Barriers to Household Risk Management: Evidence from India*

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First version: August 16, 2008

This version: October 14, 2009

* This project is a collaborative exercise involving many people. The work in Andhra Pradesh was directed by Giné, Townsend and Vickery. The work in Gujarat was directed by Cole, Tobacman, and Topalova. In Andhra Pradesh, we gratefully acknowledge the financial support of the Switzerland State Secretariat for Economic Affairs (SECO), the Global Association of Risk Professionals (GARP), and the World Bank Commodity Risk Management Group (CRMG). We thank ICRISAT, and particularly K.P.C. Rao, for their efforts in collecting the survey data, and employees of BASIX and ICICI Lombard for their assistance. In Gujarat, we would like to thank SEWA for their tremendous contributions to the research agenda, and in particular Chhayaben Bhavsar; USAID / BASIS for financial support, and the Centre for Microfinance for generous financial and superb administrative and research support, the latter provided in particular by Aparna Krishnan and Monika Singh. Paola de Baldomero Zazo, Nilesh Fernando, Lev Menand and Gillian Welch provided excellent research assistance. We also thank participants at a number of seminars and conferences for their helpful comments and feedback. The views expressed in this paper are those of the authors, and do not reflect the opinions of the Federal Reserve Bank of New York, the Federal Reserve System, the World Bank or the International Monetary Fund.

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Abstract

Financial engineering offers the potential to significantly reduce consumption fluctuations faced by individuals, households, and firms. Yet much of this promise remains unrealized. In this paper, we study the adoption of an innovative rainfall insurance product designed to compensate low-income Indian farmers in case of deficient rainfall during the primary monsoon season. We first document relatively low levels of adoption of this new risk management technology: only 5-10% of households purchase insurance, even though rainfall variability is overwhelmingly cited by households as the most important risk they face. We then conduct a series of randomized field experiments to test theoretical predictions of why adoption may be low. Insurance purchase is sensitive to price, with an estimated extensive price elasticity of demand between -0.66 and -0.88. Credit constraints, identified through the provision of random liquidity shocks, are a key barrier to participation, a result also consistent with household self-reports. Several experiments find an important role for trust in insurance participation. We find mixed evidence that subtle psychological manipulations affect purchase, and no evidence that modest amounts of financial education changes participation decisions. Based on our experimental results, we suggest preliminary lessons for improving the design of household risk management contracts.

A key insight of financial theory is that households should hold a diversified market portfolio that minimizes non-systematic risk. In practice, however, many important idiosyncratic risks are not pooled across households, even when the source of risk is exogenous and publicly observable, and thus not subject to informational problems like moral hazard and adverse selection. For example, many households appear exposed to shocks to local weather conditions, regional house prices, commodity prices like rice, heating oil and gasoline, as well as local and regional income fluctuations. Often, financial contracts simply do not exist to help households hedge these risks. In a few cases, hedging contracts exist, but their use is generally not widespread. These facts suggest a puzzle, emphasized by Shiller (1993): "It is odd that there appear to have been no practical proposals for establishing a set of markets to hedge the biggest risks to standards of living."

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

This is a setting where the welfare benefits of risk diversification appear especially high. Eighty-nine percent of households in our sample report that variation in local rainfall is the most important risk they face. Furthermore, Giné, Townsend and Vickery (2007) document that these local rainfall shocks are nearly uncorrelated with systematic risk factors like stock market returns that are relevant for asset pricing, implying that a well-diversified investor would require only a low risk premium to bear rainfall risk.

Despite these potential benefits, we document relatively low participation in the risk management product. Only 5-10% of households in our study areas purchase insurance. (Notably, the participation rate is significantly higher, around 20-30%, amongst households who receive randomized one of our insurance treatments: either a home visit from an insurance representative, an informational flyer, or video information about the product). Also, the majority of participating households purchase only a single policy, which hedges only 2-5% of expected agricultural income.

Our goal is to test the relative importance of different theories which may help explain this low participation rate. We do so through a set of randomized experiments, conducted in rural areas of two Indian states, Andhra Pradesh and Gujarat. These experiments involve household visits by insurance educators, as well as randomized distribution of flyers and video messages. For example, we estimate the price elasticity of demand for insurance by randomly varying the price of the policy. To understand the role of credit constraints, we randomly assign certain households positive liquidity shocks. To measure the importance of trust, we vary whether the household receives a product endorsement by a trusted local agent. Other experiments test the role of financial literacy, as well as product framing and other biases documented in the behavioral finance literature.

These experiments provide causal estimates of the effect on insurance participation of key factors suggested by neoclassical theory and the behavioral finance literature. To our knowledge, this study represents the first randomized evaluation of demand for an insurance product. We present the first experimental evidence of the effect of trust on financial market participation, and contribute to literatures on household finance, risk management, financial innovation, and risk sharing. Our evidence combines results from two disparate regions, allowing a test of external validity. Where comparable, our similar results across the two study areas suggest that our results are driven by predictable human behavior, rather than idiosyncratic features of the areas studied.

Our first hypothesis is simply that demand is low because the insurance is expensive relative to actuarial value, reflecting either market power, or high fixed costs of distributing and administering the product. High transaction costs and prices are a ubiquitous feature of financial services offered to the poor in developing countries. For example, Cull, Demirguc-Kunt and Morduch (2009) document in the context of microcredit contracts that annual operating costs associated with nonbank microfinance loans range from 17%-26% of loan value, far above corresponding values in developed countries. These costs must be either passed onto borrowers in the form of high interest rates, or ameliorated through subsidies from donors or others.

Consistent with comparable evidence from the microfinance literature, we estimate based on historical rainfall data that the rainfall insurance product is priced at a significant premium to actuarial value. Estimated expected payouts range from 19%-44% of insurance premia across our study areas. This compares to expected payouts equal to 65%-76% of premia for auto and homeowners insurance in the United States[1]. Furthermore, in one of our study areas we randomize the price of the insurance product, and estimate a statistically significant negative elasticity of insurance demand of between -0.66 and -0.88. This elasticity implies insurance demand would approximately double if the product could be offered at the same terms as US insurance contracts.

This result relates closely to a large consumer finance literature estimating the sensitivity of credit demand to loan interest rates. For example, Karlan and Zinman (2008) present causal evidence from South Africa that demand for microloans is significantly sensitive to interest rates, contrary to previous assertions that credit demand amongst the poor is close to rate inelastic. Our evidence complements this literature, which focuses on the price elasticity of demand for credit, rather than insurance. To our knowledge our paper represents the first estimate of the elasticity of insurance demand derived using a randomized controlled trial approach.

Our second hypothesis is that insurance demand is retarded by liquidity constraints facing poor rural households. The intuition for this prediction is that rural households face a tradeoff between the benefits of insurance and the costs of spending scarce collateral to purchase insurance rather than to use for other uses, like agricultural investments. This logic is formalized by Rampini and Viswanathan (2009), whose model predicts that more constrained entrepreneurial firms engage in less risk management, contrary to the prediction of previous models such as Froot, Scharfstein and Stein (1993).

We find several pieces of evidence consistent with this prediction. First, farmers who are randomly surprised with a positive liquidity shock at the time of a visit the household visit are more than twice as likely to purchase insurance policies. In addition, 64% of non-participating farmers in the Andhra Pradesh sample cite “insufficient funds to buy” as their primary reason for not purchasing insurance. Finally, insurance demand is significantly positively correlated with household wealth, a plausible proxy for the degree of credit constraints.

[1] Data on US insurance premia was generously provided to us by David Cummins of Temple University, based on information from the 2007 Best’s Aggregates and Averages. This publication reports the aggregate ratio of claims to premiums earned for a range of insurance products. This ratio 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 is significantly lower, 20.4%, for earthquake insurance, although that likely reflects a small sample bias due to the infrequency of earthquake claims).

Third, we find evidence that households have only a partial understanding of the risk management product, and that factors related to trust and financial literacy influence insurance demand to an economically significant degree. An endorsement from a trusted third party increases the probability of purchase by 40%, while introducing subtle associations between the product and symbols of the household's own religion also significantly increases demand. The simple act of conducting a household visit, even not combined with other treatments, significantly increases insurance purchase, even though the rainfall insurance is readily available to all households in our survey villages. These findings appear consistent with a standard model augmented with costs of attention or information gathering (along the lines of Reis, 2006), or limited trust (Guiso, Sapienza, and Zingales, 2007). Also consistent with models of costly attention, a significant fraction of households are unable to correctly answer simple questions about the way insurance payoffs are calculated, and about concepts relating to probability, and the time value of money.

Fourth, we test whether insurance demand is influenced by subtle psychological manipulations in the way the product is presented to the household. A significant role for these factors would be more difficult to reconcile with a rational model, but is consistent with various behavioral biases documented elsewhere (e.g., Bertrand et. al., 2009). In fact, we find limited evidence that these cues influence household behavior, although our power to reject the null hypothesis is relatively low.

Based on these empirical results, we draw several preliminary conclusions about the optimal design for this and other household risk management contracts. The importance of liquidity constraints suggests policies should be designed to provide payouts as quickly as possible, especially during the monsoon season when our data suggests households are particularly credit constrained. Along these lines, the rainfall insurance underwriter ICICI Lombard has begun installing a network of automatic rain gauges, allowing them to immediately measure rainfall, calculate policy returns and begin delivering payouts to households. A second possible improvement would be to alleviate liquidity constraints by combining the insurance product with a short-term loan, or equivalently, to originate loans with interest rates that are explicitly state-contingent based on rainfall outcomes.

The sensitivity of insurance demand to price underlines the benefits of developing ways to minimize transactions costs and improve product market competition among suppliers of rainfall insurance.

The estimated significance of trust and vendor experience suggests that product diffusion through the population may be relatively slow, as a track record is established. Optimal contract design should potentially facilitate this learning by paying a positive return with sufficient frequency. Giné, Townsend and Vickery (2007) show that existing design deemphasizes this motive: ICICI Lombard rainfall insurance policies in 2006 produced a high maximum return of 900%, but a positive return in only 11% of cases. An important tradeoff, though, is that "catastrophe"-type insurance may be relatively more beneficial for the household, since it provides payouts that are concentrated in states of nature where the marginal utility of consumption is particularly high.

Our findings have broad implications for the design of nascent but growing household risk management markets. In the United States, for example, the Chicago Mercantile Exchange trades futures contracts linked to house prices, temperature, frost, snowfall, and hurricanes, while a number of insurance firms offer retail-level rainfall risk management policies to US firms and individuals. Prediction markets allow households to take positions on macroeconomic events such as recessions or election outcomes (Wolfers and Zitzewitz, 2004). Innovations in mortgage contracts, such as adjustable-rate mortgages and negative amortization contracts provide households the opportunity to significantly manipulate their exposure to interest rate risk.

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

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

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

Our findings also contribute to a growing literature on household financial decision-making. Perhaps most advanced is work studying low levels of household participation in equity markets. Guiso, Sapienza, and Zingales (2007) find that trust is an important determinant of stock market participation. We find similar evidence for insurance market participation, using exogenous variation in trust generated by our experimental design. Hong, Kubik and Stein (2004) find that social interaction influences the stock market participation of individual households, while Hong and Stein (2005) find that social networks influence money manager investment decisions. Cole and Shastry (2009) find that household education plays an even larger role.

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

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

The rest of this paper proceeds as follows. Section I discusses the theoretical motivation for the empirical tests in the paper. Section II provides a description of the insurance products. Section III describes the economic context. Sections IV and V describe the design of the randomized trials in Andhra Pradesh and Gujarat respectively. Sections VI and VII present results for field experiments in these two states. Section VIII compares the experimental results to non-experimental evidence. Section IX concludes.

I. Determinants of insurance participation

A standard full-information neoclassical model makes several predictions about demand for insurance. For example, Giné, Townsend and Vickery (2008) present a simple static model of insurance market participation under credit constraints. The model predicts that insurance demand is increasing in: (i) risk aversion; (ii) the expected payoff relative to the price of the policy inclusive of any additional transaction costs to the consumer; (iii) liquidity (i.e. willingness-to-pay is decreasing in the degree of credit constraints at the time insurance is purchased); (iv) the size of the risk exposure; and (v) the correlation between losses and insurance payouts (i.e. willingness-to-pay for insurance is decreasing in basis risk).

Many of these predictions have indeed been found to hold in insurance markets in the United States and other developed countries, typically through observational studies (Babbel, 1985; Pauly et. al., 2003). Our experimental design allows us to directly estimate the causal effect of price and liquidity constraints on the probability of insurance purchase. We find that insurance demand is sensitive to both of these factors.

However, other authors also point to a variety of insurance puzzles inconsistent with these standard predictions. Cutler and Zeckhauser (2004) argue that "insurance purchases do not match theoretical predictions," and that "financial markets, despite their vast resources and wide participation, are not a major bearer of large private risks." (p. 2-3). For example, many consumers pay high premia for insurance on consumer durables, yet remain uninsured against much more significant risks such as disability and other catastrophic health events.

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

We provide what we believe is the first experimental evidence for the role of trust in financial market participation. In one experiment, we randomly vary whether our hired insurance representative is endorsed at the start of their household visit by a trusted third party, namely by a microfinance customer service agent who visits the village regularly and is well known to households. In a second experiment, in which insurance information is disseminated through paper flyers, we randomize whether the flyer design includes subtle references to either the Muslim or Hindu faith. We then study how the effect of these cues interacts with the religion of the household receiving the flyer. In both cases, we find that insurance participation is significantly higher when the product information is associated with a trusted source.

In other experiments, we vary the amount of financial education provided to the household, to test the role of financial literacy in insurance purchase decisions. To the extent financial illiteracy correlates with noisiness of beliefs about the effects of financial products, illiteracy will reduce the perception that rainfall insurance will help smooth consumption, and therefore will reduce demand.

Insights from the economics and psychology literature suggest behavioral factors may also contribute to the divergence between insurance theory and practice. Laboratory experiments find the framing of a choice affects individuals' willingness to pay for insurance. For example Johnson, Hershey, Meszaros and Kunrether (1993) conduct a survey in which willingness to pay for flight insurance, covering a single airline flight, is elicited. The mean willingness to pay for a policy covering "*any act of terrorism*" is \$14.12, compared to \$12.03 for a policy covering an accident for *"any reason.*" In a standard model, the willingness to pay for the first policy must be weakly smaller than that for the second. Other psychology research finds that framing can affect an individual's willingness to take risk (Mittal and Rose, 1998). Finally, in a large field experiment in South Africa, Bertrand, Karlan, Mullainathan, Shafir and Zinman (2009) find that subtle advertising cues significantly influence credit demand; for example, including the picture of a man rather than a woman on an advertising flyer for a consumer loan changes loan demand by as much as a shift of up to 2.2% in the *monthly* interest rate.

Following this literature, we test a number of framing hypotheses. For example, we study one of the classic framing effects, the "Asian Disease" preference reversal puzzle described in Tversky and Kahneman (1981), by varying whether the policy benefits are described in terms of losses or in gains. (Some households are told the policy "would have paid in 2 of the past 10 years," while others are told that it "would not have paid money in 8 of the past 10 years.") These tests are described in more detail in Section V.

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

Formal risk management tools like the rainfall insurance product studied here improve welfare only if existing risk-sharing mechanisms are inadequate (Townsend, 1994; Morduch, 1995; Lim and Townsend, 1998). Most closely related to the current study, Paxson (1992) finds that Thai households save a significant fraction of transitory income shocks driven by rainfall fluctuations. Miller and Paulson (2007) find that remittance income responds to rainfall shocks, ameliorating income fluctuations.

A range of evidence suggests, however, that these mechanisms are insufficient to fully insure Indian farmers against rainfall shocks, especially for poor households. First, Morduch (1995) summarizes evidence that households in India engage in a variety of 'income smoothing' activities that reduce the variability of income, but at the cost of lower average income. Binswanger and Rosenzweig (1993) estimate a structural model which estimates that a one-standard deviation increase in rainfall volatility would reduce agricultural profits by 15% for the median household, but 35% for the bottom quartile of households ordered by wealth. Second, Morduch (1995) and Townsend (1994) present evidence that the degree of consumption smoothing is higher for wealthy households than poor households. Moreover, rainfall fluctuations affect all households in a local geographic area, making some other risk-sharing mechanisms like inter-household transfers and local credit and asset markets less effective.

Qualitative responses from our Andhra Pradesh sample are also consistent with the proposition that households are not fully insured against rainfall shocks. Eighty-nine percent of farmers in the Andhra Pradesh sample cite rainfall variability as the most important source of risk faced by the household. The most popular reason for purchasing insurance is 'security and/or risk reduction', cited by 55% of purchasers. Conversely, only a small fraction (between 2% and 25% depending on the sample) of non-buyers cite 'do not need insurance' as an explanation for non-purchase. (See Section VIII for more details.)

II. Product description

Rainfall insurance is one of a range of financial innovations made available to households in developing countries in recent years. In India, the growth in the availability of micro-insurance products, including rainfall, but also health, life, property and livestock insurance, has been spurred by financial liberalization over the past decade, as well as political pressures on insurance companies to serve rural areas. The first rainfall insurance policies were developed by ICICI Lombard, a large general insurer, with technical support provided by the World Bank.[3] Policies were first offered to households in the Indian state of Andhra Pradesh

[3] ICICI Lombard is a joint venture between ICICI Bank (India) and Fairfax Financial Holdings (Canada). The first rainfall insurance product was developed with the technical assistance of the World Bank and the International Task Force for Commodity Risk Management. Such partnerships may be potentially valuable

in 2003, initially on a pilot basis. Today, policies are offered by a number of vendors, and sold in many regions of India, as well as other developing countries.

Rainfall insurance contracts in India generally specify a threshold amount of rainfall, often intended to approximate the minimum required for successful growth of a given crop. The policyholder is eligible to receive a payment if cumulative rainfall is lower than this threshold over a pre-specified period of time, such as the entire growing season, or a fraction thereof. For ICICI Lombard policies, the payout amount increases linearly with the size of the rainfall deficit relative to the threshold, reaching a maximum payout at a second threshold meant to approximate total crop failure. Policies covering the harvest period of the monsoon have a similar structure, except that the policy pays off when rainfall is particularly high, because flood or excess rain generally damages crops during the harvest.

A representative example of an ICICI Lombard insurance contract is presented in Figure 1. Thresholds in the figure come from a policy offered in 2004 to households in one of our Andhra Pradesh study mandals (a mandal is roughly equivalent to a U.S. county). In the example, the product pays zero when cumulative rainfall during a particular 45 day period exceeds 100mm. Payouts are then linear in the rainfall deficit relative to this 100mm threshold, jumping to Rs. 2000 when cumulative rainfall is below 40mm.[4]

[INSERT FIGURE 1 HERE]

ICICI Lombard, IFFCO-TOKIO and other Indian rainfall insurance underwriters generally do not sell policies directly to households. Instead, they partner with local microfinance institutions or other grass-roots distribution networks. Insurance sales and claims processes are streamlined to minimize transaction costs. The household purchases policies through a local sales representative in their village, who collects money and fills out paperwork at the client's house. No claim needs to be filed in the event of a payout; the insurance company simply calculates payouts based on measured rainfall at the relevant gauge, and then delivers them through local agents, usually by setting up a table in the recipients' village to deliver payouts.

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for spurring innovation; since intellectual property rights are weak for financial services (Tufano, 2003), it may be difficult for innovators to otherwise recoup up-front research and development costs.

[4] In derivatives terminology, using millimeters of rainfall as the underlying, this contract is equivalent to a long put with a strike of 100, a short put with a strike at 40, and a binary option with a strike at 40.

Below we describe more specific details for policies sold in our two study regions, which are located in the states of Andhra Pradesh (where formal rainfall insurance was first introduced to India in 2003) and in Gujarat (where insurance was first offered in 2006).

A. Andhra Pradesh

In the Andhra Pradesh study villages, insurance is sold to households by BASIX, a large 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 also sell other financial services like microfinance loans.

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

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

B. Gujarat

Rainfall insurance contracts were first marketed in Gujarat in 2006 by SEWA, a large non-government organization that serves women, in three districts in Gujarat: Ahmedabad, Anand, and Patan. The 2006 policies were also underwritten by ICICI Lombard and shared many features of the Andhra Pradesh contracts. In Anand and Ahmedabad, two district-specific policies were offered: one for crops requiring higher levels of rainfall, such as cotton, and one for crops requiring lower levels of rainfall, such as sorghum.

Responding to feedback from the insurance sales team, SEWA streamlined their product offering in 2007, opting for a single-phase policy from a different insurance provider, IFFCO-TOKIO. This product provides a payout when rainfall is at least 40% below a specified "normal" level over the entire monsoon. Payouts are calculated as a nonlinear function of the percentage deficit in rainfall relative to this normal level. Premia for the IFFCO-TOKIO product are particularly low; each policy, nominally designated for half an acre of farmland, sold in 2007 for Rs. 44 to Rs. 86 (approximately $1-2 US dollars). This reflects the fact that SEWA's members are among the poorest households in the state, and SEWA was committed to designing a product accessible to all.

C. Contract details

Table 1 presents contract details for insurance contracts offered to farmers in Andhra Pradesh in 2006, and in Gujarat in 2007, the years of our policy interventions. In Andhra Pradesh, contracts are sold for three phases as described above; the first two phases provided coverage against deficient rainfall, while the third phase paid in the event of excess rainfall. In Andhra Pradesh, farmers were allowed to purchase policies phase-by-phase, allowing customized coverage across different parts of the monsoon.[5]

[INSERT TABLE 1 HERE]

Columns labeled "Premium" list policy premia, which vary between Rs. 44 and Rs. 340 (or around $1-8 US). As noted above, premia are particularly low for the IFFCO-TOKIO policies offered in Gujarat in 2007. As a point of reference, the average daily wage for an agricultural laborer in our survey areas is around Rs. 40-50, although incomes for landed farmers or more skilled workers are significantly higher. Households were not limited in the number of policies, and could purchase as many as they desired.

For the five insurance contracts in the table, we are able to calculate a measure of expected payouts using historical rainfall data. In each case, we simply apply the contract specifications in the table to past monsoon seasons, in each case using at least 30 years of historical data. (See Giné, Townsend and Vickery, 2007, for more details of the approach.) Calculated expected payouts across these five contracts average 40% of the policy premia; the range is 19% to 57%.

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

The remainder of the table lists insurance contract details. As an example, consider the Gujarat policy labeled "Ahmedabad / low" for 2006. The policy payout for Phase I is determined as follows. First, if the rainfall index for the phase exceeds the "strike" of 100mm, no payout is made. For each 1mm of deficit below 100mm, the policyholder is paid Rs. 5 (listed under the column "payout slope"). If phase rainfall is below 10mm, the policy holder receives a single payment of Rs. 500.

In 2007 in Gujarat, to ensure households would have enough liquidity to purchase the product, SEWA requested a policy size with a maximum payout of Rs. 1000. Of course, households were free to purchase multiple policies. This policy was comprised of a single phase, from June 1 to August 31. Policy design specified a notional "normal" level of rainfall, roughly equal to the historic average in that district. Payouts are made if measured rainfall is at least 40% below this level, with the amount of payout increasing (non-linearly) in the size of the rainfall deficit. For example, as shown in Table 1, the price of a policy in Patan in 2007 is Rs. 85.5. If monsoon rainfall is 80% below the normal level of 389.9mm, the policy would provide a payoff of Rs. 400.

In Gujarat, rainfall was sufficiently high in both 2006 and 2007 that no payout was triggered. However, in Andhra Pradesh, three policies out of five paid out at least once between 2004 and 2006. In the district of Mahbubnagar, Atmakur policies paid Rs. 214 in 2006, Rs. 40 in 2005 and Rs. 613 in 2004 on average. Policies indexed to the Mahabubnagar station provided a payout in 2004 averaging Rs. 575. In the Anantapur rainfall station, the policy paid Rs. 113 in 2006 and Rs. 4 in 2005. In the Hindupur and Anantapur districts, the policy paid Rs. 126 in 2006, Rs. 24 in 2005, but there was no payout in 2004. The Kondagal policy did not provide a payout in any of the three years.

D. Is insurance valuable to households?

Table 1 documents that expected insurance payouts are only around 40% of premiums on average. This figure appears lower than in insurance contracts in developed countries, where actuarial value of insurance contracts are generally 60-70% of market premiums. While unsurprising given the higher prices for loans and other types of financial services in developing countries, this stylized fact raises a clear question: at the prices offered, how valuable is the insurance product to households?

In the Appendix we simulate a simple calibrated model of insurance to investigate this question in more detail. The model simulates the benefits of two types of insurance policies, one which provides insurance against any type of loss, and another whose payouts are concentrated in particularly low realizations of the income shock. This "catastrophe" product is calibrated to the actual features of the ICICI Lombard insurance, which as shown by Giné, Townsend and Vickery (2007) produces a positive return only in the 11% of lowest rainfall realizations. Although we make conservative assumptions in this calibration exercise, the results suggest that the insurance product is valuable at reasonable levels of risk aversion, particularly for the "catastrophe" product calibrated to the actual features of the insurance contract offered to households in our study villages.

III. Summary statistics

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

A. Sample selection: Andhra Pradesh

The 2006 household sample is the same (except for attrition) as an earlier, 2004 household survey. (Regressions in Giné, Townsend and Vickery, 2008, are based on this earlier survey.) The sampling frame for the 2004 survey is a census of approximately 7,000 landowner households across 37 villages in Mahbubnagar and Ananthapur. Amongst this population, a stratified random sample is selected. The strata are: households who purchased rainfall insurance in 2004 (267 households), households who attended an insurance marketing meeting but did not purchase insurance (233 households), households in villages where insurance was offered but did not attend a marketing meeting (252 households), and households in villages where insurance was not offered in 2004 (308 households). The total sample size is thus 1060. A random sample of households was selected within each of these strata. Between 2004 and 2006 there is attrition of 10.2%, due primarily to death and household migration. The sample for the 2006 field experiments is thus 952 households.

B. Sample Selection: Gujarat

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

We survey 15 households in each of these 100 villages. While SEWA intended to make the product available to any interested party, their main goal was to provide insurance to their members; hence, our sampling frame is the set of SEWA membership lists for the 100 survey villages. Of the 15 households, five are selected at random from the list of village SEWA members. An additional five are randomly selected from the subset of village SEWA members who also have a positive savings account balance. (This was done because SEWA households are poor, and we were concerned liquidity constraints may have limited take-up.) The final five households are selected (non-randomly) based on suggestions from a local SEWA employee that they would be likely to purchase rainfall insurance.[6]

A baseline survey of this sample of 1500 households was conducted in May 2006 by a professional survey team. Following the survey, treatment status was assigned, and rainfall insurance was offered in 2006 to 30 of the 100 villages, selected randomly. A follow-up survey was conducted in October of 2006. In 2007, SEWA elected to continue to phase in the insurance product, offering it to an additional 20 villages, selected randomly from villages that were not offered insurance in 2006. Thus, in 2007, the year of our insurance experiments, rainfall insurance is made available in half the 100 villages.

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

C. Sample Demographic Characteristics

Table 2 presents summary statistics for surveyed households in both states, as well as weighted population statistics for comparison[7]. Because the surveys for Andhra Pradesh and

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

[7] The population means for Andhra Pradesh are calculated using the population weights—recall that the main sample oversamples individuals who purchased rainfall insurance. In Gujarat, the population numbers are drawn from the set of five individuals who were selected at random from the SEWA membership rolls, and thus represent averages for the population of SEWA members, not for the entire population of the surveyed villages.

Gujarat were developed independently, the set of variables is not identical. To the extent possible, we harmonize definitions and present consistent summary statistics. Full definitions and descriptions of the construction of each variable are presented in Appendix Table A. The table presents both sample and population statistics.

[INSERT TABLE 2 HERE]

Agriculture is the primary income source for 65% of households in Andhra Pradesh, and 72% of households in Gujarat. Household size is roughly similar for both samples, with a mean of 6.26 in Andhra Pradesh, and 5.85 in Gujarat. The fraction of historically disadvantaged minorities is low in Andhra Pradesh, but high in Gujarat, where 43.7% of households are 'scheduled caste,' or former 'untouchables' reflecting SEWA's membership of poor, self-employed women.

Table 2 also presents summary statistics for household education, wealth and income. Overall, the state of Gujarat is substantially wealthier than Andhra Pradesh, with more productive soil. However, the Gujarat survey targeted the poor (SEWA members), while the Andhra Pradesh sample over-surveys landowning households.

We ask households to report annual household income, and to list different types of financial and non-financial assets, from which we derive a measure of household wealth. By these measures, the Gujarat households are better off, reporting an average annual income of Rs. 27,800, as against Rs. 17,000 in Andhra Pradesh. Reported consumption expenditures also suggest Gujarat households are wealthier; reported mean monthly per capita expenditure in Andhra Pradesh is Rs. 560, half of the Gujarat level. Unreported in Table 2, we also compute an alternative measure of living standards potentially less subject to measurement error, based on a count of the type of assets or durable goods a household owns (items include television, radio, fan, tractor, thresher, bullock cart, furniture, bicycle, motorcycle, sewing machine, and telephone). By this measure, the Andhra Pradesh households are wealthier; the mean number of assets held is 2.71 in Andhra Pradesh, but only 2.30 in Gujarat. Average educational attainment of the survey respondent is similar across the two samples, however note that a higher fraction of the survey respondents in Gujarat are women.

D. Education and Financial Literacy

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

[INSERT TABLE 3 HERE]

Since years of schooling may be a poor proxy for education, for the Gujarat sample, we ask a number of questions to directly measure numeracy and financial literacy. Respondents are offered Rs. 1 for each question answered correctly, paid immediately, providing some motivation to answer correctly. First we administer a math test. The average math score is 64%. Almost all respondents correctly answer the simplest question ("what is 4 plus 3") while many more had difficulty with multiplication ("3 times 6") and division ("one-tenth of 400"). Since respondents are not allowed to consult with friends or neighbors when answering, it is reasonable to think that in the real world, they may perform better when answering these questions.

To understand how households process information about index-based insurance, in both Andhra Pradesh and Gujarat we read a brief description of a hypothetical insurance product (temperature insurance), and test household comprehension. After reading this description once, households are asked several simple hypothetical questions about whether the policy would pay out. Our sample did relatively well on this exam, recording correct answers 80% of the time for the Andhra Pradesh sample, and 68% for the Gujarat sample.

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

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

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

E. Risk Attitudes, Discount Rates, and Expectations

Individuals' attitudes towards risk may be important when deciding whether to purchase insurance. Since the expected return of an insurance product is negative, the product is demanded only to the extent that household's value reduced income risk. Risk aversion is difficult to measure, because people often do not make the same decisions in real-world contexts as they do when answering hypothetical questions used to elicit risk aversion.

We follow Binswanger (1980) and measure risk aversion using actual lotteries, for real (and substantial) amounts of money. We give individuals a choice of a set of lotteries, ranging from a perfectly safe lottery which pays Rs. 50 with certainty, to a lottery that pays Rs. 110 in Andhra Pradesh (Rs. 100 in Gujarat) with probability ½ and Rs. 0 with probability ½. Only 10% and 14% of the sample select the safe option in Andhra Pradesh and Gujarat respectively, while only 10% in both samples select the riskiest lottery (which would only be selected by a household that is locally risk-neutral or risk-seeking). We convert these values into an index between 0 and 1, where higher values of the index indicate greater risk aversion. Appendix Table C describes the lotteries, decisions made by participants, and our risk measure.

Rainfall insurance represents an investment made at the beginning of the growing season, for a (potential) payout that will be paid two to four months in the future. Higher discount rates will therefore make the insurance less attractive. Household discount rates are proxied by eliciting the minimum amount a household would be willing to accept in lieu of a Rs. 10 payment in one month.[8] Consistent with other evidence, respondents reported relatively high discount rates: the average elicited discount rate is 99% in Andhra Pradesh, and 54% in Gujarat.

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

F. Sample Insurance Participation Rates

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

[INSERT TABLE 4 HERE]

In Andhra Pradesh, the total number of contracts sold across the 37 survey villages increases on average between 2003 and 2006. (Although the fraction purchasing falls over time amongst villages where insurance is offered, the number of villages where coverage is available is increasing.) Insurance purchase rates are much higher in our sample than amongst the population as a whole, reflecting that the sample was originally designed to oversample purchasers, and reflecting the household treatments. In 2006, 26.8% of households in our sample purchase insurance, concentrated amongst those who receive household visits, compared to only 2.9% of the population in survey villages (calculated by weighting by sampling weights).

Total purchases in the study area villages in Gujarat also follow an increasing path. 109 contracts are sold in 2006, and 1107 contracts in 2007. Finally, Panel B of Table 4 presents information on transitions between buyers and non-buyers for the two samples.

IV. Field experiments: Andhra Pradesh

In 2006, we conduct door-to-door household visits prior to the beginning of the growing season to 700 randomly selected households of the 1,054 in our original 2004 sample. The remaining households serve as a control group.

During the household visit, a trained ICRISAT employee explains the rainfall insurance product to the household, and answers questions. Households have an opportunity to purchase insurance policies on-the-spot during the visit. In case the household is interested in the product but does not have sufficient cash-on-hand, the household may also purchase insurance later through their local BASIX office or sales agent. Alternatively, if the insurance educator has sufficient time, they may offer to visit the household again at a later agreed-on time (before they leave the village) to collect payment.

A. Manipulations

We randomize the content of these 700 household visits along three dimensions. First, we offer a random amount of compensation for the household's time, of either Rs. 25 or Rs. 100, paid at the end of the household visit (half the households receive the larger amount). Thus, we offer random liquidity shocks to households. Recall that the premium for one phase of insurance ranges between Rs. 80 and Rs. 125, so receiving Rs. 100 provides roughly enough cash-on-hand to purchase one policy.

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

Third, we randomize whether the household received additional education about the measurement of rainfall in millimeters and its conversion into soil moisture. Farmers report that they generally decide when to sow crops by measuring the depth of soil moisture in the ground after the beginning of the monsoon. Only 10% of households in 2004 could accurately measure rainfall in millimeters. However, all the insurance contract terms are set in millimeters.

For 350 of the 700 households, we present information about millimeters by showing the household, using a ruler, the length of 10mm and 100mm, and then showing them a chart of how 100mm of rain translates into average soil moisture for the soil type on their farm (either black or red). These conversion charts were prepared with the assistance of an ICRISAT agronomist. For the other 350 households, marketers do not provide this information. Based on feedback from the ICRISAT team of insurance educators, this education was presented quite briefly (an additional 2-3 minutes relative to a standard household visit).

These three treatments are applied randomly and independently across households. In previous years, BASIX also conducted village-level meetings to introduce the insurance product to farmers. However, in 2006, BASIX agreed not to conduct these meetings in the villages where interventions were conducted, to avoid any risks of confounding the effects of household visits on participation.

V. Field Experiments: Gujarat

Field experiments in Gujarat were conducted in 2007, rather than 2006. In 2007, SEWA used various techniques to market rainfall insurance to its members, including flyers, videos, and discount coupons. To test hypotheses of demand for household insurance, treatments were randomly assigned at the individual level. Three sets of treatments were assigned, for three separate classes of respondents.

- Group 1 (2,391 households): *Households first treated in 2006*. For the 30 villages which had already been offered insurance in 2006, SEWA distributed flyers with one of six individually assigned messages, described below.

- Group 2 (315 households): *Survey respondents in households first treated in 2007*. In the 20 villages which were first offered insurance in 2007, SEWA used personal video players to deliver a 90-second marketing message directly to household-decision makers.[9] These households received one of four possible video treatments, described below, and discounts ranging from Rs. 5 - 30.

- Group 3 (1,100 households): *Non-survey respondents in households first treated in 2007*. These households were not part of the original baseline survey, but received marketing visits. These households received one of 8 videos.

To keep track of which message each household received, all households were given a non-transferable coupon for a discount, whose serial number indicated the marketing message the household received. The size of this discount was Rs. 5 for those receiving flyers (Group 1), and either 5, 15, or 30 Rs. for video households (Groups 2 and 3). The video and flyer marketing interventions are described in more detail below.

[9] 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.

A. Marketing Treatments

Previous research from marketing and economics suggest that many factors may affect an individual's decision to purchase insurance (Johnson et. al., 1993). In the video experiments, the following manipulations are used. (Table 5 Panel B, and Appendix Table B, provide detailed descriptions of the treatment assignments.)

- SEWA Brand (Yes or No): SEWA has worked for years in the villages in the study, while the insurance companies, ICICI Lombard and IFFCO-TOKIO, are virtually unknown to the rural population. In the 'Strong SEWA brand" (Yes) treatment, the videos include clear indications that the product is being offered by SEWA. Alternatively, SEWA is not mentioned in the video.
- Peer / Authority (Peer Figure or Authority Figure): Individuals learn about new products from various sources, who may have varying levels of credibility. In the 'Peer' treatment, a product endorsement is delivered by a local farmer. In the 'Authority' treatment, a teacher delivers the endorsement.
- Payout ("2/10 yes" "8/10 no"): This framing treatment emphasized either the probability the product would pay out, or the probability the product would not pay out. In the '2/10' treatment, households are told that '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/Vulnerability (Safety or Vulnerability): The Safety treatment describes the benefits of insurance, as something that will protect the household and ensure prosperity. The Vulnerability treatment warned the household of the difficulties it may face if a drought occurs and it does not have insurance.

These treatments are crossed, though not all possible combinations are employed. For Group 2 households, four videos are used (A-D in Appendix Table B). As the project's research agenda includes estimating causal effects of insurance on consumption smoothing, the SEWA brand is included in all videos, due to our prior hypothesis that it would have a positive impact. For the households that receive marketing treatment, but were not part of the original survey, one of the eight different videos is randomly assigned.

The flyer treatments in the 30 villages in which insurance was offered in both 2006 and 2007 test two different manipulations designed to further our understanding of how formal insurance products may interact with informal risk-sharing.

- Individual or Group (Individual or Group): the `Individual' treatment, the flyer emphasizes the potential benefits of the insurance product for the individual who purchases the policy. The Group flier emphasizes the value of the policy for the family of the purchaser.
- Religion (Hindu, Muslim, or Neutral): This treatment sought to provide cues on group identity that may be either consistent or inconsistent with risk-sharing. A photograph on the flier depicts a farmer, who is either standing near a Hindu temple (Hindu Treatment), a Mosque (Muslim Treatment), or a nondescript building. The individual is also given a matching first name, which is either characteristically Hindu, characteristically Muslim, or neutral.

Three lines of research also motivate these manipulations. First, informal networks facilitate risk-sharing (Karlan et al, 2008). Since social preferences are stronger within groups, the abstract emphasis in the Group treatment, or the specific group cues in the religion treatments, could cause subjects to attend more to the robustness of their existing risk-sharing networks.

Second, religious groups have the capacity to provide ex post insurance. Chen (2008) shows that plausibly-exogenous negative income shocks during the Indonesian financial crisis led to greater participation in local religious activities, and such participation was associated with more consumption smoothing.

Third, a practical marketing question is when and how messages should be targeted based on specific demographic characteristics. Successful targeting can induce higher demand, but mis-calibrated targeting might induce particularly negative reactions and is therefore a risky strategy.

B. Discounts

In the 20 villages where a video is played to households, we offered each household a coupon valid for a discount on the first rainfall insurance policy that a household purchased. We randomize the size of this discount across households. 40% of households receive a Rs. 5 discount, 40% receive Rs. 15, and 20% receive Rs. 30. This allows us to estimate the price elasticity of demand for rainfall insurance.

VI. Results: Andhra Pradesh

Table 6 presents experimental results from Andhra Pradesh. We regress a dummy variable for whether the household purchases insurance on indicators for the various treatment interventions.

In columns (1)-(3) we report basic effects of the treatments on participation. In columns (4)-(6) we include a set of additional interaction terms. Columns (1), (2) and (3) differ according to the inclusion or exclusion of village fixed effects and other household controls (the specific controls are listed in the notes to Table 6). Because the treatments are randomly assigned, the estimates of the treatment effects are consistent both with and without the controls; however, including controls may absorb additional variation leading to more precise parameter estimates. In columns (4), (5) and (6), we interact each of the treatments in turn with one of three variables: a dummy for whether the household is unfamiliar with the insurance provider BASIX, the log of household wealth, and the log of household consumption. These specifications test whether our treatments have differential effects on rich or poor households, or households with differing degrees of familiarity with the insurance vendor.

[INSERT TABLE 6 HERE]

Examining the first three columns, we first find that the size of the cash transfer paid to the household during the marketing experiment is the most important determinant of insurance participation among the interventions we consider. For example, increasing the payment from Rs. 25 to Rs. 100 increases the probability of purchase by 34.7 percentage points in column (1), statistically significant at the 1 percent level. Thus, cash on hand is an important determinant of insurance participation, consistent with the simple model of insurance participation under credit constraints presented in Giné, Townsend and Vickery (2008), and consistent with qualitative survey evidence discussed in Section VIII. The last coefficient in columns (5) and (6) tests whether this effect is stronger amongst poor or rich households. Although not statistically significant, in both cases this coefficient is negative, suggesting a stronger effect amongst poor households (the coefficient in column (6) has a p-value of 0.12).

Our second finding is that trust has an important effect on insurance purchase decisions. Endorsement of the household visit by a local BASIX representative increases the probability of insurance purchase by 6.2-6.5 percentage points amongst the whole sample. However, notably, as shown in column (4), this effect is entirely driven by households who are familiar with BASIX, such as prior customers. For this subgroup, endorsement by a trusted agent increases the probability of insurance purchase by 10.9 percentage points, equivalent to 41% of the sample average purchase rate. In contrast, for households unfamiliar with BASIX, the point estimate for the effect of endorsement on purchase is actually negative (it is equal to the sum of 10.9 plus -18.3 = -7.4). In addition, the non-interacted coefficient for the variable "household is unfamiliar with BASIX" in column (4) is also negative and statistically significant at the 5 percent level; that is households unfamiliar with the insurance vendor BASIX are less likely to purchase the insurance product, even without a direct endorsement from the local LSA.

These findings are strikingly inconsistent with a full-information neoclassical benchmark. However, they are instead consistent with various other types of non-experimental evidence that trust is an important determinant of financial market participation, such as Guiso, Sapienza and Zingales (2007).

Third, we find that the act of conducting a household marketing visit has a large, statistically significant effect on insurance take-up, even when not combined with other treatments. Although the product is available to all households in the village, a household visit alone increases the probability of insurance purchase by between 12.1 and 17.7 percentage points depending on the specification. This may reflect the added convenience of being able to purchase insurance 'on-the-spot', or be due to the effect of the additional information provided by the ICRISAT insurance marketing agent.

Finally, the education module administered to a subset of households has no statistically significant effect on insurance participation. This module was directed towards increasing the household's understanding of how millimeters of rainfall (used to calculate insurance payouts) relate to soil moisture, which farmers use to decide when to sow. This module was generally implemented quite quickly, which may explain this negative finding. That is, although other evidence suggests that a sizeable number of households do not fully understand the insurance product, this modest amount of financial education is not sufficient to significantly shift household participation rates.

VII. Results: Gujarat

Results from the Gujarat experiments are presented in Tables 7 and 8. In total, 29.4% of households who received video treatments purchased rainfall insurance, while 23.7% of households that received flyer treatments purchased insurance. This difference is statistically significant. While SEWA marketers report that the video marketing was very effective, the difference in take-up reflects both the difference in media, and the fact that the villages that received the flyers had already been exposed to weather insurance, in 2006. Since the insurance policies did not provide a payout in any of the districts in Gujarat in 2006, subsequent take-up may have been depressed.

[INSERT TABLE 7 HERE]

A. Flyer results

We conduct the flyer analysis for the entire sample (Panel A), for the subsample with distinctly Muslim names (Panel B), and for the sample with distinctly Hindu names (Panel C). 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 the respondent based on the respondent's name.[10]

In columns (1) and (2) of Panel A, we regress a dummy for whether the household purchases insurance on dummies for the main flyer treatments: whether the individual pictured (and named) was Hindu, Muslim, or religion unidentified (omitted category); whether the flyer emphasized the benefits to the group, or to the individual. We find no main effects from these treatments, and again the point estimates are small.

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

[10] The 265 respondents on which our two independent coders disagreed have been omitted from the analysis in Panels B and C of Table 7.

SEWA membership is open to both Hindu and Muslim households, and in general the groups live in close proximity and harmony. Gujarat has nevertheless been subject to ethnic tension.[11] We therefore conduct the analysis separately for individuals from each community.

Panel B reports the results for the 127 respondents with Muslim names. Despite the small sample size, we are able to measure statistically and economically significant effects. Columns (3) and (4) show that the group treatment increases take-up by a very substantial 24.4%--however, this occurs only when religious identity is not cued. The point estimate on (Muslim * Group) is -25.5%, while the estimate on (Hindu * Group) is even larger, at -41.5%.

We find symmetric results for the Hindu population in Panel C. When Group is emphasized, take-up increases by 4.9% (though this estimate is not statistically significant). The (Group * Muslim) interaction is however, large and negative (-9.4%).

Together, these results suggest that emphasizing the communal nature of insurance stimulates demand for insurance products, but only when these cues emphasize like group members. We draw particular comfort from the fact that the findings are symmetric among Muslim and Hindu respondents.

B. Video results

In Table 8, we regress purchase on a dummy for whether there was a strong SEWA brand emphasis, whether a peer endorsed the product (against an authority figure), whether the policy is described as paying out in 2 of 10 years (against not paying out in 8/10 years), and the discount amount in Rupees. We also include a dummy for whether the household was surveyed. The first column reports results without village fixed-effects; the second column presents results with village fixed-effects.

When estimating main effects, the psychological manipulations vary in size, but have no statistically significant effect: the point estimates for SEWA Branding, Peer Endorsement, Payout Framing, or Positive / Negative frame are typically economically close to zero, and not statistically different from zero at conventional significance levels. A test of the joint hypothesis that there is no effect of any of these framing effects cannot be rejected (F-statistic 1.13, p-value .37).

The dummy variable for "surveyed" is positive and large. Those households that were surveyed are 16-18 percentage points more likely to purchase insurance than those who were

[11] In 2002 in particular there was significant violence between the two communities.

not part of the survey. However, surveyed households were not randomly assigned, and the identified effect thus includes any effect of being surveyed, combined with the fact that surveyed households were selected precisely because they were more likely to purchase insurance.

Discount coupons for the insurance policy were distributed to the household along with the presentation of the marketing video. Each household was randomly assigned a coupon with value Rs. 5, Rs. 15, or Rs. 30. Forty percent of households received the Rs. 5 coupon; 40% received the Rs. 15 coupon; and the rest received the Rs. 30 coupon. The coupon was non-transferable, and the name and address of the respondent were written on the coupon.

The point estimate on the coefficient for the size of the discount in Rupees is 0.005, significant at the 1 percent level. Moving from a discount of Rs. 5 discount to a Rs. 30 increases the probability of purchase of insurance by 12.5 percentage points, from a base of 26.3%.

We calculate the price elasticity of demand in the following manner. We estimate the coefficient on the discount, β_d, separately for each district.[12] Denote P as price and Q as quantity. Taking β_d for ΔQ, the average take-up rate in the district for Q, 1 for ΔP, and then the weighted average price to which households were exposed, we calculate the price elasticity of demand for all three districts. The elasticity of demand is highest in Ahmedabad and Anand, at 0.83, and 0.875, respectively, and lowest in Patan, at 0.66.

Columns (3) and (4) of Panel A present the same regressions restricted to the households that had already participated in the baseline survey. The estimated effect of the discount is smaller, but less precisely estimated, with both 0 and .005 falling within the 95 percent confidence range. The sample size in columns (5) and (6), which represent non-surveyed households, is much larger, and more precisely estimated.

Panel B expands the analysis to include both main effects, and the interaction of these effects with price. The null hypothesis that all experimental manipulations have no effect can be rejected at the 5 percent level.

[12] District-specific analysis is necessary because the base price of the insurance product variess across districts, as districts have different historical rainfall patterns. In 2007 the price was Rs. 72 in Anand, Rs. 44 in Ahmedabad, and Rs. 86 in Patan. Coupon amounts were varied between Rs. 5, Rs. 15, and Rs. 30 in all three districts.

The main effect of a "vulnerability" framing is large and significant, with a point estimate of 20.9% (column (2)). The coefficient on (Discount * Vulnerability Frame) is negative and significant at the 10 percent level. For households receiving a Rs. 5 discount, the combined effect of the vulnerability frame was 14.4%, significant at the 5 percent level. For households receiving larger discounts, the framing had no statistically significant effect on purchase.

Similarly, the SEWA brand actually has a negative main effect, though again the size is mitigated as the amount of the discount increases. The effect at a Rs. 5 discount was -7% (significant at the 5% level), while the effect for larger amounts was insignificant.

VIII. Discussion and non-experimental evidence

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

1. Demand for rainfall insurance is strongly dependent on price. We estimate a price elasticity of demand for insurance between -0.66 and -0.88, depending on the region studied.

2. Insurance demand is extremely sensitive to cash on hand. Providing the household with enough cash to purchase a policy increases participation by 34.5%. This is 3.5 times as large as the effect of cutting the price of the policy by Rs. 30 (equivalent to a 22-46% discount).

3. Associating the insurance product with individuals or symbols that are trusted by the household significantly increases insurance participation. For example, in the Andhra Pradesh experiments, a brief endorsement of the insurance marketer by a trusted local individual increases participation by 10 percentage points (or 40%), again equivalent to reducing the price of the product by 30%.

4. Insurance demand is sensitive to other non-standard factors that are difficult to reconcile with a simple neoclassical story. The act of conducting a household marketing visit has a significant effect on the decision to purchase insurance, even though insurance is easily available to all households in the village. Also, emphasizing the benefits of the insurance to a group rather than an individual has a significant effect on insurance participation for a subset of the sample. That said, many of the subtle marketing treatments we consider do not have a statistically significant effect on insurance participation. These subtle cues seem to be less important in our setting than trust, price and credit constraints, in contrast to the stronger effects of subtle cues found by Bertrand et. al., (2009).

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

Below, we review some non-experimental evidence about the determinants of rainfall insurance demand, and compare these results to the experiment-based conclusions summarized above.

A. Non-experimental evidence

Operational constraints limit the number of hypotheses that can be tested in a randomized setting. As additional evidence, we conduct a correlational analysis of the determinants of insurance purchase for the 2006 Andhra Pradesh and Gujarat samples. Results are presented in Table 9. Where possible, common variables from the two survey areas are defined in a consistent way, to allow comparison across the two survey regions. Our main findings are described below:

i. 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.

ii. Variables measuring households' ability to answer probability, math and insurance questions presented in Table 3 (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.

iii. Prior experience with the insurance product and vendor are 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 whether the household's village had experienced positive rainfall insurance payouts in 2004 and 2005.

iv. Interestingly, higher risk aversion is *negatively* correlated with insurance purchase in both the Andhra Pradesh and Gujarat samples, replicating a finding in Giné, Townsend and Vickery (2008) using an earlier 2004 sample. Giné et. al. show that this apparently perverse result is concentrated amongst households without knowledge of BASIX or of insurance, suggesting uninformed risk-averse households are unwilling to experiment with the insurance product, given their limited experience with it.

[INSERT TABLE 9 HERE]

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, Townsend and Vickery (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.

As a final source of non-experimental evidence, Table 10 presents household qualitative self-reports based on our 2006 surveys, as well as 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'. This response is particularly common in Andhra Pradesh, where it is cited by over 80% of households 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 matches closely 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 there is limited demand for insurance.

Finally, focusing further on the Andhra Pradesh sample, a common response to the 2004 survey is "do not understand the product". Notably, the fraction of households citing this reason falls significantly between 2004 and 2006, from 21% to only 2%. This perhaps suggests some evidence that households are learning about the insurance product as they become more familiar with it.

[INSERT TABLE 10 HERE]

B. Boosting household risk management: Tentative lessons

The micro-insurance industry is still in its infancy, and suppliers of such insurance products are experimenting with different product types to work out the best ways to attract customers and create useful products. From our results presented above, 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.

Firstly, the importance of liquidity constraints suggests policies should be designed to provide payouts as quickly as possible, especially during the monsoon season when our data suggests households are particularly credit constrained. Towards this end, ICICI Lombard has begun installing a network of automatic rain gauges, allowing them to immediately measure rainfall, calculate policy returns and begin delivering payouts to households. A second possible improvement is that it may be beneficial 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.

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, would be effective in boosting participation, although it is not clear whether such subsidies are welfare-improving overall.)

Third, the estimated significance of trust and a history of positive past insurance payouts suggests that product diffusion through the population may be relatively slow, as the product develops a track record of paying out positive returns. A potential contract design improvement to facilitate this learning would be to amend the contract to pay a positive return with sufficient frequency (Giné, Townsend and Vickery, 2007, find that the distribution of ICICI Lombard rainfall insurance policies in 2006 is highly skewed; the policy produces a high maximum return of 900%, but a positive return in only 11% of phases). 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.

IX. Conclusions

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

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

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

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Appendix: A Calibrated model of insurance benefits

This section presents a simple model of insurance participation, which we calibrate to the rainfall insurance contracts studied in this paper, to the measured risk aversion of our survey households, and to empirical evidence on the effect of drought on Indian household income. Based on the results, we reach two main conclusions:

i. Although the insurance contracts studied in our empirical work have expected payoffs equal only to around 40% of premiums, such contracts are still welfare enhancing for households at standard levels of risk aversion, and at measured levels of risk aversion for the households in our sample.

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

Beyond this simple exercise, a promising area for future research would be to analyze the demand for insurance more rigorously in an explicitly dynamic life-cycle framework calibrated to Indian data.

B.1 Setup

We consider a simple model in which a household with initial wealth W* faces a zero mean 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:

[B.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 multiperiod framework, u(.) would be interpreted as the consumer's value function, in a single period model it would be interpreted as the felicity function).

The timing of events is simply: (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 consider two insurance policies, denoted as "linear loss" and "catastrophe" insurance. Both policies produce a positive payoff only when S is negative. In the first, the insurance payoff is a linear function of S whenever S is negative. In the second, insurance pays off only when S is below a lower threshold S_0. That is, the payoff structure is:

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

[B.3] $\text{Payoff}_{\text{CATASTROPHE}} = \max [0, -\beta_{CAT} . (S - S_0)]$

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, Townsend and Vickery (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.

B.2 Calibration and simulation

We then simulate this model to calculate the benefits of purchasing insurance for households with different levels of the coefficient of relative risk aversion. We approximately calibrate the model to fit features of the Indian data and of observed insurance contracts. We are somewhat 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.

First, we set initial wealth equal to Rs. 50,000, which is approximately 2-3 years of income based on the summary statistics reported in the body of the paper. (Thus, we are somewhat more conservative than practice in 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.)

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

Third, 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 30% of the premium (which is similar to, although somewhat more conservative than, the 40% ratio reported in Table 1), and also that the probability of a positive payoff under the catastrophe insurance policy is 11%, the estimate in Giné, Townsend and Vickery (2007). Finally, we assume that the policy premium is Rs. 100 (thus, the expected payout is Rs. 30).

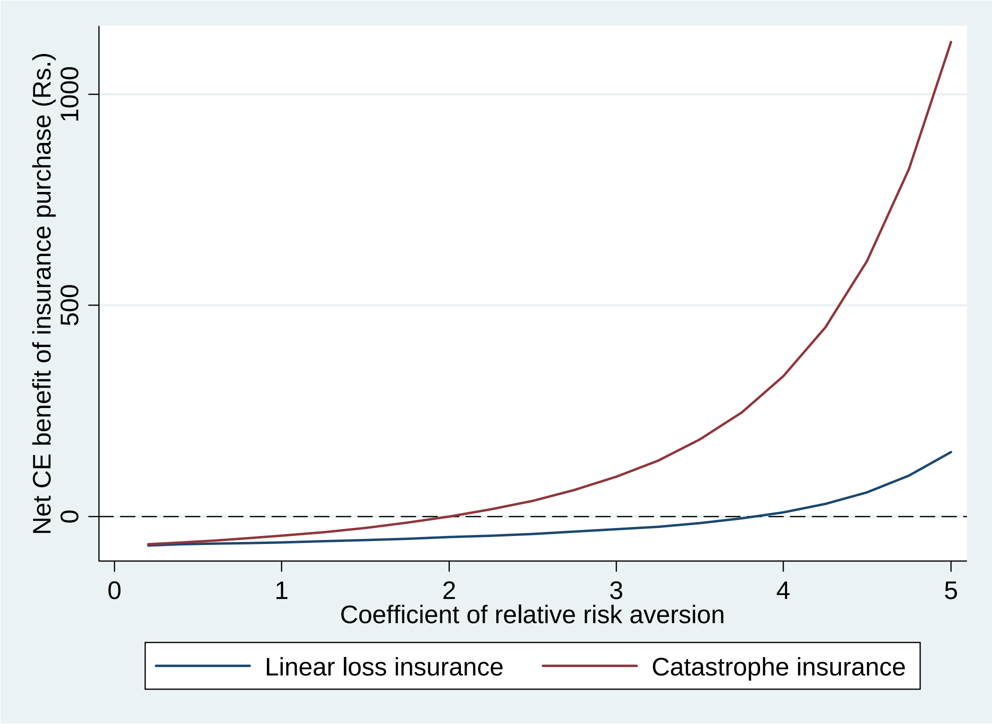
Given these inputs, to simulate the model, we take 100,000 draws of the income shock S, and calculate expected utility under the assumption that the household does, and then does not, purchase insurance. From this, we calculate the benefit of insurance purchase for households with different levels of relative risk aversion.

B.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.

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. 30.



By definition, the net benefits of insurance are strictly increasing in risk aversion. More notably, the benefits of insurance are significantly larger for the catastrophe insurance contract, 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.

As shown on the Figure, the benefits of purchasing the policy are positive for a coefficient of relative risk aversion of 2.0 under the catastrophe insurance contract, and 3.8 for the linear loss policy. 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 of at least 4, even if a reference level of wealth of zero is chosen.

Figure 1: Rainfall Insurance Contract Example

ICICI Lombard rainfall insurance divides the monsoon into three phases, each 35-45 days in length. The graph below illustrates how cumulative rainfall during the phase translates into an insurance payout. Figures in brackets are actual trigger points and payouts for a representative insurance contract, namely payouts on rainfall insurance linked to castor for the middle (podding/flowering) phase of the monsoon in the Narayanpet mandal of the Mahbubnagar district, in the state of Andhra Pradesh.

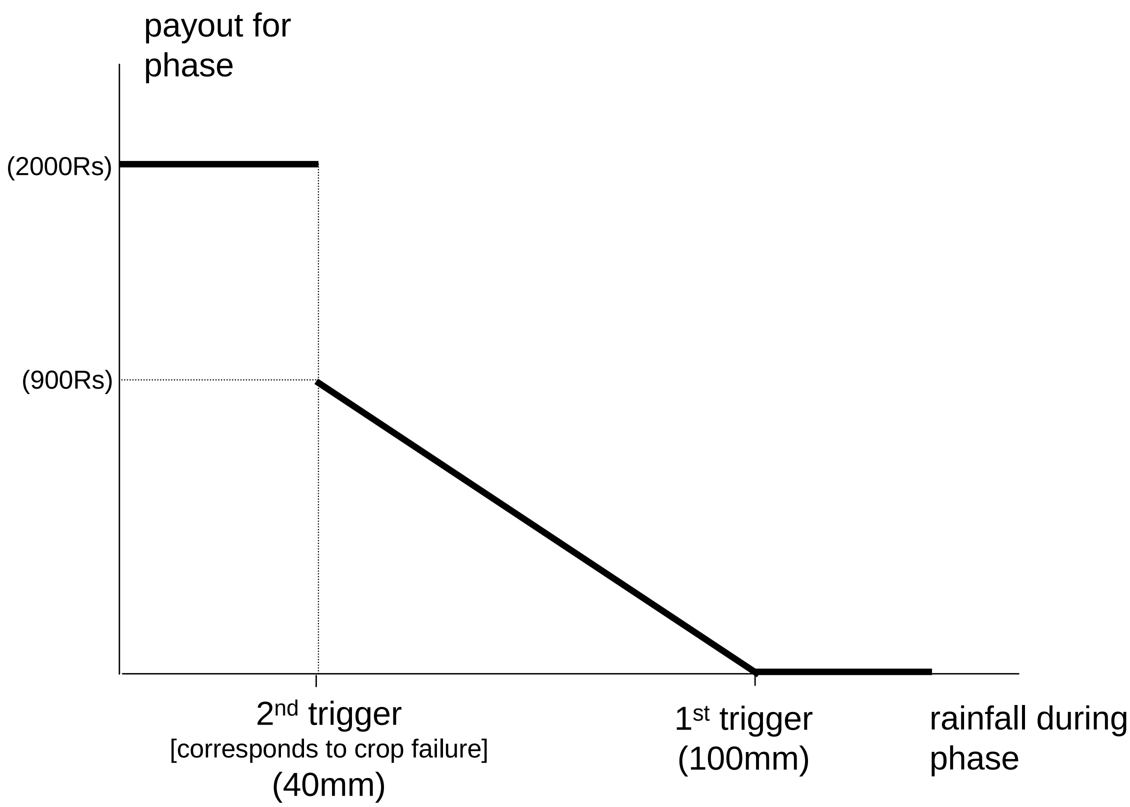


Table 1: Rainfall Insurance Contract Specifications

Panel A: ICICI Policies

Year	District / Type	Premium	Payout slope	Limit	Expected payout: Rs.	Expected payout: % of premium	Phase I: Premium	Phase I: Strike	Phase I: Exit	Phase II: Premium	Phase II: Strike	Phase II: Exit	Phase III: Premium	Phase III: Strike	Phase III: Exit
Andhra Pradesh															
2006	Anantapur	340	10	1,000	113	33%	125	30	5	120	30	5	105	500	575
2006	Atmakur	280	10	1,000	n.a.	n.a.	105	45	5	95	55	5	90	500	570
2006	Hindupur	295	10	1,000	n.a.	n.a.	80	25	0	120	15	0	105	500	580
2006	Kondagal	290	10	1,000	n.a.	n.a.	115	55	5	95	60	5	90	330	410
2006	Mahabubnagar	270	10	1,000	115	43%	80	70	10	80	80	10	120	375	450
Gujarat															
2006	Ahmedabad / low	144	5	500	28	19%	n.a.	100	10	n.a.	65	5	n.a.	550	650
2006	Ahmedabad / high	197	5	500	66	34%	n.a.	150	50	n.a.	90	10	n.a.	550	650
2006	Anand / low	155	5	500	n.a.	n.a.	n.a.	100	10	n.a.	65	5	n.a.	550	650
2006	Anand / high	204	5	500	n.a.	n.a.	n.a.	120	20	n.a.	90	10	n.a.	550	650
2006	Patan	257	5	500	114	44%	n.a.	100	10	n.a.	75	5	n.a.	550	650

Panel B: IFFCO-Tokio Policies

		Premium	Normal Rain	Expected payout: Rs.	Expected payout: % of premium	Payout (in Rs.) as function of rainfall deficit from "normal rain": 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 premia, payout slope, exit, and expected payouts are given in Indian rupees (an approximate exchange rate at the time of this study is $1US = Rs. 43). ICICI policies, in Panel A, covered three phases, roughly corresponding to planting, flowering, and harvest; insurance policies could be purchased separately for each phase in Andhra Pradesh. The "strike" amount indicates the rainfall level in mm below (Phase I and II) or above (Phase III) which a payout was 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, in Panel B, consist of one phase. The policies specify a "normal" level of rainfall (in mm) and the payout is a non-linear function of the percentage shortfall from this "normal" rain.

Table 2: Summary Statistics

	Andhra Pradesh				Gujarat			
	Sample		Population		Sample		Study Population	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Demographic characteristics								
Household size	6.26	2.82	6.38	2.98	5.85	2.46	6.02	2.58
Scheduled Caste or Scheduled Tribe (1=Yes)	11.6%	32.0%	17.8%	38.2%	43.7%	49.6%	42.9%	49.6%
Muslim (1=Yes)	3.90%	19.4%	3.85%	19.2%	8.7%	28.2%	7.5%	26.3%
Household head is male (1=Yes)	93.7%	24.0%	93.1%	25.2%	75.7%	42.9%	75.6%	43.0%
Household head 's age	47.6	12.1	49.8	12.5	48.9	13.2	49.5	13.1
Educational attainment secondary school or higher (1=Yes)	33.2%	47.1%	29.5%	45.6%	33.0%	47.0%	32.3%	46.8%
Wealth and consumption								
Wealth (Rs. 000s)	913	2,011	816	1,992	n.a.	n.a.	n.a.	n.a.
Monthly per capita expenditures (Rs. 000s)	520	456	490	327	1,238	1,612	1,112	1,570
Utility function								
Risk aversion	0.567	0.246	0.585	0.233	0.540	0.316	0.561	0.326
Basis risk								
Pct. of cultivated land that is irrigated	40.4%	42.7%	30.6%	40.5%	43.7%	47.1%	36.6%	46.2%
Familiarity with insurance and insurance vendor								
Average insurance payouts in the village 2004 and 2005	0.396	0.386	0.383	0.385	n.a.	n.a.	n.a.	n.a.
Household bought weather insurance in 2004 (1=Yes)	25.3%	43.5%	3.11%	17.4%	n.a.	n.a.	n.a.	n.a.
Does not know insurance provider (1=Yes)	26.5%	44.1%	33.1%	47.1%	n.a.	n.a.	n.a.	n.a.
Household has some type of insurance (1=Yes)	80.5%	39.2%	78.3%	40.8%	63.8%	48.1%	45.8%	49.9%
Technology diffusion / networks								
Household belongs to a water user group (BUA or WUG) (1=Yes)	1.85%	13.35%	1.44%	11.74%	n.a.	n.a.	n.a.	n.a.
Number of groups that the household belongs to	0.723	0.618	0.658	0.595	n.a.	n.a.	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. Column (1)-(2) and (5)-(6), respectively, report sample averages and standard deviations while columns (3)-(4) and (7)-(8) report population averages and standard deviations constructed using population weights. In Andhra Pradesh, a stratified random sample of 952 households was selected from a census of approximately 7,000 households. In Gujarat, the experiment sample includes 1,500 households selected from the membership rolls of SEWA. One third of these 1,500 were selected at random from among SEWA membership rolls--these 500 were used to calculate the "Study Population" characteristics. The remaining 1,000 were identified by SEWA as individuals for whom the insurance product might be suitable. Appendix A provides for definition of variables.

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

Panel A: Education and Financial Literacy	Andhra Pradesh	Gujarat
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, Financial Literacy	n.a.	34.5%
Average Score, Math Questions	n.a.	61.7%
Average Score, Probability Questions	n.a.	71.8%
Average Score, Insurance Questions	79.6%	68.2%
Knowledge of millimeters	21.0%	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?	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?	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?	n.a.	24.8%
(d) Is it safer to plant one single crop, or multiple crops?	n.a.	30.6%
Panel C: Insurance Questions		
Andhra Pradesh		
I. Imagine you have bought insurance against drought. If it rains less than 50mm by the end of Punavarsu Kartis, you will receive a payout of 10Rs for every mm of deficient rainfall (that is, each mm of rainfall below 50mm).		
a) It rains 120 mm. Will you get an insurance payout?	85.8%	n.a.
b) It does not rain at all:		
i) Will you get an insurance payout?	83.0%	n.a.
ii) How much of a payout would you receive?	80.6%	n.a.
c) It rains 20mm:		
i) Will you get an insurance payout?	81.5%	n.a.
ii) How much of a payout would you receive?	76.0%	n.a.
Gujarat		
II. 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?	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?	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?	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. Panel A presents data on education and measures of cognitive ability and financial literacy. Panel B reports the percent of respondents that correctly answered the financial literacy questions administered to households in Gujarat. Panel C reports the percent of respondents that correctly answered the insurance questions used in Andhra Pradesh and Gujarat. See Appendix A for definition of variables in Panel A.

Table 4: Aggregate Summary Data of Insurance Purchases

Panel A: Insurance sales

	Andhra Pradesh									Gujarat	
	Study area villages			Study area villages where insurance sold in 2004			Entire state			Study area villages	
	Number of villages where insurance sold	Share of households purchasing insurance	Total number of contracts	Number of villages where insurance sold	Share of households purchasing insurance	Total number of contracts	Number of villages where insurance sold	Share of households purchasing insurance	Total number of contracts	Number of villages where insurance sold	Total number of contracts
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
2003	2	15.2%	92	--	--	--	17	11.4%	194	--	--
2004	25	4.0%	282	25	4.0%	282	43	7.4%	318	--	--
2005	12	5.4%	641	11	5.8%	637	422	6.6%	3,214	--	--
2006	37	2.9%	564	25	3.1%	491	538	7.6%	6,039	30	109
2007	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	49	1107

Panel B: Repeat buyers

Andhra Pradesh				Gujarat		
2004	2005	2006	Percent	2006	2007	Percent
No	No	No	50.1%	No	No	58.8%
No	No	Yes	15.6%	No	Yes	21.6%
No	Yes	No	1.1%	Yes	No	11.7%
Yes	No	No	12.7%	Yes	Yes	7.9%
No	Yes	Yes	0.5%			
Yes	No	Yes	6.2%			
Yes	Yes	No	2.7%			
Yes	Yes	Yes	2.1%			

Notes: Data from Andhra Pradesh come from BASIX administrative records. Data from Gujarat come from SEWA records. Panel A, Columns (1) - (6) report insurance sales in the Andhra Pradesh study villages. Columns (7)-(9) report data for all villages where policies were sold in the state of Andhra Pradesh. Columns (10)-(11) report insurance sales in the Gujarat study villages. Panel B reports the incidence of repeat buyers across different years in the sample in Andhra Pradesh and Gujarat.

Table 5: Study Design

Panel A: Andhra Pradesh	Share of households receiving treatment		
Treatments	Total		
Household visit	67%		
Village endorsed	45%		
Visit endorsed	23%		
Education module	33%		
High reward	29%		

Panel B: Gujarat	Share of households receiving treatment		
Video Treatments	Total	Surveyed	Non-Surveyed
SEWA association	59%	100%	47%
Peer endorsed	56%	100%	44%
2/10 yes	49%	50%	48%
Positive frame	84%	49%	93%
Discount = Rs. 5	42%	48%	41%
Discount = Rs. 15	38%	34%	40%
Discount = Rs. 30	19%	18%	20%
Flyer Treatments	Total		
Individual emphasis (not Group)	52%		
Muslim emphasis	35%		
Hindu emphasis	34%		
Non-religious emphasis	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. Flyer treatments were used in villages where rainfall insurance was offered in both 2006 and 2007 in Gujarat. Full details on the size of the various groups, and how treatments are crossed are given in Appendix B Tables 1 and 2.

Table 6: Experimental results, Andhra Pradesh

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

Treatment interaction variable	None	None	None	Does not know BASIX	Log of wealth	Log, per capita consumption
	(1)	(2)	(3)	(4)	(5)	(6)
Treatments						
Visit (1=Yes)	0.177***	0.132***	0.121***	0.121***	0.123***	0.123***
	(0.040)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)
Endorsed by LSA (1=Yes)	0.063*	0.065	0.062	0.109**	-0.134	-0.155
	(0.038)	(0.042)	(0.042)	(0.047)	(0.173)	(0.394)
Education module (1=Yes)	-0.018	-0.023	-0.021	-0.033	-0.106	-0.301
	-0.031	-0.035	-0.035	(0.039)	(0.161)	(0.395)
High reward (1=Yes)	0.347***	0.338***	0.325***	0.322***	0.485***	1.002***
	(0.031)	(0.036)	(0.037)	(0.041)	(0.180)	(0.432)
Village endorsed (1=Yes) x Visit (1=Yes)	-0.014	0.062	0.067	0.065	0.062	0.067
	(0.038)	(0.051)	(0.051)	(0.051)	(0.052)	(0.051)
VAR				-0.058**	-0.028	0.046
				(0.029)	(0.020)	(0.034)
Treatment Interactions						
VAR x Endorsed by LSA				-0.183**	0.033	0.036
				(0.076)	(0.029)	(0.065)
VAR x Education module				0.047	0.015	0.046
				(0.065)	(0.027)	(0.065)
VAR x High reward				0.020	-0.027	-0.111
				(0.078)	(0.030)	(0.071)
F-test: Joint significance of LSA endorsement and (Village endorsed x Visit) [p-value]	0.193	0.014	0.013	0.002	0.684	0.824
Household controls	No	No	Yes	Yes	Yes	Yes
Village fixed effects	No	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.268	0.268	0.268	0.268	0.268	0.268
Observations	952	952	952	952	952	952

Notes: Data come from surveys conducted in Andhra Pradesh in 2006. 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. The 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; log of wealth; log of monthly per capita expenditures; 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 at 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 (BUA) or water user group (WUG)). See Appendix A for definition of variables. Columns (3)-(6) include the interaction in turn of three household characteristics: (i) knowledge of the insurance provider BASIX; (ii) log(total wealth) and (iii) log(per capita consumption) with each of the individual treatment variables.

Table 7: Experimental Results for Flyer Treatments, Gujarat

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

	(1)	(2)	(3)	(4)
Panel A: Entire Sample				
Muslim treatment (1=Yes)	-0.002	-0.003	0.042	0.044
	(0.021)	(0.021)	(0.030)	(0.028)
Hindu treatment (1=Yes)	0.001	0.007	0.015	0.025
	(0.022)	(0.021)	(0.029)	(0.028)
Group treatment (1=Yes)	0.017	0.013	0.058*	0.060**
	(0.017)	(0.017)	(0.031)	(0.030)
Muslim x Group			-0.091**	-0.099**
			(0.043)	(0.042)
Hindu x Group			-0.026	-0.037
			(0.043)	(0.041)
Village fixed effects	No	Yes	No	Yes
Mean of dependent variable	0.237	0.237	0.237	0.237
Observations	2389	2389	2389	2389
Panel B: Muslim Households				
Muslim treatment (1=Yes)	0.026	0.059	0.128	0.174*
	(0.087)	(0.076)	(0.102)	(0.096)
Hindu treatment (1=Yes)	-0.102	-0.045	0.087	0.164*
	(0.079)	(0.078)	(0.106)	(0.097)
Group treatment (1=Yes)	0.063	0.051	0.253**	0.253**
	(0.070)	(0.064)	(0.119)	(0.108)
Muslim x Group			-0.226	-0.244
			(0.180)	(0.149)
Hindu x Group			-0.375**	-0.415***
			(0.156)	(0.145)
Village fixed effects	No	Yes	No	Yes
Mean of dependent variable	0.173	0.173	0.173	0.173
Observations	127	127	127	127
Panel C: Hindu Households				
Muslim treatment (1=Yes)	-0.013	-0.009	0.037	0.037
	(0.025)	(0.023)	(0.034)	(0.032)
Hindu treatment (1=Yes)	-0.006	-0.002	-0.000	0.010
	(0.025)	(0.024)	(0.034)	(0.031)
Group treatment (1=Yes)	0.016	0.008	0.056	0.049
	(0.020)	(0.019)	(0.037)	(0.035)
Muslim x Group			-0.103**	-0.094**
			(0.049)	(0.047)
Hindu x Group			-0.011	-0.023
			(0.050)	(0.047)
Village fixed effects	No	Yes	No	Yes
Mean of dependent variable	0.269	0.269	0.269	0.269
Observations	1997	1997	1997	1997

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 are reported in parenthesis below the coefficients. The symbols *,**,*** denote significance at the 10, 5 and 1 percent level, respectively. Columns (2) and (4) include village fixed effects. Panel A presents the results for the entire sample; Panel B presents the results for those with identifiably Muslim names, and Panel C for those with identifiably Hindu names.

Table 8: Experimental Results for Video Treatments, Gujarat

	Main Effects					
	All		Surveyed		Non-Surveyed	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A.						
"Vulnerability" Frame	0.046	0.042	0.046	0.034		
	(0.056)	(0.054)	(0.056)	(0.051)		
Pays 2/10 Years	-0.027	-0.034	-0.052	-0.022	-0.020	-0.031
	(0.024)	(0.023)	(0.056)	(0.050)	(0.026)	(0.025)
Discount (measured in Rs.)	0.005***	0.005***	0.001	0.003	0.006***	0.006***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.002)	(0.001)
Sew Brand Strong	-0.026	-0.030			-0.026	-0.029
	(0.026)	(0.025)			(0.026)	(0.025)
Peer Endorser	-0.029	-0.019			-0.030	-0.022
	(0.026)	(0.025)			(0.026)	(0.025)
Surveyed Household	0.158***	0.177***				
	(0.045)	(0.043)				
	Main Effects and Interactions					
Panel B.	All		Surveyed		Non-Surveyed	
"Vulnerability" Frame	0.191**	0.209**	0.192**	0.167*		
	(0.094)	(0.090)	(0.095)	(0.089)		
Pays 2/10 Years	-0.065	-0.068*	-0.163*	-0.133	-0.035	-0.046
	(0.042)	(0.040)	(0.095)	(0.087)	(0.047)	(0.045)
Discount (measured in Rs.)	0.003	0.004	0.002	0.004	0.004	0.005*
	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)
Sew Brand Strong	-0.010**	-0.096**			-0.100**	-0.099**
	(0.047)	(0.045)			(0.047)	(0.045)
Peer Endorser	0.022	0.028			0.021	0.032
	(0.047)	(0.045)			(0.047)	(0.045)
Surveyed Household	0.165**	0.153**				
	(0.077)	(0.072)				
Discount x "Vulnerability Frame"	-0.011*	-0.013**	-0.012*	-0.010*		
	(0.006)	(0.006)	(0.006)	(0.006)		
Discount x Pays 2/10 Years	0.003	0.003	0.009	0.009	0.001	0.001
	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.003)
Discount x Sew Brand Strong	0.005*	0.005*			0.005*	0.005*
	(0.003)	(0.003)			(0.003)	(0.003)
Discount x Peer Endorser	-0.004	-0.004			-0.004	-0.004
	(0.003)	(0.003)			(0.003)	(0.003)
Discount x Surveyed Household	0.000	0.002				
	(0.005)	(0.005)				
Village fixed effects	No	Yes	No	Yes	No	Yes
Mean of dependent variable						
Observations	1,413	1,413	315	315	1,098	1,098

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 are reported in parenthesis below the coefficients. The symbols *,**,*** denote significance at the 10, 5 and 1 percent level, respectively. Columns (2), (4) and (6) include village fixed effects.

Table 9: 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	-0.219***	-0.283***	-0.154***	-0.212***	-0.123**	-0.098*
	(0.055)	(0.055)	(0.056)	(0.055)	(0.056)	(0.056)
Above average expected monsoon rain (normalized)	0.008	-0.169***	0.000	-0.126***	-0.006	-0.110***
	(0.014)	(0.036)	(0.014)	(0.035)	(0.015)	(0.034)
Pct. of cultivated land that is irrigated	0.070**	0.178**	-0.013	0.055	-0.015	0.083
	(0.033)	(0.073)	(0.036)	(0.072)	(0.038)	(0.065)
Wealth, income and credit constraints						
Log of wealth	0.024*	0.156***	-0.008	0.117***	-0.032*	0.182***
	(0.013)	(0.033)	(0.015)	(0.034)	(0.018)	(0.037)
Log of monthly per capita expenditures	0.000	-0.004	-0.031	-0.028	0.010	-0.028
	(0.027)	(0.028)	(0.035)	(0.027)	(0.037)	(0.027)
Familiarity with insurance and BASIX						
Average village insurance payouts in 2004 and 2005	0.121***		0.025		0.000	
	(0.037)		(0.042)		(0.000)	
Household bought weather insurance in 2004 (1=Yes)	0.112***		0.043		0.070*	
	(0.033)		(0.035)		(0.038)	
Financial literacy		0.036**		0.017		0.009
		(0.018)		(0.019)		(0.018)
Probability skills		0.049***		0.042**		0.035**
		(0.018)		(0.017)		(0.017)
Insurance skills (normalized)	0.074***	0.014	0.054***	-0.054***	0.055***	-0.045**
	(0.014)	(0.019)	(0.016)	(0.019)	(0.018)	(0.019)
Household has some type of insurance (1=Yes)	0.143***	0.294***	0.115***	0.231***	0.120***	0.218***
	(0.037)	(0.038)	(0.038)	(0.039)	(0.038)	(0.039)
Does not know insurance provider (1=Yes)	-0.169***		-0.133***		-0.131***	
	(0.031)		(0.033)		-0.035	
Technology diffusion and networks						
Household belongs to a water user group (BUA or WUG) (1=Yes)	0.177*		0.158		0.109	
	(0.105)		(0.105)		(0.108)	
Number of groups which the household belongs to	0.041*		0.030		0.016	
	(0.023)		(0.023)		(0.024)	
Demographic Characteristics						
Scheduled Caste or Scheduled Tribe (1=Yes)	-0.057	-0.208***	0.007	-0.159***	-0.010	-0.137***
	(0.046)	(0.037)	(0.046)	(0.037)	(0.049)	(0.040)
Muslim (1=Yes)	-0.013	0.142**	0.000	0.083	-0.147*	0.134**
	(0.077)	(0.059)	(0.075)	(0.058)	(0.087)	(0.068)
Household head is male (1=Yes)	0.036	0.122***	0.050	0.059	0.046	0.014
	(0.064)	(0.046)	(0.064)	(0.045)	(0.064)	(0.044)
Log of household head's age	-0.005	-0.145	0.065	-0.138*	0.085	-0.276***
	(0.056)	(0.146)	(0.058)	(0.072)	(0.059)	(0.073)
Log of household size	0.002		-0.070		-0.028	
	(0.040)		(0.048)		(0.049)	
Educational attainment secondary school or higher (1=Yes)	0.040	0.068	0.005	0.040	0.022	0.065
	(0.031)	(0.055)	(0.033)	(0.058)	(0.035)	(0.058)
Village fixed effects	No	No	No	No	Yes	Yes

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. 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 repressors. Columns (5) and (6) include village fixed effects. See Appendix A for definition of variables.

Table 10: Stated Reasons 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: Data from Andhra Pradesh come from the survey conducted in July 2006. Nonpurchasing 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 survey conducted in 2006.

Appendix A: Definition of Variables

Variable name	Definition of variable
Demographic Characteristics	
Log of Household Size	Logarithm of 1 + household size
Scheduled Caste or Scheduled Tribe	Dummy variable equal to 1 if household belongs to a scheduled caste or tribe
Muslim	Dummy variable equal to 1 if household's religion is Muslim
Household head's gender (1=male)	Dummy variable equal to 1 if household's head is male
Log of household head 's age	Logarithm of age of head of household
Educational attainment secondary school or higher	Dummy variable equal to 1 if educational attainment secondary school or higher
Utility function	
Risk aversion in July 2006	Variable equals to 1 if respondent selects to bet 25/25 Rs. when flipping a coin, 0.75 if bet 20/60 Rs. is chosen, 0.6 if bet 15/80 Rs., 0.5 if bet 10/95 Rs., 0.33 if bet 5/105 Rs. and equals to 0 if the chosen bet is 0/110 Rs.
Subjective discount rate as of July 2006	The variable is defined as follows: (q1-200)/200. q1 can take different values depending on respondents' answer whether she prefers 200 Rs now or the following amounts in one month: 201, 205, 210, 220, 240, 260, 300, 400 or 1000.
Beliefs about return on insurance	
Above average expected monsoon rain (normalized)	Normalized dummy variable equal to 1 if households expects rain for the monsoon is above average in May 2006
Basis risk	
Pct. of cultivated land that is irrigated	Acres of cultivated land that is irrigated over total owned land.
Pct. of castor and groundnut	Acres of cultivated land with castor and groundnut over total cultivated land
Wealth, income and credit constraints	
Household has Tap water	Dummy variable equal to 1 if household has piped water in residence
Wealth in 1000 Rs.	Addition of value of house, value of plots surrounding house, present market value of livestock, liquid savings and value of owned land in thousands of Rs.
Logarithm of wealth	Logarithm of 1 + wealth
Has any livestock, cattle, birds etc.	Dummy variable equal to 1 if household has any livestock
Monthly Per Capita Expenditures	Total monthly consumption expenditures divided by household size
Logarithm of Monthly Per Capita Expenditures	Logarithm of 1 + Monthly Per Capita Expenditures
Main income is from agriculture	Dummy variable equal to 1 if household's more than 50% of household's income comes from agriculture (sale of agricultural products plus wages from agricultural labor)
Total Annual Income	Total Annual Income in Rs
Own Land	Total acres owned
Amount of Land owned (bigha=.5 acres)	Total bighas of land owned
Number of plots	Total number of plots cultivated
HH had credit in May 2006 (1=Yes)	Dummy variable equal to 1 if household's had credit in May 2006
Household was credit constrained in July 2006 / June 04 (1=Yes)	1 - dummy variable equal to 1 if household assigns money to savings or to give to family in the hypothetical case of being unexpectedly given Rs 1000 in July 2006
HH has savings account in May 2006 (1=Yes)	Dummy variable equal to 1 if household's had savings account in May 2006

Appendix A: Definition of Variables

Variable name	Definition of variable
Familiarity with insurance and BASIX	
Average insurance payouts in the village 2004 and 2005	Average insurance payouts during 2004 and 2005 in the village where household lives
HH bought weather insurance in 2004 (1=Yes)	Dummy variable equal to 1 if household bought weather insurance in 2004
Trust in basic relative to general trust in institutions	Level of trust in basic minus average level of trust in politicians, the media, progressive farmers in your village and the local Gram Panchayat (town council)
Don't know where rainfall gauge is (1=Yes)	Dummy variable equal to 1 if respondent doesn't know where the nearest rain gauge is
Don't know Basic (1=Yes)	Dummy variable equal to 1 if respondent doesn't know what BASIX is
Household has other insurance (1=yes)	Dummy variable equal to 1 if household has other insurances of any type besides those from Basic
Difference between perceived and actual length of 60 mm	Distance in mm. between what the respondent thinks 60mm. are and the actual 60 mm
Difference between payout over price in 2006, 2004	Insurance's payout over insurance's price in 2006 minus insurance's payout over insurance's price in 2004
Insurance skills (normalized)	The variable is a number between 0 and 1. The correct answer to each question gets 1 point: if it rains 120mm, if it doesn't rain at all and if it rains 20 mm the respondent knows if she gets insurance payout and how much; she was also asked how much were 60mm. Then that sum is divided by 6 to get an average measure of ability to understand insurance plans
Knowledge of millimeters (Percent Answering Question Correctly)	Dummy variable equal to 1 if respondent knows exactly how much are 60mm.
Technology diffusion and networks	
Household is considered a progressive farmer (1=Yes)	Dummy variable equal to 1 if household is progressive
HH belongs to Gram Panchayat / elected body (1=Yes)	Dummy variable equal to 1 if any household member belongs to Gran Panchayat
HH belongs to a water user group (BUA or WUG) group (1=Yes)	Dummy variable equal to 1 if any household member belongs to BUA/WUG
Number of groups that the household belongs to	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
Treatments	
Visit (1=Yes)	Dummy variable equal to 1 if household was visited
Endorsed by LSA (1=Yes)	Dummy variable equal to 1 if household was endorsed by LSA
Education module (1=Yes)	Dummy variable equal to 1 if household attended the education module about the insurance
High reward (1=Yes)	Dummy variable equal to 1 if household was given a reward of 100 Rs compared to 25 Rs.
Village was endorsed (1=Yes) x Visit (1=Yes)	Dummy variable equal to 1 if household was visited and lives in a village that was endorsed

Appendix B Table 1: Study Design, Andhra Pradesh

Visit	Village Endorsed	Individual Treatment: Household Endorsed	Individual Treatment: Education Module	Individual Treatment: 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. The study villages were first randomly assigned to three groups: those in which no marketing treatment would take place; those in which a village-level marketing meeting would be held; and those in which individual household visits would be conducted. Households in the villages which received marketing visits were randomly assigned one of eight possible combinations of marketing treatments.

Appendix B Table 2: Study Design, Gujarat

Group 1: Flyer Treatments

Group	Individual/Group	Religion	Sample size
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**

Surveyed Households

Group	Payouts	Frame	Sample size
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	Sew Brand	Peer/Authority	Payouts	Sample size
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)			Sample size
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.

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.