Patterns of Rainfall Insurance Participation in Rural India

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PRELIMINARY DRAFT – COMMENTS WELCOME

Abstract:

This paper describes the contract design and institutional features of an innovative rainfall insurance policy offered to smallholder farmers in rural India, and presents 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' mode; namely, measures of familiarity with the insurance vendor play a key role in insurance takeup decisions, and risk averse households are found to be less, not more, likely to purchase insurance. We suggest that these results in part reflect household uncertainty about the product itself, given their lack of experience with it.

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1. Introduction

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, 2005) discusses ten case studies in countries as diverse as Nicaragua, the Ukraine, Malawi and India. Each is a study of 'index insurance', that is, an insurance product whose payouts are linked to a verifiable, 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 (eg. 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 protect themselves against fluctuations in agricultural income. Morduch (1995) summarizes a range of evidence of this kind of household 'income smoothing' behavior; for example, Indian farmers near subsistence level spatially diversify their plots, and devote a larger share of land to safer, traditional varieties of rice and castor compared to riskier, high-yielding varieties. These activities reduce the variability of agricultural income, but at the expense of lower average crop yields.

This paper studies in detail a particular rainfall insurance product developed by the insurance firm ICICI Lombard[1], which has been offered in recent years to smallholder farmers in the Andhra Pradesh region of southern India. The product provides a return 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 (the cost for one policy covering all three phases of the Kharif is around Rs 200-300, equivalent to $5-6US). The product is sold to farmers by BASIX, a microfinance institution, and rainfall risk is underwritten by ICICI Lombard.

A basic research question for the study of microinsurance markets is estimating the cross-sectional determinants of household insurance takeup, and identifying the impediments to trade that prevent remaining households from participating. After documenting in detail the institutional details and contractual features of the insurance product, we present empirical evidence on the determinants of rainfall insurance participation, based on a survey of rural households implemented by ICRISAT and the World Bank in late 2004. We first evaluate insurance 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 plant a large proportion of castor and groundnut, the two crops insured under the program are more likely to purchase insurance. We also find that takeup rates are higher amongst wealthy households, and lower amongst households who appear to be credit constrained. These findings are consistent with a simple extension of the 'benchmark' model to include borrowing constraints.

Other pieces of evidence are more difficult to reconcile with the benchmark model. First, the most quantitatively significant determinants of insurance takeup are variables measuring the household's degree of familiarity with or trust in BASIX, the insurance provider; namely whether

[1] ICICI Lombard is a general insurer offering a range of individual, commercial and rural policies. It is jointly owned by ICICI Bank, India's largest private sector bank and Lombard, a Canadian property and casualty insurance company. See www.icicilombard.com.

the household is an existing BASIX customer at the time of insurance purchase, and whether the household is a member of a borewell users association (BUA), groups that BASIX, who is also a provider of micro-credit, targets for group-liability lending. Participation is also higher amongst households that are opinion-leaders, such as current or former members of the area Gran Panchayat (local council) as well as self-identified 'progressive' households. Second, we find that risk-averse households are somewhat *less* likely to take up rainfall insurance, not more likely as the neoclassical framework would suggest. This result is most pronounced amongst households who are less familiar with the insurance provider, BASIX, or do not use other types of insurance.

We tentatively interpret these finding to suggest that many households may be uncertain about the insurance product itself, leading risk-averse households, households with higher costs of evaluating new technologies, and households who place less trust in the insurance provider, to eschew purchasing insurance. This finding is consistent with qualitative evidence: lack of understanding about the product was the most commonly cited explanation for not purchasing insurance, cited with 25 per cent frequency amongst non-purchasing households. This result is consistent with model of near-rationality or limited cognition rather than a full-information rational expectations benchmark.

These results represent an early step towards understanding barriers to household participation in 'micro-insurance' products, and should be viewed as a progress report of our research to date. Followup survey work implemented during the the 2006 Kharif, involving a randomized field experiment, will provide more detailed results about the determinants of participation, as well as the impact of insurance participation on other household decisions.

The remainder of this paper proceeds as follows. Section 2 discusses the costs and benefits of index insurance. Section 3 describes the contract features of rainfall insurance product, and related institutional details. Section 4 discusses theoretical literature about the determinants of insurance participation, and states hypotheses to be tested. Section 5 discusses our survey, and presents summary statistics. Section 6 presents the empirical results on the determinants of insurance participation. Section 7 concludes, and discusses future research directions.

2. 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-level measure of average crop yields, that is correlated with household income. The goal of such insurance is to insulate the consumption of rural households against fluctuations in rainfall, temperature, commodity prices, natural disasters and other aggregate shocks that are plausibly exogenous to the household unit.

A properly designed index insurance policy minimizes moral hazard and adverse selection problems that distort behavior in many insurance markets. This is because payouts are determined by exogenous, publicly verifiable 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 construction is transparent to policy-holders, and the realization of the index verifiable to them, (ii) the calculation of the index is free of tampering or manipulation, (iii) the distribution of the realization the index can be accurately estimated, so that the product can be appropriately priced, and the expected return estimated by potential policyholders (iv) the index can be measured inexpensively, and calculated in a timely manner, and (v) the realization of the index, or a transformation of the index, is highly correlated with household income and consumption.

The most widespread form of index-like agricultural insurance currently available in India is the government-operated National Agriculture Insurance Scheme, or NAIS. In participating states, farmers are required to purchase NAIS insurance if they take a crop loan (typically for seeds) from a formal financial institution; other farmers can also choose to purchase the insurance voluntarily (Kalavakonda and Mahul, 2005; Mahul and Rao, 2005). NAIS insurance payouts are based on area yields on individual crops, measured via crop-cutting experiments. Policyholders in each designated policy area are given a payout based on the shortfall (if any) on the measured crop yield relative to a threshold value set according to historical yields, which are estimated over a rolling window (the window depends on the crop, but is generally 3-5 years).

Like most government crop insurance programs, NAIS operates at a substantial loss. Between late 1999 and early 2004, NAIS collected premia of Rs. 12.5 billion, but paid Rs. 47.5 billion in claims (Mahul and Rao, 2005). Kalavakonda and Mahul (2005), who present a detailed case-study of the operation of NAIS in the southern Indian state of Karnataka, find a claims-to-premia ratio of approximate 7 to 1 for the between 2000 and 2002; taking administrative costs into account, policy premia provide only 12 per cent of program costs.[2]

Despite these heavy subsidies and the scheme's availability to all farmers, NAIS has a relatively low penetration rate. In the 2004 Kharif, 12.7 million farmers across India were even partially covered by the program, representing 9 per cent of the total rural population of 138 million households (sources: Mahul and Rao, 2005; 2001 Indian Census). Moreover, insurance participation is particularly low amongst small and marginal farmers. In Karnathaka in 2002, Kalavakonda and Mahul estimate that 11.6 per cent of small and marginal farmers participated in NAIS, compared to 27.0 per cent of medium and large farmers. This disparity exists despite explicitly targeted subsidies; small and marginal farmers received a 40 per cent premium subsidy in 2002 (Kalavakonda and Mahul, 2005).

This low participation rate likely in part reflects shortcomings in the design and marketing of NAIS insurance contracts. First, NAIS appplies a uniform premium rate throughout India for each crop type, rather than a premium based on the actuarial expected payout in the local geographic area. This mispricing induces adverse selection; farmers in high-risk areas enjoy a larger subsidy than those in low risk areas, and are more likely to participate. Second, Kalavakonda and Mahul (2005) suggest that knowledge of the scheme is relatively limited amongst bankers and

[2] NAIS was introduced in 2000, replacing the Comprehensive Crop Insurance Scheme (CCIS), which covered only farmers borrowing from formal financial institutions. The CCIS also generally operated at a substantial loss. Over the period 1985-2001, the two schemes combined paid out claims in excess of premia collected in all but three years (1988, 1994 and 2000).

district administration officials, and that purchasing and claiming insurance involves sometimes burdensome administrative costs. Third, not all crops are covered by the scheme (for example, tea, coffee, rubber and sugarcane are excluded). Fourth, in some areas, the designated geographic unit is relatively large, generating excessive basis risk between the farmer's yield and the yield on the crop cutting experiments. Fifth, claims can take a substantial period of time to be settled. Table 3 of Kalavakonda and Mahul (2005) shows that insurance claims are on average made available to households around 12 months after the end of the growing season. Given the credit constraints and high discount rates of households in developing countries, this delay is likely to be a significant disincentive to participate in the insurance program. Unfortunately, little systematic evidence exists to disentangle the relative importance of these and other explanations for the low NAIS partipation rate.

Partially in response to the design problems outlined above, a number of private institutions have begun to offer alternatives to the NAIS crop insurance program. Several of these, including the product considered in this paper, provide a payoff based on rainfall at local rain gauges. Rainfall insurance presents several advantages relative to area-level crop insurance:

1. Cost. Rainfall data is already collected at a disaggregated level for other purposes by the Indian Meterological Department (IMD), and readily available at little or no cost. In contrast, area-yield index insurance requires a large sample of crop-yield measurements, involving significant fixed costs. (These fixed costs are likely to be prohibitive for private insurers seeking to develop alternative products to NAIS).

2. Availability of Historical Data. Reliable daily rainfall data is available at the mandal level over a historical period of several decades. By modelling this data, it is possible to generate a relatively accurate estimate of the actuarial value of a wide variety of potential insurance contracts.

3. Objectivity of index construction. Maintaining a standardized methodology for measuring crop yields is not trivial, since yields depend on the seed type used, amount of fertilizer and other inputs applied to the crop and other factors. This subjectivity also introduces the potential for manipulation of the index. In contrast, the methodology for the measurement of rainfall is relatively well-agreed upon.

4. Timely calculation and payment of returns. Since rainfall data becomes available on an almost real-time basis, in principle it is possible to calculate payouts and pay policyholders in a timely fashion. This feature is potentially attractive to households; for example in situations where initial monsoon rains are followed by an extended dry period, necessitating a replanting of crops.

The primary disadvantage of index-based rainfall insurance is basis risk; that is, rainfall is imperfectly correlated with household income and consumption. Basis risk arises from several sources: (i) the relationship between measured rainfall and crop yields varys with soil type, slope of the plot, temperature and other factors (eg. rainfall at night is more likely to soak into the soil rather than evaporating); (ii) Rainfall measured at the local weather station is not perfectly correlated with rainfall at an individual plot; (iii) Crop yields at the plot level are affected by non-weather factors like pests and disease that are not closely correlated with rainfall.

Area-yield insurance also involves basis risk; yields at the plots where crop-cutting measurements are taken will deviate from yields and earned income on other nearby plots, due to idiosyncratic differences in agricultural practices, soil, rainfall, the impact of disease and so on. However, the basis risk is likely to be less than for rainfall insurance, since it is directly an index of crop yields, and thus sidesteps the imperfect correlation between rainfall and average yields.

In summary, rainfall insurance has both advantages and disadvantages relative to area-yield insurance, and an optimal insurance arrangement would likely depend on both types of indices. Despite caveats associated with basis risk, deficient rainfall clearly represents a key risk faced by rural Indian households. Table 1 presents self-reported rankings (taken from our survey data) of the importance of various different types of risk faced by households. An overwhelming proportion of households (88 per cent) cite drought as the most important risk they face. Crop failure and crop disease are generally cited as the second and third most important types of risk. In contrast, other types of risk, such as the death of a household member or livestock, shocks to commodity prices, fires and flood, are cited either relatively or very infrequently. Consistent with these self-reports, World Bank (2005) estimates that a severe drought in Ananthapur and Mahbubnagar, the districts studied in our empirical work, would reduce average rice yields by 45% and 26% respectively, a potentially devestating loss of income for a household living near subsistence level.

[INSERT TABLE 1 HERE]

3. 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 ICICI Lombard (the insurance division of ICICI, a large Indian financial services corporation), with technical assistance provided by the Commodity Risk Management Group of the World Bank. ICICI Lombard then partners with local financial institutions who markets and sells the product to farmers. In the districts where the product was first piloted in 2003, and where our survey villages are located, this role is performed by BASIX, a microfinance institution.

This section documents the design, marketing and institutional context of the rainfall insurance sold in the Mahaboobnagar and Anantapur districts of Andhra Pradesh since 2003. We focus on a discussion of contract design in 2004, the year of our survey evidence, although in Section 3.4 we also discuss changes in the contract design for policies sold in 2005 and 2006. Our discussion draws in part on Lilleor, Giné, Townsend and Vickery (2005) and World Bank (2005).

3.1 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 other food crops, such as pulses, but they are also more sensitive to drought. In addition, since the seeds are relatively expensive, some farmers purchase them using crop loans, but when harvest fails these loans are often difficult to repay (Hess, 2002).

The coverage for both castor and groundnut policies is the Kharif (monsoon season), which is the prime cropping season, running from June to September. The contract divides the Kharif into three phases, sowing, podding/flowering and harvest, and pays out if rainfall levels fall below particular threshold or 'trigger' values during each phase. An upper and lower threshold is specified for each of the three phases. If accumulated rainfall exceeds the upper threshold, the policy pays zero for that phase. Otherwise, the policy pays a fixed amount for each mm of rainfall below the threshold, until the lower threshold is reached. If rainfall falls below the lower threshold, the policy pays a fixed, higher payout. The total payout for the Kharif is then simply the sum of payouts across the three phases. In other words, the total payout p_t is given by:

$$p_t = \sum_{i=1}^{3} \left(I\left[r_i^{**} < r_{it} < r_i^{*} \right] (r_i^{*} - r_{it})\, p_i^{*} + I\left[r_{it} < r_i^{**} \right] p_i^{**} \right) \qquad [1]$$

where I is an indicator function equal to 1 if rainfall falls in the range specified and 0 otherwise, r_{it} is the actual accumulated rainfall in phase *i* of year *t*, the upper and lower trigger levels for each phase are given by r_i^{*} and r_i^{**} respectively, the payout per mm of deficient accumulated rainfall is given by p_i^{*}, and the maximum lump sum payout for each phase is given by p_i^{**}. Since excess rains at the end of the Kharif can seriously damage the harvest, the policy also includes an additional payout if rainfall exceeds a daily threshold for several consecutive days.

The timing of the phases, thresholds and other parameters of the model were determined using the PNUTGRO crop model (Gadgil, Rao and Rao, 2002) and interactions with individual farmers. The upper threshold r_i^{*} corresponds to the crop's water requirement or the average accumulated rainfall of the mandal (whichever is lowest), while the second trigger r_i^{**} is intended to equal the water requirement necessary to avoid complete harvest failure. Translated into financial market terminology, the relationship between rainfall and payoffs resembles a 'collar' option for each phase.

The policy premium was calculated based on projected payouts using historical rainfall data (at least 25 years of data for each rain gauge was used). The premium was initially calculated to be equal to the sum of the expected payout, 25 percent of its standard deviation and 1 percent of the maximum sum insured in a year. To this was added a 25 per cent administrative charge paid to ICICI Lombard, as well as a 10.2 per cent 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 and an average yearly income of Rs 15-30,000. However, sales were not limited to this group, and any household in the targeted villages was eligible to purchase the insurance product.

3.2 An Example

As an example of an actual insurance contract, Table 1 presents contract details and actual payouts for the castor insurance policy sold in the Mahaboobnagar district in 2004. The Mahaboobnagar district includes three mandals (counties) with a reference weather station, Atmakur, Mahaboobnagar and Narayanpet. There is only a single weather station in each mandal, so policies in a given mandal are linked to same rainfall measurement.

[INSERT TABLE 2 HERE]

In Narayanpet, the per-policy premium for a castor insurance policy covering all three phases of the monsoon was Rs 200. One policy is considered to be equivalent of one acre of coverage. In 2004, the start date for the monsoon was set at a fixed calendar date, June 10, and the first phase is 35 days in length. Narayanpet received 12 mm of rain in the first phase; 84 mm of rain in the second phase and 177 mm 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 level 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 (Rs 240 = [100 mm - 84 mm] * Rs15). Rainfall exceeded the upper threshold value in the third phase. Thus, insured households in Narayanpet received total payout of Rs 1740 per acre. Insured households in Mahaboobnagar received only Rs 350, since rains were better throughout most of the Kharif. Payouts for excess rainfall were Rs 1500, Rs 3000 or Rs 6000 for 4, 6 or 7 consecutive days of more than 10 mm of rain per day, respectively. This resulted in an additional payout of 1500 per acre in Atmakur, which experienced 4 consecutive days of heavy rain.

3.3 *Distribution and Marketing*

The microfinance institution BASIX was chosen by ICICI Lombard to market and distribute the rainfall insurance product to farmers.[3] BASIX has extensive local distribution networks, since it also provides microfinance loans to households in villages where the insurance product is marketed. Moreover, since defaults on micro-credit loans in rural areas tend to be associated with deficient rainfall, BASIX has clear incentives to market and disperse rainfall insurance, in particular to their own clients.

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 to offer and market the insurance in a given village in 2004: (i) the presence of BASIX customers in the village to ensure some degree of trust in the institution; (ii) preferably 200-300 of acres of groundnut and/or castor in the village to ensure that there is a market for the weather insurance; (iii) a reasonable number of small and medium size farms with 2-10 acres of land; and (iv) the village is within 20 km of the nearest rainfall reference station, to minimize basis risk. BASIX constructed a list of eligible villages based on these four criteria. However, due to late finalization of the insurance contract design, time constraints prevented BASIX from marketing to all eligible villages (BASIX had only 10 days to market and sell the insurance product before the start of the coverage period).

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[3] BASIX was among the first microfinance providers in India, established in 1996. It now works with over 190,000 poor households in 44 districts and 8 states of India and is growing rapidly. See www.basixindia.com for more details.

BASIX's strategy in marketed villages was to first explain the insurance product to a trusted opinion leader or progressive farmer. This opinion leader would then function as the motivator in the village and inform his fellow villagers about the product and an upcoming marketing meeting to be held a few days later. A general introduction to the insurance product was provided at the marketing meeting. Attendees who indicated their interest in the product would then be visited by BASIX representatives in their home; policies were sold during these home visits. Apart from the initial visit to the chosen motivator, BASIX agents would generally spend one day in each village for marketing and sales.

Based on conversations with BASIX representatives, differences in insurance take-up rates across pilot villages are associated with the choice of the motivator, his understanding of the insurance product, his respect in the village and own interest in the insurance, the extent of BASIX's market presence in the village, the number of rainy spells prior to and on the day of marketing (it being hard to sell a weather insurance against lack of rain on a rainy day), and the liquid assets amongst farmers on the day of marketing. According to BASIX, this varied substantially across households; some 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.

3.4 Evolution of contract design and marketing between 2004 and 2006

Based on feedback from farmers and BASIX field agents, the rainfall insurance contract design has been refined in several respects since 2004. First, separate policies for castor and groundnut were combined into a single policy covering each rain gauge. This decision was made partially to simplify marketing of the product, partially to make the policy seem more appealing to farmers growing other crops, and partially to reflect a judgement that deficient rainfall has similar enough effects on castor and groundnut that separate policies are unnecessary.

Other aspects of the product design have remained relatively stable up to 2006. The insurance product still divides the Kharif into three phases representing planting, growing and harvesting; in 2006 these phases were respectively 35, 35 and 40 days in duration. The first phase is triggered by the beginning of the monsoon rains; specifically, by the recording of at least 50mm of rain in the month of June, considered to be the first month of the monsoon.

3.5 Aggregate insurance participation statistics

In 2003, the weather insurance was sold to 148 farmers in two villages, mostly to members of borewell users associations. In 2004, the product design was improved, the marketing was intensified and expanded to new areas. In the 2004 Kharif, insurance was sold to 315 farmers across 43 villages.[4] 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). Summary statistics for insurance takeup in 2003 and 2004 are presented in Table 3 below.

[INSERT TABLE 3 HERE]

4. 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 a given insurance contract will be (i) increasing in the household's risk aversion, (ii) increasing in the expected payout on the insurance, (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.

[4] According to the 1991 IndiaStat census, villages in Mahaboobnagar district consist on average of 230 farming households out of 320 households. Anantapur villages district consist on average of 350 farming households out of 540 households. Thus, overall takeup rates as still low as a proportion of the total population.

To fix ideas, in Appendix A 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 for insurance 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, a substantial fraction of US housholds 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 somewhat 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 prediction of the separating equilibrium in Rothschild and Stiglitz (1976).

Models of adverse selection and moral hazard have 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 are able to influence the measurement of rainfall at the gauge (eg. through tampering). We have no evidence to believe that this is a problem in practice.

Mulligan and Philipson (2003) present a variation on the benchmark symmetric information model discussed above by introducing fixed participation costs. They argue that this model better explains empirical patterns in insurance takeup; for example their model predicts that wealthier households are more likely to participate in insurance markets, since they are likely to purchase enough insurance to offset the fixed participation cost. This prediction of a positive correlation between wealth and participation is consistent with evidence in Cawley and Philippon (1999) from the life insurance and annuities markets, and Brown, Wyn and Levan (1997) from the health insurance market.

However, it is not obvious that any significant fixed costs apply in our setting. The loading for administration costs is simply proportional to the amount insured (a 25 per cent loading for each contract purchased), and there is no discount for purchasing multiple policies. It is possible there may be other, non-monetary fixed costs though, for example the time cost of attending the marketing meeting to learn about the insurance product, or psychic costs associated with understanding the product, and weighing whether it is a desirable product. We also consider credit constraints to be an alternative explanation for a positive correlation between wealth and insurance participation, a point discussed in more detail below.

4.1 Predictions

Bearing this literature and our benchmark model in mind, below we discuss several key hypotheses that we take to the data in Section 5.

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

This first hypothesis is simply that insurance participation decisions are consistent with the benchmark model described above. That is, participation is increasing in risk aversion and the size of the risk to be insured, and decreasing in basis risk.

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

Historical rainfall patterns are publicly observable, which suggests households with rational expectations should share common expectations about the distribution of payouts on the insurance. However, to the extent that households do in fact have irreducible differences in beliefs, households who expect lower rainfall levels during the Kharif would view the insurance contract as having a higher expected return, and should be more likely to participate. In other words, the expected payoff of the insurance should be taken with respect to the household's subjective probability distribution of returns on the insurance product.

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).*

The existing literature on insurance participation places relatively little emphasis on credit constraints. However, in our setting, financial constraints may play a key role in determining insurance participation. Poor households in our sample live near to subsistence levels of income, and at the beginning of the monsoon season 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 for these households may be extremely high, because the alternative use of funds (ie. investment in sowing) yields such a high rate of return.

We illustrate this effect directly through a simple extension of the benchmark model presented in Appendix A. Our model considers a household with CARA utility, so in the baseline case without borrowing constraints, risk aversion and willingness-to-pay for insurance are independent of household wealth. However, in our extension, we assume the household has limited funds, which can either be used to purchase insurance or invest in sowing (eg. seeds, fertilizer etc.). Under this extension, willingness to pay for insurance is unambiguously lower in the region where credit constraints bind, and furthermore, within that region, willingness-to-pay is uniformly increasing in wealth. This result reflects a simple intuition: if the household has few assets, the shadow value of wealth is very high, reflecting the high marginal product of the alternative use of those funds, investment in sowing. In this environment, allocating scarce funds to to insurance premia may be unattractive, even if the household is risk averse.

Hypothesis 4: Networks, trust and 'early adoption'.

The empirical setting we study also relates closely to the literature on technology adoption (Grilliches, 1957, Caswell and Zilberman, 1985). We study a new financial innovation; the households we study have been offered the opportunity to purchase rainfall insurance at most only once before, in 2003. It is likely that households are operating in an environment of incomplete information with respect to the insurance product. For example, even with the aid of the contract term sheet, they may have only a partial understanding of historical rainfall patterns, and thus not be able to accurately estimate the actuarial value of the contract. Alternatively, the household may be uncertain about the probability with which the insurance provider can be trusted, or the timing of payouts. These concerns are likely to be heightened due to the short or non-existent history of the product in our survey villages.

We do not formally extend our theoretical framework to model the incentives associated with early adoption. However, empirically we consider two hypotheses relating to factors we believe may influence takeup of a new product. These are:

(i) Trust in Insurance Provider: In an environment where a new product not well understood, it seems likely that households will draw inferences based on their previous experience with the product supplier, in this case the microfinance company BASIX. Closely related, households are likely to rely on information gleaned from social networks (ie. whether households who purchase insurance interact closely with other participating households).

(ii) Costs of early adoption: Conditional on their degree of trust in the insurance provider, variation in the household's ability to understand the product, and willingness to experiment with it, are likely to shape insurance participation decisions, especially in the case of a new product. We study whether members of the Gram Panchayat (local council), and 'progressive households', households who self-identify as being viewed as village leaders by other households, participate to a differential extent in the insurance product. The age and education of the household head are also likely to influence a household's ability to comprehend the insurance product.

5. The Survey

A household survey was conducted in Andhra Pradesh after the end of the 2004 Kharif to provide information household's experience with BASIX 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 sampling frame for the survey is a census of landowner households across 37 villages in the Mahboobnagar and Ananthapur districts of Andhra Pradesh. We survey all villages where at least five households purchase BASIX rainfall insurance for the 2004 Kharif; this screen accounts for the selection of 25 of the 37 villages. The other 12 villages are ‘control’ villages, namely, villages identified by BASIX as being suitable for insurance marketing, but where no insurance policies were marketed or sold in 2004 due to time constraints. Since there is no participation in the control villages and we include village dummy variables in our analysis, the empirical analysis in this paper is based only on data from households in the 25 treatment villages.

Across all 37 villages, the total sample size is 1052 households, including 752 households from marketed villages and 300 households from non-marketed ‘control’ villages. In non-marketed villages, we survey households at random from a village census of landowners. In treatment villages, we stratify our sample to survey as many active participants in the insurance program as possible. We then sample randomly from each strata, again based on a village census of landowners. Data on the stratification methodology for marketed villages is presented in Table 4 below.

[INSERT TABLE 4 HERE]

The three strata used are (i) household purchased insurance (267 households), (ii) household member attended the insurance marketing meeting but did not purchase insurance (233 households) and (iii) household did not attend the marketing meeting (252 households). The sample of 267 purchasers represents a large fraction of the total of 315 households from Table 3 that purchased BASIX rainfall insurance in 2004.[5]

Weighted statistics in Table 4 reflect the size of the underlying population from which the sample is drawn, based on the landowner census and BASIX administrative records on which households attended marketing meetings or purchased insurance. The treatment villages in total

[5] The difference reflects purchasers in villages where fewer than five households purchased insurance.

represent a population of 5805 households across 25 treatment villages. 600 households in these villages attended the marketing meeting; 500 of these attending households were surveyed.

The lower half of the table presents weighted and unweighted sample sizes for households where there are no missing values for any of the right-hand-side variables used for the baseline regressions in Section 6. This is the case for 97 per cent (727 out of 752) of surveyed households in the 25 marketed villages. For the other 3 per cent of households, we impute missing values iteratively as a linear function of variables without missing values.[6]

Note that we use 'purchased insurance' as the dependent variable in most of our 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 from Table 4 to recover consistent estimates of the slope coefficients. (If instead stratification was based on right-hand-side variables, either weighted or unweighted regressions would provide consistent estimates of model parameters).

5.1 Summary statistics and variable construction

Summary statistics for the dataset are presented in Table 5 below. All statistics in the table are weighted by our sampling weights to reflect population values. Thus, the full sample averages are generally close to the non-buyer averages, since overall insurance takeup rates are low; 4.6% of households in marketed villages purchased insurance, 267 out of a population of 5805 landowner households.

Basic demographic and wealth data confirms that our sample consists of poor and middle-income smallholder farmers. Median landholdings are 4 acres (mean landholdings are 5.8 acres). Household heads have an average of 3.3 years of formal education, although the median household head has no formal education. 97 per cent of household heads have spent their entire life in their home village. Median and mean household liquid assets at the beginning of the Kharif are Rs 8,300

[6] No single variable is missing for more than 1.2 per cent of marketed households. Our regression results are almost unchanged if we restrict our sample to households without missing data, rather than impute missing values.

(approximately US$200) and Rs 14,100 (approximately US$300); this is the sum of cash, bank account deposits, jewelry, silver, gold, self-help-group revolving funds and miscellaneous liquid assets. Median and mean self-reported total wealth, the sum of liquid assets, livestock, the self-reported value of the households' land and its primary dwelling, are Rs 77,400 and Rs 113,200 respectively.

There are significant differences between the demographic characteristics of insurance buyers and non-buyers. Buyers are around one-third wealthier, report around 50 per cent more land, and nearly twice as much in liquid assets. Buyers are also less risk averse than the overall sample. Around a third of insurance purchasers belong to borewell user associations (BUAs), compared to only a small fraction (4 per cent) of the overall population. 46 per cent of buyers had outstanding credit from BASIX at the start of the Kharif, compared to 7 per cent of the overall population. Buyers are twice as likely to be members of the area Gran Panchayat (local council) and are also more likely to self-identify as 'progressive' households.

Summary statistics in Table 5 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' measures the proportionate amount that a household head would 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. We ask households to assess the probabilities 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 summarized presented in

Table 5 is the area under this probability 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 expected start to the monsoon).

Finally, the variable 'credit constraints' is a covariate intended to proxy for whether the household was credit constrained around the time that the insurance participation decision was made. The household was asked whether it asked for some form of credit during the monsoon season. We construct a dummy variable which we set equal to 1 if the household applied for credit but was denied, or the household cited supply-side reasons, specifically 'no creditworthiness' or 'no access to lender' as their primary explanation for not applying for credit.

6. Insurance Participation: Empirical Results

6.1 Self-reported explanations for insurance takeup decisions

Households in our sample who attended a village insurance market meeting were asked to provide up to three reasons for their decision to purchase or not purchase BASIX rainfall insurance after the meeting. These responses were then classified into categories by the ICRISAT interviewer. Frequencies of each classified response are presented in Table 6. The table presents frequencies for the most important, second most important and third most important reasons cited by households; the final column weights these three responses (giving most weight to the most important reason cited by households).[7]

[INSERT TABLE 6 HERE]

Amongst purchasers, households' self-reported explanations emphasize the risk-reduction benefits of insurance. 'Security/risk reduction' was the most popular response provided, while the second most cited category is 'household needs harvest income'. 65 per cent of households cited one of these two explanations as their most important reason for purchasing the insurance.

[7] Not all households answered these questions, which explains why the sample sizes are slightly smaller than the corresponding samples from Table 4.

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 per cent of the weighted responses. 12.5 per cent of responses cited either the high expected payout or low premium of the insurance. A small fraction of households (5.7 per cent) purchased the insurance because of reasons related to ‘luck’.

Strikingly, the most frequently cited reason amongst non-purchasers is that the consumer did not understand the insurance product; this explanation represents 25% of weighted responses. 21% of responses stated that the household did not have sufficient cash or credit to pay the premium, consistent with the hypothesis that credit constraints explain part of insurance participation. 24% of responses cited 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 indicated a view that the actuarial value of insurance was low relative to premiums: ie. either that the insurance was too expensive (14.1% of responses), or that payouts are too small (2.5% of responses). Only a small percentage of household responses (2.5%) stated that the household had no need for the insurance against rainfall risk. Reasons associated with ‘do not trust BASIX’, ‘other’, ‘dislike insurance’, ‘purchased in 2003 by not satisfied/no payout’ and ‘cloud seeding promised by government’ were also cited by small numbers of households.

Many of these qualitative responses match well with the simple ‘benchmark’ model of insurance participation under symmetric information. Namely, the degree of risk-reduction, the payout relative to the premium, and the degree of basis risk are all important factors considered by households when deciding whether to purchase the insurance.

Two types of responses however are inconsistent with the benchmark model. Firstly, the results suggest a significant proportion of households who purchased the insurance did so on the advice of other farmers or village leaders they trusted; conversely 25 per cent of explanations for non-purchase cited a lack of understanding of the product. These results are not consistent with a perfect-information, perfect-cognition benchmark; instead they suggest a Bayesian process of learning about the product.

Secondly, a significant proportion of households cite a lack of liquid funds or credit to pay for the premium, suggestive of the potential role of credit constraints in insurance purchase decisions. This is inconsistent with the benchmark model, but consistent with a benchmark model with borrowing constraints (as shown in Appendix A).

6.2 Insurance participation 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 for the 2004 Kharif, and 0 otherwise. We estimate two specifications, one includes a larger number of variables, while the other is more parsimonious (we exclude several statistically insignificant variables from the first specification).

Results are presented in Table 7. Estimates are classified to indicate our interpretation of their relationship to the hypotheses proposed in Section 3. To reiterate, we test reduced-form implications of a standard 'benchmark' model of insurance participation under symmetric information, and then consider variations on the benchmark model introducing credit constraints heterogeneous beliefs, and so on.

The first two columns of results normalize 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 columns 3 and 4, we present the same results after dividing the coefficients by the population mean insurance 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 (eg. a coefficient of 1 indicates that a one unit shock to the explanatory variable doubles the probability of insurance participation for a household whose initial participation probability equals 4.6%, the population average).

[INSERT TABLE 7 HERE]

I. Benchmark model. A first prediction of the benchmark model is that insurance participation is decreasing in basis risk between insurance payouts and household income, and increasing in the size of the risk to be insured. Coefficients in Table 7 under the 'basis risk' subheading appear generally consistent with this prediction. Firstly, we include two variables that measure the proportion of the household's cultivated land used for castor and groundnut in the previous harvest (the 2003 Kharif). Since these are the two crops against which insurance policies are written, the basis risk from using the insurance to hedge against rainfall risk is presumably smaller when these crops predominate, assuming the crop model is correctly specified. This is consistent with the empirical results. Both 'percentage of groundnut' and 'percentage castor' are positively signed, and statistically significant at the 1 per cent level, showing that takeup is higher amongst households who in the past have grown a higher share of these crops. The coefficients in columns 3 and 4 show that for a household who starts at the population takeup probability of 0.046, moving from growing no groundnut to all groundnut approximately doubles the probability of purchasing insurance. The corresponding change for castor is 46 per cent.

We find that households with a high percentage of land under irrigation are marginally more likely to purchase insurance (statistically significant at the 10 per cent level in the parsimonious model). Households with more irrigated land are less sensitive to rainfall shocks, so if this variable is viewed as a proxy for the size of the risk to be insured, this coefficient has the opposite sign to that predicted by the benchmark model of insurance. However, it is also possible that this variable is in fact proxying for household wealth, since irrigated land is significantly more valuable than non-irrigated land. Interpreted in this way, the finding appears consistent with other results for estimates of household wealth discussed below. Finally, the household is asked if they use accumulated rainfall as the primary indicator of whether to sow, rather than soil moisture, weather forecasts or other factors. Only a small proportion of households (7.5 per cent) answered yes to this question, and this variable is not statistically significant in the participation regression.

The second prediction of the benchmark model is that risk-averse households have a higher willingness-to-pay for insurance. In fact we find the opposite; risk-averse households are less, not more likely to purchase rainfall insurance, significant at the 5% level in both specifications. Quantitatively, shifting the risk aversion parameter from its minimum to maximum value (ie. 0 to 1) reduces the probability of purchase by 22 per cent (1.0 percentage points) in the baseline model, and 24 per cent (1.1 percentage points) in the parsimonious specification. Potential explanations for this seemingly perverse result are discussed in more detail in Sections 6.3 and 6.4.

The survey also includes data on two other aspects of the household's utility function: ambiguity aversion and patience. Although both variables are 'correctly' signed (ie. ambiguity-averse households and households with a high discount rate are less likely to purchase insurance), neither variable is statistically significant.

II. Credit constraints and wealth. In Appendix A we show that binding borrowing constraints, equivalent in our example to low household wealth, imply a higher shadow value of wealth and a lower willingness-to-pay for insurance. As a first test of this hypothesis, the baseline regression includes two wealth variables, log(landholdings) and log(non-land wealth), both measured at the beginning of the Kharif. Although neither wealth measure is individually significant (the two measures are strongly collinear), they are jointly significant ($p<0.01$). Given the collinearity between the two measures, the parsimonious specification excludes log(wealth). In this specification, log(1+landholdings) becomes statistically significant at the 1 per cent level. Quantitatively, a doubling of land holdings increases the probability of insurance purchase by 26 per cent (or 1.2 percentage points). As previously discussed, conditional on total landholdings households with a higher percentage of irrigated land are also marginally more likely to purchase insurance, also consistent with a positive correlation between wealth and takeup.

Our covariates also include a direct proxy for credit rationing. This variable is equal to one if either the household was refused credit at least once during the Kharif, or did not apply for credit because it expected to be refused or had no access to financial institutions (see the section on

Summary Statistics for more information). This coefficient is negatively signed as predicted; it is statistically significant at the 10 per cent level in the baseline model, and at the 10.1 per cent level in the parsimonious specification. Quantitatively, switching on this dummy variable reduces the probability of insurance purchase by 13 per cent (or 0.6 percentage points).

III. Heterogeneous beliefs. We next estimate whether a proxy for heterogeneous beliefs about the payout on insurance influence participation decisions. We include a variable that measures the household's pessimism regarding the expected start date of the monsoon (see the discussion of summary statistics for information about the construction of this variable). Our prediction is that households who expect the monsoon to start later will expect a higher return on the insurance, because the product payout is inversely correlated with rainfall, and be more likely to take up the product. This measure of pessimism is positively correlated with insurance takeup, although not statistically significant.

IV. Familiarity with insurance vendor, and 'early adoption'. The qualitative responses presented in Section 6.1 suggest that some or all households do not fully understand the insurance product, and that many relied on recommendations from other farmers or village leaders for insurance participation decisions. Here we test two hypotheses discussed out earlier about household behaviour in this kind of 'incomplete information' environment. The first hypothesis is that households with a greater degree of familiarity and 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 sold by BASIX representatives to BUA members. BUA members are more likely to have previous experience with BASIX and a BUA also provides a close-knit network of households who share information and advice.

Household membership in a BUA has a very large and statistically significant effect on participation decisions; our marginal effects estimates suggests it increase the probability of insurance participation by a factor of 13-14 times, statistically significant at the 1 per cent level. A second variable measuring familiarity with BASIX also has an important effect on participation decisions, namely whether the household was an existing BASIX borrower at the beginning of the Kharif. Existing BASIX customers are 3.1-3.6 times more likely to purchase insurance than non-customers, also statistically significant at the 1 per cent level.

Households who attended an insurance marketing meeting were also asked to anwer yes/no to an additional question, simply: ‘do you trust the insurance provider, BASIX?’. Since this question was not asked of all households, it is not included in the specification here; however results from Table 9, where we estimate a model only on the subsample of meeting attendees, show that households who self report trust in BASIX are also more likely to purchase insurance, even conditional on BUA membership and the ‘credit from BASIX’ dummy (see Section 6.4 for more details).

Together, these three covariates imply that, even though insurance is available in principle to all households in the village, the household’s familiarity and trust in the insurance provider constitute the most important determinant of households purchase decisions. In later analysis, we show that these variables increase both the probability the household will attend an insurance marketing meeting, and the probability of insurance purchase conditional on meeting attendance.

Relating to the second ‘early adoption’ hypothesis, we include three variables to test the hypothesis that participation rates depend on costs of understanding and weighing the risks associated with the new product. The first is a dummy equal to 1 if the household reports itself to be ‘progressive’, that is, a household that other villagers approach for advice. The second is a dummy for whether the household head has ever been a member of the village Gran Panchayat (town council). Both these covariates predict higher insurance participation rates, and are statistically significant at at least the 5 per cent level. The third covariate is the education of the household head in years. This variable is positively signed, although not statistically significant. Also included here is the age of the household head, our informal hypothesis being that the costs of understanding the new product may, other things being equal, be lower for younger individuals. Our empirical estimate suggests that a doubling of household age reduces the probability of insurance participation by 30-37% (1.4-1.7 percentage points), significant at the 10 per cent level in the baseline model and the 5 per cent level in the parsimonious specification.

V. Other covariates. The probit model in Table 7 also includes a set of household demographic characteristics: log household size, gender of the household head, and a dummy for whether the household head had spent their entire life in the village. None of these variables are statistically significant. The probit regression also includes a dummy variable for each treatment village (coefficients not reported in the table).

6.3 Risk-aversion interaction effects

An apparently puzzling finding from Table 7 is that risk-averse household are less, rather than more, likely to purchase rainfall insurance, opposite to the predicton of the benchmark model. One potential explanation for this result is that measured risk aversion is in fact another proxy for wealth and/or the extent of credit constraints. A second possible explanation is low takeup amongst risk-averse households reflects their aversion to uncertainty about the insurance product itself, and the potential risks associated with it.

To test this second hypothesis, we interact risk aversion with three variables that indicate the household's familarity either with BASIX or with the concept of insurance: namely dummy variables for (i) whether the household is a BUA member, (ii) whether the household has outstanding credit from BASIX at the beginning of the Kharif and (iii) whether the household holds any other type of insurance. Under the 'product uncertainty' hypothesis, our risk aversion result will be stronger amongst households which report less familiarity with insurance and the insurance provider along these three dimensions. We re-estimate the two specifications from Table 7 including these additional interaction terms, and present the results in Table 8.

[INSERT TABLE 8 HERE]

The results provide some support for the ‘product uncertainty’ hypothesis. Each of the interaction terms is positively signed as predicted, and they are jointly significant at the 10 per cent level. The interaction term: ‘Risk Aversion x Credit From Basix’ is individually significant at the 5 per cent level when included on its own (Column 3), and at the 10 per cent level when all three interaction terms are included (Column 1). The point estimates imply that for a household where each of the interaction terms is turned on, the point estimate on risk aversion actually switches to the ‘correct’ sign, although the net coefficient is not statistically different to zero.

Our tentative conclusion is that the negative correlation between risk aversion and insurance takeup and risk aversion is strongest amongst households who are most uncertain about the insurance product intself. This appears consistent with qualitative evidence that a significant fraction of households who attended the marketing meeting cited ‘lack of understanding’ as their primary reason for not participating in the product.

6.4 Conditional probit results

In 2004, BASIX follows a two-step procedure in selling 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.[8]

In Table 9 we present estimates using a conditional probit approach that reflects these 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 attended the marketing meeting, and 0 otherwise. The second equation is estimated only on the subsample of households who attended the marketing meeting, and has a dependent variable equal to one if the household purchases insurance; that is, it studies participation conditional on attendance. (To be clear, we do not have an instrument for meeting attendance. These second step

[8] In around one-third of cases the household purchased the insurance policy at the marketing meeting itself. In two-thirds of cases, the household expressed interest at the meeting, and was then visited by a BASIX representative in their home, at which time the insurance policy was bought and paid for.

results are simply conditional estimates, they should not be interpreted as being representative of the effects of exogenous meeting attendance on takeup). Results are presented in Table 9.

[INSERT TABLE 9 HERE]

Many of our main findings hold in a similar way across both steps of the insurance participation decision. Most notably, BUA members and BASIX borrowers are both more likely to attend the marketing meeting as well as more likely to purchase insurance conditional on attendance. Thus demonstrates the high rates of participation amongst these groups do not just reflect encouragement by BASIX for these groups to attend the meeting, since this mechanism alone would generate selection bias to produce negative coefficients on these variables in the second step.

Consistent with these results, households who had attended an insurance marketing meeting are also asked the yes/no question: ‘do you trust the insurance provider, BASIX?’. This variable is included in amongst the second step coefficients in Table 9. The coefficient is positive and statistically significant at the 5 per cent level. A positive response to this question increases the probability of insurance purchase by 0.25 (compared to an average second step participation probability of 0.58); of the same sign and similar magnitude to the coefficient on ‘BASIX borrower’. An important caveat, however, is that we ask this question of the household at the time of survey (ie. namely, after they have made the insurance purchase decision and potentially received a payout). Thus, reverse causality is a potential concern; households who purchase insurance and receive a payout may grow to trust BASIX more than an otherwise identical household which does not purchase insurance.

Finally, we also note some interesting differences across the two steps. Male household heads are marginally more likely to attend a marketing meeting, however they are significantly less likely to purchase insurance conditional on attendance. Younger and more educated household heads are also more likely to purchase insurance conditional on attendance, although they are not more likely to attend. Risk aversion is negatively correlated with both meeting attendance and conditional purchase of insurance, however the coefficient on risk aversion is marginally statistically significant only in the first stage. Given that there is selection bias into meeting attendance, these differences should not be interepreted too literally, however.

6.5 Estimates on non-BUA sample

The large coefficient on 'BUA member' raises potential concerns that the strength of other relationships in the data may differ significantly between BUA and non-BUA members. To confirm that BUA members do not drive the patterns in participation identified above, we re-estimate the two specifications on the subset of households who are not BUA members. Results from this robustness check are presented in Table 10.

[INSERT TABLE 10 HERE]

The results reveal no large differences in coefficient estimate compared to the full-sample regressions presented in Table 7. As before, risk aversion is negatively correlated with insurance participation, and a higher share of castor and groundnut predicts a higher probability of insurance takeup (the coefficient on castor is no longer statistically significant, however). As before, BASIX customers are significantly more likely to purchase insurance after controlling for other household characteristics.

6.6 Effects on household behavior

In a more general setting than our simple theoretical model, introducing a new market for insuring risk to a household's decision problem will influence other aspects of household decisionmaking, such as savings and portfolio choice (eg. Angeletos and Calvet, 2002; Ayigari 1994). This is essentially the case made in Morduch (1996), that in the face of risk, households in developing countries engage in income-smoothing strategies which reduce income volatility at the expense of lower expected income. Conversely, introducing a market to smooth risk may allow households to invest more in high-yield agricultural strategies, aware that the purchase of insurance reduces the household's exposure to downside risk.

We do not test this hypothesis in any detail in this paper, leaving it to future research. However, one question in the household survey asks households who purchased insurance to qualitatively state whether purchasing insurance influenced behavior along several dimensions such as labor supply, and the amount of fertilizer and seeds purchased for the Kharif. Households by a large margin reported that they did not change their behavior in response to purchasing the insurance; only 6 of 267 households who purchased insurance reported any change in decisionmaking. It is unclear whether this reflects that the size of the insurance policy, or that households are purchasing insurance for the first time. However, we view this evidence as being extremely preliminary; we expect our future research to provide much more powerful test of the link between insurance participation and household ‘income smoothing’ decisions.

6.7 Summary and discussion of results

The empirical work in this section presents cross-sectional patterns in insurance participation decisions for low and middle-income households in rural India. In some respects, our results are consistent with a simple ‘textbook’ model of insurance participation under symmetric information: namely, participation is decreasing in proxies for basis risk between insurance payouts and farm income. However, at least three salient features of our results are not obviously consistent with the benchmark model: (1) participation is lower for less wealthy households and households facing credit constraints; (2) participation is decreasing in risk aversion, and (3) informational factors relating to the household’s familiarity and trust in the insurance provider BASIX, as well as the extent to which they are a village leader to which other households ask for advice, represent key determinants of insurance participation.

As previously discussed, our results on wealth and credit constraints appear consistent with an extension of the simple ‘benchmark’ model to include borrowing constraints. Insurance participation has also been found to be increasing in wealth in developed countries, a fact which is generally attributed to either asymmetric information or fixed insurance market participation costs (Mulligan and Philipson, 2003). It is notable that we find the same result in a setting where neither of these explanations appear likely to hold. This perhaps suggests that credit constraints may influence insurance participation decisions in developed countries also.

Our finding that credit constraints play a role in insurance participation decisions has practical implications for the insurance contract design. A first implication is that insurance payouts should be made as promptly as possible after rainfall is measured and verified. Figure 1 below plots systematic variation in credit constraints over the course of the calendar year. This Figure was constructed based on a question posed to households to name the Khartis (14 day period) when they are most and least credit constrained. These responses were then summed across households for each Kartis. The Figure shows that, unsurprisingly, households become more credit constraints around the beginning of the sowing season. Households are least credit constrained in November when crops are harvested and sold. In 2004, insurance payouts were not made by BASIX to farmers until around November. The fact that credit constraints appear to influence insurance participation, combined with the cyclical pattern of credit constraints over the calendar year suggests that households would benefit from earlier stage-by-stage payment of insurance payouts.

[INSERT FIGURE 1 HERE]

A second potential improvement would be to combine insurance with a a short-term loan that helps credit-constrained households to pay for the premium (stated differently, the insurance is a source of state-dependent collateral for the loan). 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 rainfall insurance and their existing suite of micro-credit products.

The overall conclusion of our empirical work is that, in the first year of its introduction to nearly all of our sample villages, the insurance product did not succeed in proportionately reaching vulnerable households who would likely benefit most from protection against deficient rainfall. By 'vulnerable', we mean poor, credit constrained, risk-averse households who have less irrigated land, have lower access to credit from micro-insurers, and are not members of social networks such as a BUA or Gran Panchayat. Along each of these dimensions, we find that vulnerable households are less likely to purchase rainfall insurance.

These facts likely in part reflect persistent real barriers to trade in insurance such as credit constraints, but also in part are due to a normal pattern of diffusion of a new product. Still in the early stages of introduction, the insurance product is not fully understood by households, and takeup rates are low (recall that our population takeup rate is only 4.6%). Early adopters of insurance are likely to be households where the cost of experimenting with the insurance is relatively low (eg. wealthy households, or households who have greater trust in the insurance provider). According to this diffusion argument, over time, lessons learned by insurance 'early adopters' will filter through to other households, generating higher penetration rates amongst poor households.

A less sanguine perspective is suggested in Morduch (2004), who highlights potentially adverse general-equilibrium implication of differential rates of insurance participation between rich and poor households in developing countries. Morduch suggests that if rainfall insurance is only purchased by the relatively 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.

7. Conclusions and Directions for Future Research

In this paper, we summarize the contract features and institutional background associated with an innovative rainfall insurance product offered to smallholder farmers in rural India, and present preliminary evidence on the determinants of insurance participation.

Our empirical estimates suggest that takeup rates are higher when basis risk is low, but also amongst wealthy, less credit constrained, less risk-averse households, as well as households viewed as leaders within the village, and those with a prior connection to the insurance provider, BASIX. We conclude that, so far, the insurance product has not been entirely successful in reaching poor, constrained, vulnerable households who would likely benefit most from protection against deficient rainfall. This stylized fact likely in part reflects persistent barriers to trade in insurance, such as credit constraints, and partially the process of diffusion of a new product. To the extent that the latter is important, relative participation amongst the vulnerable should be expected to increase over time.

In contrast to the well-developed literature on micro-credit, research on ‘micro-insurance’ is still in its infancy. This paper represents a preliminary step towards documenting the contract features of ‘real world’ micro-insurance contracts, and understanding the barriers to trade in insurance for households in developing countries. However, many interesting questions remain unanswered, for example:

(i) What is the causal effect of rainfall insurance on income-smoothing and consumption smoothing behavior by households?

(ii) How large is the price elasticity of demand for this type of insurance? Does the elasticity vary across different groups? This is an important policy question, given that state and federal Indian governments have begun to provide subsidies to encourage insurance takeup, especially amongst the poor.

(iii) What is the pattern of diffusion of insurance participation over time? To what extent are patterns of cross-sectional variation in insurance participation different for a mature product such as NAIS, that that is well-understood by households, rather than a new product like the one considered here?

(iv) How does rainfall insurance interact with existing risk-bearing mechanisms, such as precautionary savings, and intra-household transfers.

(v) What is the optimal insurance contract design, taking into account basis risk, credit constraints, and the timing of payouts?

(vi) How should, and do, providers of microinsurance spread risks through capital markets, capital buffers and reinsurers. To what extent do capital market imperfections influence the pricing of microinsurance contracts to households?

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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[[NEED TO COMPLETE THESE]]

Appendix A: Simple model of insurance participation under symmetric information

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 (ie. the value of e is revealed).
3. Insurance payouts (if any) are made. The household consumes its income y plus any payout on the insurance.

The policy costs premium p. The payout on the insurance is $r = -e + \mu + u$. μ is the household's expectation of the average payout of the insurance. 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 the insurance it consumes $c = y^* + \mu + u – p$, while if it does not purchase the insurance it consumes $c = y^* + e$. Under these assumptions the household's willingness-to-pay is given by:

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

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 (ie. $W \geq I + p$). Any wealth not used for insurance or seeds is assumed to be stored at an interest rate of zero until the income uncertainty is resolved.

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 the formula [A.1]. This will also be true for any level of wealth if the household is able to borrow and lend at the same interest rate. Thus, in either case, participation decisions are 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 the 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] $$f(W) - f(W-p_{max}) = \mu - \gamma[\sigma^2_y - \sigma^2_u].$$

$f(W) - f(W-p_{max}) = {}_{W-p}\!\int^{W} f'(x)dx$. Since f(.) is concave, $f(W) - f(W-p)$ is decreasing in W. Since $f(W) - f(W-p)$ is increasing in p, thus $dp_{max} / dW > 0$, that is, the willingness-to-pay for insurance is increasing in wealth. This result reflects a simple intuition. In this setup, wealthier households have a higher wilingness-to-pay for insurance because their shadow value of internal funds is lower. 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 at the time it purchases the insurance (ie. the shadow value of W is lower).

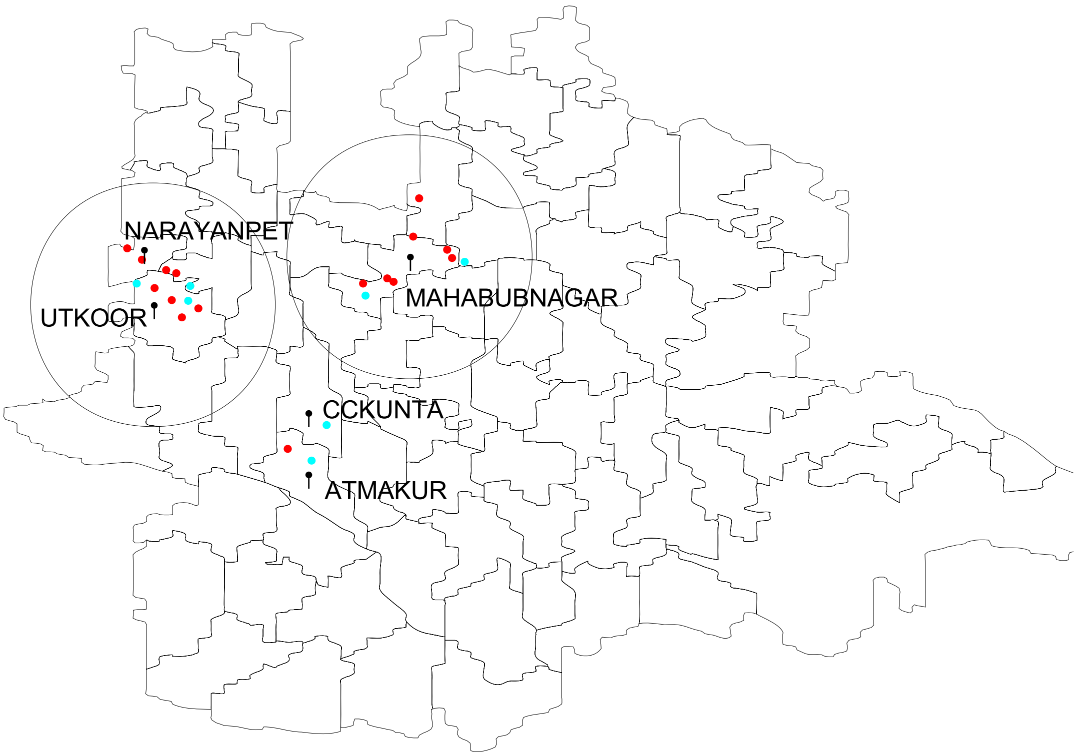
Appendix B: Definition of Variables

Variable name	Source within Survey	Significance of variable
Accumulated rainfall	Section D: Weather Perceptions, Question 7	Dummy variable equal to 1 if the top reason that determines when to sow either groundnut or castor is accumulated rainfall
Ambiguity aversion	Section P: Games, Question 3	Dummy variable equal to 1 if respondent chooses Bag One.
Trust in insurance provider	Section E: Rainfall Insurance, Question 31	Dummy variable equal to 1 if respondent trusts KBS Bank, BASIX, and the insurance salesperson
Member of BUA	Section I: Networks, Question 8 second part	Dummy variable equal to 1 if any household member belongs to BUA/WUG
Previous loans from Basix	Section K: Credit, Question 4	Dummy variable equal to 1 if household has received loans from Basix
Credit constraint	Section K: Credit, Question 3a and 3b	Dummy variable equal to 1 if household cites lack of collateral as a reason for not having loans despite asking for them
Crop damage by drought	Section C: Agriculture, Question 46	Dummy variable equal to 1 if the reason for crop damage was drought
Household head's education level	Section A: Household Roster, Question 16	Education code
Household size	Section A: Household Roster, Question 1	Counts the number of household members that are listed in the roster
Motivation for buying insurance	Section E: Rainfall Insurance, Question 14b	Coded as 1 for Security = answers 6, 8, 9 & 10; 2 for Advise = answers 3, 4 & 5; 3 for Product = answers 1, 2 & 7; 4 for Luck = answer 4
Motivation for not buying insurance	Section E: Rainfall Insurance, Question 25	Coded as 1 for Product = answers 1, 2, 4, 6 & 12; 2 for No need = answer 8; 3 for No cash = answer 3; 4 for Rgauge far = answer 5; 5 for No payout = answer 7; 6 for Not understand = answer 9; 7 for No trust = answer 10; 8 for Other = answer 13
Impatience	Section P: Games, Question 2	((100/q2)-1)*100
Presence of other non-weather insurance	Section L: Savings & Insurance, Question 10	Dummy variable equal to 1 if household has crop insurance, life insurance, and/or other insurance
Ability to understand insurance plans	Section E: Rainfall Insurance, Questions 1, 2, 3, 5 & 7	The variable is a number between 0 and 1. The correct answer to each question gets 1 point (respectively: no, yes, no, yes, no) and then that sum is divided by 5 to get an average measure of ability to understand insurance plans
Percent of cultivated irrigated land	Section C: Agriculture, Question 2, 5, 8, 10 & 17	Acres (q2 if q8=1 or q10 is not blank) of irrigated land (q17=2, 3, or 4) / total land owned (q2 if q5=1)
Progressive household	Section I: Networks, Question 8	Dummy variable equal to 1 if household is progressive
Lived in village whole life	Section B: General Household Characteristics, Question 7, tick if all life	Dummy variable equal to 1 if household head has lived in village for whole life
Log of household head's age	Section A: Household Roster, Question 4	Log(age of head of household)
Log of household size	Section A: Household Roster, Question 1	Log(1+Household size)
Log of acres owned	Section C: Agriculture, Question 2 & 5	Log(1+Acres owned)
Log of household value (house + land)	Section B: General Household Characteristics, Question 13; Section C: Agriculture,	Log(100+house value+land value). Land value (Section C) = acres*cost (q2*q7) if own=1 (q5=yes); house value (Section B) = q13

Variable name	Source within Survey	Significance of variable
	Question 2, 5 & 7	
Log of wealth	Section B: General Household Characteristics, Question 13; Section F: Livestock, Question 3; Section L: Savings & Insurance, Question 5	Log(1+savings in Mrigashira Kartis+market value+house value); savings in Mrigashira Kartis (Section L) = sum over q5; market value (Section F) = q3; house value (Section B) = q13
Acres owned	Section C: Agriculture, Question 2 & 5	Q2 if q5 = 1
Attend rainfall insurance meeting	Section E: Rainfall Insurance, Question 13	Dummy variable equal to 1 if attended meeting to explain and sell rainfall insurance
Member of Gran Pranchayet	Section B: General Household Characteristics, Question 5	Dummy variable equal to 1 if any household member belongs to Gran Pranchayet
Patience	Section P: Games, Question 2	Q2/100
Percent of castor planted in 2003	Section C: Agriculture, Question 47 & 48	Total acres of castor planted in 2003 / total area planted in 2003
Percent of groundnut planted in 2003	Section C: Agriculture, Question 47 & 48	Total acres of groundnut planted in 2003 / total area planted in 2003
Pessimism	??	
Risk aversion	Section P: Games, Question 1	Dummy variable equal to 1 if respondent selects choice "A"
Buyer identifier	E. Rainfall Insurance, Question 16	Dummy variable equal to 1 if the household bought insurance for 2004
Value of savings in Mrigashira Kartis	Section L. Savings & Insurance, Question 5	Sum of q3 across all categories
Sex of the household head	Section A: Household Roster, Question 3	Dummy variable equal to 1 for male

Figure 1: Spatial distribution of survey villages

Mahabubnagar District



Ananthapur District

[[INSERT HERE]]

Figure 2: Credit constraints over the calendar year

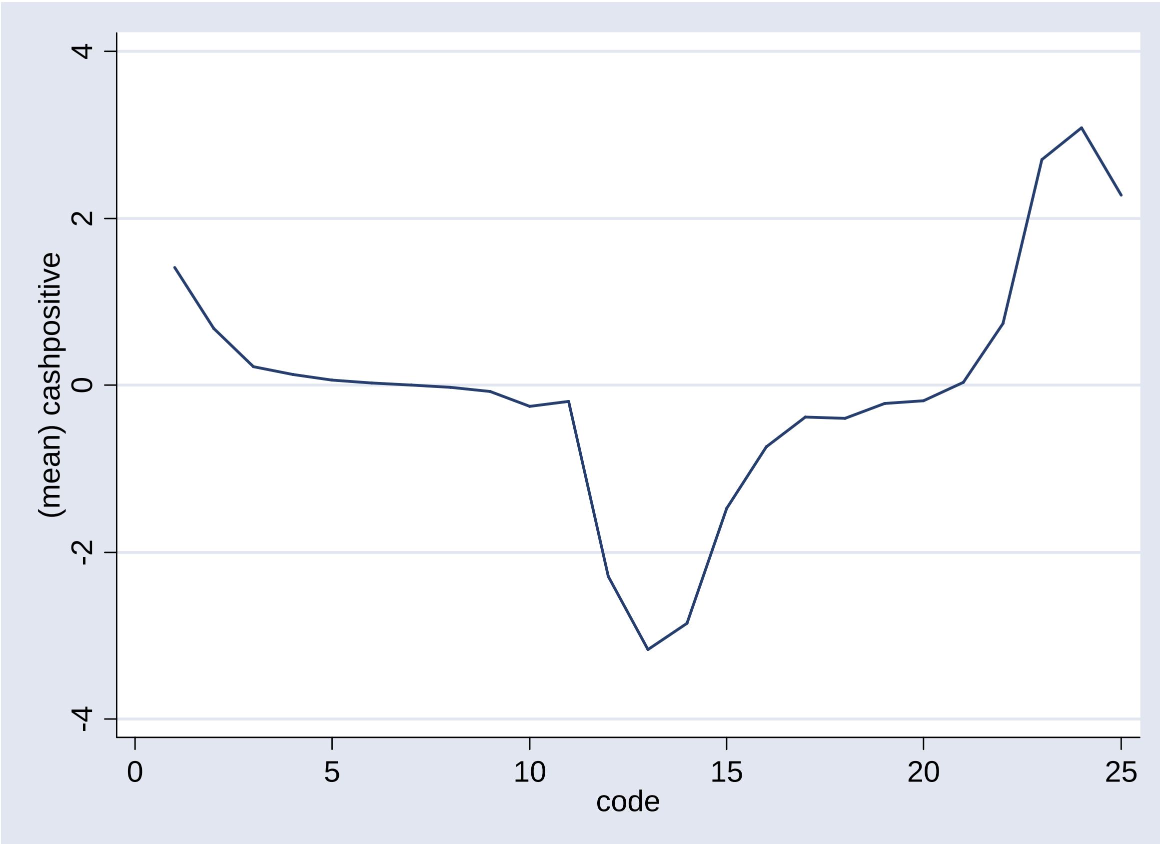


Table 1: Sources of risk

Households were asked to list the most important, second most important and third most important sources of risk that they face. 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. Questions 5 and 6 from Part O of the survey: Risk Response.

What are the major sources of risk that you face?

	Frequency			weighted
	1st reason	2nd reason	3rd reason	sum
Drought	925	69	9	49.9%
Crop Failure	31	521	200	22.8%
Crop Disease	51	320	149	16.1%
Dramatic drop in crop prices	6	35	142	3.9%
Unsuccessful Investment	4	28	48	2.0%
Loss of livestock/disease	7	27	12	1.5%
Price changes	1	8	38	1.0%
Illness	3	13	9	0.8%
Job Loss	6	10	5	0.7%
Sudden death of household member	7	6	3	0.6%
Other, specify	2	2	6	0.3%
Fires	5	0	0	0.3%
Flood	2	1	0	0.1%
Loss of land	0	2	0	0.1%
Total	**1050**	**1042**	**621**	100%

Table 2: Terms of a Rainfall Insurance Contract in Mahboobnagar

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	-
		*4**	-	-	-	-	4 days	1500
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.
*Phase 4: September 1- October 10 for excess rainfall of more than 10 mms per day for 4-7 consecutive days. Payouts are Rs 1500 for 4 or 5 days, Rs 3000 for 6 days, Rs 6000 for 7 days or more.

Table 3: Insurance Participation in 2003 and 2004

	Number of buyers		Number of which were BASIX clients		Number of acres covered		Total sum insured (Rs)		Number of villages	
	2003	**2004**	**2003**	**2004**	**2003**	**2004**	**2003**	**2004**	**2003**	**2004**
Rain gauges of Mahaboobnagar district										
Atmakur	56	32		27		83		498,000	1	4
Mahaboobnagar		75		26		128		768,000		12
Narayanpet	92	125		90		199		1,183,200	1	12
Rain gauge of Anantapur district										
Hindupur		83		50		160		960,000		15
Total	**148**	**315**		**193**		**570**		**3,409,200**	**2**	**43**

[[ADD 2005 AND 2006]]

Table 4: Sampling Methodology, Marketed Villages

All households	observations	
	Unweighted	Weighted
Sample size	752	5805
Did not attend marketing meeting	252	5205
Attended marketing meeting	500	600
Purchased insurance	267	267
Did not purchase insurance	233	333
Households with non-missing data	observations	
	Unweighted	Weighted
Sample size	727	5654
Did not attend marketing meeting	246	5081
Attended marketing meeting	481	573
Purchased insurance	256	256
Did not purchase insurance	225	317

Table 5: Summary Statistics

		Mean (and Median, where applicable)			Std. Dev.	Min	Max
		Buyers	Non-buyers	Full Sample			
Utility function							
Risk aversion*		0.223	0.404	0.396	0.49	0.00	1.00
Ambiguity aversion*		0.496	0.548	0.546	0.50	0.00	1.00
Patience		0.832	0.799	0.801	0.13	0.30	1.00
Beliefs about return on insurance							
Pessimism		0.336	0.305	0.306	0.31	0.00	1.00
Basis risk							
Use acc. rainfall to decide to sow*		0.047	0.077	0.075	0.26	0.00	1.00
% of cultivated land that is irrigated		0.508	0.267	0.278	0.40	0.00	2.20
% cultivated land used for groundut		0.215	0.225	0.224	0.35	0.00	1.00
% cultivated land used for castor		0.259	0.249	0.250	0.31	0.00	1.00
Credit constraints							
Household is constrained*		0.754	0.813	0.810	0.39	0.00	1.00
Leadership / networks							
Member of borewell user association*		0.348	0.022	0.037	0.19	0.00	1.00
Progressive household*		0.527	0.311	0.321	0.47	0.00	1.00
Member Gran Praychet*		0.125	0.052	0.055	0.23	0.00	1.00
Knowledge of insurance and BASIX							
Past credit from BASIX*		0.465	0.047	0.066	0.25	0.00	1.00
Has other insurance*		0.750	0.552	0.561	0.50	0.00	1.00
Know insurance in abstract		0.772	0.303	0.325	0.42	0.00	1.00
Wealth (beginning of Kharif)							
Liquid savings (Rs, 000s)	[mean]	23.360	13.673	14.112	18.92	0.00	453.00
	[median]	14.900	8.000	8.300			
Total wealth (Rs, 000s)	[mean]	148.714	111.609	113.289	125.37	11.11	2318.00
	[median]	119.750	75.200	77.430			
Landholdings (acres)	[mean]	8.783	5.697	5.836	4.98	1.00	79.50
	[median]	6.000	4.000	4.000			
Other variables							
Education of household head (years)	[mean]	5.250	3.214	3.306	4.43	0.00	18.00
	[median]	5.000	0.000	0.000			
Age of household head	[mean]	43.469	47.163	46.996	11.30	21.00	80.00
	[median]	43.000	46.000	46.000			
Head spent whole life in village*		0.977	0.970	0.970	0.17	0.00	1.00
Gender of household head (1=male)		0.938	0.918	0.919	0.27	0.00	1.00
Household size	[mean]	6.734	6.501	6.511	2.83	1.00	17.00
	[median]	6.000	6.000	6.000			
Unweighted number of observations		256	471	727			
Weighted number of observations		256	5399	5655			

* Denotes a dummy variable where 1=yes.

Table 6: 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			weighted
	1st reason	2nd reason	3rd reason	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			weighted
	1st reason	2nd reason	3rd reason	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 7: 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**	
	Baseline specification	Parsimonious model	Baseline specification	Parsimonious model
Utility function				
Risk aversion	-0.010	-0.011	-0.217	-0.239
	(2.28)**	(2.39)**	(2.28)**	(2.39)**
Ambiguity aversion	-0.001		-0.022	
	(0.17)		(0.17)	
Patience	0.013	0.013	0.283	0.283
	(1.06)	(0.95)	(1.06)	(0.95)
Beliefs about return on insurance				
Pessimism	0.012		0.261	
	(1.19)		(1.19)	
Basis risk				
Use acc. rainfall to decide to sow	0.003		0.065	
	(0.41)		(0.41)	
% of cultivated land that is irrigated	0.005	0.007	0.109	0.152
	(1.23)	(1.69)*	(1.23)	(1.69)*
% cultivated land used for groundut	0.043	0.043	0.935	0.935
	(3.79)***	(3.58)***	(3.79)***	(3.58)***
% cultivated land used for castor	0.021	0.021	0.457	0.457
	(2.85)***	(2.74)***	(2.85)***	(2.74)***
Wealth and credit constraints				
log(wealth in Rs, start of Kharif)	0.006		0.130	
	(1.35)		(1.35)	
log(landholdings, start of Kharif)	0.004	0.012	0.087	0.261
	(0.93)	(3.87)***	(0.93)	(3.87)***
Household is constrained (1=yes)	-0.006	-0.006	-0.130	-0.130
	(1.76)*	(1.64)	(1.76)*	(1.64)
Familiarity with insurance and BASIX				
Member of borewell user association	0.619	0.644	13.458	14.002
	(6.22)***	(6.14)***	(6.22)***	(6.14)***
Credit from BASIX (1=yes)	0.098	0.118	2.131	2.566
	(6.21)***	(6.79)***	(6.21)***	(6.79)***
Has other insurance (1=yes)	0.003		0.065	
	(0.78)		(0.78)	
Technology diffusion				
Progressive household	0.010	0.011	0.217	0.239
	(2.34)**	(2.59)***	(2.34)**	(2.59)***
Member Gran Panchayat	0.018	0.019	0.391	0.413
	(2.05)**	(2.09)**	(2.05)**	(2.09)**
Education of household head (years)	0.002		0.043	
	(1.14)		(1.14)	
log(age of household head)	-0.014	-0.017	-0.304	-0.370
	(1.90)*	(2.49)**	(1.90)*	(2.49)**
Other covariates				
Head spent whole life in village (1=yes)	-0.019		-0.413	
	(1.00)		(1.00)	
Gender of household head (1=male)	-0.004		-0.087	
	(0.57)		(0.57)	
log(household size)	0.001		0.022	
	(0.18)		(0.18)	
Village dummies	yes	yes	yes	yes
Number of observations	752	752	752	752
Pseudo R^2	0.38	0.38	0.38	0.38

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

Table 8: 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 also includes village dummy variables (results omitted).

	Baseline specification			
	combined	interaction terms added individually		
Interaction terms				
Risk aversion * BUA	0.003	0.016		
	(0.18)	(0.98)		
Risk aversion * credit from BASIX	0.022		0.024	
	(1.93)*		(2.17)**	
Risk aversion * other insurance	0.004			0.009
	(0.51)			(1.00)
F-test [joint significance, p-value]	0.10			
Underlying variables				
Risk aversion	-0.017	-0.012	-0.014	-0.016
	(2.48)**	(2.61)***	(3.13)***	(2.30)**
BUA	0.573	0.452	0.608	0.612
	(4.24)***	(3.83)***	(6.22)***	(6.17)***
Credit from BASIX	0.037	0.097	0.034	0.096
	(2.52)**	(6.20)***	(2.41)**	(6.22)***
Other insurance	0.000	0.003	0.002	-0.002
	(0.06)	(0.81)	(0.74)	(0.34)

	Parsimonious specification			
	combined	interaction terms added individually		
Interaction terms				
Risk aversion * BUA	0.003	0.015		
	(0.16)	(0.88)		
Risk aversion * credit from BASIX	0.021		0.023	
	(1.72)*		(1.98)**	
Risk aversion * other insurance	0.005			0.010
	(0.62)			(1.05)
F-test [joint significance, p-value]	0.12			
Underlying variables				
Risk aversion	-0.018	-0.013	-0.014	-0.018
	(2.51)**	(2.63)***	(3.09)***	(2.36)**
BUA	0.582	0.481	0.615	0.619
	(4.21)***	(3.90)***	(6.14)***	(6.08)***
Credit from BASIX	0.051	0.111	0.048	0.110
	(3.02)***	(6.55)***	(2.91)***	(6.56)***
Other insurance	0.001	0.004	0.003	-0.001
	(0.14)	(1.08)	(1.03)	(0.23)

Table 9: Meeting Participation and Purchase Conditional on Participation

Dependent variable = 1 if purchased insurance or attended meeting, = 0 otherwise. Weighted probit model . Robust z-statistics in parentheses. Coefficients normalized to display marginal effects. Regression also includes village dummy variables (results omitted).

	Baseline specification		Parsimonious specification	
	attended meeting	bought conditional on attendance	attended meeting	bought conditional on attendance
Utility function				
Risk aversion	-0.027	-0.074	-0.031	-0.064
	(1.57)	(0.96)	(1.73)*	(0.84)
Ambiguity aversion	-0.001	-0.057		
	(0.11)	(0.99)		
Patience	-0.009	0.122	0.005	0.190
	(0.17)	(0.51)	(0.10)	(0.81)
Beliefs about return on insurance				
Pessimism	0.020	0.325		
	(0.48)	(1.61)		
Basis risk				
Use acc. rainfall to decide to sow	0.080	0.045		
	(2.29)**	(0.39)		
% of cultivated land that is irrigated	0.041	0.012	0.053	0.012
	(2.32)**	(0.15)	(2.96)***	(0.15)
% cultivated land used for groundut	0.097	0.399	0.095	0.341
	(2.55)**	(2.52)**	(2.37)**	(2.24)**
% cultivated land used for castor	0.039	0.270	0.045	0.214
	(1.33)	(2.04)**	(1.45)	(1.59)
Wealth and credit constraints				
log(wealth in Rs, start of Kharif)	0.039	0.009		
	(2.24)**	(0.12)		
log(landholdings, start of Kharif)	-0.014	0.041	0.030	0.116
	(0.70)	(0.47)	(2.26)**	(2.37)**
Household is constrained (1=yes)	-0.027	0.094	-0.020	0.059
	(1.87)*	(1.48)	(1.37)	(0.93)
Familiarity with insurance and BASIX				
Member of borewell user association	0.400	0.533	0.403	0.538
	(4.43)***	(3.84)***	(4.36)***	(3.87)***
Credit from BASIX (1=yes)	0.236	0.228	0.239	0.244
	(5.19)***	(3.08)***	(5.06)***	(3.48)***
HH reports that it trusts BASIX (1=yes)		0.256		0.255
		(2.34)**		(2.29)**
Has other insurance (1=yes)	0.008	0.041		
	(0.61)	(0.66)		
Technology diffusion				
Progressive household	0.039	0.048	0.047	0.029
	(2.18)**	(0.76)	(2.65)***	(0.49)
Member Gran Panchayat	0.063	0.061	0.073	0.059
	(1.90)*	(0.64)	(2.14)**	(0.63)
Education of household head (years)	0.004	0.065		
	(0.61)	(2.07)**		
log(age of household head)	0.005	-0.398	-0.011	-0.425
	(0.17)	(3.04)***	(0.40)	(3.50)***
Other covariates				
Head spent whole life in village (1=yes)	0.005	-0.325		
	(0.13)	(1.66)*		
Gender of household head (1=male)	0.033	-0.337		
	(1.56)	(2.45)**		
log(household size)	-0.011	0.188		
	(0.57)	(2.06)**		
Village dummies	yes	yes	yes	yes
Number of observations	752	464	752	464
Pseudo R^2	0.26	0.30	0.24	0.27

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

Table 10: Participation Rates; Non-BUA Members

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).

	Baseline specification	Parsimonious model
Utility function		
Risk aversion	-0.009	-0.010
	(2.49)**	(2.55)**
Ambiguity aversion	-0.004	
	(1.56)	
Patience	0.015	0.014
	(1.45)	(1.22)
Beliefs about return on insurance		
Pessimism	0.011	
	(1.30)	
Basis risk		
Use acc. rainfall to decide to sow	0.003	
	(0.48)	
% of cultivated land that is irrigated	0.001	0.003
	(0.25)	(0.88)
% cultivated land used for groundut	0.030	0.033
	(3.37)***	(3.33)***
% cultivated land used for castor	0.006	
	(1.12)	
Wealth and credit constraints		
log(wealth in Rs, start of Kharif)	0.007	
	(2.20)**	
log(landholdings, start of Kharif)	0.001	0.010
	(0.40)	(4.08)***
Household is constrained (1=yes)	-0.003	-0.003
	(1.16)	(0.94)
Familiarity with insurance and BASIX		
Credit from BASIX (1=yes)	0.130	
	(6.54)***	
Has other insurance (1=yes)	0.003	
	(0.95)	
Technology diffusion		
Progressive household	0.004	0.006
	(1.32)	(1.74)*
Member Gran Panchayat	0.013	0.013
	(1.94)*	(1.80)*
Education of household head (years)	0.001	
	(0.38)	
log(age of household head)	-0.015	-0.017
	(2.42)**	(2.86)***
Other covariates		
Head spent whole life in village (1=yes)	-0.004	
	(0.36)	
Gender of household head (1=male)	-0.003	
	(0.41)	
log(household size)	-0.001	
	(0.15)	
Village dummies	yes	yes
Number of observations	752	752
Pseudo R^2	0.28	0.26

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