Patterns of Rainfall Insurance Participation in Rural India

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Abstract

We describe the contract design and institutional features of an innovative rainfall insurance policy offered to smallholder farmers in rural India, and present preliminary evidence on the determinants of insurance participation. Insurance takeup is found to be decreasing in basis risk between insurance payouts and income fluctuations, increasing in household wealth and decreasing in the extent to which credit constraints bind. These results match with predictions of a simple neoclassical model appended with borrowing constraints. Other patterns are less consistent with the benchmark model. Namely, participation in village networks and measures of familiarity with the insurance vendor are strongly correlated with insurance takeup decisions, and risk averse households are found to be less, not more, likely to purchase insurance. We suggest that these results reflect household uncertainty about the product itself, given their limited experience with it.

Keywords: rainfall insurance, household finance, risk sharing, India

JEL Codes: O10, O16, G2, G22

Insurance markets are growing rapidly in the developing world. As part of this growth, innovative new products allow individual smallholder farmers to hedge against agricultural risks, such as drought, disease and commodity price fluctuations. For example, a recent World Bank volume (World Bank, 2005a) discusses ten case studies in countries as diverse as Nicaragua, the Ukraine, Malawi and India. Each is a study of index insurance, an insurance product whose payouts are linked to a publicly observable index such as rainfall recorded on a local rain gauge. Advocates argue that index insurance is transparent, inexpensive to administer, enables quick payouts, and minimizes moral hazard and adverse selection problems associated with other risk-coping mechanisms and insurance programs.

These financial innovations hold significant promise for rural households. Shocks to agricultural income, such as a drought-induced harvest failure, generate movements in consumption for households who are not perfectly insured, and at the extreme, may lead to famine or death. Available evidence suggests households in developing countries are partially although not fully insured against income shocks (e.g. Townsend 1994, Morduch 1995, Lim and Townsend 1998). Moreover, weather events tend to affect all households in a local geographic area, making other risk-sharing mechanisms like inter-household transfers and local credit and asset markets less effective at ameliorating the impact of the shock. Other evidence suggests that households engage in costly ex ante risk-mitigation strategies to reduce fluctuations in agricultural income. Morduch (1995) summarizes a range of evidence of this kind of household income smoothing; for example, Indian farmers near subsistence level spatially diversify their plots, and devote a larger share of land to lower-yielding, traditional varieties of rice and castor. These activities reduce the variability of agricultural revenues, but at the expense of lower average income.

This paper studies a particular rainfall insurance product offered in recent years to smallholder farmers in the Andhra Pradesh region of southern India. The product provides a payout based on rainfall during three separate phases of the Kharif, or monsoon season, and is inexpensive enough to be accessible to farmers of modest income (one policy covering all three phases of the Kharif costs around Rs. 150-250, equivalent to $4-6US). The product is sold to farmers by BASIX, a microfinance institution, and rainfall risk is underwritten by the insurance firm ICICI Lombard and their reinsurers.

A basic research question for the study of micro-insurance markets is estimating the cross-sectional determinants of household insurance takeup, and identifying the impediments to trade that prevent remaining households from participating. After describing the insurance product, we present empirical evidence on the determinants of insurance participation, based on a household survey implemented by ICRISAT and the World Bank in late 2004. We first evaluate takeup patterns against a simple neoclassical benchmark, which predicts that insurance participation is increasing in risk aversion and the variance of risk, and decreasing in basis risk between insurance payouts and the risk to be insured. We find some evidence consistent with the basis risk prediction; namely households who historically plant a high share of castor and groundnut, the two crops for which contracts are designed, are more likely to purchase insurance. Takeup rates are also higher amongst wealthy households, and lower amongst households identified as credit constrained. These findings are consistent with an extension of the benchmark model to include borrowing constraints.

Other evidence is more difficult to reconcile with the benchmark model. First, amongst the quantitatively most significant determinants of insurance takeup are variables measuring the household's degree of familiarity with the insurance vendor, such as whether the household is an existing BASIX customer. Participation is also higher amongst households that are members of the village Gram Panchayat (local council), and those that are connected to other village networks, especially when a larger number of other members or the household's primary network also buy insurance. Second, risk-averse households are somewhat less likely to purchase rainfall insurance, not more likely as the neoclassical framework would suggest. This result is concentrated amongst households who are unfamiliar with the vendor, BASIX, or do not use other types of insurance.

We interpret these finding to suggest that many households are uncertain about the insurance product itself, leading risk-averse households, households with higher costs of evaluating new technologies, and households who are less familiar or place less trust in the insurance provider to eschew purchasing insurance. This interpretation is also consistent with qualitative evidence. Lack of understanding about the product was the most common explanation cited by households for not purchasing insurance, while a significant fraction of purchasers cite 'advice from others' as a reason for their decision to buy.

These results represent a first step towards understanding barriers to household participation in micro-insurance contracts, and should be viewed as a progress report of our research to date. Some features of our results may reflect the process used to market the product. For example, the results relating to the role of networks and familiarity with BASIX may be due at least in part to more intensive marketing of the insurance product to village opinion-leaders and existing customers. In ongoing research, we study insurance participation using a randomized field experiemental design that explicitly controls the type of information and marketing received by households. This is also the approach taken by Cole, Tobacman, and Topalova (2008), who study takeup of a rainfall insurance product by households in Gujarat. Like our study, Cole et. al. find that wealth is positively correlated with insurance takeup. These authors also find that the framing of the insurance product has a large impact on the household's insurance participation decision.

Section 1 of this paper outlines the concept of index insurance. Section 2 describes the insurance contract features and related institutional details. Section 3 discusses theoretical determinants of insurance participation, and states hypotheses to be tested. Section 4 discusses the survey, and presents summary statistics. Section 5 presents empirical results. Section 6 concludes.

I. The Promise of Index Insurance

Index insurance provides a payout based on the realization of a publicly-verifiable aggregate index, such as rainfall at a local rain gauge or an area-wide measure of crop yields. The goal of such insurance is to insulate income and consumption against aggregate shocks that are plausibly exogenous to the household.

A properly designed index insurance policy minimizes or eliminates moral hazard and adverse selection problems that otherwise distort behavior in insurance markets. This is because payouts are determined by exogenous information which is unaffected by either unobserved household characteristics (adverse selection) or ex-post household decisions (moral hazard). Desirable features of an index include the following: (i) the index is transparent and verifiable to policy-holders, (ii) the calculation of the index is free of tampering or manipulation, (iii) the probability distribution of the index can be accurately estimated, so that the product can be appropriately priced, and the expected return assessed by households, (iv) the index can be measured inexpensively and in a timely fashion, and (v) the realization of the index, or a transformation of the index, is highly correlated with household income and consumption risk.

The most widespread index-type insurance available in India is the government-operated National Agriculture Insurance Scheme (NAIS), which provides a payout based on measured area-level yields on individual crops. In participating states, farmers are required to purchase NAIS insurance if they take a crop loan from a formal financial institution; other farmers can purchase insurance voluntarily (Kalavakonda and Mahul, 2005; Mishra, 1996). For more information, we refer readers to section S.1 of the supplemental appendix to this paper, available online at http://wber.oxfordjournals.org, where we describe the features of NAIS in more detail, and summarize the costs and benefits of NAIS relative to rainfall insurance.

A necessary feature of any insurance contract is that payoffs are correlated with household income and consumption. Available evidence suggests deficient rainfall is a key risk faced by rural Indian households. In section S.2 of the supplemental appendix we present self-reported rankings from our survey data of the importance of different risks faced by households. An overwhelming proportion (88%) of households cite drought as the most important risk they face. Crop failure for reasons other than drought, and crop disease, are cited second and third most frequently. Consistent with these self-reports, World Bank (2005b) estimates that a severe drought in Ananthapur and Mahbubnagar, the districts studied in our empirical work, would reduce rice yields by 45% and 26% respectively, a potentially devastating loss of income for a household near subsistence level.

II. Policy Design and Marketing

The rainfall insurance product studied in this paper is designed to insure farmers in semi-arid tropical areas of India against deficient rainfall. It was developed by the general insurer ICICI Lombard, with technical assistance provided by the World Bank. ICICI Lombard partners with local financial institutions who market the product to farmers. In the Mahaboobnagar and Anantapur districts of Andhra Pradesh, where the product was piloted in 2003, and where our survey villages are located, this role is performed by BASIX, a microfinance institution.

Below, we describe the insurance contract design, focusing on 2004, the year of our survey evidence. Our discussion draws in part on World Bank (2005a) and Giné, Lilleor, Townsend and Vickery (2005). Cole and Tufano (2007) also present additional detail about the product background, and BASIX's commercial incentives in marketing rainfall insurance policies.

2004 Contract Design

Rainfall insurance policies for 2004 were designed for the two main cash crops in the region: castor and groundnut. These two crops are more profitable than food crops, such as pulses, but are also more sensitive to drought. In addition, since the seeds are relatively expensive, some farmers purchase them using crop loans, but when the harvest fails these loans are often difficult to repay (Hess, 2002).

The coverage for all policies is the Kharif (monsoon season), which is the prime cropping season, running from June to September. The insurance contract divides the Kharif into three phases, sowing, podding/flowering and harvest. The payout structure in each phase is summarized in Figure 1. An upper and lower threshold is specified for each phase. The policy pays zero if accumulated rainfall exceeds the upper threshold. Otherwise, the policy pays a fixed amount for each mm of rainfall below the upper threshold, until the lower threshold is reached. If rainfall falls below the lower threshold, the policy pays a fixed, higher payout. The total payout is the sum of payouts across the three phases.

[[INSERT FIGURE 1]]

The timing of phases, thresholds and other parameters of the contract were determined using the PNUTGRO crop model (Gadgil, Rao and Rao, 2002) and interactions with farmers. The upper threshold corresponds to the crop's water requirement, while the second trigger is intended to equal the water requirement necessary to avoid complete harvest failure.

The policy premium was initially benchmarked on projected payouts using historical rainfall data (at least 25 years of data for each rain gauge was used). The premium was initially calculated as the sum of the expected payout, 25% of its standard deviation, 1% of the maximum sum insured in a year, plus a 25% administrative charge and 10.2% government service tax. In some cases, the premium dictated by this formula was then reduced, since it was believed to exceed farmers' willingness to pay. The policy was targeted towards small and medium-size farmers with 2-10 acres of land. However, sales were not limited to this group; any household in the targeted villages was eligible to purchase the insurance product.

Example

Table 1 presents contract details and actual payouts for castor insurance policies sold in Mahaboobnagar in 2004. Mahaboobnagar includes three mandals (counties) with a reference weather station, Atmakur, Mahaboobnagar and Narayanpet, against which contracts are written.

[[INSERT TABLE 1]]

For example, in Narayanpet, the per-policy premium for a policy covering all three phases of the monsoon is Rs. 200. One policy is considered to be equivalent of one acre of coverage. In 2004, the start date for the monsoon is a fixed calendar date, June 10, and the first phase is 35 days in length. Narayanpet received 12mm of rain in the first phase, 84mm of rain in the second phase and 177mm of rain in the third phase. This resulted in a maximum lump sum payout of Rs. 1500 in the first phase, since accumulated rainfall fell below the lower trigger of 60 mm. Rainfall during the second phase was also deficient, but exceeded the lower trigger level, resulting in a payout at Rs. 240 per acre insured (240 = [100mm - 84mm] x 15). Rainfall exceeded the upper threshold value in the third phase. Thus, insured households in Narayanpet received total payouts of Rs. 1740 per policy.

BASIX Distribution and Marketing

BASIX has extensive local distribution networks, since it also provides microfinance loans to households in villages where the insurance product is marketed. The insurance product was piloted in 2003 in two villages in Mahaboobnagar, and expanded to 43 pilot villages in Mahaboobnagar and Ananthapur in 2004. BASIX used four criteria to determine whether a village was suitable for insurance marketing in 2004: (i) the presence of exisiting BASIX customers to ensure some degree of trust in the institution; (ii) 200-300 acres of groundnut and/or castor crops; (iii) a reasonable number of farms with 2-10 acres of land; and (iv) a village location within 20km of the nearest rainfall reference station, to minimize basis risk. Due to time constraints, BASIX offered insurance in only a subset of villages meeting these four suitability criteria.

BASIX's strategy in marketed villages was to first explain the insurance product to a trusted opinion leader, who then functioned as a motivator, informing other households about the product and an upcoming marketing meeting to be held a few days later. BASIX provided a general introduction to the insurance product at the marketing meeting. Policies were sold both at the meeting itself, and at individual visits to interested households following the meeting. BASIX agents generally spent one day in each village for insurance marketing and sales.

In conversations with us, BASIX representatives ascribed differences in insurance takeup rates across pilot villages to the choice of the motivator (e.g. their understanding of insurance product and status in the village), the extent of BASIX's market presence, the number of rainy spells prior to and on the day of marketing (it being hard to sell rainfall insurance on a rainy day!), and the liquid assets of farmers on the day of marketing. This varied substantially; in some villages farmers had just received payments for their milk delivery and therefore had cash in hand, while in other villages, particularly in Anantapur, government subsidies for groundnut seeds had recently been made available, and most farmers had spend their savings purchasing seeds.

Based on feedback from farmers and BASIX field agents, the rainfall insurance contract design was refined in two important respects between 2004 and 2006. First, separate castor and groundnut policies were combined into a single policy for each rain gauge, to simplify marketing and appeal to farmers growing other crops, and based on a judgement that separate policies generate limited benefits for policyholders. Second, the start of the first phase is triggered by the monsoon rains (namely, by the recording of at least 50mm of rain since June 1), rather than a fixed calendar date. Giné, Townsend and Vickery (2007) present more information about the 2006 contracts, and analyze the statistical properties of contract returns, by constructing a time-series of putative insurance returns using historical rainfall data. Giné et. al. find that the insurance policy primarily insures against severe rainfall events, paying out a positive return in only 11% of phases, but providing a maximum return of around 900%.

In 2003, rainfall insurance was sold to 148 farmers in two villages, mostly members of borewell users associations. This increased to 315 farmers across 43 pilot villages in 2004. Policies sold covered 570 acres of crop, insuring a total sum of Rs. 3,409,200, equivalent to Rs. 10,822 per farmer (USD $240, based on an exchange rate of $1US = Rs. 45). Section S.3 of the supplemental appendix presents a table of insurance participation in 2003-04 across survey mandals.

III. Determinants of Insurance Participation: Theoretical Predictions

What does economic theory predict regarding the determinants of insurance market participation? In a simple setting without asymmetric information, a household's willingness-to-pay for an insurance contract will be (i) increasing in risk aversion, (ii) increasing in the expected insurance payout, (iii) increasing in the size of the insured risk, and (iv) decreasing in basis risk (in other words, increasing in the correlation between the insurance payout and the risk to be insured, or more generally, the household's consumption risk). As shorthand, we refer to this as the benchmark model of insurance participation.

To fix ideas, in the Appendix we present a simple parametric example of this benchmark model for a household with mean-variance expected utility. The model yields a simple closed-form expression for the household's willingness to pay which illustrates the four comparative statics predictions listed above.

It is often noted, however, that many households remain uninsured against significant income risks (for example, many US households do not have health insurance). Deviating from the full-information benchmark, a large literature has considered adverse selection and moral hazard as potential explanations for barriers to trade in insurance (eg. Abbring, Chiappori and Pinquet, 2003; Cawley and Philipson, 1996; Rothschild and Stiglitz, 1976). Empirical evidence for asymmetric information models of insurance is mixed. For example, Cawley and Philipson (1996) find that conditional on observables, life insurance premia are *decreasing* in the quantity of insurance purchased, opposite to the separating equilibrium in Rothschild and Stiglitz (1976).

Models of adverse selection and moral hazard are of limited applicability to the rainfall insurance contract studied here. Historical rainfall patterns at mandal rain gauges are public information, ruling out adverse selection, while moral hazard only presents a problem to the extent that households tamper with the measurement of rainfall at the gauge. We have no evidence to believe that this is a problem in practice. In private communication, a World Bank representative who has visited IMD weather stations reports to us that these stations are secure, fenced locations, and that rainfall measurements are checked for inconsistencies.

Mulligan and Philipson (2003) introduce fixed participation costs to a benchmark insurance demand model. They argue such costs help account for empirical patterns like the positive correlation between wealth and insurance participation identified by Cawley and Philipson (1996). However, it is not obvious whether any significant fixed costs apply in our setting. Administrative loadings are proportional to the amount insured, and there is no discount for multiple policies. One possibility is that since insurance policies are indivisible, it may be difficult for poor households to purchase even a single policy. Alternatively, there may be other, non-monetary fixed costs, for example the time cost of attending the marketing meeting, or cognitive costs associated with understanding the product.

Predictions

Hypothesis 1: Benchmark model. *Insurance participation is higher when risk aversion is high, basis risk is low, and the risk to be insured is large.*

Our first hypothesis is simply that insurance participation decisions are consistent with the benchmark model described above.

Hypothesis 2: Heterogeneous Beliefs. *Insurance participation is higher when beliefs imply higher expected payouts.*

Historical rainfall patterns are publicly observable, which suggests households may share common expectations about the distribution of insurance payouts. However, to the extent that beliefs differ, households who expect lower rainfall would view the insurance contract as having a higher expected return, and be more likely to participate.

Hypothesis 3: Credit constraints. *Insurance participation is higher when households are less credit constrained (that is, when the shadow value of liquid assets is lower).*

In our setting, financial constraints potentially play a key role in insurance participation decisions. One one hand, credit constrained households may value the reduction in income volatility provided by insurance more highly, because they have a lesser ability to smooth consumption ex post. On the other hand, at the start of the monsoon when insurance purchase decisions are made, credit constrained rural households have limited funds to purchase seeds, fertilizer and other materials needed for sowing. Even if such households are risk-averse and would benefit from insurance, the shadow value of liquid assets may be extremely high at such times, making the purchase of insurance unattractive.

We illustrate the intuition of this second mechanism through an extension of the benchmark model in the Appendix. We consider a household with mean-variance utility, so in the baseline model, risk aversion and willingness-to-pay for insurance are independent of wealth. However, in the extension, we assume the household has limited funds, which can be used to purchase insurance or invest in sowing (e.g. seeds, fertilizer etc.). We show willingness to pay for insurance is unambiguously lower when credit constraints bind, and within that region is uniformly increasing in wealth. This result reflects a simple intuition: the more binding are credit constraints, the higher the shadow value of financial wealth, reflecting the high marginal product of the alternative use of those funds, investment in sowing.

We emphasize that this result may not obtain unambiguously in a multi-period setting, because credit constrained households would also place higher value ex post on the smoothing of income provided by insurance, and because they are more likely to be constrained at the beginning of future monsoons. (We view building such a fully-specified dynamic model as an interesting topic for future research.) This suggests the correct sign of the relationship between credit constraints and insurance demand is potential ambiguous, and must be established empirically.

Hypothesis 4: Trust, limited cognition and networks

Our empirical setting also relates closely to the literature on technology adoption and diffusion (Grilliches, 1957, Caswell and Zilberman, 1985). We study a new financial product. Households in our sample have been offered the opportunity to purchase rainfall insurance at most only once previously. Even with the help of the BASIX agent, the household may be uncertain about the contract design, or the timing or magnitudes of payouts. Alternatively, the household may not fully trust the insurer to pay out on claims. Although we do not formally extend our theoretical framework to model these factors, we consider three interrelated hypotheses relating to takeup of a new product that is not well-understood by households:

(i) Familiarity With Insurance Provider: In an environment where a product is not well understood, it seems plausible households will draw inferences based on their degree of experience and familiarity with the vendor, BASIX, and their trust in it.

(ii) Networks: Closely related, households are likely to rely on information gleaned from social networks, such as whether other trusted farmers also purchase insurance.

(iii) Limited cognition: Households may vary in their cognitive ability to understand the product, and their willingness to experiment with it. We study whether members of the Gram Panchayat (local council), and self-identified progressive households disproportionately purchase insurance. We also hypothesize that younger and more educated household heads will understand the product more easily, and be more likely to participate.

IV. The Survey

Our data comes from a household survey conducted after the 2004 Kharif, designed to study households' experiences with ICICI Lombard rainfall insurance. The survey questions were developed by ourselves and implemented by ICRISAT (International Crops Research Institute for the Semi-Arid Tropics) in late 2004.

The survey sampling frame is a census of landowner households across 37 villages in Mahboobnagar and Ananthapur. We survey villages where at least five households purchase insurance in 2004, accounting for the selection of 25 of the 37 villages. The other 12 villages are controls identified by BASIX as being suitable for insurance marketing, but where no policies were sold in 2004 due to time constraints. Since there is no participation in the control villages, empirical analysis in this paper is based only on data from the 25 marketed villages.

Amongst marketed villages, we select a stratified random sample of households, so as to survey as many purchasers of insurance as possible. We survey all households who purchase insurance (267 households), and a random sample of households who attend an insurance marketing meeting but do not purchase insurance (233 households), and households who do not attend a marketing meeting (252 households). The total sample size is thus 752, drawn from a population of 5805 landowner households in the 25 marketed villages. The takeup rate of the insurance product, correspondingly, is 267 / 5805 = 4.6%. This is quite low, reflecting the short history of the insurance product.

The survey non-response rate is extremely low. None of the 267 insurance purchasers in the marketed villages refused to participate, and ICRISAT reports to us that the frequency of non-response amongst non-purchasers is also close to zero. (This in part reflects the fact that the survey was administered after the end of the monsoon, when households are less busy). The sample of 267 purchasers represents a large fraction of the 315 total households across all villages that purchased rainfall insurance from BASIX in 2004.

Note that we use ‘purchased insurance’ as the dependent variable in most of the regressions. Since we also stratify on this variable, our sampling approach is an example of choice-based sampling (Manski and Lerman, 1977). Following Manski and Lerman, we estimate a weighted probit regression using the sampling weights discussed above to recover consistent estimates of the slope coefficients.

Summary statistics and variable construction

Summary statistics for the sample are presented in Table 2. Full-sample averages are weighted by population weights, and thus are close to non-buyer averages, given the low takeup rate. For 25 households data is missing for one or more variables, in which case we impute missing values iteratively as a function of other variables. No single variable is missing more than 11 times, and our empirical results are almost unchanged if we restrict the sample to households without missing data, rather than imputing missing values. Full details of each variable’s construction is presented in section S.4 of the supplemental appendix available online.

Demographic and wealth data confirms our sample consists of poor and middle-income smallholder farmers. Mean landholdings are 5.8 acres (median = 4 acres). Household heads have an average of 3.3 years of formal education, although the median household head has no formal education. 97% of household heads have spent their entire life in the village. Mean household liquid assets are Rs. 14,100 (median = Rs. 8,300), equivalent to US$300 (US$200), the sum of cash, bank account deposits, jewelry, silver, gold, revolving funds and miscellaneous liquid assets.

There are significant differences between the characteristics of insurance buyers and non-buyers. Buyers are less risk averse, and report around 50% more land and nearly twice as much in liquid assets. Around a third of insurance purchasers belong to borewell user associations (BUAs), compared to only a small fraction (4%) of the overall population. 46% of buyers have outstanding credit from BASIX at the start of the Kharif, compared to 7% of the overall population. Each of these differences in means is statistically significant at the 5% level, as shown in the table.

Summary statistics in Table 2 include several variables intended to elicit parameters of the household head's utility function. The variable 'risk aversion' is measured on a 0 to 1 scale, and is constructed from a game where the household head chooses between a series of gambles indexed by increasing risk and return; the household is then given a cash payout of between 0 and Rs. 200 based on their answer and the outcome of a coin toss. A related question is used to elicit a dummy variable for ambiguity aversion. The variable 'patience' indicates the proportionate amount that a household head must receive today for them to be indifferent to a fixed amount promised in one month's time. The average for this variable is 0.8, suggesting a high monthly discount rate for the households in the sample.

We also construct a variable that measures household pessimism regarding the start of an average monsoon season. Households are asked to assess the probability of the monsoon starting after several different dates, from which we estimate the household head's subjective probability density function for the start of the monsoon. The pessimism variable is the area under this density function one standard deviation or more to the right of the historical average start of the monsoon season (thus a larger value represents more weight on a later monsoon start).

Finally, the variable 'credit constraints' is a proxy for whether the household is credit constrained, based on the household's explanation for why they do not have one more loan. If the household cites a supply-side reason such as 'lack of collateral' or 'bank will not give additional loan' this variable is set equal to 1. It is set equal to 0 if the household responds 'no need for credit', 'do not like to be in debt' or 'other'.

V. Empirical Results

We first ask households who attend a marketing meeting to provide up to three reasons for their decision whether to purchase BASIX rainfall insurance, ranked in order of importance. Table 3 presents frequencies of these responses. The final column is a weighted sum across the three responses (giving more weight to higher-cited reasons).

[[INSERT TABLE 3]]

Amongst purchasers, households' self-reported explanations emphasize the risk-reduction benefits of insurance. 'Security/risk reduction' is the most popular response, while the second most cited reason is 'household needs harvest income'. 65% of households cite one of these explanations as the most important reason for purchasing insurance. Responses also emphasize the role of networks and learning: 'advice from progressive farmers', 'other trusted farmers purchased insurance' and 'advice from village officials' together comprise 19% of the weighted responses. 12.5% of responses cited either the high expected payout or low premium of the insurance. A small fraction of households (5.7%) purchase insurance because of reasons related to 'luck'.

Strikingly, the most frequently cited reason amongst non-purchasers is that the consumer does not understand the insurance product, representing 25% of weighted responses. 21% of responses state the household did not have sufficient cash or credit to pay the premium, consistent with the hypothesis that credit constraints are important for insurance participation. 24% of responses cite responses related to basis risk: either 'rain gauge is too far away', or 'household does not grow castor or groundnut'. 16.6% of weighted responses state that the actuarial value of insurance is low relative to premiums: i.e. either that the insurance is too expensive (14.1% of responses), or the payouts are too small (2.5% of responses). Only a small percentage of household responses (2.5%) stated the household has no need for insurance against rainfall risk.

Many of these qualitative responses match well with the benchmark model of insurance participation under symmetric information. Namely, the degree of risk-reduction, the expected payout relative to the premium, and the degree of basis risk are all important factors considered by households when making purchase decisions. Two types of responses however are inconsistent with the benchmark model. Firstly, the results suggest a significant proportion of households who purchase insurance do so on the advice of trusted farmers or village leaders; conversely 25% of explanations for non-purchase cite a lack of understanding of the product. Secondly, a significant proportion of non-purchasers cite a lack of liquid funds or credit to pay for the premium, suggestive of the importance of credit constraints.

Regression Estimates

We next estimate a reduced-form probit regression model of insurance participation. The dependent variable is equal to 1 if the household purchases BASIX rainfall insurance in 2004, and 0 otherwise. Results are presented in Table 4.

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

[[INSERT TABLE 4]]

I. Benchmark model. A first prediction of the benchmark model is that insurance participation is decreasing in basis risk between payouts and household income, and increasing in the size of the risk to be insured. Coefficients in Table 4 under ‘basis risk’ appear consistent with these predictions. In particular, we include two variables measuring the proportion of cultivated land used for castor and groundnut in the previous year, 2003. Since these are the two crops against which policies are written, the basis risk from using insurance to hedge rainfall risk is presumably smaller when these crops predominate. Consistent with this prediction, both ‘percentage groundnut’ and ‘percentage castor’ are positively signed and statistically significant at the 1% level. Coefficients in column 2 show that for a household at the population takeup probability of 0.046, moving from growing no groundnut to all groundnut increases the probability of purchasing insurance in 2004 by 59% (34% for castor).

A caveat on these findings is that crop choice is endogenous, and we do not have an econometric instrument for the crop types grown. Thus, it is possible that an omitted third factor drives both the percentage of castor and groundnut grown, and the decision to purchase insurance. For example, progressive or informed farmers may be more likely to grow high-yielding cash crops, and also more likely to purchase insurance. An alternative variable for measuring basis risk would be distance to rain gauge, or some other direct measure of the difference in weather between the farm and the weather station. We do not follow this approach, because we study only a small number of villages, and because we include village fixed effects, which preclude the use of village-level covariates. In future research, we do plan to use distance to rain gauge as a measure of basis risk to study insurance participation for a much larger sample of villages.

The second prediction of the benchmark model is that risk-averse households have a higher willingness-to-pay for insurance. In fact we instead find that risk-averse households are marginally *less* likely to purchase rainfall insurance, significant at the 10% level. Quantitatively, shifting the risk aversion parameter from its minimum to maximum value (i.e. 0 to 1) reduces the probability of purchase by 25% (1.1 percentage points). Potential explanations for this result are explored below.

The regression also includes proxies for two other dimensions of the household’s utility function: ambiguity aversion and discount rate. Neither of these variables is statistically significant.

However, given that we infer these variables indirectly, it is likely that this is in part explained by measurement error, leading to attenuation bias and low power to reject the null hypothesis.

II. Credit constraints and wealth. In the Appendix we show that borrowing constraints, equivalent in our setup to low wealth, imply a high shadow value of wealth and lower willingness-to-pay for insurance. The baseline regression includes two wealth variables, log(1+landholdings) and log(wealth), both measured at the beginning of the Kharif. Both measures are positively signed, and although neither is individually significant, they are jointly significant at the 2% level. (These variables are strongly collinear; in an unreported regression excluding log(wealth), the coefficient on land quadruples, and becomes statistically significant at the 1% level.)

Our covariates also include a direct proxy for credit rationing, derived as described earlier from household self-reports about why they do not have one more loan. This coefficient is negatively signed as predicted, and statistically significant at the 1% level. Quantitatively, switching on this variable reduces the probability of takeup by 30% (1.4 percentage points).

III. Heterogeneous beliefs. We next estimate whether a proxy for beliefs about the insurance payout influences participation. We include a variable that measures the household's expectation about the start date of the monsoon. Households who expect the monsoon to start later will expect a higher payout, because the insurance payout is inversely correlated with rainfall from a fixed calendar date. This measure of pessimism is positively correlated with takeup as predicted, although it is statistically insignificant. This lack of significance may however reflect measurement error in our expectations variable, leading to low power to reject the null.

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

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

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

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

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

Since we do not directly measure the intensity of insurance marketing, we cannot easily disentangle these two explanations. In ongoing research, we conduct a randomized trial in which we control the type of marketing and information received by households. (Households are visited by an insurance educator and given an opportunity to purchase insurance policies; we randomize various features of the household visit.) Thus, the estimates should be viewed as preliminary, pending results from this randomized trial. We note however that in either case our findings are inconsistent with the full information benchmark. All households in the village are eligible to purchase insurance, so in a model where all households are rational and fully informed, the intensity of insurance marketing should have no effect on insurance participation.

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

Surprisingly, education is not statistically significantly correlated with insurance participation decisions. This result contrasts with Giné and Yang (2007), who find that education increases the effect of weather insurance provision on the decision to take a crop loan amongst households in Malawi. We do not propose a single explanation for these differences, however a potential reconciliation is that households in Malawi had no prior experience with the insurance provider, while BASIX is well known to most households in our sample. Thus, for our sample, the household's opinion of, and trust in, BASIX is likely to be relatively more important when evaluating the quality of the insurance product. Also, we note that Giné and Yang (2007) study a different question to ours, not the decision to purchase insurance *per se*, but the effect of insurance provision on the decision to take out a loan. Finally, it is possible that education is measured with error, and thus we may not have sufficient power to detect the relationship between education and insurance takeup (the coefficient, although not significant, is correctly signed).

Risk-aversion interaction effects

An apparently puzzling finding from Table 4 is that risk-averse household are less, rather than more, likely to purchase rainfall insurance, opposite to the prediction of the benchmark model. Here we explore a potential explanation for this result, namely that risk-averse households are also averse to uncertainty about the insurance policy itself, and the potential risks associated with it, given their imperfect understanding of the product.

To test this hypothesis, we interact risk aversion with three variables indicating the household's familiarity either with BASIX or the concept of insurance, namely dummy variables for: (i) whether the household belongs to a BUA, (ii) whether the household is a debtor of BASIX at the start of the Kharif, and (iii) whether the household holds any other type of insurance. Under the 'product uncertainty' explanation, we expect the wrong-signed risk aversion coefficient to be concentrated amongst households that are unfamiliar with BASIX or with insurance. We then re-estimate the specification from Table 4 including these three additional interaction terms together, and then one at a time. Results are presented in Table 5.

[[INSERT TABLE 5]]

The estimates are consistent with the ‘product uncertainty’ explanation. Each interaction term is positively signed as predicted, and the coefficients are jointly significant at the 5% level. The interaction term: ‘Risk Aversion x Credit from BASIX’ is individually significant at the 5% level when included alone (Column 3), and at the 10% level when all three interaction terms are included (Column 1). Our point estimates imply that for a household where each interaction term is switched from 0 to 1, the combined coefficient on risk aversion switches from -0.024 to +0.017 (although the combined coefficient is not statistically different to zero, perhaps reflecting that our risk aversion variable is a noisy proxy for the true risk aversion of the household, leading to attenuation bias and a low power to reject the null).

A potential source of measurement error is that our risk aversion variable is measured with respect to a gamble of moderate size. Rabin (2000) argues that risk aversion measured using small gambles is likely to overstate risk aversion applicable to gambles with large payoffs. However, Bombardini and Trebbi (2007), exploiting a natural experiment, find empirically using Italian data that a coefficient of relative risk aversion of unity approximates household behavior for both small and large gambles, providing support for our approach to measuring risk aversion. Note also that it is not necessary that we correctly measure the absolute level of risk aversion is measured correctly, only that we correctly order the relative degree of risk aversion across households.

Conditional probit

As described earlier, BASIX follows a two-step procedure in marketing rainfall insurance. Households are first invited to attend a marketing meeting. Households who attend are then educated about insurance, and given the opportunity to purchase policies.

In section S.5 of the supplemental appendix we present estimates using a conditional probit model that accounts for the two sequential steps of the insurance participation decision. We estimate two equations; the first equation is estimated on the whole sample, and has a dependent variable equal to 1 if the household attends the marketing meeting and 0 otherwise. The second equation is estimated on the subsample of households who attend the marketing meeting, and has a dependent variable equal to one if the household purchases insurance; that is, it studies participation conditional on meeting attendance. In general, our baseline estimates hold in a similar way across both steps. Most notably, BUA members and BASIX borrowers are both more likely to attend the marketing meeting, and more likely to purchase insurance conditional on attendance (statistically significant at least at the 5% level). Thus suggests the high rates of participation amongst these groups do not just reflect encouragement by BASIX to attend the meeting, since this mechanism alone would generate selection bias to produce *negative* coefficients on these variables in the second step.

Other analysis

Table 6 presents calculations of the quantitative magnitude of the insurance purchases of participating households. Households on average purchase 1.8 policies at a cost of Rs. 362, corresponding to 1.5% of liquid assets at the start of the Kharif, and 0.7% of 2004 gross Kharif agricultural revenue. These numbers are relatively small, consistent with our claim that households are experimenting with a new, imperfectly understood product, although still non-trivial (for example, in a US context, these figures would be equivalent to an expenditure on insurance of $700-$1400 per year for a small business owner with annual sales revenue of $100,000-200,000). It is important to highlight that returns on the insurance are quite skewed. A maximum payout corresponding to crop failure levels of rainfall across all three phases of the Kharif, yields a payout of 35% of gross farm revenue for an average household purchasing 1.8 policies.

[[INSERT TABLE 6]]

Finally, the large coefficients on ‘BUA member’ and ‘BASIX customer’ raise potential concerns that the strength of other relationships may be significantly different across members and non-members of these two groups. As a robustness exercise, in unreported regressions we re-estimate our baseline results on the subsample of households who are not BUA members or BASIX customers. Our point estimates are similar, although the statistical significance of the results is sometimes reduced, reflecting the smaller sample size (results available on request).

VI. Summary and Conclusions

We describe an innovative rainfall insurance product offered to smallholder farmers in the Andhra Pradesh region of southern India, and present preliminary evidence on the determinants of insurance participation. Our results highlight two main deviations from a benchmark model of insurance participation. First, credit constraints appear to be an impediment to purchasing insurance. Households with less land and less wealth, as well as households who directly report being credit constrained, are less likely to participate in insurance, consistent with the extension of a benchmark one-period model of insurance to include financial constraints. Insurance participation is also increasing in wealth in developed countries, a fact attributed to asymmetric information or fixed participation costs (Mulligan and Philipson, 2003). It is notable that we find the same result in a setting where these explanations appear unlikely to hold.

Second, a variety of results together suggest limited familiarity with the insurance product plays a key role in participation decisions: (i) Takeup rates are higher amongst prior customers of the insurance vendor BASIX, or members of BUAs, who are amongst BASIX's primary clients; (ii) risk averse households are less likely to purchase insurance, but only amongst households who are unfamiliar with insurance or with BASIX; (iii) households connected to village networks are more likely to purchase insurance, especially when other members of the household's primary group participate; (iv) respondents who likely have lower cognitive costs of understanding and experimenting with insurance, such as young farmers and self-identified 'progressive' farmers, are more likely to purchase the product; (v) in self-reports, a significant fraction of households cite advice from other farmers and limited understanding of the product as important determinants of participation decisions.

Our finding of the significance of credit constraints has practical implications for insurance contract design. A first implication is that insurance payouts should be made as promptly as possible after rainfall is measured and verified. Our survey asks households to identify which times of the year they are in most need of additional liquid assets; unsurprisingly, households report that they are most credit constrained at the start of the sowing season, and least constrained in November when crops are harvested and sold. However, in 2004, insurance payouts were not paid to farmers until around November. Our results suggest farmers would benefit from payouts being made available as soon as possible, preferably phase-by-phase as each stage of the Kharif is completed. One impediment to early payouts is that the Indian Meteorological Department takes an average of two months to verify rainfall data. ICICI Lombard is in the process of setting up a network of automated rain gauges, which in the future will facilitate faster payouts as well as minimize basis risk.

A second potential innovation would be to combine insurance with a short-term loan that helps credit-constrained households pay for the premium (stated differently, BASIX could offer state-contingent loans). A product of this type is studied by Giné and Yang (2007). We raised this possibility with BASIX; they are currently reluctant to mix products in this way, because they want to clearly establish to customers the conceptual difference between insurance and micro-credit products.

The overall conclusion of our empirical work is that, early in its introduction, the insurance product we study has not yet succeeded in proportionately reaching the most vulnerable households (e.g. poor, credit-constrained households, or households that are not members of social networks), who presumably would benefit most from protection against drought. This likely in part reflects persistent barriers to trade in insurance such as credit constraints, but also in part is due to a normal pattern of diffusion of a new product. Early adopters are likely to be households where the cost of experimenting is low. Participation will then filter through to other households over time.

A less optimistic perspective is provided by Morduch (2006), who highlights potentially adverse general-equilibrium implication of differential rates of insurance participation between rich and poor households. Morduch suggests that if rainfall insurance is only purchased by the wealthy, such households may have additional income to bid up the price of local non-traded goods during periods of low rainfall, making non-purchasers worse off. He also suggests that formal insurance may undermine existing risk-sharing mechanisms, by raising the threat point of households who seek to withdraw from implicit risk sharing arrangements.

Relatively little academic research on micro-insurance has been conducted to date, and many important questions remain unanswered. Some examples include: (i) the causal effect of rainfall insurance on income-smoothing and consumption smoothing; (ii) the price elasticity of demand for insurance, an important policy question given potential government subsidies on insurance contracts; (iii) the interaction between rainfall insurance and existing risk-bearing mechanisms; and (iv) the pattern of diffusion of insurance participation over time. In ongoing research, we are conducting a randomized field experiment amongst survey households, which we believe will help shed light on some of these questions.

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Appendix: Simple model of insurance participation under symmetric information

In this Appendix we present a simple model of insurance participation under symmetric information with and without credit constraints. Section A.3 summarizes the empirical predictions of this model.

A.1 Basic setup

Consider a risk-averse household with quadratic expected utility $E[U(c)] = E(c) - \gamma.var(c)$. (This mean-variance form is consistent with a household with CARA utility facing normally distributed shocks.) Household income is assumed to be $y = y^* + e$, where e has zero mean and variance σ^2_y. The household has access to an insurance policy that insures against this income volatility e.

The timing of events is as follows:

1. The household decides whether to purchase insurance.
2. Income is realized (i.e. e is revealed).
3. Insurance payouts (if any) are made. The household consumes its income y plus any insurance payout.

The policy costs premium p. The payout on the insurance is $r = -e + \mu + u$. μ is the household's expectation of the average insurance payout. u reflects basis risk associated with the insurance; u has mean 0 and variance σ^2_u (if $\sigma^2_u = 0$ the insurance perfectly offsets the variability in income due to e). Thus, if the household purchases insurance it consumes $c = y^* + \mu + u - p$, while if it does not purchase insurance it consumes $c = y^* + e$. Under these assumptions the household's willingness-to-pay is given by:

[A.1] $$p_{max} = \mu + \gamma[\sigma^2_y - \sigma^2_u]$$

Thus, the household has a higher willingness to pay if: (i) it is more risk averse (higher γ), (ii) the insurance involves smaller basis risk (lower σ^2_u), (iii) the insured risk is larger (higher σ^2_y) or (iv) the expected payout of the insurance is higher (higher μ).

A.2 Credit Constraints

Now consider a simple extension of this model which introduces credit constraints. Assume that farmers begin with wealth W, which they may use either to purchase insurance or invest in seeds. This investment in seeds then determines household income; mean household income $y^* = f(I)$ where I is investment in seeds, and f(.) is concave. Households are unable to borrow against their future income to purchase seeds or buy insurance (i.e. $W \geq I + p$). Any wealth not used for insurance or seeds is assumed to be stored at an interest rate of zero.

If the household has a high level of wealth, it will simply invest up to the point where f(I) = 1. In this case, willingness to pay for insurance is still given by formula [A.1]. Participation is independent of W, reflecting the fact that the household has CARA utility.

In the region where W is low and credit constraints bind, the household decides whether or not to purchase the insurance, and invests all residual wealth in seeds. Thus, if the household purchases insurance, investment is $I = W - p$, and household consumption is $c = f(W\text{-}p) + \mu + u$. If the household does not purchase insurance, investment in seeds is given by $I = W$, and consumption is $c = f(W) + e$. Taking expectations of these two expressions, the household's willingness to pay is given implicitly by:

[A.2] $$f(W) - f(W\text{-}p_{max}) = \mu - \gamma[\sigma^2_y - \sigma^2_u].$$

$f(W) - f(W\text{-}p_{max}) = \int_{W-p}^{W} f'(x)dx$. Since f(.) is concave, f(W) - f(W-p) is decreasing in W, and therefore $dp_{max} / dW > 0$, that is, the willingness-to-pay for insurance is increasing in wealth. Also, since $f'(W) > 1$, p_{max} is lower in the region in credit constraints than in the region where credit constraints do not bind.

A.3 Summary of results

This simple model of insurance participation under symmetric information predicts that willingness-to-pay for insurance will be higher when:

(i) Risk aversion is high (high γ).

(ii) The risk to be insured is large.

(iii) Basis risk is low.

(iv) The household is less credit constrained (i.e. the shadow value of W is lower).

Figure 1: Structure of Insurance Contract

BASIX rainfall insurance divides the monsoon season into three phases. The graph below shows how rainfall during the phase translates into the insurance payout for the phase. Figures in brackets are actual trigger points and payouts for a representative insurance contract, namely Phase 2 payouts on rainfall insurance linked to castor for the Narayanpet mandal of Mahboobnagar.

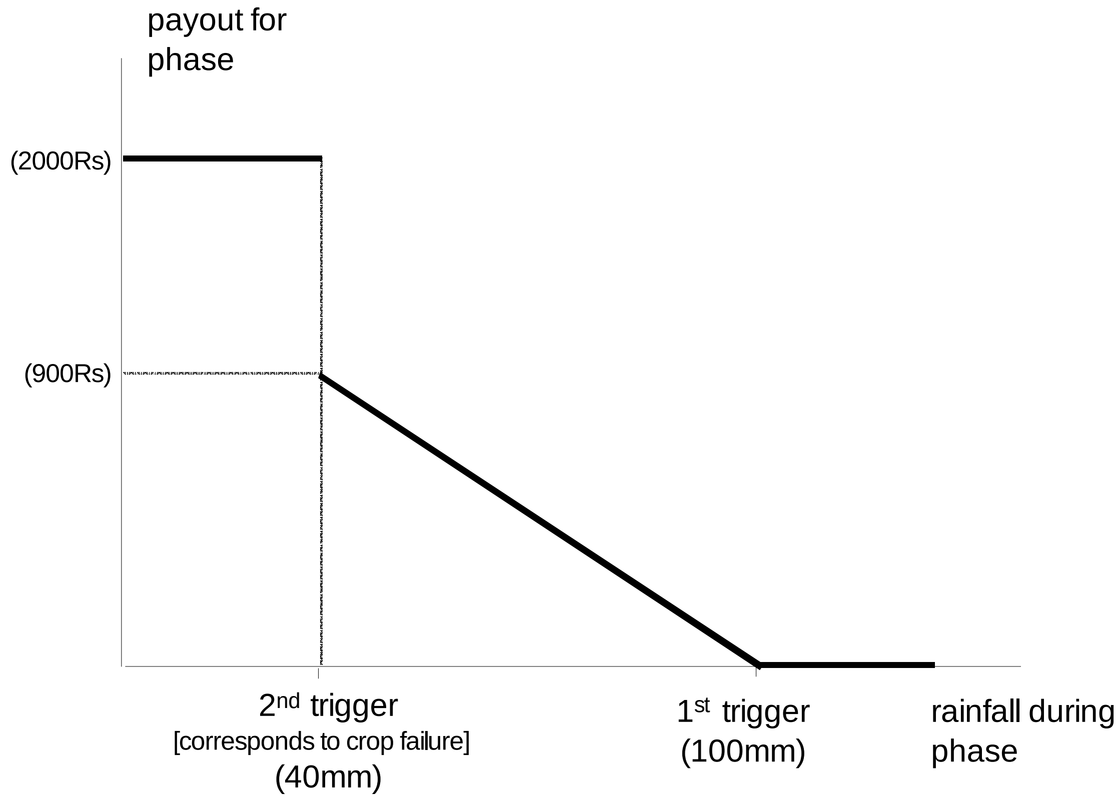

Table 1: Example Terms of Rainfall Insurance Contracts

This table presents data on the terms of 2004 rainfall insurance contracts linked to castor in Mahboobnagar. 1st trigger level refers to the level of rainfall above which the phase payout is zero. Payout per mm deficient rain lists the amount paid for each mm below the 1st trigger level, until the 2nd trigger is reached. Below the 2nd trigger level, the policy pays the maximum lump sum payout listed.

Mandal	Premium per acre Rs	Phase	1st trigger level mm.	Payout per mm deficient rain Rs	2nd trigger level mm.	Maximum lump sum payout Rs	Actual rain mm.	Actual payouts per acre Rs
Atmakur	250	*1*	60	10	25	1500	94.2	-
		2	100	15	5	2000	90.0	150
		3	75	15	30	2500	184.0	-
Mahboobnagar	150	*1*	60	10	20	1500	31.0	290
		2	100	15	50	2000	96.0	60
		3	75	15	50	2500	171.0	-
Narayanpet	200	*1*	60	10	20	1500	12.0	1500
		2	100	15	40	2000	84.0	240
		3	75	15	50	2500	177.0	-

Note: Phase 1: June 10 - July 14, phase 2: July 15 - August 28, phase 3: August 29 - October 12.

Table 2: Summary Statistics

		Mean (and Median, where applicable)				Std. Dev.	Min	Max
		Buyers	Non-buyers	Significant diff. in means?	Full Sample			
Utility function and beliefs								
Risk aversion*		0.733	0.829	1%	0.824	0.190	0.000	1.000
Ambiguity aversion*		0.507	0.553	-	0.551	0.498	0.000	1.000
Patience		0.830	0.801	5%	0.802	0.135	0.300	1.000
Pessimism about insurance return		0.334	0.308	-	0.309	0.310	0.000	1.000
Basis risk								
Use acc. rainfall to decide to sow*		0.052	0.076	-	0.075	0.264	0.000	1.000
% land used for groundut		0.216	0.225	-	0.224	0.348	0.000	1.000
% land used for castor		0.263	0.252	-	0.252	0.314	0.000	1.000
Credit constraints								
Household is constrained*		0.760	0.811	-	0.808	0.394	0.000	1.000
Leadership / networks								
Member: borewell user association*		0.345	0.022	1%	0.037	0.189	0.000	1.000
Progressive household*		0.513	0.306	1%	0.316	0.465	0.000	1.000
Member Gram Panchayet*		0.041	0.016	-	0.018	0.132	0.000	1.000
Number groups hh is member of		1.097	0.836	1%	0.848	0.745	0.000	4.000
Knowledge of insurance and BASIX								
Past credit from BASIX*		0.303	0.030	1%	0.043	0.203	0.000	1.000
Has other insurance*		0.753	0.553	1%	0.562	0.496	0.000	1.000
Income (during Kharif)								
Farming income		55.538	29.605	1%	30.801	178.622	0.000	5621.360
Nonfarming income		3.092	3.096	-	3.096	3.301	0.000	40.000
Wealth (beginning of Kharif)								
Liquid savings (Rs, 000s)	[mean]	22.952	13.500	1%	13.936	18.761	0.000	453.000
	[median]	14.800	8.000	1%	8.000			
Total wealth (Rs, 000s)	[mean]	558.668	346.183	1%	355.987	504.892	21.400	21360.500
	[median]	349.550	228.000	1%	232.250			
Landholdings (acres)		8.661	5.663	1%	5.801	4.952	0.300	79.500
% of cultivated land that is irrigated		0.495	0.270	1%	0.280	0.405	0.000	2.200
Other variables								
Education of household head (years)		5.301	3.179	1%	3.277	4.425	0.000	18.000
Age of household head		43.642	47.060	1%	46.902	11.437	21.000	80.000
Head spent whole life in village*		0.970	0.971	-	0.971	0.169	0.000	1.000
Gender of household head (1=male)		0.936	0.920	-	0.921	0.270	0.000	1.000
Household size		6.674	6.485	10%	6.494	2.808	1.000	17.000
Unweighted number of observations		267	485		752			
Weighted number of observations		267	5538		5805			

* Denotes a dummy variable where 1=yes.

Table 3: Self-Reported Reasons for Insurance Purchase

Households who attended the marketing meeting were asked to list the most important, second most important and third most important reasons why they did or did not purchase insurance. Responses were classified into the categories listed below. The 'weighted sum' percentage is the sum across all three categories where 1st, 2nd and 3rd most important reasons are given weights of 1, 2/3 and 1/3 respectively.

Why did the household purchase insurance?

	Frequency			
	1st reason	2nd reason	3rd reason	weighted sum
Security/risk reduction	139	53	20	40.1%
Need harvest income	25	62	12	15.6%
Advice from progressive farmers	17	28	12	8.8%
High payout	9	27	11	6.8%
Other trusted farmers purchased insurance	16	11	16	6.3%
Low premium	17	10	6	5.7%
Luck	4	22	21	5.7%
Advice from village officials	9	14	3	4.3%
Product was well explained	5	9	4	2.7%
Lot of castor	7	2	6	2.3%
Lot of groundnut	4	5	2	1.8%
Total	**252**	**243**	**113**	100%

Why did the household not purchase insurance?

	Frequency			
	1st reason	2nd reason	3rd reason	weighted sum
Do not understand the product	45	59	11	24.9%
No cash / credit to pay the premium	58	21	11	21.4%
Rain gauge too far away	38	39	9	19.0%
Too expensive	32	23	7	14.1%
No castor, groundnut	13	6	1	4.9%
Do not trust BASIX	5	8	2	3.1%
Other	6	7	0	3.0%
No need	6	4	1	2.5%
Payouts are too small	3	7	4	2.5%
Dislike insurance	4	7	1	2.5%
Purchased in 2003 but not satisfied	2	1	0	0.8%
Purchased in 2003 but no payout	2	1	0	0.8%
Cloud seeding promised by government	0	1	3	0.5%
Total	**214**	**184**	**50**	100%

Table 4: Baseline Estimates

Dependent variable = 1 if purchased insurance, = 0 if did not purchase. Weighted probit model . Robust z-statistics in parentheses. Coefficients normalized to display marginal effects. Regression also includes village dummy variables (results omitted).

	Marginal effects	Marginal effects scaled by population takeup rate
Utility function		
Risk aversion	-0.011	-0.246
	(1.84)*	(1.84)*
Ambiguity aversion	-0.000	-0.004
	(0.07)	(0.07)
Patience	0.009	0.193
	(0.95)	(0.95)
Beliefs about return on insurance		
Pessimism	0.004	0.094
	(1.19)	(1.19)
Basis risk		
Use acc. rainfall to decide to sow	-0.000	-0.005
	(0.05)	(0.05)
% cultivated land used for groundut	0.027	0.595
	(3.40)***	(3.40)***
% cultivated land used for castor	0.016	0.338
	(2.84)***	(2.84)***
Wealth and credit constraints		
log(wealth in Rs, start of Kharif)	0.004	0.079
	(1.19)	(1.19)
log(landholdings, start of Kharif)	0.002	0.054
	(0.70)	(0.70)
F-test: wealth and land [p-value]	0.02**	0.02**
% of cultivated land that is irrigated	0.003	0.075
	(1.12)	(1.12)
Household is constrained (1=yes)	-0.014	-0.299
	(3.29)***	(3.29)***
Familiarity with insurance and BASIX		
BUA member (1=yes)	0.368	7.996
	(4.70)***	(4.70)***
Credit from BASIX (1=yes)	0.066	1.438
	(4.83)***	(4.83)***
Has other insurance (1=yes)	0.003	0.074
	(1.35)	(1.35)
Technology diffusion / networks		
Progressive household	0.007	0.144
	(2.12)**	(2.12)**
Member Gram Panchayat	0.081	1.759

	(2.87)***	(2.87)***
No. other groups hh is member of	0.007	0.161
	(3.51)***	(3.51)***
No. of well known households	0.000	0.003
	(0.36)	(0.36)
No. well known hhs who bought insurance	0.006	0.124
	(5.06)***	(5.06)***
Other covariates		
log(education of household head in years)	0.001	0.029
	(1.09)	(1.09)
log(age of household head)	-0.015	-0.318
	(2.59)***	(2.59)***
Head spent whole life in village (1=yes)	-0.030	-0.654
	(1.79)*	(1.79)*
Gender of household head (1=male)	-0.008	-0.184
	(1.37)	(1.37)
log(household size)	0.002	0.035
	(0.41)	(0.41)
Village dummies	yes	yes
Number of observations	752	752
Pseudo R^2	0.44	0.44

Robust z-statistics in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Risk Aversion Interation Effects

Dependent variable = 1 if purchased insurance, = 0 otherwise. Weighted probit model. Robust z-statistics in parentheses. Coefficients normalized to display marginal effects. Regression includes same variables as baseline regression results (other results omitted; similar to previous table).

	Baseline specification			
	combined	interaction terms added individually		
Interaction terms				
Risk aversion * BUA	0.005	0.024		
	(0.25)	(1.23)		
Risk aversion * credit from BASIX	0.028		0.032	
	(1.74)*		(2.14)**	
Risk aversion * other insurance	0.008			0.014
	(0.72)			(1.18)
F-test [joint significance, p-value]	0.043**			
Underlying variables				
Risk aversion	-0.024	-0.016	-0.018	-0.021
	(2.42)**	(2.81)***	(3.22)***	(2.17)**
BUA	0.262	0.078	0.344	0.082
	(1.82)*	(2.84)***	(4.43)***	(4.72)***
Credit from BASIX	-0.001	0.064	-0.003	0.066
	(0.08)	(4.73)***	(0.32)	(4.92)***
Other insurance	-0.003	0.004	0.003	-0.008
	(0.32)	(1.43)	(1.38)	(0.79)

Table 6: Economic Magnitude of Insurance Expenditures

The table below calculates average expenditures on rainfall insurance, and the maximum payout on insurance purchased, as a fraction of average household liquid assets and gross farm revenues for the 2006 Kharif. Expenditures and payouts are based on the average of 1.81 policies per purchasing household.

Average number of policies per purchasing household: 1.81

			as fraction of....	
	per policy	per policyholder (based on 1.81 policies per household)	liquid assets, start of Kharif	gross farm revenue
Insurance expenditure	200	362	1.5%	0.7%
Maximum payout	6000	10860	84.1%	35.4%