs associated with providing insurance (staff training, weather data subscription, etc.), marketing the product would only be profitable in the long run if participation rates are relatively high. Information on insurance participation rates for our samples are presented in Table 4.

[INSERT TABLE 4 HERE]

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[6] Because it would have been prohibitively expensive to revisit all households one month from the interview date, households were instructed that this was a hypothetical question.

[7] Discount rates are elicited by asking a set of hypothetical questions: "Would you prefer to receive *x* Rupees today, or Rs. 10 in one month", where *x* is varied across a range of values.

In Andhra Pradesh, the sample take-up rate trends upwards over time. In 2003, the first year the policy was offered, adoption is low: only 148 households purchase policies. In 2004, adoption increases, and 35.5% of our sample purchases insurance. In 2006, this number falls to 26.8%.

Take-up in Ahmedabad also follows a (modestly) increasing path, and is relatively high for a new product: in 2006, the first year the product was offered, approximately 23% of the surveyed households offered insurance purchased a policy in 2006. In 2007, this increases slightly.

Repeat adoption is somewhat uncommon in Andhra Pradesh. 7.6% of those purchasing insurance in 2005 purchase it again in 2006, although 24.6% of those purchasing in 2004 purchasing it again in 2006. In the 30 original treatment villages in Gujarat, a significant fraction of those purchasing in 2006 also repurchase in 2007.

IV. Field experiments: Andhra Pradesh

In 2006, we conduct door-to-door insurance marketing visits prior to the beginning of the growing season to 700 randomly selected households of the 1,054 in our original 2004 sample. The remaining households do not receive any treatments.

During the marketing visit, a trained insurance marketer explains the rainfall insurance product to the household, and offers the household an opportunity to purchase insurance policies on-the-spot. In case the household is interested in the product but does not have cash on hand to pay for the insurance, the household may also purchase insurance later thorugh their local BASIX office or sales agent. Also, if the marketer has sufficient time, they may offer to visit the household again at a later agreed time (before they leave the village) to collect payment.

A. Manipulations

We randomize the marketing received by these 700 households along three dimensions. First, we offer a random amount of compensation for the household’s time, of either Rs. 25 or Rs. 100, paid at the end of the marketing visit (half the households receive the larger amount). Thus, we offer random liquidity shocks to households. Recall that the premium for one phase of insurance is 80 Rs, so receiving Rs. 100 provides enough cash-on-hand to purchase one policy.

Second, we randomize whether the marketer is endorsed by a BASIX representative, known as an LSA (or Local Service Agent). This agent is well known and trusted amongst village households, since BASIX has a good reputation and a high penetration rate in our survey villages. For 350 of the 700 treated households, the local BASIX representative introduces the marketer to the household. ‘Endorsement’ means that the BASIX representative encourages the household to listen to the marketer, and declares that the marketer is trustworthy. (The BASIX LSA does not, however, help explain or sell the product.) For the other 350 households, the marketer, who is unknown to the villagers, visits the household alone, and is not endorsed by the BASIX representative.

Third, we randomize whether the household received additional education about the measurement of rainfall in millimeters and its conversion into soil moisture. Farmers report that they generally decide when to sow crops by measuring the depth of soil moisture in the ground after the beginning of the monsoon. Only 10 percent of households in 2004 could accurately measure rainfall in millimeters. However, all the insurance contract terms are set in millimeters. For 350 of the 700 households, we present information about millimeters by showing the household, using a ruler, the length of 10mm and 100mm, and then showing them a chart of how 100mm of rain translates into average soil moisture for the soil type on their farm (either black or red). These conversion charts were prepared with the assistance of an ICRISAT agronomist. For the other 350 households, marketers do not provide this information.

These three treatments are applied randomly and independently across households. These interventions are summarized in Panel A of Table 4. In previous years, BASIX conducted village-level meetings to introduce the insurance product to farmers. However, in 2006, BASIX agreed not to conduct these meetings in the villages where interventions were conducted.

[INSERT TABLE 5 PANEL A HERE]

V. Field Experiments: Gujarat

In 2007, SEWA uses two primary methods to market rainfall insurance to its members. For the 30 villages who were also offered insurance in 2006, SEWA markets the insurance by distributing flyers describing the product. In the 21 villages which were first offered insurance in 2007, SEWA uses personal video players (similar to a video iPod) to deliver a ninety-second marketing message directly to household-decision makers.[8]

To estimate the causal effect of different marketing treatments, we randomize the content of marketing received by households within these two groups, flyer and video. Information about the experimental design for the marketing interventions in Gujarat is presented in Panel B of Table 5.

[INSERT TABLE 5 PANEL B HERE]

SEWA conducts video marketing in 1,415 households in the 21 villages first offered insurance in 2007, and delivers 2,391 flyers in the 30 villages treated in both 2006 and 2007. The content of each video and each flyer is randomized across households. To keep track of which households in the flyer villages receive which messages, households are given a non-transferable coupon for a discount, which indicates the marketing message the household receives. In the 21 villages where video advertisements are shown, the size of the discount is also varied (orthogonally) as well. The video and flyer marketing interventions are described in more detail below.

A. Marketing Treatments

Previous research from marketing and economics suggest that many factors may affect an individual's decision to purchase insurance. In the video experiments, the following manipulations are used. They are summarized in Table 5 Panel B. Detailed description of the various interventions is given in the appendix. The number of households in each treatment category is given in the final column of the table.

- · SEWA Brand (Yes or No): SEWA has worked for years in the villages in the study, while ICICI Lombard, the insurance company, is virtually unknown to the rural population. In the 'Yes' treatment, the videos include clear indications that the product is being offered by SEWA. In the 'No' treatment, SEWA is not mentioned in the video. We hypothesize that including the SEWA brand will lead to higher take-up, as consumers will have greater levels of trust in the product. Trust has been shown to be an important determinant of financial market participation (Guiso et.al, 2007).

[8] The use of video players allows SEWA to explain the product to the households in a consistent manner. It allows for a more careful experimental treatment, as it reduces the role of the individual delivering the marketing messages.

- Peer / Authority (Peer Figure or Authority Figure): Individuals learn about new products from various sources. In the ‘Peer’ treatment, a product endorsement is delivered by a local farmer. In the ‘Authority’ treatment, a teacher delivers the endorsement.
- Payout (8/10 or 2/10): This framing treatment emphasized either the probability the product would pay out, or the probability the product would not pay out. In the ‘8/10’ treatment, households are told that ‘the product would not have paid out in approximately 8 of the previous 10 years’. In the ‘2/10’ treatment, households are told that ‘the product <u>would</u> have paid out in approximately 2 of the previous 10 years’. These statements convey the same information, but one through a positive frame, the other through a negative frame.
- Positive/Negative (Positive or Negative): The Positive treatment described the benefits of insurance, as something that will protect the household and ensure prosperity. The Negative treatment warned the household of the difficulties it may face if a drought occurs and it does not have insurance.

These treatments are crossed, though not all possible combinations are employed. For households that are surveyed, four videos are used (A-D in Table 5 Panel B). Because an important goal of the study is to measure the effect on take-up, the SEWA brand is included in all videos, due to our prior hypothesis that it would have a positive impact. For the households that receive marketing treatment, but are not surveyed, one of eight different videos is randomly assigned.

The flyer treatments in the 30 original villages test two different manipulations, described below:

- Individual or Group (Individual or Group): the `Individual' treatment, the flyer emphasizes the potential benefits of the insurance product for the individual who purchases the policy. The Group flier emphasizes the value of the policy for the family of the purchaser.
- Religion (Hindu, Muslim, or Neutral): A photograph on the flier depicts a farmer, who is either standing near a Hindu temple (Hindu Treatment), a Mosque (Muslim Treatment), or a nondescript building. The individual is also given a matching first name, which is either characteristically Hindu, characteristically Muslim, or neutral.

B. Discounts

In the 21 villages where a video is played to households, we present households a coupon offering a discount on the rainfall insurance. We randomize the size of this discount across households. 40% of households receive a Rs. 5 discount, 40% receive Rs. 10, and 20% receive Rs. 20. From this randomization, we estimate the price elasticity of demand for rainfall insurance.

VI. Results: Andhra Pradesh

Table 6 presents experimental results from Andhra Pradesh. We regress a dummy variable for whether the household purchases insurance on indicators for the various treatment interventions. In column (1) we report results without additional controls; in other columns we also include a set of household characteristics as controls. Because the treatments are randomly assigned, the estimates of the treatment effects are consistent both with and without the controls; however, including controls may absorb additional variation leading to more precise parameter estimates.

[INSERT TABLE 6 HERE]

The size of the cash transfer paid to the household during the marketing experiment is the most important determinant of insurance participation amongst the treatment interventions we consider. Increasing the payment from Rs. 25 to Rs. 100 increases the probability of purchase by 34.5 percentage points in column 1, statistically significant at the 1 percent level. Thus, cash on hand is an important determinant of insurance participation, consistent with the simple model of insurance participation under credit constraints presented in Gine et al. (2008).

Our second finding is that trust has an important effect on insurance purchase decisions. Endorsement of the household visit by a local BASIX representative increases the probability of insurance purchase by 10 percentage points amongst households familiar with BASIX. Notably, for households unfamiliar with BASIX, endorsement has no statistically significant effect on insurance purchase decisions. (This effect is measured as the sum of the coefficient on ‘endorsed by LSA’, and interaction term ‘endorsed by LSA x don’t know BASIX’.) This finding is inconsistent with a full-information neoclassical benchmark. However, it is consistent with various other types of non-experimental evidence that trust is an important determinant of financial market participation (Guiso et. al., 2007).

Third, we find that the act of conducting a household marketing visit has a large, statistically significant effect on insurance take-up, even when not combined with other treatments. Although the product is available to all households in the village, a household visit alone increases the probability of insurance purchase by 17.8 percentage points. This may reflect the added convenience of being able to purchase insurance 'on-the-spot', or be due to the effect of the additional information provided.

Finally, the education module administered to a subset of households has no statistically significant effect on insurance participation. This module was directed towards increasing the household's understanding of the linkage between millimeters of rainfall, the index used for insurance payouts, and soil moisture, the measure used by farmers in Andhra Pradesh to decide when to sow. This module was designed to take 5-10 minutes to complete. Although other evidence suggests that a sizeable number of households do not fully understand the insurance product, this modest amount of financial education is not sufficient to significantly shift household participation rates.

VII. Results: Gujarat

Results from the Gujarat experiments are presented in Table 7 Panel A and B. Panel A reports results from the flyer treatments, and Panel B reports results from the video treatments. In total, 29.3% of households who received video treatment purchase rainfall insurance, while 25.9% of households that receive flyer treatments purchase insurance. This difference is statistically significant. While SEWA marketers report that the video marketing was considered to be very effective, it would not be correct to conclude that videos were more effective than flyers: the difference in take-up reflects both the difference in media, and the fact that the villages that received the flyers had already been exposed to weather insurance (recall that in 2006, the insurance policies did not produce a positive payout in any of the regions).

[INSERT TABLE 7 PANELS A AND B HERE]

A. Flyer results

In columns (1) and (2) of Panel A, we regress whether the household purchases insurance (set to 100 if the household purchased insurance, and 0 if not), on dummies for the main flyer treatments: whether the individual pictured (and named) was Hindu, Muslim, or religion unidentified (omitted category); whether the flyer emphasized the benefits to the group, or to the individual.[9] We find no effects from these treatments, and again the point estimates are small.

In columns (3) and (4) of Panel A we fully saturate the model, adding interactions for "Muslim * Group" and "Hindu * Group." We find some evidence that the message on the flyers had an effect. For the non-religious framing, the group effect increased take-up by approximately six percentage points. However, when religion was cued, the emphasis on group had no effect. A test of all the main effect and interactions from column (4) rejects the hypothesis that the flyer cues have no effect at the 9.2% level.

In Panel B, we regress take-up (with purchase=100, non-purchase=0), on dummy indicator for whether there was a strong SEWA brand emphasis, whether a peer endorsed the product (as against an authority figure), whether the policy is described as paying out in 2 of 10 years (against not paying out in 8/10 years), and the discount amount in Rs. We also include a dummy for whether the household was surveyed. Standard errors are corrected for clustering at the village level. The first column reports results without village fixed-effects; the second column results with village fixed-effects.

We find the following. The subtle psychological manipulations have no statistically significant effect: the point estimates for Sewa Branding, Peer Endorsement, Payout Framing, or Positive / Negative frame are typically economically close to zero, and not statistically different from zero at conventional significance levels, and somewhat precisely estimated. A test of the joint hypothesis that there is no effect of any of these framing effects cannot be rejected (F-statistic 1.13, p-value .37).

The dummy variable for "surveyed" is positive and large. Those households that were surveyed are 15-17 percentage points more likely to purchase insurance than those who were not part of the survey. However, surveyed households were not randomly assigned, and the identified effect thus includes any effect of being surveyed, combined with the fact that surveyed households were selected precisely because they were more likely to purchase insurance.

B. Video results

Discount coupons for the insurance policy were distributed to the household along with the presentation of the marketing video. Each household was randomly assigned a coupon with

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[9] We emphasize that these dummies bear no relation to whether the *respondent* was Hindu or Muslim. The flyers were distributed to all non-survey households in village: most were Hindu, but we do not observe any information (except purchase decision) from non-surveyed households.

value Rs. 5, Rs. 15, or Rs. 30. Forty percent of households received the Rs. 5 coupon; forty percent received the Rs. 15 coupon; and 20% of households received the Rs. 30 coupon. The coupon was non-transferable, and the name and address of the respondent were written on the coupon.

The point estimate on the coefficient for the size of the discount is 0.47, with a t-statistic of 3.5. Moving from a discount of Rs. 5 discount to a Rs. 30 increases the probability of purchase of insurance by 12.5 percentage points, from a base of 26.3%.

We calculate the price elasticity of demand in the following manner. We estimate the coefficient on the discount, β_d, separately for each district. Denote P as price and Q as quantity. Taking β_d for ΔQ, the average take-up rate in the district for Q, 1 for ΔP, and then weighted average price to which households were exposed, we calculate the price elasticity of demand for all three districts.[10] The elasticity of demand is highest in Ahmedabad and Anand, at 0.83, and 0.875, respectively, and lowest in Patan, at 0.66.

VIII. Discussion, and comparison to non-experimental evidence

Combining our evidence from Andhra Pradesh and Gujarat, we draw a number of conclusions about the factors influencing demand for rainfall insurance:

1. Demand for rainfall insurance is downward sloping, with a price elasticity of demand between 0.66 and 0.88, depending on the region studied.

2. Insurance demand is extremely sensitive to cash on hand. Providing the household with enough cash to purchase a policy increases participation by 34.5%. This is 3.5 times as large as the effect of cutting the price of the policy by Rs. 20 (equivalent to a 30% discount).

3. Trust plays an important role in participation in this sector of the financial system, consistent with the model and (non-experimental) empirical results of Guiso et. al. (2007). We find that endorsement of the insurance marketer by a trusted individual increases participation by 10 percentage points (or 40%).

4. Insurance demand is sensitive to other non-standard factors that are difficult to reconcile with a simple neoclassical story. The act of conducting a household marketing visit has a significant effect on the decision to purchase insurance, even though insurance is easily

[10] The base price of the insurance product varys across districts, as each has different historical rainfall patterns. In 2007 the price is Rs. 72 in Anand, Rs. 44 in Ahmedabad, and Rs. 86 in Patan. Coupon amounts were varied between Rs. 5, Rs. 15, and Rs. 30 in all three districts.

available to all households in the village. Also, emphasizing the benefits of the insurance to a group rather than an individual as a significant effect on insurance participation for a subset of the sample.

That said, most of the subtle marketing treatments we consider do not have a statistically significant effect on insurance participation. These subtle cues seem to be less important in our setting than trust, price and credit constraints, in contrast to the stronger effects of subtle cues found by Bertrand et. al. (2005).

5. The provision to the Andhra Pradesh sample of a small amount of additional financial education has no statistically significant effect on insurance participation. This may reflect either that households are already well-informed, or that our education module is insufficient to significantly boost the financial literacy of the households in our sample.

Below, we consider a range of non-experimental evidence about the determinants of rainfall insurance takeup. We consider the extent to which this additional evidence is consistent with the conclusions from experimental results summarized above.

A. Comparison to non-experimental evidence

Gine, Townsend and Vickery (2008) study in detail the variables that predict insurance participation for their 2004 household survey. These results are described in more detail in Gine et. al. (2008) and in Appendix C. In brief, the results are as follows. Insurance take-up is found to be decreasing in basis risk between insurance payouts and income fluctuations, increasing in household wealth and decreasing in the extent to which credit constraints bind. These results match with predictions of a simple neoclassical model appended with borrowing constraints. Other patterns are less consistent with the benchmark model. Namely, participation in village networks and measures of familiarity with the insurance vendor are strongly correlated with insurance take-up decisions, and risk averse households are found to be less, not more, likely to purchase insurance.

This analysis is repeated for the 2006 Andhra Pradesh and Gujarat insurance take-up decisions. Results are presented in Table 8. Where possible, common variables from the two survey areas are defined in the same way, to allow comparison across the two survey regions.

[INSERT TABLE 8 HERE]

In general, the strength of the randomized experiments reduces the power to identify other non-experimental influences on insurance participation, relative to Gine et. al. (2008). However a number of results are found which are consistent with their previous results. First, skill with insurance is also positively correlated with the decision to purchase. It should be noted that this skill is tested *before* the households are exposed to insurance. We also find for the Gujarat sample that Muslim households are more likely to purchase insurance.

While wealth and landholding are not individually significant, they both, along with personal consumption expenditure, enter the regression positively, and a joint test of their significance rejects the null that they are not jointly correlated with the insurance purchase decision. This is consistent with previous evidence from our experiments and from Gine et. al. (2008) that credit constraints are an important influence on household insurance participation decisions.

As an additional type of non-experimental evidence, Table 9 presents household self-reports from survey households in Andhra Pradesh about their reasons for deciding not to purchase rainfall insurance (for the subset of households that do not participate). The most common reason given in 2004 is 'do not understand it'. Notably, the fraction of households citing this reason falls significantly between 2004 and 2006, perhaps some evidence that households are learning about the insurance product as they become more familiar with it. In 2006, by far the most common reason cited by households is 'insufficient funds to buy it'. This response is more than six times more popular than the next most popular explanation 'it is not good value'. This qualititative evidence exactly matches our experimental results, where the treatment involving random liquidity shocks has by far the most significant effect on insurance participation rates.

[INSERT TABLE 9 HERE]

B. Boosting household risk management: Some tentative lessons

The 'micro-insurance' industry is in its infacy, and suppliers of such insurance products are experimenting with different product types to work out the best ways to reach consumers and stimulate demand.

From our results presented above, we draw a number of tentative conclusions about factors that may help boost demand for household risk management amongst the population of rural Indian farmers:

1. Unsurprisingly, we find that insurance demand is highly sensitive to price. Thus, minimizing transaction costs, and boosting competition amongst suppliers of insurance, leading to lower premia, would significantly boost takeup.

2. Both experimental and non-experimental evidence suggests that liquidity constraints are an important barrier to household risk management. One design change that would potentially help to ameliorate these credit constraints would be to provide the

insurance contract alongside a loan covering the monsoon (or put differently, write a loan contract to the farmer whose payments are contingent on monsoon rainfall).

3. Non-standard factors such as trust and financial literacy appear to be important determinants of household participation in the insurance product, especially in this early stage of its life cycle. Thus, proper certification of the product and the product vendors, for example through endorsement by local elders, is likely to be helpful in encouraging households to participate.

IX. Conclusions

A primary function of financial markets and the financial system is to diversify risks across households. In recent years a variety of financial innovations have emerged with the potential to improve household risk management, including housing futures based on Case-Shiller house price indices, prediction markets linked to economic and political events, and a range of index insurance products designed for hedging weather, price and other risks predominately in developing countries. Despite their appealing features, these financial innovations, however, are still in their infancy, and take-up is low.

Our evidence based on field experiments of rainfall insurance participation in two regions of India, points to several factors as key barriers to household participation in such risk management products. First, household purchase rates are very price-elastic, suggesting that minimizing transactions and administrative costs, and fostering competition amongst insurance providers, is important to increasing insurance penetration rates. Second, random shocks to cash-on-hand have a very large effect on participation, suggestive of an important role for credit constraints. This is consistent with non-experimental evidence. Third, trust appears to matter significantly for financial market participation, consistent with non-experimental evidence presented in other recent research.

We do not view these barriers to household risk management as insurmountable, nor do we view the relatively low takeup to date as reflecting as a lack of demand for pooling risk. Technological advances may improve the product offering, by linking payouts to rainfall and temperature (as is being done at present), or by offering payouts based on foliage coverage from satellite photos. Contractual improvements, such as introducing local information revelation through joint liability models, with some auditing from the insurance company, may improve these products. Yet, we nevertheless conclude that, taken together, the results suggest that it may take a significant amount of time, and substantial marketing efforts, to increase adoption of risk management tools at the household level.

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Appendix A: Risk Aversion Lottery Results

Below we present the percentage of households who select each different option amongst the Biswanger lotteries offered, in both Andhra Pradesh and Gujarat.

Appendix A Table: Binswanger Lotteries

Andhra Pradesh

Heads	Tails	ΔE / Δrisk	Percent Choosing 2006
25	25	1.00	10.31%
20	60	0.75	25.61%
15	80	0.60	17.96%
10	95	0.50	25.29%
5	105	0.33	10.95%
0	110	0.00	9.88%

Gujarat

Heads	Tails	ΔE / Δrisk	Main Sample (N=1500)
25	25	1.00	14.02%
22	47	0.76	12.27%
20	60	0.73	15.36%
17	63	0.72	15.56%
15	75	0.71	9.32%
10	80	0.58	15.63%
5	95	0.45	7.91%
0	100	0.00	9.93%

Appendix B: Detailed Description of Gujarat Interventions

Households are (non-randomly) assigned into two groups: the video group, and the flyer group. Because of limited resources SEWA was able to provide video marketing to only a limited number of households. SEWA marketers attempted to reach all survey respondents with video marketing, and as many additional households as possible.

Table 2, Panel B describes the groups in detail. We here include the text associated with the various treatments.

Video Treatments

(i) Payout Framing: Loss vs. Gain

<u>“8/10 no.”</u>

If you had owned this policy for each year in the past ten years, the policy would not have paid money in eight of those past ten years.

<u>“2/10 yes”</u>

If you had owned this policy for each year in the past ten years, the policy would have paid money in eight of those past ten years.

(ii) Payout Framing: Positive vs. Negative

<u>Postivie Framing</u>

“If you purchase this insurance, you will help ensure that you will have a good outcome, no matter what the weather is.” This message was coupled with a picture of lush field.

<u>Negative Framing</u>

“Without insurance, if there is a drought and your crops fail, you may suffer,” combined with a picture of a parched field and a distraught farmer.

(iii) Peer vs. Authority

In the “peer” treatment, the actress on the video introduces herself as a fellow SEWA member. In the “Authority” treatment, the same actress introduced herself as a local community leader.

Flyer treatments

(i) Hindu vs. Muslim vs. Non-Religious

In the flyer, a person described a positive experience with the insurance. In the "Hindu" treatment, he had a Hindu name, and there was a Hindu temple in the background. In the "Muslim" treatment, he had a Muslim name, with a mosque in the background. Finally, in the "Non-Religious" treatment he had a neutral name, with a non-descript building in the background.

(ii) Flyer treatment: Group vs. Individual

The "Individual" treatment emphasized the potential benefits of the insurance product for the individual who purchases the policy. The Group flier emphasizes the value of the policy for the family of the purchaser.

Appendix C: Description of baseline results of Gine, Townsend and Vickery (2008)

Gine, Townsend and Vickery (2008) examines in detail predictors of take-up using data from a 2004 household survey of the Andhra Pradesh sample. The main findings from this regression are summarized below. In all the results below, We estimate a reduced-form probit regression model of insurance participation. The dependent variable is equal to 1 if the household purchases BASIX rainfall insurance in 2004, and 0 otherwise. Results are presented in Table 6.[11] We focus on the binary variable of whether the household purchases at least one insurance policy, because few households purchase multiple policies. The main findings are as follows:

I. Credit constraints and wealth. The baseline regression includes two wealth variables, log(1+landholdings) and log(wealth), both measured at the beginning of the Kharif. Both measures are positively signed, and although neither is individually significant, they are jointly significant at the 2% level. (These variables are strongly collinear; in an unreported regression excluding log(wealth), the coefficient on land quadruples, and becomes statistically significant at the 1% level.) The regression also include a direct proxy for credit rationing, derived from household self-reports about why they do not have one more loan. This coefficient is negatively signed as predicted, and statistically significant at the 1% level. Quantitatively, switching on this variable reduces the probability of takeup by 30% (1.4 percentage points).

Each of these results suggests that binding credit constraints reduce the probability of insurance takeup. This is also consistent with the experimental evidence presented below.

II. Early adoption, limited cognition and networks. Qualitative responses suggest a significant fraction of households do not fully understand the insurance product, and that many relied on recommendations from others for insurance participation decisions. Here we test three hypotheses described earlier about household behavior in this kind of incomplete information environment.

[11] The first column of results normalizes coefficients to reflect the marginal effect of a one-unit change in the explanatory variable on the probability of insurance purchase. For expository purposes, in column 2, we present the same results dividing the coefficients by the population mean participation rate of 0.046; these coefficients indicate the *percentage* change in the probability of takeup for a one-unit shock to the relevant covariate (i.e. a coefficient of 1 indicates one unit shock to the explanatory variable doubles the probability of insurance participation for a household whose initial participation probability equals the population average).

The first hypothesis is that households with a greater degree of familiarity with or trust in BASIX, the insurance provider, will have higher participation rates. First, we include a dummy variable equal to 1 if the household is a member of a borewell user association (BUA). A BUA is a group of households who jointly use and maintain a water bore or set of bores. Historically, BASIX provides group lending to BUAs, and in 2003, when the insurance was first piloted, the insurance was explicitly targeted to BUA members. BUA members are more likely to know the BASIX sales representative in the village, and a BUA also provides a close-knit network of households who share information and advice.

Membership of a BUA has a very large and statistically significant effect on participation decisions; our marginal effects estimates suggest it increases the probability of insurance participation by a factor of 8 ($p < 0.01$). A second variable indicating whether the household is an existing BASIX borrower at the start of the Kharif also strongly predicts takeup. Quantitatively, existing BASIX customers are 143% more likely to purchase insurance ($p<0.01$). These two variables (along with Gram Panchayat membership) are quantitatively the strongest predictors of insurance participation decisions.

Second, we provide suggestive evidence on the role of social networks in insurance takeup decisions. First, households who are members of the village Gram Panchayat are significantly more likely to purchase insurance ($p < 0.01$), as are households who are members of a larger number of other formal and informal village networks ($p < 0.01$), such as self help groups, Raithu Mitra groups and caste committees. More directly, we also include a variable that measures the number of other well-known households in the respondent's self-identified primary social group who purchased insurance. This variable is positive and statistically significant ($p < 0.01$). Quantitatively, an additional purchasing household amongst the respondent's primary group raises the probability of the household purchasing insurance by 12%.

These results and the qualitative responses discussed earlier suggest that social networks, and trust in the insurance provider are key determinants of insurance takeup. However, caution should be exercised in interpreting these results, since we cannot rule out the hypothesis that our estimates reflect unobserved heterogeneity across groups (see Manski, 1993, for a discussion in the context of measuring local network effects). In particular, the strength of our findings may in part reflect the approach taken by BASIX in marketing the insurance to households. BASIX first contacted opinion leaders in the village, and asked them to help publicize the insurance and the insurance marketing meeting. BASIX also reached out to existing customers when marketing the insurance. In other words, the intensity of marketing is an omitted variable, which is likely to be correlated with networks and prior experience with BASIX.

The third hypothesis is that households vary in their cognitive ability to understand the terms of the insurance product. We first consider self-identified 'progressive' households, that is, farmers that other villagers ask for advice (perhaps because they are more knowledgeable or intelligent). Such households are 14% more likely to purchase insurance ($p < 0.05$) than non-progressives. Households with a younger household head, or a household head that has lived outside the village, are also statistically significantly more likely to purchase insurance ($p < 0.01$ and $p < 0.10$ respectively). A doubling of the household head's age reduces the probability of insurance purchase by 32%, consistent with our prior that the cost of evaluating new products and technologies is lower for younger individuals.

Surprisingly, education is not statistically significantly correlated with insurance participation decisions. This result contrasts with Giné and Yang (2007), who find that education increases the effect of weather insurance provision on the decision to take a crop loan amongst households in Malawi. We do not propose a single explanation for these differences, however a potential reconciliation is that households in Malawi had no prior experience with the insurance provider, while BASIX is well known to most households in our sample. Thus, for our sample, the household's opinion of, and trust in, BASIX is likely to be relatively more important when evaluating the quality of the insurance product.

III. Risk aversion. A standard model of insurance participation would predict that risk-averse households have a higher willingness-to-pay for insurance. In fact we instead find that risk-averse households are marginally *less* likely to purchase rainfall insurance, significant at the 10% level. Quantitatively, shifting the risk aversion parameter from its minimum to maximum value (i.e. 0 to 1) reduces the probability of purchase by 25% (1.1 percentage points). Gine et al (2008) show however that this result is present only amongst households without a past relationship with BASIX, the insurance vendor. They interpret this evidence to suggest that risk-averse households are also averse to uncertainty about the insurance policy itself, and the potential risks associated with it, given their imperfect understanding of the product.

Figure 1: Rainfall Insurance Contract Example

ICICI Lombard rainfall insurance divides the monsoon into three phases, each 35-40 days in length. The graph below illustrates how cumulative rainfall during the phase translates into an insurance payout. Figures in brackets are actual trigger points and payouts for a representative insurance contract, namely payouts on rainfall insurance linked to castor for the middle (podding/flowering) phase of the monsoon in the Narayanpet mandal of the Mahboobnagar district, in the state of Andhra Pradesh.

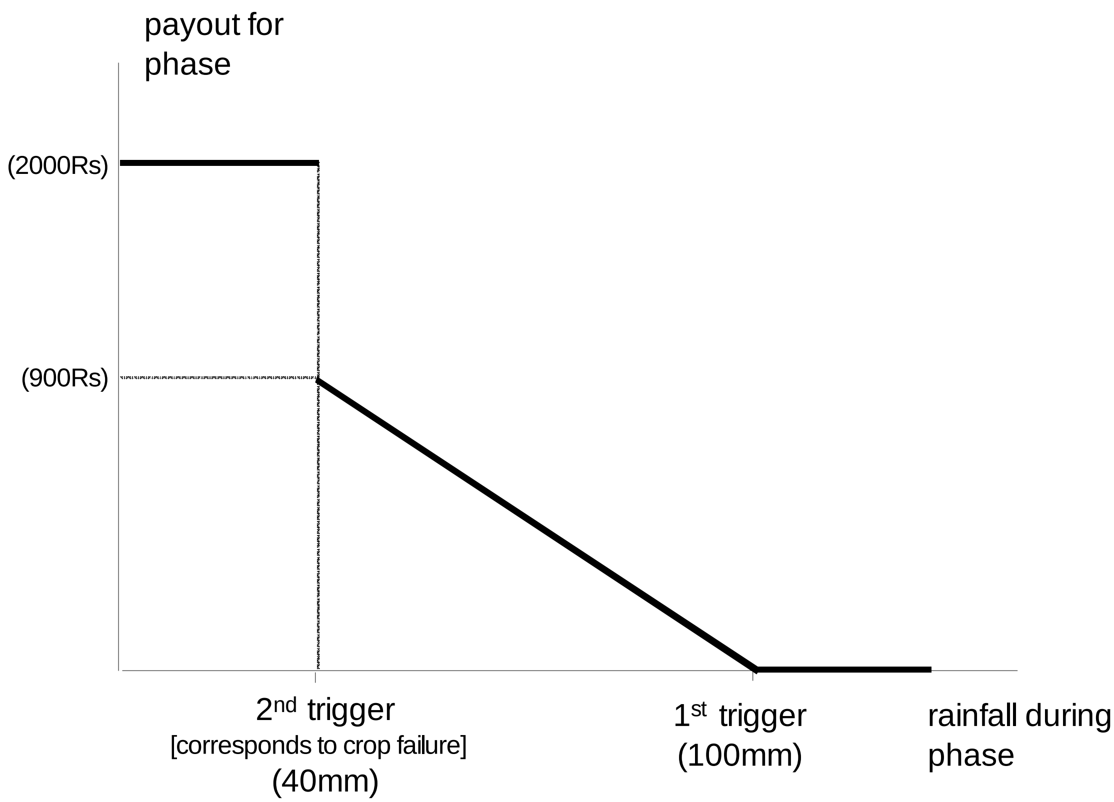

Table 1: Rainfall Insurance Contract Specifications

Panel A: ICICI Policies					Phase I		Phase II		Phase III	
Year	Type	Premium	Notional	Limit	Strike	Exit	Strike	Exit	Strike	Exit
Andhra Pradesh										
2006	Anantapur	340	10	1,000	30	5	30	5	500	575
2006	Atmakur	280	10	1,000	45	5	55	5	500	570
2006	Hindupur	295	10	1,000	25	0	15	0	500	580
2006	Kondagal	290	10	1,000	55	5	60	5	330	410
2006	Mahabubnagar	270	10	1,000	70	10	80	10	375	450
Gujarat										
2006	Ahmedabad High									
2006	Ahmedabad low	144	5	500	100	10	65	5	550	650
2006	Ahmedabad high	197	5	500	150	50	90	10	550	650
2006	Anand low	155	5	500	100	10	65	5	550	650
2006	Anand high	204	5	500	120	20	90	10	550	650
2006	Patan	257	5	500	100	10	75	5	550	650

Panel B: IFFCO-Tokio Policies				Rs. Payout, as a function of Rainfall Deficit from "Normal Rain"						
		Premium	Normal Rain	40%	50%	60%	70%	80%	90%	100%
Gujarat 2008										
2007	Ahmedabad	43.82	607.4	100	150	200	300	400	700	1000
2007	Anand	71.91	783.6	100	150	200	300	400	700	1000
2007	Patan	85.51	389.9	100	150	200	300	400	700	1000

Table 2: Panel A, Summary Statistics

	Andhra Pradesh		Gujarat	
	Mean	Std. Dev	Mean	Std. Dev
Utility function				
Risk aversion in July 2006	0.566	0.259	0.653	0.258
Subjective discount rate as of July 2006	0.991	1.417	0.569	0.439
Basis risk				
Pct. of cultivated land that is irrigated	40.5%	42.7%		
Wealth, income and credit constraints				
Household has electricity	-	-	72%	45%
Household has Tap water	26%	44%	47%	50%
Wealth index (pca)	0.00	1.45	0.26	0.13
Has any livestock, cattle, birds etc.	72%	45%	62%	49%
Monthly Per Capita Expenditures	520	456	**1,239**	**1,612**
Main income is from agriculture	49%	50%	72%	45%
Main income is from own cultivation	34%	47%	19%	39%
Main income is from agricultural labor	10%	31%	45%	50%
Main income is from non agricultural labor	17%	37%	27%	44%
Total Annual Income	58,122	98,124	**27,877**	**28,852**
Total Annual Income **-** Cultivators	39,759	115,309	39,409	45,727
Total Annual Income **-** Agricultural Workers	9,321	5,240	18,515	15,453
Total Annual Income **-** Wage workers (casual & regular)	44,686	37,761	32,445	25,723
Own Land	100%	0%	48%	50%
Amount of Land owned (bigha=.5 acres)	13.0	15.0	6.03	8.72
Number of plots	1.79	1.04	1.64	1.13
HH had credit in May 2006 (1=Yes)	89.8%	28.5%	71.8%	45.0%
Household was credit constrained in July 2006 (1=Yes)	70.2%	45.8%		
HH has savings account in May 2006 (1=Yes)	46.6%	47.4%	63.4%	48.2%
Familiarity with insurance and BASIX				
Average insurance payouts in the village 2004 and 2005	0.395	0.382		
Expected rain for 2006 above average, normalized	0.000	1.000		
Trust in basix relative to general trust in institutions	0.791	1.678		
Don't know where rainfall gauge is (1=Yes)	48.1%	47.7%		
Don't know Basix (1=Yes)	26.5%	44.1%		
HH bought weather insurance in 2004 (1=Yes)	25.3%	43.5%		
Household has some type of insurance with Basix (1=Yes)	1.3%	10.6%		
Household has other insurance (1=yes)	80.5%	41.3%		
Difference between perceived length of 60 mm and 60mm	0.363	0.285		
Difference between payout over price in 2006, 2004	-0.077	0.342		
HH belongs to a BUA / WUG group (1=Yes)	1.85%	13.4%		
Technology diffusion / networks				
Household is considered a progresive farmer (1=Yes)	15.5%	35.9%		
HH belongs to Gram panchayat / elected body (1=Yes)	1.6%	12.3%		
Number of groups that the household belongs to	0.723	0.618		
Demographic Characteristics				
Household Size	6.26	2.82	5.94	2.49
Scheduled Caste	10%	30%	35%	48%
Scheduled Tribe	2%	13%	8%	28%
Muslim	4%	19%	9%	28%
Household head's gender (1=male)	93.7%	24.0%		
Log of household head 's age	3.828	0.263		
Highest education level is hiher or equal to secondary school	0.332	0.471		

Table 2, Panel B: Comparable Wealth Comparisons

	Andhra Pradesh		Gujarat	
	Mean	Std. Dev.	Mean	Std. Dev.
A Tractor	4.5%	20.7%	2.2%	14.7%
A thresher	0.6%	7.6%	0.8%	8.9%
A bullock cart	23.4%	42.4%	4.3%	20.2%
Furniture	88.0%	32.5%	98.4%	12.6%
A bicycle	46.5%	49.9%	32.2%	46.8%
A motorcycle	14.7%	35.4%	7.8%	26.9%
A sewing machine	6.6%	24.9%	5.8%	23.4%
Any electric appliances	63.7%	48.1%	64.6%	47.8%
A telephone	23.0%	42.1%	13.8%	34.5%
Average of Comparable Wealth Index	2.71		2.30	

Table 3: Cognitive Ability, Financial Literacy, and Insurance Comprehension

	Andhra Pradesh	Gujarat
Education		
Higest level of education:		
Primary school	66.8%	42.0%
Secondary school	7.55%	28.70%
High school	18.2%	11.6%
College or above	7.45%	17.62%
Financial Literacy (Percent Answering Question Correctly)		
(a) If you borrowed Rs. 100 an an interest rate of 2% per month. After 3 months, if you had made no payments, would you owe more than, less than, or exactly Rs. 102?	n.a.	59.05%
(b) Suppose you need to borrow Rs. 500, to be repaid in one month. Which loan would be more attractive for you: Loan 1, which requires a repayment of Rs. 600 in one month; or Loan 2, which requires a repayment of Rs. 500 plus 15% interest?	n.a.	23.50%
(c) If you have Rs. 100 in Savings account earning 1% interest per annum, and prices for goods and services rise 2% over a one-year period, can you buy more, less, or the same amount of goods in one year, as you could today?	n.a.	24.83%
(d) Is it safer to plant one single crop, or multiple crops?	n.a.	30.56%
All questions Taken Together	n.a.	34.49%
Average Score, Math Questions	n.a.	0.62
Average Score, Probability Questions	n.a.	0.72
Averag Score, "Temperature Insurance" Questions	0.80	0.68
Risk Aversion	0.57	0.46
Binswanger Measure of Risk Aversion		(0.32)
Insurance Questions (Percent Answering Question Correctly)		
Imagine you have bought insurance against drought. If it rains less than 50mm by the end of Punavarsu Kartis, you will receive a payout of 10Rs for every mm of deficient rainfall (that is, each mm of rainfall below 50mm).		
a) It rains 120 mm. Will you get an insurance payout?	85.77%	
b) It does not rain at all:		
i) Will you get an insurance payout?	83.00%	
ii) How much of a payout would you receive?	80.61%	
c) It rains 20mm:		
i) Will you get an insurance payout?	81.47%	
ii) How much of a payout would you receive?	76.03%	
Knowledge of milimeters (Percent Answering Question Correctly)		
Starting from the thick black line, can you show me how far 60mm is? [Use the plastified sheet, record the letter on the sheet that the respondent points to]	20.92%	

Table 4: Insurance Takeup Summary Statistics

	Andhra Pradesh 2006
Share of surveyed hh who bought insurance 2006	24.36%
Share of Basix customers in May 2006 who bought insurance	37.19%
Share of non-Basix customers in May 2006 who bought insurance	22.68%
	Gujarat 2006
Share of surveyed hh who bought insurance	23%
Share of Landless who bought insurance	18%
Share of Landowners who bought insurance	27%

Repeat Adoption, Gujarat and Andhra Pradesh

	Gujarat	Andhra Pradesh
Purchased in:		
2004	n/a	265
2005	n/a	66
2006		255
2007		-
2004 only	n/a	150
2005 only	n/a	11
2006 only		163
2007 only		-
% that purchased in 2004 and 2005 over 2004 buyers	n/a	10.57%
% that purchased in 2004 and 2006 over 2004 buyers	n/a	24.53%
2004 and 2007	n/a	-
% that purchased in 2005 and 2006 over 2005 buyers	n/a	7.58%
2005 and 2007	n/a	-
2006 and 2007		-
% that purchased in 2004, 2005 and 2006 over 2004 buyers	n/a	8.30%
2005-2007	n/a	-
2004-2007	n/a	-

Purchased in 04, 05, 06	Pct of Sample	Gujarat
NNN	50.14	Buyers in 06 and 07
NNY	15.57	NN
NYN	1.05	NY
YNN	12.70	YN
NYY	0.48	YY
YNY	6.21	
YYN	2.67	
YYY	2.10	

Table 5, Panel A: Study Design, Andhra Pradesh

Visit	Village Endorsed	Household Endorsed	Education Module	High Reward	Sample Size
Yes	Yes	Yes	Yes	Yes	54
Yes	Yes	No	Yes	Yes	57
Yes	Yes	No	Yes	No	62
Yes	No	No	Yes	No	67
Yes	Yes	Yes	No	Yes	45
Yes	Yes	Yes	Yes	No	65
Yes	Yes	Yes	No	No	74
Yes	Yes	No	No	Yes	56
Yes	No	No	Yes	Yes	45
Yes	No	No	No	Yes	45
Yes	Yes	No	No	No	61
Yes	No	No	No	No	69
No	No	No	No	No	112
No	Yes	No	No	No	235
				Total sample	**1,047**

Table 5, Panel B: Study Design, Gujarat

Impact Evaluation, Gujarat	Treatment Villages	Comparison Villages
2006	33	67
2007	52	48

Experiments, Gujarat

Video (Surveyed Households)			**Sample size**
Group	Payouts	Frame	
A	8/10 no	Positive	75
B	8/10 no	Negative	81
C	2/10 yes	Positive	78
D	2/10 yes	Negative	81
Total			*315*

Videos (Non-Surveyed Households)				
	Sewa Brand	Peer / Authority	Payouts	
1	Yes	Peer	8/10 no	124
2	No	Peer	8/10 no	126
3	Yes	Authority	8/10 no	150
4	No	Authority	8/10 no	131
5	Yes	Peer	2/10 yes	137
6	No	Peer	2/10 yes	135
7	Yes	Authority	2/10 yes	147
8	No	Authority	2/10 yes	150
Total				*1100*

Discounts (For Households Receiving Video Treatment)		
D1	Rs. 5 (40% of households)	692
D2	Rs. 10 (40% of households)	692
D3	Rs. 20 (20% of households)	346

Flyers

Group	**Individual/Group**	**Religion**	
F1	Individual	Neutral	378
F2	Individual	Muslim	438
F3	Individual	Hindu	416
F4	Group	Neutral	368
F5	Group	Muslim	398
F6	Group	Hindu	393
Total			*2391*

Table 6: Experimental results, Andhra Pradesh

	All			
	(1)	(2)	(3)	(4)
Targeted Marketing				
Visit (1=Yes)	0.178***	0.146***	0.142	0.142
	(0.029)	(0.024)	[0.025]***	[0.025]***
Endorsed by LSA (1=Yes)	0.063	0.100**	0.059	0.058
	(0.041)	(0.040)	[0.037]	[0.038]
Education module (1=Yes)	-0.018	-0.022	0.003	-0.17
	(0.041)	(0.036)	[0.042]	[0.079]*
High reward (1=Yes)	0.345***	0.335***	0.334	0.338
	(0.032)	(0.035)	[0.036]***	[0.037]***
Interactions				
Village was endorsed (1=Yes) x Visit (1=Yes)	-0.013	0.012	0.017	0.012
	(0.053)	(0.032)	[0.032]	[0.033]
Don't know Basix (1=Yes) x Endorsed by LSA (1=Yes)		-0.154*		
		(0.080)		
Secondary schooling (1=Yes) x Education module (1=Yes)			-0.082	
			[0.046]	
Risk aversion in July 2006 x Education module (1=Yes)				0.265
				[0.092]**
Utility function				
Risk aversion in July 2006		-0.070**	-0.065	-0.155
		(0.028)	[0.031]*	[0.020]***
Subjective discount rate as of July 2006		0.000	0.001	0.000
		(0.008)	[0.008]	[0.009]
Basis risk				
Pct. of cultivated land that is irrigated		0.004	0.008	0.009
		(0.019)	[0.019]	[0.020]
Wealth, income and credit constraints				
HH had credit in May 2006 (1=Yes)		0.001	0.009	0.010
		(0.034)	[0.039]	[0.038]
Household was credit constrained in July 2006 (1=Yes)		-0.041	-0.039	-0.040
		(0.035)	[0.035]	[0.036]
HH had savings account in May 2006 (1=Yes)		-0.035	-0.034	-0.036
		(0.047)	[0.047]	[0.048]
Familiarity with insurance and BASIX				
Average insurance payouts in the village 2004 and 2005		0.121***	0.12	0.123
		(0.034)	[0.036]**	[0.037]**
Expected rain in May 2006 for the monsoon is above average normalized		-0.012	-0.012	-0.011
		(0.009)	[0.009]	[0.010]
Trust in basix relative to general trust in institutions		0.009	0.01	0.01
		(0.006)	[0.006]	[0.006]
Don't know where rainfall gauge is (1=Yes)		-0.078	-0.077	-0.075
		(0.053)	[0.052]	[0.054]
Don't know Basix (1=Yes)		-0.039	-0.072	-0.068
		(0.041)	[0.038]*	[0.039]
HH bought weather insurance in 2004 (1=Yes)		0.06	0.062	0.065
		(0.045)	[0.045]	[0.044]
Household has some type of insurance with Basix (1=Yes)		0.043	0.042	0.037
		(0.124)	[0.125]	[0.130]
HH belongs to a BUA / WUG group (1=Yes)		0.062	0.061	0.058
		(0.060)	[0.061]	[0.063]
Technology diffusion / networks				
Someone in the HH belongs to Gram panchayat / any elected body (1=Yes)		-0.167**	-0.176	-0.178
		(0.066)	[0.064]**	[0.062]**
Number of groups that the household belongs to		0.026*	0.026	0.027
		(0.013)	[0.013]*	[0.012]*
Demographic Characteristics				
Highest education level is hiher or equal to secondary school		0.000	0.027	0.001
		(0.039)	[0.047]	[0.041]
Mean Dependent Variable	0.268	0.268	0.268	0.268
Observations	952	952	952	952
R-squared	0.25	0.31	0.31	0.31

Dependent variable in regressions 1-4 is bought insurance (1=Yes).All regressions include the following controls: Difference between perceived length of 60 mm and 60mm, log of household head 's age, household head's gender (1=male), logarithm of household size, logarithm of land owned in acres, household is considered a progresive farmer (1=Yes), difference between payout of insurance over price in 2006 and 2004 . All regressions include village fixed effects and are clustered at village level.

Table 7, Panel A: Flyer Treatments

Muslim Treatment	-0.26	-0.39	4.21	4.43
	(2.33)	(2.26)	(3.29)	(3.25)
Hindu Treatment	0.13	0.67	1.46	2.47
	(1.94)	(1.99)	(3.01)	(2.97)
Group Treatment	1.87	1.34	6.00 *	6.07 **
	(1.84)	(1.83)	(3.16)	(2.76)
Muslim * Group			-9.26 **	-9.98 **
			(4.38)	(4.22)
Hindu * Group			-2.66	-3.66
			(4.79)	(4.54)
N	2391	2391	2391	2391
Village FE	No	Yes	No	Yes

Table 7, Panel B: Video Interventions and Demand

Panel B: Video Treatments

	Purchased Insurance Yes=100	
Sewa Brand Strong	-2.59	-3.03
	(2.74)	(2.73)
Peer Endorser	-2.93	-1.94
	(3.11)	(3.13)
Pays 2/10 Years	-2.68	-3.39
	(2.31)	(2.11)
Positive Language	-4.56	-4.19
	(5.12)	(5.02)
Discount Rs.	0.47 ***	0.50 ***
	(0.13)	(0.13)
Surveyed Household	15.81 **	17.75 ***
	(6.46)	(6.49)
N	1413	1413
Village FE	N	Y

Table 8: Predictors of Take-Up, Common Regressions

	Common Specifications					
	Andhra Pradesh			Gujarat		
	All	Icrisat	Basix	All	Landowners	Landless
Targeted Marketing						
Visit (1=Yes)	0.159***	0.144***	0.019*	0.069	0.089	0.054
	(0.025)	(0.026)	(0.008)	(0.054)	(0.088)	(0.059)
Endorsed by LSA (1=Yes)	0.067*	0.064*	0.007			
	(0.033)	(0.034)	(0.010)			
Education module (1=Yes)	-0.014	-0.019	0.009			
	(0.037)	(0.027)	(0.017)			
High reward (1=Yes)	0.332***	0.362***	-0.020			
	(0.033)	(0.024)	(0.017)			
Village was endorsed (1=Yes) x Visit (1=Yes)	-0.003	0.016	-0.030			
	(0.042)	(0.040)	(0.024)			
Utility function						
Risk aversion in July 2006	-0.068	-0.050	-0.033**	0.180**	0.269**	0.129
	(0.043)	(0.056)	(0.014)	(0.066)	(0.130)	(0.120)
Subjective discount rate as of July 2006	0.002	-0.001	0.005*	-0.005	-0.029	0.041
	(0.010)	(0.009)	(0.003)	(0.040)	(0.065)	(0.061)
Basis risk						
Pct. of cultivated land that is irrigated	0.037	0.010	0.028			
	(0.032)	(0.024)	(0.019)			
Wealth, income and credit constraints						
Wealth index (pca)	0.000	-0.003	0.002	0.016	0.004	0.030
	(0.007)	(0.008)	(0.003)	(0.019)	(0.022)	(0.026)
Logarithm of Monthly Per Capita Expenditures	-0.007	-0.012	0.001	0.029	0.012	0.062
	(0.021)	(0.019)	(0.007)	(0.032)	(0.049)	(0.046)
Number of plots	0.016	0.015	-0.002	0.029	0.044	
	(0.015)	(0.016)	(0.001)	(0.039)	(0.050)	
Logarithm of land owned in acres	0.004	0.000	0.005	0.032	0.046	
	(0.012)	(0.012)	(0.004)	(0.042)	(0.066)	
HH had credit in May 2006 (1=Yes)	0.004	-0.005	0.011	0.041	0.106*	0.008
	(0.044)	(0.042)	(0.016)	(0.045)	(0.056)	(0.063)
Household was credit constrained in July 2006 (1=Yes)	-0.047	-0.025	-0.025			
	(0.037)	(0.026)	(0.020)			
HH has savings account in May 2006 (1=Yes)	-0.039	-0.021	-0.016	0.020	-0.017	0.046
	(0.044)	(0.038)	(0.013)	(0.043)	(0.073)	(0.075)
Familiarity with insurance and BASIX						
Expected rain in May 2006 for the monsoon is above aver	-0.001	0.004	-0.005**	0.021	0.080	-0.065
	(0.014)	(0.013)	(0.002)	(0.060)	(0.099)	(0.105)
Household has some type of insurance with Basix (1=Yes)	0.057	0.005	0.048	0.134	0.199	-0.041
	(0.124)	(0.080)	(0.059)	(0.092)	(0.129)	(0.123)
Insurance skills (normalized)	0.040***	0.029**	0.012**	0.098*	0.086	0.149**
	(0.012)	(0.013)	(0.004)	(0.054)	(0.102)	(0.060)
Household has other insurance (1=yes)	0.117***	0.109***	0.009	-0.072	-0.074	0.028
	(0.023)	(0.017)	(0.011)	(0.082)	(0.116)	(0.126)
HH belongs to a BUA / WUG group (1=Yes)	0.144**	-0.061	0.196**			
	(0.059)	(0.090)	(0.068)			
Demographic Characteristics						
Logarithm of household size	-0.016	-0.015	-0.008	0.039	0.045	0.033
	(0.029)	(0.034)	(0.008)	(0.054)	(0.081)	(0.083)
Scheduled Caste	0.040	0.037	0.000	0.063	0.084	0.020
	(0.049)	(0.037)	(0.017)	(0.048)	(0.070)	(0.064)
Scheduled Tribe	-0.246**	-0.242**	-0.005	0.017	0.142	-0.067
	(0.082)	(0.088)	(0.018)	(0.088)	(0.152)	(0.109)
Muslim	0.063*	0.096**	-0.035*	0.187*	0.269**	0.104
	(0.029)	(0.033)	(0.015)	(0.105)	(0.113)	(0.172)
Household head's gender (1=male)	0.015	0.018	-0.002	0.013	0.099	-0.052
	(0.068)	(0.061)	(0.006)	(0.032)	(0.061)	(0.061)
Log of household head 's age	-0.006	-0.002	-0.003	-0.102	-0.152*	0.014
	(0.048)	(0.064)	(0.017)	(0.064)	(0.083)	(0.084)
Highest education level is hiher or equal to secondary scho	0.029	0.015	0.019**	-0.031	-0.036	-0.039
	(0.029)	(0.028)	(0.006)	(0.043)	(0.052)	(0.074)
Observations	932	932	932	456	225	231
R-squared	0.29	0.31	0.13	0.24	0.29	0.35

Table 9: Reason for Non-Adoption		
Andhra Pradesh		
	2006	2004
1. Insufficient funds to buy it	63.9%	21.5%
2. It is not good value (low payout/ high premiums)	9.8%	20.0%
3. Have heard from others that it is a bad product	2.6%	0.0%
4. Do not trust provider	6.5%	3.1%
5. Do not need it	2.3%	2.6%
6. Do not understand it	4.3%	25.0%
7. No castor, groundnut	0.0%	4.9%
8. It does not pay out when I suffer a loss	9.3%	19.1%
9. Have bought it before, but it paid out a low amount	0.8%	0.8%
10. Have not bought it before but heard it paid out low amount	0.4%	0.0%
11. None of the above	0.2%	3.0%
Total	100.0%	100.0%