Barriers to Household Risk Management: Evidence from India

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Barriers to Household Risk Management:

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Barriers to Household Risk Management: Evidence from India

Abstract

Why do many households remain exposed to large exogenous sources of non-systematic income risk? We use a series of randomized field experiments in rural India to test the importance of price and non-price factors in the adoption of an innovative rainfall insurance product. We find demand is significantly price-elastic, but that even if insurance were offered with payout ratios similar to US, widespread coverage would not be achieved. We then identify key non-price frictions that limit demand: liquidity constraints, particularly among poor households, lack of trust, and limited salience. We suggest potential improvements in contract design to mitigate these frictions.

JEL: C93, D14, G22, O12, O16.

Key Words: Insurance, Consumer Finance, Liquidity Constraints, Trust, Economic Development.

This paper studies an innovative financial contract designed to insure rural Indian households against a key source of exogenous income risk: rainfall variation during the monsoon season. Rainfall is the primary determinant of income variability in semi-arid areas, and drought is cited by 89 percent of households in our sample as the most important risk they face. The product, rainfall insurance, is sold commercially before the start of the monsoon, and pays off based on rainfall recorded at a local weather station. Policies are sold in unit sizes as small as $1 US. The product we study has inspired development agencies around the world, and there are currently at least 36 pilot projects introducing index insurance in developing countries.[1] However, despite the potentially large welfare benefits of rainfall risk diversification, take-up of rainfall insurance, while growing over time, is currently still low. This fact motivates the major research question we address in this paper: What frictions prevent the adoption of financial products that pool important sources of income risk faced by households?

We test the importance of various determinants of demand for rainfall insurance using a series of randomized experiments in rural areas of two Indian states, Andhra Pradesh and Gujarat. One reason why rainfall insurance adoption is low is that prices are higher, relative to expected payouts, than insurance in developed countries. We estimate the price elasticity of demand by randomly varying the price of the insurance policy and find significant price sensitivity, with an elasticity of -0.66 to -0.88. This implies demand would increase by 25-50% if insurance could be offered with payout ratios similar to US insurance contracts. However, our experiments suggest that even if prices were close to actuarially fair, most households would still not purchase the product. In other words, even an increase in adoption of 25-50% from current levels would not get close to universal participation.

As a result, we then examine non-price frictions that may reduce household demand for the product (see also Giné, Townsend and Vickery, 2008, and Dean Karlan et al., forthcoming, for a discussion of these frictions). We find several types of evidence suggesting that liquidity constraints limit demand, consistent with theoretical models like Adriano Rampini and S. Viswanathan (2010). Households purchase insurance at the start of the growing season when there are many competing uses for the limited cash available. To understand how liquidity constraints affect insurance demand, we randomly assign certain households high cash rewards. Giving the household enough cash to buy one policy increases take-up by 150% of the baseline

[1] See for example http://www.ifad.org/ruralfinance/pub/weather.pdf

take-up rate. This effect is several times larger than cutting the price of the product by half. Notably, this treatment effect is magnified amongst poor households, who are likely to have less access to the financial system. In addition to this experimental evidence, in surveys, sixty-four percent of non-participating farmers in the Andhra Pradesh sample cite “insufficient funds to buy” as their most important reason for not purchasing insurance. Finally, wealthier households (a proxy for access to finance) are more likely to purchase insurance.

Beyond liquidity and price, households do not fully trust the insurance product. To measure the importance of trust, we vary whether the insurance educator receives an endorsement by a trusted local agent during the household visit or not. Demand is 36 percent higher when the insurance is offered from a source the household trusts (i.e. the insurance educator is endorsed by a known local agent). In a subset of the Gujarat experiments, demand increases if an insurance flyer includes symbols of the household’s own religion, also consistent with trust effects.

Trust may be particularly important because many households have only limited numeracy skills and financial literacy, likely reducing their ability to independently evaluate the insurance. For example, households are only able to correctly answer simple addition and multiplication questions 60% of the time. In cross-sectional regressions, demand is higher in villages which previously experienced a payout, and amongst households with previous experience with insurance, higher measured financial literacy and greater familiarity with probability concepts.

Finally, while average take-up is 28 percent among treated households in Andhra Pradesh and 24-29 percent in Gujarat, it is close to zero amongst the general population in the same villages that did not receive any treatments. Thus, being assigned a visit from an insurance educator, or a flyer treatment, increases take-up significantly, even for households not receiving the high cash reward or other beneficial treatments. This result is suggestive of the importance of limited attention or salience for demand (Ricardo Reis, 2006) and consistent with the “last mile” challenge of promoting financial inclusion.

Our study also allows us to dismiss the importance of some factors often thought important for the demand for financial products, but which have little or no effect on demand in our setting. We assess the impact of a short education module and a set of framing effects from the economics and psychology literature. The education module has no significant effect on demand. Our point estimates for the framing effects considered are generally close to zero, and the standard error bounds are tight enough to imply smaller effects than those found in Marianne Bertrand et al. (2010), to the extent we can compare them.

In sum, insurance demand is price sensitive, and reducing prices (e.g., through greater efficiency or competition, or government subsidies) would significantly increase take-up. But this would still not be enough to induce most households to buy. Liquidity constraints, trust and salience are important non-price influences on demand. At the end of the paper, we suggest potential improvements in contract design that can help mitigate these frictions.

Our evidence contributes to a large literature on financial contracting and incomplete risk-sharing (Stefano Athanasoulis and Robert Shiller, 2000, 2001; Townsend, 1994; Franklin Allen and Douglas Gale, 1994; Andreas Fuster and Paul Willen, 2010) and points to specific frictions that limit risk pooling. We focus on a risk where the welfare benefits of diversification are likely to be especially large. Previous research shows that farmers use a range of mechanisms to mitigate rainfall risk, such as borrowing and saving, remittances, and asset sales (e.g. Christina Paxson, 1992; Dean Yang and HwaJung Choi, 2007). However, other evidence suggests that these channels only partially insulate consumption and welfare from rainfall risk (e.g. Sharon Maccini and Dean Yang, 2009; Stefan Dercon and Pramila Krishnan, 2000; Esther Duflo and Chris Udry, 2004), and also that farmers engage in costly ex-ante "income smoothing," shifting towards safer but less profitable production activities to reduce risk exposure (Mark Rosenzweig and Hans Binswanger, 1993; Morduch, 1995). One factor limiting consumption insurance is that rainfall shocks affect all farmers in a close geographic area, reducing the benefits of risk-sharing between neighbors or through local credit and asset markets.[2]

Our findings also contribute to a growing literature on household finance and risk management (Annamaria Lusardi and Olivia Mitchell, 2007; Cole and Guari Shastry, 2009). Amongst our contributions, we provide what we believe is the first experimental evidence of how trust influences financial market participation, extending previous research by Luigi Guiso, Paola Sapienza and Luigi Zingales (2008) and others.

Finally, our results relate closely to the literature on adoption of new technologies and financial products in agriculture. Duflo, Michael Kremer and Jonathan Robinson (2010) focus on

[2] Indeed, Townsend (1994) finds that within-village risk-sharing in India is relatively close to the full insurance benchmark, even though *aggregate* village incomes and consumption vary significantly over time.

behavioral biases that may prevent adoption of profitable agricultural investments; Giné and Yang (2009) study the adoption of a loan bundled with rainfall insurance to purchase improved seeds, while Karlan et al. (2009) study demand for a loan bundled with crop price insurance.

The paper proceeds as follows. Section I describes the insurance product and theoretical determinants of demand, and presents summary statistics. Section II describes the experimental design. Sections III and IV present and discuss experimental results. Section V presents non-experimental evidence. Sections VI concludes and discusses implications for the design of index insurance contracts.

I. Product description, data collection and determinants of insurance take-up

A. Product description

The rainfall insurance policies studied here are an example of "index insurance", that is, a contract whose payouts are linked to a publicly observable index like rainfall, temperature or a commodity price. Index insurance markets are expanding in many emerging market economies (World Bank, 2005; Jerry Skees, 2008). The first Indian rainfall insurance policies were developed by ICICI Lombard, a large general insurer, with technical support from the World Bank. Policies were first offered on a pilot basis in the state of Andhra Pradesh in 2003. Today, rainfall insurance is offered by several firms and sold in many parts of India. See Giné, Lev Menand, Townsend and Vickery (forthcoming) for a non-technical description of this market and further institutional details.

Contract details. – Table 1 presents contract details for the insurance policies offered in our study areas in Andhra Pradesh in 2006, and in Gujarat in 2007, the years of our field experiments. Policies are underwritten by ICICI Lombard in Andhra Pradesh and by IFFCO-Tokio in Gujarat. In both cases, payoffs are calculated based on measured rainfall at a nearby government rainfall station or an automated rain gauge operated by a private third-party vendor. ICICI Lombard policies divide the monsoon season into three contiguous phases of 35-45 days, corresponding to sowing, flowering, and harvest.[3] Separate policies are sold for each phase at a

[3] Since monsoon onset varies across years, the start of the first phase is defined as the day in June when accumulated rainfall since June 1 exceeds 50mm. If <50mm of rain falls in June, the first phase begins automatically on July 1.

premium between Rs. 80 and Rs. 120 ($2-3 US).[4] A policy covering all three phases (column "Combined Premium") costs Rs. 260 to Rs. 340 ($6-8 US), including a Rs. 10 discount. IFFCO-Tokio policies are based on cumulative rainfall over the entire monsoon season (defined as June 1 to August 31) at government rainfall stations. Policy premiums are lower, between Rs. 44 and Rs. 86, reflecting a commitment to make policies accessible to even the poorest households. Households in both regions were free to purchase any whole number of policies as desired.

Each insurance contract specifies a threshold amount of rainfall, designed to approximate the minimum required for successful crop growth. As an example, the Phase I ICICI Lombard policy in Mahbubnagar pays zero when cumulative rainfall during the 35-day coverage phase exceeds the strike of 70mm. Payouts are then linear in the rainfall deficit relative to this threshold, jumping to Rs. 1000 when cumulative rainfall is below the exit of 10mm, meant to correspond approximately to a point of crop failure. IFFCO-Tokio policies have a similar structure, paying out whenever rainfall during the entire monsoon season is at least 40% below a specified average level for that district (normal rain).

The exception to this basic structure is the Phase III ICICI Lombard contracts, which cover the harvest period. These pay off when rainfall is excessively high, rather than excessively low, to insure against flood or excess rain that damages crops prior to harvest.

Marketing and sales. – Microfinance institutions or non-government organizations (NGOs) typically sell rainfall policies on behalf of insurance companies, and handle payout disbursals. An important advantage of rainfall insurance is that payouts are calculated automatically by the insurer based on measured rainfall, without households needing to file a claim or provide proof of loss. This significantly reduces administrative expenses.

In Andhra Pradesh, insurance is sold to households by BASIX, a microfinance institution with an extensive rural network of local agents known as Livelihood Services Agents (LSAs). These LSAs have close, enduring relationships with rural villages and sell a range of financial services including microfinance loans and other types of insurance. In our Gujarat study areas, rainfall insurance is marketed by SEWA, a large NGO that serves women.

Actuarial values, observed payouts and pricing. – For four policies in Table 1, we are able to calculate a measure of expected payouts using historical rainfall data. In each case, we

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[4] As a point of reference, the average daily wage for agricultural laborers in our survey areas at the time of the study is around Rs. 50, although incomes for landed farmers or more skilled workers are significantly higher.

simply apply the contract terms in the table to calculate what average payouts would have been in past seasons, if the contract had been available (see Giné et al., 2007, for details). Historical daily rainfall data is available from 1970-2006 for the Andhra Pradesh contracts, and from 1965-2003 for the Gujarat contracts. These data are not available for three Andhra Pradesh stations, where payouts are based on automated rain gauges, or for Anand in Gujarat.

Calculated expected payouts range from 33% to 57% of premiums, with an average of 46%. Consistent with the generally higher price of financial services in developing countries, these levels are below those of U.S. auto and homeowner insurance contracts, where the payout ratios average 65-75%.[5] Giné et al., (2007) also show that the distribution of insurance returns on ICICI Lombard rainfall insurance contracts is highly skewed. Policies produce a positive return in only 11% of phases. The maximum return, observed in about 1% of phases, is 900%.

In Gujarat, sufficient rain fell in 2006 and 2007 that no payout was triggered. In Andhra Pradesh, every policy paid out at least once between 2004 and 2006. Some payouts were quite modest (Rs. 40 in 2006 for the Atmakur policy), while others were large (Rs. 1,796 in 2004 near Narayanpet). Using administrative data for all policies sold by BASIX in Andhra Pradesh from 2003 to 2009, Giné et al. (forthcoming) find an average ratio of total insurance payouts to total premiums of 138%. The difference between this figure and our historical estimated return may reflect unusual shocks such as the severe drought of 2009, or structural changes such as greater monsoon volatility (B.N. Goswami et al., 2003). Given the limited history of existing rainfall data and the skewness of the insurance return distribution, however, statistical tests of structural change are not likely to be powerful.

In part A of the Online Appendix we simulate a simple model of insurance demand to investigate more formally whether the insurance is potentially valuable to households at the prices offered, in the absence of non-price frictions such as liquidity constraints or limited trust. This model is calibrated to match the payout ratio and distributional features of ICICI Lombard contracts, in which payouts are realized on only around 10% of phases, but with high maximum returns. We assume a conservative level of 40% for the payout-to-premium ratio, and consider a range of assumptions about basis risk. Results suggest that the insurance product is valuable at

[5] US insurance premiums data were generously provided by David Cummins of Temple University, based on the 2007 Best's Aggregates and Averages. The ratio of aggregate claims to premiums is 76.2% for private passenger auto liability insurance, 68.4% for private passenger auto physical damage, and 64.7% for homeowners insurance. The ratio for earthquake insurance is much lower, 20.4%, but this may reflect the relatively small number of recent earthquake events.

reasonable levels of risk aversion, below the measured risk aversion levels for our sample. This exercise provides a first suggestive source of evidence that non-price factors contribute to low observed rainfall insurance take-up rates.

B. Summary statistics

We study households located in the Mahbubnagar and Anantapur districts of Andhra Pradesh, and the Ahmedabad, Anand, and Patan districts of Gujarat. Below we describe representative summary statistics of these households, based on surveys conducted in 2006.

Sample selection. – In Andhra Pradesh, summary statistics are based on a survey of 1,047 landowner households in 37 villages. This survey sample is exactly the same set of households used for our field experiments (details of the experimental design are presented in Section II). These households were originally selected in 2004 based on a stratified random sample from a census of approximately 7,000 landowner households (see Giné et al. 2008 for details).

In Gujarat, our survey data are drawn from 100 villages selected on two criteria: SEWA operated in the village, and the village was within 30 km of a rainfall station.[6] Field experiments in 2007 were conducted in a randomly selected 50 of these 100 villages. Survey data presented below are based on a baseline survey of 1,500 SEWA members in these villages, conducted in May 2006. The survey sample should be viewed as being representative of SEWA members in these 100 villages.[7] However, this sample is only a subset of the households subject to field experiments in 2007, the year of our Gujarat interventions. (Again, see Section II for details).

Basic demographic characteristics. – Table 2 presents summary statistics for both sets of surveyed households. While there are differences in design across the Gujarat and Andhra Pradesh surveys, to the extent possible, we harmonize variable definitions. Full definitions of the construction of each variable are presented in the Data Appendix.

Overall, the state of Gujarat has richer soil and is substantially wealthier than Andhra Pradesh. However, in Gujarat, insurance is sold to poor households (SEWA members), while in

[6] 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.
[7] For the Gujarat household survey 15 households were selected per village: five randomly selected from the SEWA member list; five randomly selected from the remaining SEWA members with a positive savings account balance; and five households selected (non-randomly) based on suggestions from a local SEWA employee that they would be likely to purchase rainfall insurance. However, the entire sample of 1,500 households has similar summary statistics to the 500 selected randomly from the SEWA list, implying that the overall sample is close to representative of SEWA's overall membership in these 100 villages.

Andhra Pradesh, we focus only on landowning households. Reported consumption expenditures are higher in Gujarat (note that this is a measure of food consumption only, and thus substantially understates total consumption). However, a wealth index based on the number of durable goods owned[8] (not reported in table) is higher in Andhra Pradesh. The value of savings deposits is similar across the two study areas, at around Rs. 1,000 ($21 US).

Risk Attitudes and Discount Rates. – Following Binswanger (1980), we measure risk aversion by allowing individuals to choose amongst cash lotteries which vary in risk and expected return. These lotteries were played for real money with households, with payouts between zero and Rs. 110. We map respondents' choices amongst these lotteries into an index between 0 and 1, where higher values indicate greater risk aversion. Table 2 reports the mean of the risk aversion index. Details of the lottery designs are presented in the Online Appendix C.

Rainfall insurance represents an investment at the start of the monsoon for a (potential) payout two to six months in the future. Higher discount rates will therefore make the insurance less attractive. Discount rates are measured by asking the minimum amount a household would be willing to accept in the future in lieu of a fixed payment today.[9] Consistent with other evidence, respondents report high discount rates: the average elicited monthly discount rate is 98% in Andhra Pradesh (implying a rupee in one month is valued about half of a rupee today), and 42% in Gujarat. Both these values were elicited at the start of the monsoon season.

Education and Financial Literacy. – The rainfall insurance products are complex to evaluate and may not be fully understood by farmers. Table 3 reports measures of household education, financial literacy, and cognitive ability. Education levels are relatively low: 67% of household heads in Andhra Pradesh and 42% in Gujarat have at most primary school education.

In Gujarat, we also administer short tests of math, financial literacy, and understanding of probabilities, paying respondents Rs. 1 for each question answered correctly. The average math score is 62%. Levels of financial literacy are much lower, with respondents doing worse than had

[8] Items include a television, radio, fan, tractor, thresher, bullock cart, furniture, bicycle, motorcycle, sewing machine, and telephone. The index is based on the first principal component of the inventory of these asset holdings.
[9] This question was asked hypothetically, rather than for actual cash sums, because it would have been prohibitively expensive to revisit all households one month from the interview date to provide cash payouts.

they simply guessed. Respondents perform better on questions testing the understanding of simple probability concepts, with on average 72% of questions answered correctly.[10]

To understand how households process information about index-based insurance, in both Andhra Pradesh and Gujarat we read a brief description of a hypothetical insurance product. Households were then asked several simple questions about whether the policy would pay out. Respondents performed at a fair level on this test, recording correct answers 79% of the time in Andhra Pradesh, and 68% in Gujarat (see Table 3, Panel C for individual questions).

II. Experimental Design

A. Theoretical considerations

Our field experiments were designed to elicit the price elasticity of rainfall insurance demand, as well as to estimate the sensitivity of demand to a range of non-price factors, including liquidity constraints, trust and framing effects described in the previous section. The structure of these experiments is described below and Table 4 reports the share of households receiving the different treatments.

Andhra Pradesh. – In May 2006, just prior to the start of the monsoon season, 700 households from the sample of 1,047 were randomly selected to be visited in their home by one of a group of trained ICRISAT insurance educators. Visits were successfully completed for 660 households (40 households could not be located after three attempts). During each visit, the educator described basic features of the rainfall insurance product, and answered any questions. Households had an opportunity to purchase insurance policies on-the-spot during the visit or could buy policies later through their local BASIX branch or LSA. If the farmer did not have enough cash on hand during the initial visit, the ICRISAT educator sometimes offered to revisit the household at a later agreed-on time to complete the purchase of insurance.

We randomize the content of these household visits independently along three dimensions. First, we offer a random amount of cash compensation for the household's time, of either Rs. 25 or Rs. 100, paid at the end of the household visit (half the households receive the larger amount). Given that the premium for one phase of insurance ranges between Rs. 80 and

[10] Financial literacy questions were adapted from Lusardi and Mitchell (2006). Tests of understanding of probability were conducted by asking respondents to gauge the likelihood of drawing a black ball from depictions of bags with different numbers of black and white balls.

Rs. 125, the Rs. 100 provides roughly enough cash-on-hand to purchase one policy. The goal of this treatment is to test the sensitivity of insurance demand to liquidity constraints.

Second, we randomly assign ICRISAT insurance educators to receive an endorsement by the local BASIX LSA. Two-thirds of villages are designated as endorsement-eligible villages. Within these villages, the LSA endorses the insurance educators for half the visited households by briefly introducing the ICRISAT insurance educator, declaring them trustworthy and encouraging the household to listen.[11] The BASIX LSA does not help explain or sell the product and is instructed to leave before the ICRISAT insurance educator begins describing the product.[12] Given BASIX's good reputation and high penetration rate, this LSA agent is well known and trusted among village households. In non-endorsed visits the ICRISAT insurance educator, who is unknown to the local villagers, visits the household alone.

Third, we randomize whether the household receives additional education about the measurement of rainfall in millimeters and its conversion into soil moisture. Farmers generally decide when to sow crops by measuring the depth of soil moisture in the ground at the onset of the monsoon. However, insurance contracts are instead set in terms of millimeters of rainfall. Table 3 shows only 23% of households can accurately indicate the length of a fixed number of millimeters. To improve understanding, for 350 households, we show the household the length of 10mm and 100mm using a ruler. The household is then presented a chart showing how 100mm of rain translates into average soil moisture for the soil type of their farm.[13] For the other 350 households, educators do not provide this information.

Gujarat: Basic experimental design. – Field experiments in Gujarat were conducted in 2007, the year after the baseline survey described above. Unlike Andhra Pradesh, where interventions were implemented through household visits, in Gujarat, SEWA used several techniques to market rainfall insurance, such as flyers, videos, and discount coupons. We randomly varied the content of each of these three marketing methods at the household level.

[11] This two-tiered assignment structure was implemented to measure possible spillovers of trust within the village. It also helped reduce the demands on BASIX staff time.
[12] ICRISAT employees recorded the degree to which the BASIX LSA followed the instructions. Instructions were followed exactly in 56% of cases. For the remainder, 25% did not show up or stayed at the house for too short a time. The remaining 19% stayed for the duration of the visit. In private conversations after the sales period, BASIX LSAs had no recollection of which individuals they had endorsed and whether they had purchased insurance.
[13] Based on time use surveys reported by the insurance educator team, this education was presented rather briefly (an additional two minutes relative to a standard household visit).

Our field experiments involve the 50 villages in Gujarat where rainfall insurance was offered in 2007. Twenty of these villages had not previously been exposed to the product, while in the remaining 30 villages SEWA had marketed insurance to households in 2006. We use different field experiments for these two groups of villages. For villages with no prior exposure to insurance, SEWA used portable *video players* to deliver a 90-second marketing message directly to household-decision makers.[14] Each treated household was randomly assigned one of eight different videos. For villages where insurance had been offered in 2006, SEWA instead distributed *flyers* to households, containing one of six randomly assigned messages.

These treatments were delivered to a cross-section of households in each village, including all the households which participated in the 2006 survey. Each treated household received a non-transferable coupon bearing their name and address, to be presented for a discount when insurance was purchased. The coupon serial number indicated which marketing message the household received. The size of this discount was randomized in the 20 villages receiving video treatments: 40% of households receive Rs. 5, 40% receive Rs. 15, and 20% receive Rs. 30. This randomization allows us to estimate the price elasticity of rainfall insurance demand. In the 30 villages receiving flyer treatments, the discount was always fixed at Rs. 5.

Gujarat: Details of video and flyer messages. – In the video experiments, we randomize the message viewed by the household along four dimensions. One experiment tests the sensitivity of demand to the prominence of the trusted SEWA brand. The other three treatments test the sensitivity of demand to framing effects. A full description of the combinations of treatments used is presented in the Online Appendix B.[15] Basic features are as follows:

- SEWA Brand (Yes or No): SEWA has worked for many years in the study villages, while IFFCO-TOKIO is almost unknown. In the "Strong SEWA brand" treatment, videos clearly indicate the product is offered by SEWA. Alternatively, SEWA is not mentioned.
- Peer vs. Authority Figure: Farmers may weigh information sources differentially when learning about insurance. In the "Peer" treatment, a product endorsement is delivered by a local farmer. In the "Authority" treatment, a teacher delivers the endorsement.

[14] 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 the individual conducting the marketing is not solely responsible for delivering the experimental message.

[15] For households that were part of our 2006 household survey, four videos are used (A-D in Online Appendix B Table 2). For this group, the SEWA brand is included in all videos. For households that receive a video marketing treatment but were not part of the original survey, one of the eight different videos is randomly assigned, four of which include the SEWA brand.

- Payout ("2/10 yes" or "8/10 no"): In the "2/10" treatment, households are told "the product *would* have paid out in approximately 2 of the previous 10 years". In the "8/10" treatment, households are told that "the product would not have paid out in approximately 8 of the previous 10 years". These statements convey the same information, but one through a positive frame, the other through a negative frame.
- Safety or Vulnerability: The "Safety" treatment describes the benefits of insurance in terms of it being something that will protect the household and ensure prosperity. The "Vulnerability" treatment warns the household of the difficulties it may face if it does not have insurance and a drought occurs.

The contents of the flyers distributed in the remaining 30 villages are randomized along two dimensions designed to test how formal insurance may interact with informal risk-sharing arrangements, mostly through the emphasis of group identity.[16] These are as follows:

- Religion (Hindu, Muslim, or Neutral): This treatment provides cues on group identity. A photograph on the flyer depicts a farmer in front of a Hindu temple (Hindu Treatment), a Mosque (Muslim Treatment), or a neutral building. The farmer has a matching first name, which is characteristically Hindu, characteristically Muslim, or neutral.
- Individual or Group (Individual or Group): in the Individual treatment, the flyer emphasizes the potential benefits of the insurance product for the individual buying the policy. The Group flyer emphasizes the value of the policy for the purchaser's family.

III. Experimental results

Because we randomize the assignment of experiments to households, our empirical strategy is straightforward. For each field experiment, we estimate a linear probability model of the probability of household insurance purchase as a function of the treatment variables, and in some specifications a set of treatment interaction terms. Results are presented in Tables 5, 6 and 7. In this section we present each set of results. In Section IV, we synthesize our combined results in terms of their implications for the importance of different barriers to insurance demand.

A. Andhra Pradesh

[16] Group identity has been found to be important both for informal risk-sharing (Karlan et al., 2009) and trust.

The four treatments implemented in Andhra Pradesh were: (i) whether the household is visited by an insurance educator; (ii) whether the educator is endorsed by an LSA, (iii) whether the educator presents the additional education module, and (iv) whether the visited household receives a high reward (Rs. 100 rather than Rs. 25). Because endorsement took place in two-thirds of villages, we include as an additional treatment the interaction of whether the village was one in which endorsements took place and whether the household received a visit, to identify spillovers from endorsement.

Results are presented in Table 5. We use data from all 1,047 households, and since treatment compliance is not perfect, the results should be interpreted as intent-to-treat effects. The unconditional insurance take-up rate is 28%. Basic treatment effects are reported in Columns (1)-(3). Column (1) includes only the treatment variables. Column (2) also includes village fixed effects, while Column (3) includes both village fixed effects and a set of household covariates (specific controls are listed in the table notes).[17] In each of these three columns, being assigned a household visit, even if not combined with other treatments, increases take-up by 11.5 to 17.2 percentage points, while a high reward increases take-up by 39.4 to 40.8 percentage points. Each of these estimates is statistically significant at the 1% level. Individual LSA endorsement alone is positively signed and marginally statistically significant (t-stat between 1.5 and 1.7). However LSA-endorsement and the village endorsement variable are jointly significant at the 2% level in columns (2) and (3), which control for village fixed effects. Finally, the effect of the education module on demand is economically small and statistically insignificant.

Columns (4)-(6) interact these treatments with three household variables in turn: an indicator for whether the household reports being unfamiliar with BASIX, an index of household wealth, and the log of per capita food consumption. Column (4) shows that LSA endorsement has sharply different effects depending on whether the household is familiar with BASIX, and thus is likely to have had past interactions with the LSA. For households familiar with BASIX, LSA endorsement increases take-up by 10.1 percentage points, statistically significant at the 5% level. In contrast, endorsement has no net effect on insurance demand amongst households unfamiliar with BASIX (the net effect is 10.1 - 17.1 = -7.0 and statistically insignificant). The other notable interaction is that in both columns (5) and (6) the effect of the high cash reward on

[17] Because treatments are randomly assigned to households, estimates of the treatment effects are consistent with or without these controls. But including them may reduce error variance, leading to more precise parameter estimates.

demand is larger amongst poor households. This estimate is statistically significant at the 10% level in column (5), and at the 1% level in column (6).

B. Gujarat: Video experiments

Amongst the 20 Gujarat villages where video treatments were implemented, we randomized the content of the video viewed and the size of the discount coupon the household received. Correspondingly, we regress insurance purchase on the discount amount in rupees and the randomized video features: (i) whether the video featured a strong SEWA brand emphasis, (ii) whether a peer rather than authority figure endorsed the product, (iii) whether the policy is framed positively as paying in 2 of 10 years (rather than not paying in 8 of 10 years), and (iv) whether the product is framed in terms of "safety" rather than "vulnerability". We also include a dummy for whether the household was part of the 2006 baseline survey.

Results are presented in Table 6. Columns (1) and (2) report basic results with and without village fixed effects, respectively, while (3) and (4) include additional interaction terms. As shown in the table, the overall take-up rate is 29%.

The size of the discount has a large effect on take-up. The coefficient on discount size is positive and statistically significant at the 1% level. The coefficient of 0.005 implies that raising the discount from Rs. 5 to Rs. 30 increases the probability of insurance purchase by 12.5 percentage points (or 43% of the sample average take-up rate). In contrast, none of the framing effects are significant at even the 10% level, and they are also jointly insignificant.

In columns (3) and (4) we interact the size of the discount with each framing effect. While in some cases the price sensitivity of demand does vary with framing treatments, we are unable to reject the null that these interaction terms are jointly zero. Finally, we find across specifications that households who participated in the 2006 baseline survey are significantly more likely to purchase insurance. However, this survey was not randomly assigned, and the identified effect thus includes any effect of being surveyed, combined with the fact that surveyed households were selected in part because they were considered more likely to buy insurance.

Panel B of Table 6 reports the sample average take-up rate in each district broken down by the size of the discount. Consistent with the regression estimates, insurance take-up is monotonically increasing in the size of the discount in each district. Also reported for two of the three policies is the estimated gross rate of return on the insurance policy, calculated as the ratio of the estimated expected payoff (taken from Table 1) to the price net of the discount. Notably, in Ahmedabad, for farmers receiving the Rs. 30 discount, our estimates suggest the insurance is significantly better than actuarially fair (expected payouts are 180% of net premiums). Despite this, less than half of eligible farmers receiving this discount choose to purchase insurance.

C. Gujarat: Flyer experiments

Flyer experiments involve randomizing the content of the flyer given to households along two dimensions: (i) the religious emphasis of the flyer: Muslim, Hindu or neutral (the latter is the omitted dummy), and (ii) whether the flyer emphasizes the benefits of insurance to the group rather than the individual. We are interested in how religious cues affect trust and concern for self vs. group. While in general Hindu and Muslim groups live in close proximity and harmony, Gujarat has nevertheless been subject to ethnic tension, particularly in 2002 when there was significant violence between the two communities.

As before, we estimate a linear probability model of how insurance demand depends on these treatments. Results are presented in Table 7. Even-numbered columns include village fixed effects, while odd-numbered columns exclude them.

Columns (1) and (2) study the entire sample, and include each intervention individually. The overall take-up rate is 23.8% (i.e. 23.8% of households given a flyer eventually purchase insurance), similar to the take-up rate in the villages where video treatments were used. None of the baseline treatments are statistically significant, however, and the coefficients are small.

The next two columns include the interactions of the two different treatments. Notably, the group emphasis treatment now has a significant positive effect on take-up when combined with a neutral religious setting. However, the use of a Muslim religious setting on the flyer (instead of a neutral one) reduces take-up by 9-10 percentage points, statistically significant at the 5% level in both cases.

To investigate this further, the final four columns of Table 7 repeat this analysis separately for households with characteristically Muslim names (columns (5) and (6)) and characteristically Hindu names (columns (7) and (8)), as identified by our research team after the completion of all field experiments.[18] We find that, amongst households receiving a group

[18] We emphasize that treatment status was assigned randomly and was orthogonal to the religious identity of the respondent. After the marketing effort was finished, Gujarati research assistants identified the religious identity of

emphasis flyer, households likely to be Muslim have a large and statistically significantly lower insurance take-up rate when the flyer includes Hindu symbols (by 32.8 or 34.2 percentage points compared to the neutral flyer). Symmetrically, for Hindu households, take-up is statistically significantly lower when the flyer includes Muslim symbols (by 10.1 or 9.6 percentage points).

Together, these results provide some evidence that emphasizing the communal nature of insurance stimulates demand for insurance products, but not if those cues emphasize group members different to the household. This finding holds for Hindu and Muslim households, although the point estimate of the effect is larger amongst the smaller Muslim population.

IV. Discussion of experimental results

So far, we have presented a short summary of our results. In this section we discuss and synthesize our three sets of field experiments in terms of their implications as a whole for the importance of different barriers to insurance participation.

A. Price relative to actuarial value

Rural finance is expensive to provide. Robert Cull, Asli Demirguc-Kunt and Jonathan Morduch (2009) document that annual operating costs for non-bank microfinance loans range from 17%-26% of loan value, far higher than corresponding costs in developed countries. We find strong evidence that rainfall insurance demand is significantly sensitive to price.[19]

The coefficient in Table 6 suggests that a decrease in price of Rs. 25 on average increases take-up by 12.5 percentage points. We use our results to calculate the price elasticity of insurance demand. Estimating the coefficient on the discount, β_d, separately for each district, we calculate that the price elasticity of demand is greatest at -0.88 in Anand, -0.83 in Ahmedabad, and smallest in Patan, at -0.66.[20]

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the respondent based on the respondent's name. The 219 respondents on which our two independent coders disagreed have been omitted from the analysis in columns (5)-(8) of Table 7.

[19] Our findings are consistent with recent evidence documenting a significant elasticity of credit demand in developing countries (Dean Karlan and Jonathan Zinman, 2008), as well as previous evidence on the elasticity of demand for insurance in the United States (David Babbel, 1985; Mark Pauly et al., 2003).

[20] Denote price by P and quantity by Q. Taking β_d for ΔQ, the average take-up rate in the district for Q, 1 for ΔP, and the weighted average price of insurance faced by households in the district as P, we calculate the price elasticity of demand (= $[\Delta Q / Q] / [P / \Delta P]$) for all three districts. District-specific analysis is necessary because the base price of the insurance product varies significantly across districts (in 2007 the price was Rs. 72 in Anand, Rs. 44 in Ahmedabad, and Rs. 86 in Patan), but the coupon amounts were varied by a constant amount (between Rs. 5, Rs. 15, and Rs. 30) in all three districts.

These estimates imply rainfall insurance demand would increase significantly (by approximately 25-50%) if insurance could be offered with the same mark-up as US insurance contracts.[21] However, even this increase would still imply that only a relatively small fraction of all households in our study areas purchase insurance. (In addition, most households only purchase a single policy, only covering a modest fraction of their exposure to rainfall risk). Most starkly, the results from Ahmedabad shown in Panel B of Table 6 suggest that more than half of households do not purchase rainfall insurance even when the policy price is set significantly below the actuarial value of the insurance policy. This suggests that non-price factors play an important role in shaping demand.

B. Liquidity constraints

Results from Andhra Pradesh suggest that a positive liquidity shock has a large positive effect on household insurance demand. Providing households with enough cash to purchase a policy increases participation by 39 to 41 percentage points, or around 140% of the average insurance purchase probability. Based on our estimated price elasticity, this is several times larger than the demand response generated by cutting the price of the policy by half. Consistent with this result, we also find two types of non-experimental evidence that suggest liquidity constraints are associated with lower insurance demand (see Section V).

Our findings provide an explanation for why insurance demand may be low amongst the poorest households, which are likely to have the lowest access to financial services, and face more severe liquidity constraints. The simple intuition is that for such households, there are large benefits of hoarding scarce liquid assets, or using those liquid assets for agricultural investment, rather than insurance. One side effect of credit expansion (e.g. greater use of central credit registries, or other improvements in enforcement) could be to increase demand for insurance.

We note that reciprocity may provide an alternative interpretation for our experimental results. Since the cash is given to the farmer by the ICRISAT representative, the former may feel

[21] To calculate these values, we multiply our price elasticity estimates by the percentage estimated difference in price between the Indian rainfall insurance contracts (from Table 1) and US insurance data (provided by David Cummins of Temple University). The US contracts provide an average payout-to-premia ratio of 70%, compared to 46% for the Indian rainfall insurance contracts; implying the price per unit of payout is 34% lower for the US contracts. Our average elasticity estimate of 0.79 implies that cutting the price of the Indian contracts by 34% would increase demand by 27% (or around 25%). The upper bound of 50% is calculated in a similar way, except comparing the price of the lowest-value Indian insurance contract to the highest-value US contract.

a sense of obligation to use those funds to purchase insurance, even though there was no requirement or pressure that they do so. While we cannot rule this possibility out entirely, we find evidence, as noted above, that the sensitivity of insurance demand to liquidity shocks is largest amongst poor households. This matches with the liquidity constraints explanation, since these households are more likely to face financial constraints and limited access to financial services. In contrast, we believe that the reciprocity explanation would be more likely to hold amongst wealthy households, for whom the cash gift is less valuable.

C. Trust

Our Andhra Pradesh results suggest that the farmer's level of trust in the ICRISAT insurance educator significantly influences insurance demand. An endorsement of this educator by a local BASIX LSA significantly increases insurance demand. Importantly, this only holds amongst households familiar with BASIX and thus for whom the word of the LSA is credible. For this subgroup, LSA endorsement increases the probability of insurance purchase by 10.1 percentage points, equivalent to 36% of the sample average purchase rate. In contrast, amongst households unfamiliar with BASIX, LSA endorsement has no effect on demand (the point estimate is actually negative, although not statistically significant).

Evidence from the Gujarat flyer experiments may also be interpreted in terms of a trust effect. These results show that for a subset of flyer treatments, insurance demand is significantly lower when the flyer emphasizes religious cues of a religion different to the treated household.

While trust has long been posited as an important determinant of demand for financial products (Neil Doherty and Harris Schlesinger, 1990, and Guiso et al., 2008), these results provide the first experimental evidence that trust matters. Trust is likely to be particularly important for financial services demand in environments like the one we study where formal legal protections are relatively weak, and household financial literacy and education is low.

D. Financial literacy and education

The education and financial literacy statistics in Table 3 document that a significant fraction of households in our study areas are unable to answer simple mathematics or financial questions, and a smaller fraction do not understand very basic features of the rainfall insurance contracts. This provides prima facie evidence that households have only a limited understanding of the product and may make systematic mistakes about insurance purchase decisions.

The short rainfall insurance education module administered in Andhra Pradesh has no significant effect on insurance demand. While this lack of a response may reflect the specific content of this particular education intervention, Cole, Thomas Sampson, and Bilal Zia (forthcoming) find in Indonesia that a significantly more involved financial education program also has little effect on financial decision-making.

E. Framing, salience and other behavioral factors

We find only limited evidence that pure framing effects identified in the psychology and behavioral economics literatures significantly affect rainfall insurance demand. Specifically, there are no significant differences in take-up amongst eight different frames of the rainfall insurance used in the Gujarat video experiments. While in some cases our power to reject the null is limited, a two standard deviation confidence interval for each individual framing treatment is generally no larger than ± 6 percentage points, and in nearly every case we can reject the null that frame shifts demand by more than 10 percentage points.

These results appear significantly weaker than Bertrand et al. (2010), who find that framing has large effects on credit demand in a large field experiment in South Africa. Our results also stand in contrast to laboratory experiments by Eric Johnson et al. (1993) and Mittal and Ross (1998), which find framing effects to be important determinants of (hypothetical) demand for insurance. One interpretation of these differences is that the impact of framing effects is likely to be heavily context-specific, and thus may vary significantly across different studies.

We do find in Andhra Pradesh that being assigned a door-to-door household visit significantly increases insurance take-up, even when not combined with other treatments. This result obtains even though the product is readily available to all village households. This may reflect the added convenience of being able to purchase insurance “on-the-spot,” or be due to the effect of the baseline information provided by the ICRISAT insurance educator. Alternatively, the household visit may simply make the insurance product more salient to the household, which in a model of limited attention (e.g. Reis, 2006) would be expected to influence demand.

V. Non-experimental evidence

Operational constraints limit the number of randomized treatments we can implement. We complement experimental evidence with measured correlations between insurance purchase decisions and household characteristics, and household self-reports about demand for insurance.

A. Correlates of insurance purchase

Similar to the analysis presented above, we simply regress a dummy for whether the household purchases insurance on a set of household characteristics drawn from the surveys conducted in Andhra Pradesh and Gujarat in 2006. Results are presented in Table 8. As far as possible, similar variables from the two survey areas are defined in a consistent way for this analysis, to allow a comparison of coefficient estimates.

Wealth is positively correlated with insurance purchase, especially for the Gujarat sample, consistent with other evidence on the role of liquidity constraints, likely to be more binding for poorer households. Second, variables presented in Table 3 measuring households' ability to answer probability, math and insurance questions (measured by the variables "financial literacy", "probability skill" and "insurance skills") are in general positively correlated with insurance purchase decisions, consistent with a hypothesis of limited cognition or imperfect information about the product.

Third, prior experience with the insurance product and vendor is positively correlated with insurance purchase. These are measured in a number of ways: by whether the household purchased insurance in previous years, whether the household is familiar with the insurance vendor, whether the household has other types of insurance, and, for Andra Pradesh, whether the household's village had experienced positive rainfall insurance payouts in 2004 and 2005.

Finally, and surprisingly, higher risk aversion is *negatively* correlated with insurance purchase in both the Andhra Pradesh and Gujarat samples. This replicates a finding of Giné et al. (2008) using an earlier 2004 sample. Giné et al. (2008) show that this apparently perverse result is concentrated amongst households without knowledge of BASIX or of insurance, suggesting that uninformed risk-averse households are unwilling to experiment with the insurance product, given their limited experience with it. Again, this appears consistent with our other evidence that limited trust and/or understanding of the product reduces insurance demand.

These results extend the experimental evidence presented earlier and, where applicable, appear consistent with the experimental findings. They are also generally consistent with the evidence in Giné et al. (2008), which presents correlates of the determinants of insurance participation using an earlier 2004 household survey. In this earlier study, 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, based on self-reported measures of financial constraints as well as proxies such as wealth. This study also finds suggestive evidence consistent with a role for trust and networks; 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.

B. Self-reported explanations for non-purchase

As a second source of non-experimental evidence, Table 9 presents household qualitative self-reports, based on our 2006 surveys as well as on the earlier 2004 Andhra Pradesh survey, about the reasons why non-purchasing households did not buy rainfall insurance.

In 2006, the most common single reason cited by households in both samples is "insufficient funds to buy insurance," with 81% of households in Andhra Pradesh citing it as the most important reason for non-purchase. Explanations relating to the quality of the product, such as "it is not good value" and "it does not pay out when I suffer a loss", are much less frequently cited by households, and relatively few households cite "do not need insurance" as a reason for non-purchase (2.8% in Andhra Pradesh and 25.2% in Gujarat).

This qualitative evidence appears consistent with our experimental results, where the treatment involving random liquidity shocks has by far the most significant effect on insurance participation rates. The responses appear consistent with the view that liquidity constraints matter significantly for purchase decisions, and also inconsistent with a view that households simply have little interest in insurance against rainfall risk.

Finally, in the Andhra Pradesh sample, a common response to the 2004 survey is "do not understand the product." The fraction of households citing this reason falls from 21% in 2004 to 2% in 2006, suggesting that households have learned about the policy over time.

VI. Improving household risk management: tentative lessons and conclusions

A primary function of financial markets and the financial system is to pool and diversify risk. In recent years a range of financial innovations has emerged with the potential to improve household risk management, including housing futures based on Case-Shiller price indices (Shiller, 2008), prediction markets linked to economic and political events, and index insurance products designed for hedging weather, price and other agricultural risks.

We are not the first to document demand for insurance that is inconsistent with standard rational models. David Cutler and Richard Zeckhauser (2004), writing that "financial markets, despite their vast resources and wide participation, are not a major bearer of large private risks," highlight the fact that many consumers pay high premiums for insurance on consumer durables, but remain uninsured against much more significant risks such as permanent disability. While informational frictions are an important source of insurance market failure in many contexts[22], in our setting households are unlikely to have significant private information about insurance payoffs, given that rainfall is exogenous and publicly observable.

The micro-insurance industry is still in its infancy. Insurance providers are experimenting with different contract features to learn the best ways to attract customers and create useful products (e.g. see Giné et al. (forthcoming) for a description of the rainfall insurance sector in India). From our empirical results, we draw a number of tentative conclusions about factors that may help increase demand for the rainfall risk management product and improve the welfare benefits of the policies.

First, the importance of liquidity constraints and high measured discount rates amongst our sample suggests that policies should be designed to provide payouts as quickly as possible, especially during the monsoon season when households appear to be particularly credit constrained. For example, payouts from a policy covering the first phase of the monsoon, if paid immediately, could be used by farmers to help fund crop replanting later in the monsoon season. In practice to date, payouts have not been made until after the end of the monsoon, in part because of delays in receiving certified rainfall data from government rainfall stations. Over time, ICICI Lombard has begun using automated rain gauges that allow them to measure rainfall immediately; this in principle should allow payouts to be made more quickly, and by increasing

[22] The role of adverse selection and moral hazard in insurance markets has been the subject of a very large literature, see for example Pierre-André Chiappori and Bernard Salanié (2000), Amy Finkelstein and Kathleen McGarry (2004), Hanming Fang, Michael Keane and Dan Silverman (2008), John Cawley and Tomas Philipson (1996) and Michael Rothschild and Joseph Stiglitz (1976).

the density of rainfall stations can also help ameliorate basis risk. A second possible improvement to ameliorate liquidity constraints would be to sell policies at harvest time (Duflo et al., 2010) or to combine the product with a short-term loan, or equivalently, originate loans with interest rates that are explicitly state-contingent based on rainfall outcomes, to help alleviate credit constraints.[23]

Second, the sensitivity of insurance demand to price underlines the benefits of developing ways to minimize transactions costs and improve product market competition amongst suppliers of rainfall insurance. It also suggests that government subsidies for rainfall insurance, like those now offered in several Indian states (Giné et al., 2010), would be effective in boosting participation, although it is not clear whether such subsidies improve overall welfare.

Third, the importance of trust and a history of positive past insurance payouts suggest that product diffusion through the population may be relatively slow, as the product develops a track record of paying positive returns. A potential design improvement to facilitate learning would be to amend the contract to pay a positive return with sufficient frequency. This needs to be weighed, however, against the fact that the value of the product is largest if payouts are concentrated during the most severe droughts, when marginal utility of consumption is highest.

Finally, findings that households have limited financial literacy and understanding of the product suggest that insurance policies could instead be targeted to groups, such as an entire village, a producer group or a cooperative, rather than to individuals. The insurance purchase decision would be taken by the group management, who are likely more educated and familiar with financial products, and may also be less financially constrained. The group could then decide or pre-arrange how best to allocate funds amongst its members in case of a payout.

Technological advances may improve the product offering, such as the use of satellite foliage coverage data to offer policies based on area crop yields. The degree of innovation already demonstrated by insurance providers, as well as this potential for further contract

[23] Giné and Yang (2009) implement a field experiment in Malawi to test whether bundling insurance with credit increased farmers' willingness to adopt a new agricultural technology. The advantage of the bundled loan over a standard loan is that it would not have to be repaid in case of a payout. As it turns out, uptake among farmers offered the bundled loan was lower than among the control group offered a standard loan. One potential explanation is that farmers were already implicitly insured by the limited liability inherent in the standard loan and hence placed little value in the insurance policy. By insuring loans, however, the lender was unambiguously better off and after the experiment was considering an increase in disbursement and a drop in the interest rate, reflecting the lower risk of lending.

improvements, suggests that micro-insurance markets hold promise to become a significant channel for pooling important sources of household income risk.

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Table 1: Rainfall Insurance Contract Specifications

Panel A: ICICI Policies					Expected payout		Phase I			Phase II			Phase III		
Year	Station	Combined premium	Payout slope	Max payout	Rs.	% of premium	Premium	Strike	Exit	Premium	Strike	Exit	Premium	Strike	Exit
Andhra Pradesh															
2006	Anantapur	340	10	3,000	113	33%	125	30	5	120	30	5	105	500	575
2006	Atmakur	280	10	3,000	n.a.	n.a.	105	45	5	95	55	5	90	500	570
2006	Hindupur	295	10	3,000	n.a.	n.a.	80	25	0	120	15	0	105	500	580
2006	Narayanpet	260	10	3,000	n.a.	n.a.	90	50	5	80	60	5	100	560	670
2006	Mahbubnagar	270	10	3,000	115	43%	80	70	10	80	80	10	120	375	450

Panel B: IFFCO-Tokio Policies				Expected payout		Payout (Rs.) as function of % rainfall deficit from "normal"						
Year	Station	Premium	Normal Rain	Rs.	% of premium	40%	50%	60%	70%	80%	90%	100%
Gujarat												
2007	Ahmedabad	44	607.4	25	57%	100	150	200	300	400	700	1000
2007	Anand	72	783.6	n.a.	n.a.	100	150	200	300	400	700	1000
2007	Patan	86	389.9	43	50%	100	150	200	300	400	700	1000

Notes: The premiums, payout slope, exit, and expected payouts are in rupees (approximate exchange rate in years of study: $1US = Rs. 45). ICICI policies, in Panel A, cover three phases, roughly corresponding to planting, flowering, and harvest. The "strike" amount indicates the rainfall level in mm below (Phase I and II) or above (Phase III) which a payout is triggered, and the "notional" indicates the rupee amount for each mm of rainfall deficit (Phase I and II) or excess (Phase III). Limit and exit levels represent maximum payouts and thresholds triggering those payouts, respectively. IFFCO-Tokio policies (Panel B), consist of a single phase. Each policy specifies a "normal" level of rainfall (in mm) and the payout is a non-linear function of the percentage shortfall from this "normal" rain. In Andra Pradesh, expected payouts are calculated using historical IMD rainfall data from 1970-2006. In Gujarat, expected payouts are calculating using historical rainfall data from 1965 to 2003.

Table 2: Summary Statistics

	Andhra Pradesh		Gujarat	
	Mean	St. Dev.	Mean	St. Dev.
	(1)	(2)	(3)	(4)
Demographic characteristics				
Household size	6.26	2.82	5.85	2.39
Scheduled Caste or Scheduled Tribe (1=Yes)	11.60%	32.04%	43.70%	49.60%
Muslim (1=Yes)	3.90%	19.37%	8.73%	28.20%
Household head is male (1=Yes)	93.75%	23.96%	75.70%	42.90%
Household head 's age	47.60	12.13	48.93	12.87
Wealth and consumption				
Monthly per capita food expenditures	310.53	126.89	555.37	417.42
Total value of all savings deposits	1,030.42	2,891.43	1,060.13	2,314.97
Land holdings (in acres)	6.31	6.17	4.11	5.49
Utility function				
Risk aversion	0.57	0.25	0.54	0.32
Subjective discount rate	0.98	1.49	0.42	0.31
Exposure to risk				
Pct. of cultivated land that is irrigated	43.93%	43.26%	43.70%	47.10%
Familiarity with insurance and insurance vendor				
Average insurance payouts in the village 2004 and 2005	0.40	0.39	n.a.	n.a.
Household bought weather insurance in 2004 (1=Yes)	25.31%	43.50%	n.a.	n.a.
Does not know BASIX (1=Yes)	26.46%	44.13%	n.a.	n.a.
Household has some type of insurance (1=Yes)	80.54%	39.25%	63.78%	48.08%
Technology diffusion / networks				
Hhold belongs to water user group (BUA or WUG) (1=Yes)	1.84%	13.35%	n.a.	n.a.
Number of groups that the household belongs to	0.72	0.62	n.a.	n.a.

Notes: Data from Andhra Pradesh come from surveys conducted in 2006, and BASIX administrative records. Data from Gujarat come from the baseline survey conducted in 2006. Data from both Andhra Pradesh and Gujarat have been winsorized at 1% from the top and bottom tails. In Andhra Pradesh, a stratified random sample was selected from a census of approximately 7,000 households. In Gujarat, the experiment sample includes 1,500 households selected from SEWA's membership. One third of these 1,500 were selected at random from among SEWA membership rolls. The remaining 1,000 were identified by SEWA as individuals for whom the insurance product might be suitable.

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

	Andhra Pradesh	Gujarat
Panel A: Education and Financial Literacy		
Highest level of education:		
Primary school or below	66.8%	42.0%
Secondary school	7.5%	28.7%
High school	18.2%	11.6%
College or above	7.4%	17.6%
Average Score, Math Questions [simple addition and multiplication: e.g. 3 times 6 = ?]	n.a.	61.7%
Average Score, Probability Questions [e.g. comparing simple fractions in terms of probabilities: see table notes for an example]	n.a.	71.8%
Average Score, Financial Literacy [see Panel B below for questions]	n.a.	35.8%
Average Score, Insurance Questions [see Panel C below for questions]	79.3%	68.2%
Understanding of millimeters	23.3%	n.a.
Panel B: Financial Literacy Questions		
(a) Suppose you borrow Rs. 100 an an interest rate of 2% per month. After 3 months, if you had made no repayments, would you owe more than, less than, or exactly Rs. 102? **[Ans: More than Rs. 102]**	n.a.	59.1%
(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? **[Ans: Loan 2]**	n.a.	23.5%
(c) 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? **[Ans: Less amount of goods]**	n.a.	24.8%
(d) Is it safer to plant one single crop, or multiple crops? **[Ans: Multiple Crops]**	n.a.	30.6%
Panel C: Insurance Questions		
Andhra Pradesh		
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? **[Ans: No]**	85.8%	n.a.
b) It does not rain at all:		
i) Will you get an insurance payout? **[Ans: Yes]**	83.0%	n.a.
ii) How much of a payout would you receive? **[Ans: Rs. 500]**	80.6%	n.a.
c) It rains 20mm:		
i) Will you get an insurance payout? **[Ans: Yes]**	81.5%	n.a.
ii) How much of a payout would you receive? **[Ans: Rs. 200]**	76.0%	n.a.
Gujarat		
An insurance company is considering selling temperature insurance. This temperature insurance would pay up to Rs. 310 if the temperature is very high during the month of July. The company will measure the daily maximum temperature in the local district headquarters. For each day the temperature is above 35 Celsius in July, the insurer will pay Rs. 10. For example, if there were ten days in July during which the temperature were greater than 35 Celsius, the policy would pay Rs. 100. If the temperature were always below 35 Celsius, the company would not pay any money. We are now going to test your understanding of the product.		
a) Suppose July was not hot, and the temperature never exceeded 28 Celsius. How much would the insurance company pay? **[Ans: None]**	n.a.	63.7%
b) Suppose the temperature in July exceeded 35 for one day only in the month. How much would the policy pay? **[Ans: Rs. 10]**	n.a.	58.9%
c) Suppose the temperature were greater than 35 degrees for every day in the month of July. How much would the insurance company pay? **[Ans: Rs. 310]**	n.a.	79.9%

Notes: Data from Andhra Pradesh come from surveys conducted in 2006. Data from Gujarat come from the baseline survey conducted in 2006. Correct answers to the financial literacy and insurance questions are indicated in bold following each question. Math questions above include problems such as: what is 4+3, how much is 3 times 6. Probability questions include problems such as: a red bag has 2 black and 5 white marbles, a blue bag has 2 black and 10 white marbles, which bag are you more likely to draw a black marble from? Knowledge of millimeters indicates the percentage of respondents who were able to correctly estimate the distance in millimeters between two points. See Data Appendix for variable definitions.

Table 4: Study Design

Panel A: Andhra Pradesh (2006)	Share of households receiving treatment	
Treatments	N	% of total
Household visit	700	67%
Village endorsed	474	45%
Visit endorsed	238	23%
Education module	350	33%
High reward	302	29%

Panel B: Gujarat (2007)	Share of households receiving treatment		
Video Treatments	Total	Surveyed	Non-Surveyed
N	1413	315	1098
Treatment Assignments			
Strong SEWA Brand	62%	100%	51%
Peer Endorsed	59%	100%	47%
Positive Frame (Pays 2/10 Years)	52%	50%	52%
Vulnerability Frame	11%	51%	0%
Discount = Rs. 5	42%	48%	41%
Discount = Rs. 15	38%	34%	40%
Discount = Rs. 30	19%	18%	20%
Flyer Treatments (N = 2391)	N	% of total	
Individual Emphasis (not Group)	1232	52%	
Muslim Emphasis	836	35%	
Hindu Emphasis	809	34%	
Neutral (Non-religious) Emphasis	746	31%	

Notes: Panel A reports the share of survey households receiving various marketing treatments in Andhra Pradesh in 2006. Panel B reports the share of households receiving various marketing treatments in Gujarat in 2007. In Gujarat, video marketing treatment was only used in villages where rainfall insurance was offered for the first time in 2007. The video treatments are as follows. In "Strong SEWA Brand", videos include clear indications that the product is being offered by SEWA. In "Peer endorsed", product endorsement is delivered by a farmer (instead of a teacher). The "Positive frame" emphasized that the product would have paid out in 2 of the last 10 years. The "Vulnerability frame" warned households of the difficulties they may face if they do not have insurance. Flyer treatments were used in villages where rainfall insurance was offered in both 2006 and 2007 in Gujarat. In "Individual emphasis", the flyer emphasized the benefit of insurance for the individual (not the family). In Muslim, Hindu, and Neutral emphasis, the flyer depicted a farmer standing near a Mosque, Hindu temple, or a nondescript building, respectively. Full details of the experimental design are provided in the Online Appendix.

Table 5: Experimental Results, Andhra Pradesh

Dependent variable is equal to 1 if the household purchases at least one rainfall insurance policy, and 0 otherwise						
	(1)	(2)	(3)	(4)	(5)	(6)
Treatments						
Visit (1=Yes)	0.172***	0.128***	0.115***	0.117***	0.114***	0.118***
	(0.038)	(0.043)	(0.043)	(0.043)	(0.042)	(0.042)
Endorsed by LSA (1=Yes)	0.064	0.067*	0.060	0.101**	0.059	0.194
	(0.041)	(0.039)	(0.040)	(0.043)	(0.040)	(0.424)
Education module (1=Yes)	0.003	0.001	0.004	-0.003	0.007	-0.630*
	(0.034)	(0.033)	(0.032)	(0.036)	(0.032)	(0.376)
High reward (1=Yes)	0.408***	0.400***	0.394***	0.387***	0.393***	1.629***
	(0.035)	(0.034)	(0.034)	(0.038)	(0.034)	(0.432)
Village endorsed (1=Yes) x Visit (1=Yes)	-0.015	0.058	0.070	0.067	0.073	0.069
	(0.041)	(0.048)	(0.049)	(0.048)	(0.048)	(0.048)
Does not know BASIX				-0.055**		
				(0.027)		
Wealth Index					0.005	
					(0.012)	
Log of per capita food consumption						0.066*
						(0.039)
Treatment Interactions						
Does not know BASIX x Endorsed by LSA				-0.171**		
				(0.077)		
Does not know BASIX x Education module				0.031		
				(0.065)		
Does not know BASIX x High reward				0.040		
				(0.077)		
Wealth Index x Endorsed by LSA					0.007	
					(0.023)	
Wealth Index x Education module					0.009	
					(0.019)	
Wealth Index x High reward					-0.037*	
					(0.022)	
Log of per capita food consumption x Endorsed by LSA						-0.024
						(0.075)
Log of per capita food consumption x Education module						0.111*
						(0.066)
Log of per capita food consumption x High reward						-0.218***
						(0.076)
F-test: Joint significance LSA endorsement and (Village endorsed x Visit) [p-value]	0.247	0.012	0.008	0.001	0.008	0.536
Household controls	No	No	Yes	Yes	Yes	Yes
Village fixed effects	No	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.282	0.282	0.282	0.282	0.282	0.282
R-squared	0.279	0.355	0.380	0.384	0.382	0.387
Observations	1047	1047	1047	1047	1047	1047

Notes: Data come from surveys and experiments conducted in Andhra Pradesh in 2006. The wealth index has been imputed and log of per capita consumption has been winsorized at 1% from the top and bottom tails. Linear probability model. Dependent variable is equal to one if the household purchased at least one phase of rainfall insurance. Robust standard errors reported in parentheses. Symbols *,**,*** denote significance at the 10, 5 and 1 percent level, respectively. Columns (2)-(6) include village fixed effects. Household controls include the following: risk aversion; above average expected monsoon rain (normalized); percent of cultivated land that is irrigated; wealth index; log of monthly per capita food consumption; insurance skills (normalized); average rainfall insurance payout in the village in 2004 and 2005; the number of community groups that the household belongs to; log household head age; log of household size; and indicator variables for SC/ST religion; the household head's gender; whether the household head's highest education level is secondary or above; whether the household bought weather insurance in 2004, has other insurance, does not know the provider and belongs to a water user group (either a borewell users association or water user group). See Appendix A for definition of variables. Columns (4)-(6) include the interaction in turn of three household characteristics with individual treatment variables. These interaction variables are: (i) knowledge of the insurance provider BASIX; (ii) index of total wealth and (iii) log(per capita food consumption).

Table 6: Experimental Results for Video Treatments, Gujarat

Dependent variable is equal to 1 if the household purchases at least one rainfall insurance policy, and 0 otherwise

Panel A. Regression estimates

	Baseline		With interactions	
	(1)	(2)	(3)	(4)
Discount (measured in Rs.)	0.005***	0.005***	0.003	0.004
	(0.001)	(0.001)	(0.003)	(0.003)
Framing effects				
Strong SEWA Brand	-0.026	-0.030	-0.100**	-0.096**
	(0.027)	(0.027)	(0.042)	(0.040)
Vulnerability Frame	0.046	0.042	0.191	0.209*
	(0.051)	(0.050)	(0.112)	(0.107)
Positive Frame (Pays 2/10 Years)	-0.027	-0.034	-0.065	-0.068
	(0.023)	(0.021)	(0.047)	(0.044)
Peer Endorsed	-0.029	-0.019	0.022	0.028
	(0.031)	(0.031)	(0.057)	(0.056)
Surveyed Household	0.158**	0.177**	0.165**	0.153*
	(0.065)	(0.065)	(0.079)	(0.077)
Discount interactions				
Discount x Vulnerability Frame			-0.011*	-0.013*
			(0.007)	(0.006)
Discount x Positive Frame			0.003	0.003
			(0.003)	(0.003)
Discount x Strong SEWA Brand			0.005**	0.005**
			(0.002)	(0.002)
Discount x Peer Endorsed			-0.004	-0.004
			(0.003)	(0.003)
Discount x Surveyed Household			-0.000	0.002
			(0.005)	(0.005)
F-test on all treatments (p-value)	0.049	0.026		
F-test on discount interactions (p-value)			0.195	0.103
Village fixed effects	no	yes	no	yes
Mean of dependent variable	0.294	0.294	0.294	0.294
R-squared	0.030	0.132	0.039	0.140
Number of observations	1413	1413	1413	1413

Panel B. Rate of return on premium and insurance takeup rates

	Ahmedabad		**Anand**		**Patan**	
Discount (Rs.)	Return (gross)	Take-up	Return (gross)	Take-up	Return (gross)	Take-up
5	0.64	25%	0.54	22%	n/a	36%
15	0.87	37%	0.61	22%	n/a	37%
30	1.81	47%	0.78	30%	n/a	44%

Notes. Data come from surveys conducted in Gujarat in 2007. A linear probability model is used, with the dependent variable set to one if the household purchased an insurance policy. Robust standard errors reported in parentheses. Symbols *,**,*** denote significance at the 10, 5 and 1 percent level, respectively. Columns (2) and (4) include village fixed effects.

Table 7: Experimental Results for Flyer Treatments, Gujarat

Dependent variable is equal to 1 if the household purchases at least one rainfall insurance policy, and 0 otherwise								
	All households				Muslim households only		Hindu households only	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatments								
Muslim emphasis (1=Yes)	-0.002	-0.004	0.043	0.045	0.134	0.160	0.041	0.041
	(0.023)	(0.023)	(0.034)	(0.034)	(0.102)	(0.113)	(0.040)	(0.039)
Hindu emphasis (1=Yes)	0.002	0.008	0.012	0.022	0.057	0.121	0.002	0.014
	(0.019)	(0.019)	(0.030)	(0.030)	(0.086)	(0.131)	(0.034)	(0.034)
Group emphasis (1=Yes)	0.020	0.015	0.060*	0.060**	0.247**	0.239*	0.058	0.053
	(0.018)	(0.018)	(0.032)	(0.028)	(0.110)	(0.135)	(0.037)	(0.033)
Surveyed Household	0.133***	0.132***	0.134***	0.133***	0.121	0.106	0.107***	0.088**
	(0.040)	(0.040)	(0.040)	(0.040)	(0.136)	(0.155)	(0.039)	(0.038)
Religion treatment interactions								
Muslim emphasis x group			-0.094**	-0.101**	-0.223	-0.230	-0.101**	-0.096*
			(0.044)	(0.042)	(0.219)	(0.192)	(0.049)	(0.048)
Hindu emphasis x group			-0.019	-0.029	-0.328**	-0.342*	-0.000	-0.015
			(0.047)	(0.045)	(0.132)	(0.171)	(0.053)	(0.051)
Village fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Mean of dependent variable	0.238	0.238	0.238	0.238	0.167	0.167	0.268	0.268
R-squared	0.016	0.120	0.018	0.123	0.085	0.349	0.013	0.134
Observations	2391	2391	2391	2391	132	132	2040	2040

Notes: Data come from surveys conducted in Gujarat in 2007. A linear probability model is used, with the dependent variable set to one if the household purchased an insurance policy. Robust standard errors reported in parentheses. Symbols *,**,*** denote significance at the 10, 5 and 1 percent level, respectively. "Group Emphasis" indicates that the flyer emphasized the benefit of insurance for the family (not the individual). In "Muslim, Hindu, and Neutral Emphasis", the flyer depicted a farmer standing near a Hindu temple, Mosque, or a nondescript building, respectively. Columns (2), (4), (6) and (8) include village fixed effects. Columns (1)-(4) present the results for the entire sample; columns (5)-(6) present the results for those with identifiably Muslim names, and columns (7)-(8) for those with identifiably Hindu names. 219 respondents on which our two independent coders disagreed have been omitted from the analysis in columns (5)-(8).

Table 8: Correlates of insurance purchase decisions

Dependent variable equals 1 if household purchases at least one rainfall insurance policy, and 0 otherwise

	Univariate		Multivariate			
	Andhra Pradesh	Gujarat	Andhra Pradesh	Gujarat	Andhra Pradesh	Gujarat
	(1)	(2)	(3)	(4)	(5)	(6)
Risk aversion	-0.217***	-0.298***	-0.142**	-0.182***	-0.102*	-0.082
	(0.058)	(0.056)	(0.059)	(0.055)	(0.059)	(0.056)
Above average expected monsoon rain (normalized)	0.001	-0.164***	-0.008	-0.122***	-0.007	-0.110***
	(0.014)	(0.037)	(0.014)	(0.035)	(0.015)	(0.035)
Pct. of cultivated land that is irrigated	0.081**	0.164**	-0.013	0.051	-0.013	0.095
	(0.033)	(0.075)	(0.036)	(0.071)	(0.037)	(0.067)
Wealth, income and credit constraints						
Wealth Index	0.020**	0.054***	-0.004	0.023*	-0.005	0.037***
	(0.010)	(0.011)	(0.013)	(0.012)	(0.013)	(0.013)
Log of monthly per capita food expenditures (winsorized)	0.002	0.108***	-0.01	0.084**	0.019	0.088**
	(0.028)	(0.036)	(0.039)	(0.037)	(0.040)	(0.039)
Familiarity with insurance and BASIX						
Average insurance payouts in the village 2004 and 2005	0.160***		0.073*			
	(0.036)		(0.042)			
Household bought weather insurance in 2004 (1=Yes)	0.113***		0.049		0.077**	
	(0.033)		(0.035)		(0.037)	
Financial literacy		0.037**		0.011		0.007
		(0.018)		(0.019)		(0.019)
Math skills		0.097		0.024		0.024
		(0.061)		(0.070)		(0.071)
Probability skills		0.056***		0.042**		0.039**
		(0.018)		(0.017)		(0.017)
Insurance skills (normalized)	0.076***	-0.010	0.047***	-0.054***	0.045***	-0.044**
	(0.012)	(0.018)	(0.014)	(0.020)	(0.015)	(0.020)
Household has other insurance policy (1=Yes)	0.161***	0.298***	0.125***	0.251***	0.115***	0.241***
	(0.030)	(0.039)	(0.032)	(0.038)	(0.034)	(0.039)
Does not know BASIX (1=Yes)	-0.138***		-0.105***		-0.117***	
	(0.029)		(0.030)		(0.032)	
Technology diffusion and networks						
Household belongs to water user group (1=Yes)	0.139		0.109		0.049	
	(0.114)		(0.111)		(0.112)	
Number of groups household belongs to	0.047**		0.035		0.022	
	(0.023)		(0.023)		(0.024)	
Demographic Characteristics						
Scheduled Caste or Scheduled Tribe (1=Yes)	-0.062	-0.217***	-0.004	-0.143***	-0.005	-0.129***
	(0.041)	(0.038)	(0.043)	(0.037)	(0.045)	(0.041)
Muslim (1=Yes)	-0.033	0.156***	-0.03	0.105*	-0.104	0.171***
	(0.070)	(0.059)	(0.071)	(0.056)	(0.080)	(0.066)
Household head is male (1=Yes)	0.037	0.126***	0.053	0.055	0.037	0.02
	(0.056)	(0.047)	(0.058)	(0.045)	(0.056)	(0.045)
Log of household head's age	0.032	-0.14	0.085	-0.118	0.104*	-0.282***
	(0.054)	(0.147)	(0.056)	(0.085)	(0.058)	(0.088)
Log of household size	0.060	0.089**	-0.005	0.079*	0.022	0.067
	(0.039)	(0.042)	(0.050)	(0.044)	(0.050)	(0.044)
Education of head is secondary school or higher (1=Yes)	0.034	0.073	0.001	0.039	0.007	0.06
	(0.030)	(0.056)	(0.032)	(0.058)	(0.033)	(0.059)
Village fixed effects	No	No	No	No	Yes	Yes
Observations	1047	772	1047	772	1047	772

Notes: Data from Andhra Pradesh come from surveys conducted in 2006 and BASIX administrative data. Data from Gujarat come from surveys conducted in 2006 and SEWA records. A linear probability model is used, with the dependent variable set to one if the household purchased an insurance policy. Robust standard errors are reported in parenthesis below the coefficients. Wealth index has been imputed and log of monthly per capita food expenditure has been winsorized at 1% from the top and bottom tails. The symbols *,**,*** denote significance at the 10, 5 and 1 percent level, respectively. Columns (1) and (2) report Univariate correlations computed by an OLS regression of the dependent variable against the variable shown in each row. Columns (3)-(6) report OLS regressions using all the variables as regressors. Columns (5) and (6) include village fixed effects. See Data Appendix for definition of variables.

Table 9: Stated Primary Reason for Insurance Non-Adoption

	Andhra Pradesh		Gujarat
	2004	2006	2006
Insufficient funds to buy insurance	27.1%	80.8%	27.9%
It is not good value (low payout / high premiums)	16.4%	7.85%	15.0%
Do not trust insurance provider	2.34%	5.23%	n.a.
It does not pay out when I suffer a loss	17.8%	2.91%	n.a.
Do not understand insurance	21.0%	2.33%	10.9%
Do not need insurance	2.80%	0.58%	25.2%
No castor, groundnut	6.07%	n.a.	n.a.
Other	6.54%	0.29%	32.7%

Notes: Self-reported primary reason for not purchasing insurance amongst farmers in Andhra Pradesh and Gujarat study areas. Data from Andhra Pradesh come from surveys conducted in 2004 and 2006. Non-purchasing households were asked the top three reasons why they didn't buy insurance. Only the primary reason cited by the household for nonadoption of insurance is reported. Data from Gujarat come from the baseline survey conducted in 2006.

Data Appendix: Definition of Variables

Variable name	Study Area	Definition of variable
Demographic Characteristics		
Household Size	Both	Number of individuals (of any age) in the household.
Scheduled Caste / Scheduled Tribe	Both	Dummy variable equal to 1 if household belongs to a scheduled caste or tribe.
Muslim	Both	Dummy variable equal to 1 if household's religion is Muslim.
Household head is male	Both	Dummy variable equal to 1 if the household head is male.
Household head 's age	Both	Age of household head in years.
Utility function		
Risk aversion	Both	Constructed from the choice over several lotteries as in Binswanger (1980). Assigns value 1 to individuals that choose the safe lottery, and for those who choose riskier lotteries, indicates the maximum rate at which they are revealed to accept additional risk (standard deviation) in return for higher expected return (ΔE / Δrisk). See online appendix for specific values of risk aversion in each sample.
Subjective discount rate	Both	Discount rate is defined as $(X-X_{now})/X_{now}$ where X is the amount that leaves the respondent indifferent between Xnow now and X in one month. In AP Xnow is Rs 200 and X can take the following values: Rs 201, Rs 205, Rs 210, Rs 220, Rs 240, Rs 260, Rs 300, Rs 400 or Rs 1000. In Gujarat, X_{now} is Rs 8 and X can take the following values: Rs 7, 8, 9, 10, 11, 12
Beliefs about return on insurance		
Above average expected monsoon rain (1=Yes)	Both	Dummy variable equal to 1 if households expects rain for the monsoon is above average, elicited before the monsoon.
Exposure to risk		
% cultivated land that is irrigated	Both	Acres of cultivated land that is irrigated over total owned land. 1% winsorization of each tail.
Wealth and Consumption		
Wealth Index	Both	First component of PCA score for a set of dummy variables for each of the following items: tractor, thresher, bullock cart, furniture, bicycle, motorcycle, sewmach, electricity, telephone.
Monthly Per Capita Food Expenditures	Both	Total monthly consumption expenditures on food divided by household size. Includes both consumption from own production and expenditures on purchased products. Food items consist of cereals and cereal products, pulses and pulse products, milk and milk products, edible oil, vegetables, fruits, meat, fish, chicken and egges, beverages, tobacco, and other food items. 1% winsorization of left and right tail. Since Andra Pradesh figures are reported by the male household head, who does not generally prepare food, estimates may be subject to underreporting.
Total value of all savings deposits	Both	Value of all deposits with any bank, post office or financial institution. 1% winsorization of left and right tail.
Familiarity with insurance and BASIX		
Average insurance payouts in the village 2004 and 2005	AP	Average insurance payouts during 2004 and 2005 in the village where household lives
HH bought rainfall insurance in 2004 (1=Yes)	AP	Dummy variable equal to 1 if household bought weather insurance in 2004
Does not know BASIX (1=Yes)	AP	Dummy variable equal to 1 if respondent does not know BASIX, the insurance provider
Household has other insurance (1=Yes)	Both	Dummy variable equal to 1 if household has other insurances of any type besides rainfall insurance sold by either BASIX (AP) or SEWA (Gujarat).
Insurance Questions	Both	Number of correct answers to the hypothetical questions detailed in Table 3, Panel C.
Math Questions	Gujarat	Number of correct answers to the following 8 questions: (1) How much is 4 + 3; (2) If you have 2 Rupees and a friend gives you Rs. 5, how many Rupees do you have?; (3) How much is 35 + 82; (4) If you have Rs. 48 and someone gives you Rs. 58, how much money do you have?; (5) What is 3 times 6?; (6) If you have four friends and would like to give each one four sweets, how many sweets must you have to give away?; (7) What is one one-tenth of 400?; (8) Suppose you want to buy misti that costs 37 Rs. You only have one 100 Rs note. How much change will you get?
Probability Questions	Gujarat	Number of correct answers to simple probability problems such as "a red bag has 2 black and 5 white marbles, a blue bag has 2 black and 10 white marbles, which bag are you more likely to draw a black marble from?"
Financial Literacy	Gujarat	Number of correct answers to the hypothetical questions detailed in Table 3, Panel B.
Understanding of millimeters (1=Yes)	AP	Dummy variable equal to 1 if respondent correctly measured the distance between two points in a hypothetical ruler. The respondent was shown a plastified paper with a ruler containing the letters A, B, C, D and E, placed in such a way that A was closest from the starting point and E furthest away. They were then asked to report the letter located 60mm from the starting point along the ruler.
Technology diffusion and networks		
HH belongs to a water user group (BUA or WUG) group (1=Yes)	AP	Dummy variable equal to 1 if any household member belongs to a water user group.
Number of groups that the household belongs to	AP	Total number of groups that the household belongs to out of the following: Raithu Mitra group, SHG (women), e.g. DWACRA, Velugu, Sanga Mitra, BUA/WUG, NGO, Education committees, Gram Panchayat / any elected body, Caste committees / caste Panchayat, other group.

NOT FOR PUBLICATION

Barriers to Household Risk Management: Evidence from India

Online Appendix [*]

Contents of this Online Appendix:

[*] This Online Appendix presents additional analyses and information relating to the paper "Barriers to Household Risk Management: Evidence from India".

Online Appendix A: A simple calibrated model of insurance demand

This Online Appendix presents a simple model of insurance participation excluding the non-price barriers (e.g. liquidity constraints, limited trust etc.) studied in our field experiments. The purpose of the model is to assess the conditions under which households would purchase the insurance product, in the absence of these non-price frictions.

The expected return on the insurance and the product design is calibrated to match the rainfall insurance products studied in our field experiments. We draw two main conclusions:

i. The model predicts the insurance will be purchased by any household with a coefficient of relative risk aversion larger than between 2 and 4, depending on assumptions about basis risk. These threshold risk aversion levels are significantly smaller than risk aversion estimates for our sample, based on field experiments.

ii. The benefits of insurance are substantially larger for "catastrophe" contracts that pay out rarely, but insure against the worst possible outcomes, simply because payout are concentrated in states of nature where the marginal utility of consumption is highest.

In summary, the model predicts that rainfall insurance demand should be high, absent non-price frictions. These conclusions are consistent with our empirical findings that non-price frictions, such as liquidity constraints, trust, financial illiteracy, etc., are important to understanding the modest insurance participation rates observed in the data.

A.1 Setup

We consider a simple model in which a household with initial wealth W* faces a zero mean normally distributed random wealth shock S, against which it may choose to buy partial insurance. The available insurance policy costs a premium P and provides a return R which is a function of the realization of S. The final wealth W of the household after the realization of the shock (in the case where the household purchases insurance) is thus given by:

[A.1] W (final wealth) = W* (initial wealth) + S (shock) + R – P (net insurance payoff).

The household's objective is to maximize a concave utility function, assumed to be of constant relative risk aversion (CRRA) form: $u(W) = W^{1-\gamma} / (1-\gamma)$. (In a multi-period framework, u(.) would be interpreted as the consumer's value function; in a single period model, it would be interpreted as their one-period reward or felicity function.)

The timing of events is: (i) household decides whether to buy insurance; (ii) S is realized; (iii) consumer realizes utility u(W). The household chooses whether or not to buy insurance to maximize E[u(W)], that is, it solves: $\max_{I \in \{0,1\}} E[u(W^* + S + I.(R - P))]$, where I is an indicator variable equal to 1 if the household purchases insurance and 0 otherwise.

We assume that the insurance payout is subject to basis risk, that is, the index used to compute insurance payouts is imperfectly correlated with the shock S. We assume that the index is: II (insurance index) = S (shock) + e, where e is also a zero mean normally distributed random variable. We index the level of basis risk by the ratio of the variance of e relative to the variance of S.

We consider two insurance policies, denoted as "linear loss" and "catastrophe" insurance. Both policies produce a positive payoff only when the insurance index II is negative. In the first, the insurance payoff is a linear function of II whenever II is negative. In the second, insurance pays off only when II is below a lower threshold II_0. That is, the payoff structure is:

[A.2] $\text{Payoff}_{\text{LINEAR LOSS}} = \max [0 , -\beta_{LL} . II]$

[A.3] $\text{Payoff}_{\text{CATASTROPHE}} = \max [0, -\beta_{CAT} . (II - II_0)]$

The motivation for considering these two contract types is that the ICICI Lombard and IFFCO-TOKIO policies are designed only to provide a payoff in particularly poor realizations of rainfall. For example, Giné et al. (2007) estimate based on historical rainfall data that the single-phase ICICI Lombard contracts offered in Andhra Pradesh in 2006 offer a maximum return of around 900%, but provide a payoff in only 11% of phases.

A.2 Calibration and simulation

We simulate this model to calculate the benefits of purchasing insurance for households with different levels of the coefficient of relative risk aversion. For these simulations, the model is calibrated to fit features of the Indian data and of observed insurance contracts. We are deliberately conservative in our calibration assumptions, so that, at least in the framework of the model, we provide a lower bound on the benefits of insurance to households.

We set initial wealth equal to Rs. 50,000. This is approximately one year of household consumption, based on the summary statistics presented in Table 2. (This is consistent with previous literature estimating the coefficient of relative risk aversion, which generally sets W equal to one year of income; see for example Bombardini and Trebbi, 2007.)

The standard deviation of the income shock S is set equal to 10,000, or 20% of W. This is approximately consistent with World Bank (2005), which estimates that a severe drought reduces rice yields in our two Andhra Pradesh study regions, Ananthapur and Mahbubnagar, by 45% and 26% respectively.

We calibrate β_{LL}, β_{CAT} and S_0 to fit to the insurance contracts offered in our two study regions in 2006. We set these parameters to ensure that payoffs under both the linear loss and catastrophe insurance contracts are 40% of the premium (which is approximately the same as the estimates reported in Table 1, although lower than actual insurance payouts in recent years). The probability of a positive payoff under the catastrophe insurance policy is set equal to 10%, the estimate in Giné et al. (2007). Finally, we assume that the policy premium is Rs. 100 (thus, the expected payout is Rs. 40).

We also allow for basis risk between the insurance index II used to calculate payouts and the rainfall income shock R. We vary the r-squared coefficient of determination between II and R widely, between values of 0.1 and 0.99. (An r-squared of 1 would imply no basis risk, while an r-squared of zero would imply that the insurance index is completely uncorrelated with the household's income shock).

Given these inputs, to simulate the model, we generate 200,000 random draws of the income shock S and the insurance index basis risk shock e, and calculate expected utility under the assumption that the household does, and then does not, purchase insurance. From this, we calculate the benefit of insurance purchase for households with different levels of relative risk aversion.

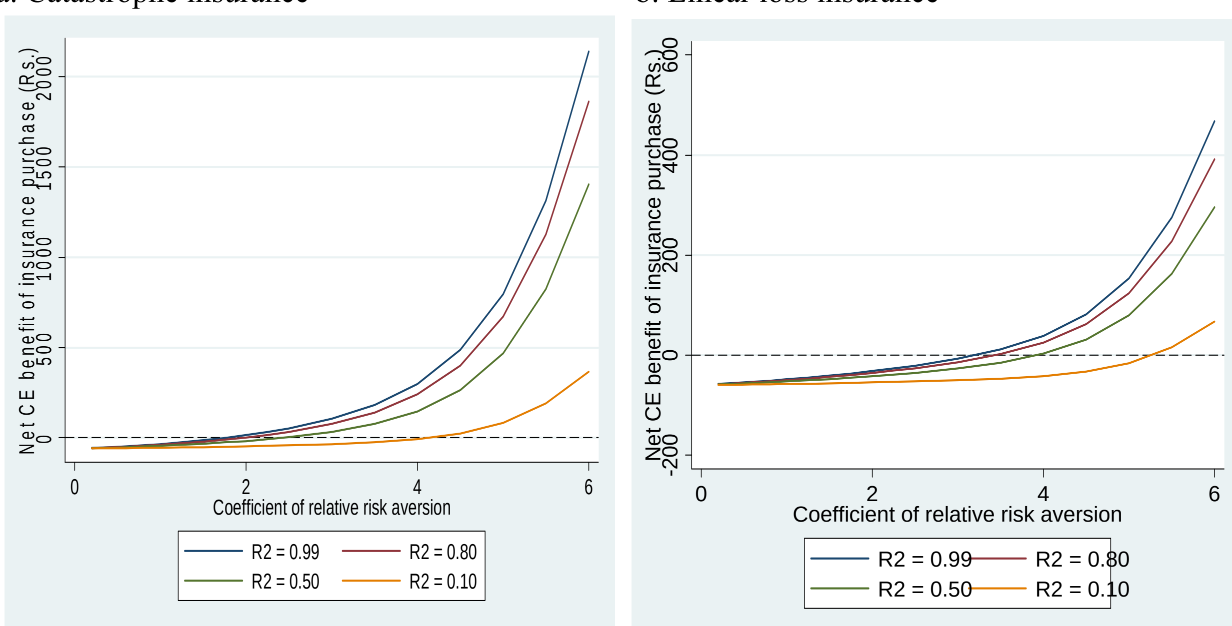
A.3 Results

Results from the simulation are presented in the figure below. The net benefits of insurance are expressed in terms of a certainty equivalent level of wealth, and are plotted against the household's coefficient of relative risk aversion, for the two different types of insurance policy, linear loss and catastrophe, assuming different levels of correlation between the insurance index and income shock: 0.99 (lowest basis risk), 0.8, 0.5 and 0.1 (greatest basis risk). While we lack rigorous evidence quantifying the magnitude of basis risk for the insurance products we study, we believe that considering a correlation of 0.1 represents a conservative upper bound for the "worst-case" level of basis risk. Households in our sample are generally located close to the rainfall stations used to calculate insurance payouts – in Andhra Pradesh this distance is only 4.27 miles on average. In addition, as discussed in the main text, households appear to face significant exposure to rainfall risk: for example, households overwhelmingly cite rainfall risk as the most important income risk they face, and academic research suggests rainfall risk, as a spatially correlated income shock, may be more difficult to smooth than other types of shocks.

Figure A.1: Benefits of insurance

The Figure plots the net benefit of insurance expressed in certainty equivalent terms for a single policy with premium Rs. 100 and actuarial value Rs. 40.

a. Catastrophe insurance b. Linear loss insurance



By definition, the net benefits of insurance are increasing in risk aversion in the range of basis risk considered. More notably, the benefits of insurance are significantly larger for the catastrophe insurance contract, shown in the left hand panel of the Figure, even though both contracts have the same actuarial value. This reflects the fact that the payouts for the catastrophe insurance contract are concentrated amongst the lowest realizations of S, when the marginal utility of wealth is highest. In addition, the simulations illustrate that higher basis risk reduces the welfare benefits of insurance. While our experiments do not allow us to study the effect of basis risk on insurance demand directly, we note in the main text that the use of technology to improve measurement of income shocks (e.g. the use of satellite foliage data) represents a promising approach to further reducing basis risk of index insurance products, likely increasing demand for such policies.

For examining the benefits of the product, we focus on the left-hand panel, which is designed to match the features of the insurance products we study in the field. We note that the benefits of purchasing insurance are positive for values of the coefficient of relative risk aversion greater than approximate 1.5 (assuming the lowest level of basis risk) to 4.0 (assuming the highest level of basis risk).[1]

These values are relatively low compared to values implied by households' choices in the Biswanger lotteries offered to households. For example, around one-fifth of households in our sample choose the entirely safe option in the Biswanger lottery. Substituting this into the formula for CRRA utility implies a coefficient of relative risk aversion significantly larger than 4, even if a reference level of wealth of zero is chosen. The implied coefficient of relative risk aversion is much larger again if a realistic reference level of wealth is chosen.

We note that evidence in developed countries sometimes finds lower estimates of the coefficient of RRA, of around 1 to 2 (e.g. Chetty, 2006; Bombardini and Trebbi, 2007). However, as Chetty notes, these coefficients are much lower than those implied by the asset pricing literature to justify observed equity premiums, suggesting that portfolio choice decisions made by households reflect a much larger degree of implied risk aversion.

A.4 Conclusions

This simple modeling exercise suggests that, in the absence of non-price frictions, a significant fraction of households would be expected to have positive demand for insurance, even with apparently expected payouts equal to 40% of insurance premiums. These conclusions are consistent with our main empirical finding that non-price frictions, such as liquidity constraints, trust, financial illiteracy, etc., are important in order to understand the modest insurance participation rates observed in the data.

[1] If the correlation between the index and income were low enough, then risk aversion and insurance purchase would no longer be positively correlated. As the correlation between the index and income decreases, expected income becomes in the limit *more* volatile if the household chooses insurance than if it does not. Correspondingly, more risk-averse individuals would have lower demand for insurance than less risk-averse households if basis risk is sufficiently high. Clarke 2010 develops a model that builds on this intuition and finds that the probability of insurance purchase has an inverted U-shape relationship with risk aversion. In an experiment with our simulations (not shown in Figure A.1), we set the level of basis risk to a very high level and verified Clarke's main finding; namely that the slope of the relationship between risk aversion and the benefits of insurance switched from being positive (as it is in Figure A.1) to negative.

Beyond this simple exercise, a promising area for future research would be to analyze the demand for insurance in a richer, explicitly dynamic life-cycle framework. Recent work by Fuster and Willen (2010) and De Nicola (2010) make a contribution along these lines.

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Online Appendix B Table 1: Study Design, Andhra Pradesh

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

Note: This table describes the experimental design for Andhra Pradesh in 2006. Study villages were first randomly assigned to two groups: those in which no endorsement visits would take place and those in which half of the visits would be endorsed. Households assigned a marketing visit in no-endorsement villages were randomly assigned one of four possible combinations of marketing treatments (education module x high reward), while households that received a marketing visit in endorsement villages were assigned one of eight possible combinations (endorsement x education module x high reward).

Online Appendix B Table 2: Study Design, Gujarat

Group 1: Flyer Treatments				Sample size
Group	Individual/Group	Religion		
1A	Individual	Neutral		378
1B	Individual	Muslim		438
1C	Individual	Hindu		416
1D	Group	Neutral		368
1E	Group	Muslim		398
1F	Group	Hindu		393
			Total sample	**2,391**
Group 2: Video--Surveyed Respondents in New Treatment Villages				
Surveyed Households				**Sample size**
Group	Payouts	Frame		
2A	8/10 no	Safety		75
2B	8/10 no	Vulnerability		81
2C	2/10 yes	Safety		78
2D	2/10 yes	Vulnerability		81
			Total sample	**315**
Group 3: Video--Non-Surveyed Respondents in New Treatment Villages				
Group	Sew Brand	Peer / Authority	Payouts	
3A	Yes	Peer	8/10 no	124
3B	No	Peer	8/10 no	126
3C	Yes	Authority	8/10 no	150
3D	No	Authority	8/10 no	131
3E	Yes	Peer	2/10 yes	137
3F	No	Peer	2/10 yes	135
3G	Yes	Authority	2/10 yes	147
3H	No	Authority	2/10 yes	150
			Total sample	**1,100**
Discounts (All Video Households)				
D1	Rs. 5			566
D2	Rs. 10			566
D3	Rs. 20			283
			Total sample	**1,415**

Note. This table describes the experimental design for Gujarat in 2007. Households in the 21 villages which were offered insurance for the first time in 2007 received video treatments. Households receiving video treatments that were in the original survey sample were shown one of four videos; other households were shown one of eight different videos. All households observing videos were offered a discount of either Rs. 5, 10, or 20 on their first policy. Households in the 30 villages where insurance was offered in both 2006 and 2007 were given one of six flyers.

Online Appendix C: Binswanger Lotteries

Andhra Pradesh

Heads	Tails	ΔE / Δrisk	Percent choosing this lottery 2006
25	25	1.00	10.3%
20	60	0.75	25.6%
15	80	0.60	18.0%
10	95	0.50	25.3%
5	105	0.33	11.0%
0	110	0.00	9.9%
Average ΔE / Δrisk		0.57	

Gujarat

Heads	Tails	ΔE / Δrisk	Main Sample (N=1500)
25	25	1.00	14.0%
22	47	0.76	12.3%
20	60	0.73	15.4%
17	63	0.72	15.6%
15	75	0.71	9.3%
10	80	0.58	15.6%
5	95	0.45	7.9%
0	100	0	9.9%
Average ΔE / Δrisk		0.42	

Notes. This table describes the Binswanger Lotteries used to measure risk aversion amongst sample groups in Andhra Pradesh and Gujarat. Each respondent chose one of the listed lotteries, which increased in risk and expected value. Our measure of risk aversion assigns a value of 1 to those who choose the safe lottery and, for those who choose riskier lotteries, indicates the maximum rate at which they are revealed to accept additional risk (standard deviation) in return for higher expected return.