

**Microinsurance: A Case Study of the  
Indian Rainfall Index Insurance Market**

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Rainfall index insurance provides a payout based on measured local rainfall during key phases of the agricultural season, and in principle can help rural households diversify a key source of idiosyncratic risk. We describe basic features of rainfall insurance contracts offered in India since 2003, and document stylized facts about market demand and the distribution of payouts. We summarize results of our previous research on this market, which provides evidence that price, liquidity constraints and trust all present significant barriers to increased takeup. We also discuss potential future prospects for rainfall insurance and other index insurance products.

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## 1. Introduction

Households in India and other developing nations are often critically exposed to extreme weather-related events, including drought, flood, tidal waves and hurricanes. For example, in a household survey conducted by us in Andhra Pradesh, 89% of surveyed rural landowners cite drought as the most important single risk faced by the household (Giné, Townsend and Vickery, 2008). Weather shocks often affect all households in a local geographic area, making some forms of risk-coping, such as seeking help from nearby family, friends and neighbors, relatively less effective. Globally, household exposure to extreme weather events is likely to increase over future decades, due to climate change as well as population growth in risk-sensitive areas.<sup>1</sup>

Efforts have been made in India and other countries in recent years to develop formal insurance markets to improve diversification of weather-related income shocks. The goal of this chapter is to survey the features of one of these markets, namely the Indian rainfall index insurance market. “Index insurance” refers to a contract whose payouts are linked to a publicly observable index; in this case, the index is cumulative rainfall recorded on a local rain gauge during different phases of the monsoon season.<sup>2</sup> This form of insurance is now available at a retail level in many parts of India, although these markets are still in their relative infancy in terms of product design and distribution.

Rainfall insurance is only one of a growing range of “micro-insurance” products gaining popularity in the developing world. Examples include policies relating to health, livestock, accidental death and disability, property, weather, and microenterprise risk. Lloyd’s (2009) estimates that around 135 million low income individuals around the world already make use of micro-insurance in some form, and estimates a potential final market size of 1.5bn to 3bn households. Growth in these markets reflects a broadening of efforts towards greater financial access for the poor to include insurance and savings products in addition to micro-credit.

As with other types of microfinance, a key challenge for micro-insurance is to design products that minimize transaction costs and ameliorate incentive problems, frictions which can otherwise

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<sup>1</sup> For example, see Balk et al. (2009), who use satellite mapping techniques to document population growth in areas subject to climate change and natural disasters.

<sup>2</sup> World Bank (2005) examines ten index insurance case studies in countries as diverse as India, Malawi, Nicaragua, and Ukraine.

make financial services to the poor prohibitively expensive. The key feature of rainfall index insurance that assists in this regard is that payouts are calculated based on a *publicly observed* and *exogenous* variable, namely local rainfall. This significantly reduces transaction costs, because the household does not need to formally file a claim, and the insurance company does not need to do an inspection to estimate the amount of loss. Since rainfall data is observed in close to real time, this also means that claims can in principle be calculated and disbursed quickly to households. The use of an index also greatly reduces incentive problems, because the household is unlikely to have significant private information about the distribution of future rainfall shocks, and because the household cannot misreport the size of its loss.

The main disadvantage of index insurance is potential basis risk between the rainfall index and the actual income loss suffered by the household. This will be greater when the distance between the insured household and the rain gauge is larger, for example, or when actual yields correlate poorly with the rainfall index. In addition, while index insurance is in part designed to minimize transaction costs, these costs may still be significant relative to the modest value of insurance purchased by an average policyholder, making the product expensive, at least by comparison to insurance in the developed world. Finally, even if the insurance product is well designed, other frictions may prevent households from purchasing it. For example, households may be liquidity constrained, may not have a sufficient level of financial literacy to properly evaluate the product, or may not fully trust the insurance provider.

As part of this chapter, we describe the basic structure of rainfall insurance contracts commonly sold in India, and present some stylized facts on the distribution of returns on the insurance. While aggregate data on market size and growth are difficult to come by, we do document changes in product demand over time, summarizing data generously provided by the microfinance institution BASIX.

We also describe stylized facts regarding the types of households that buy insurance, and factors that inhibit demand for insurance, summarizing results of academic research conducted by three of us [see Cole et al., 2009 and Giné et al., 2008]. Amongst our findings, we show that product demand is quite price sensitive, suggesting that increased economies of scale and competition could lead via lower prices to significant increases in insurance takeup. Our previous research

also shows that other frictions are also important for takeup, however, such as financial constraints and the level of trust of the household in the insurance provider. We conclude with a discussion of the future of rainfall insurance and other related index insurance products.

## **2. Monsoon variation and production risk**

In 2007, agriculture in India accounted for 18.6% of GDP, employed more than 60% of the country's population and used 43% of its arable land (Hohl and Kannan, 2007). The country largely depends on temporal and spatial diversification of rainfall to smooth weather-induced volatility in incomes, especially since only 30% of arable land is irrigated (Gadgil et al. 2002; Rao et al. 2000).

Several papers show that household incomes in India are sensitive to rainfall variation. Parchure (2002) estimates that around 90% of variation in Indian crop production levels is due to rainfall volatility. Using macro data from 1951-2003, Gadgil and Gadgil (2006) find that despite substantial decreases in the contribution of agriculture to Indian GDP, severe droughts have resulted in decreases between 2% and 5% of GDP throughout the period. A World Bank (2006) study of adaptation strategies to droughts in Andhra Pradesh finds that, based on simulations of a crop model, severe droughts (one in 30 years) are likely to decrease rice yields from 29% to 62% depending on the district. Yield losses of rain-fed crops also appear high, with different crops being particularly vulnerable in different districts. Rosenzweig and Binswanger (1993) also present evidence that weather shocks significantly affect agricultural profits, based on ICRISAT panel data from the 1980s.

Figure 1 shows the actual onset of the monsoon over Kerala as announced by the Indian Meteorological Department (IMD) as deviations in days from the normal onset of June 1st. It is clear that there is significant volatility. This volatility however would be less of a concern if available forecasts of the onset were accurate, so farmers could use them to adapt their agriculture production decisions accordingly. The IMD issues a single long-range forecast of the onset of the monsoon over Kerala around May 15. Despite recent advances in forecasting techniques, even the onset conditional on the IMD forecast still displays substantial volatility. Figure 2 shows the difference between the forecast and actual onset in days for each year. (For example, in year 2005, the IMD forecasted that the monsoon would arrive in Kerala on June 13,

while it actually arrived on June 5, so the difference is 8 days.) This residual uncertainty in the monsoon is reflected in a long and rich folk tradition of methods to predict the arrival of the rains.<sup>3</sup>

Our survey data from Andhra Pradesh provides direct evidence that uncertainty about monsoon onset is costly. In 2006, about a quarter of our sample had replanted in the past, and 73 percent had abandoned the crop at least once in the past 10 years due to insufficient rains post-sowing. Respondents report that the extra expenses borne by those that replant are large, equivalent to 20% of average total production expenses. This suggests that farmers would benefit from having accurate priors about the onset of the monsoon (Gadgil et al. 2002).

In Giné, Townsend and Vickery (2010), we find evidence that farmers' beliefs about the monsoon are related to the benefits of having more accurate priors. In particular, farmers with less access to risk coping mechanisms have more accurate priors; this increased accuracy leads to average income gains of 8 to 9 percent of agricultural production.

### **3. Do households need formal rainfall insurance?**

Innovative risk management tools like the rainfall insurance products discussed in this chapter here are beneficial for household welfare only if other existing *risk-sharing* mechanisms are inadequate (Townsend, 1994; Morduch, 1995; Lim and Townsend, 1998). This term encompasses a wide range of different methods that households use to protect their consumption and living standards from adverse events such as a poor monsoon. Some examples:

- Drawing on accumulated savings of liquid assets (e.g. cash, bank account balances etc.).
- Selling other assets (e.g. jewelry, land, livestock etc.).
- Borrowing from moneylenders, microfinance institutions (MFIs), banks or other financial institutions.
- Informal risk-sharing arrangements with neighbors, friends, family etc. (For example, if the household suffers an adverse shock, there may be an increase in remittance income sent by family members living abroad, or financial assistance provided by other

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<sup>3</sup> This accumulation of indigenous knowledge over thousands of years is reflected in literature, folk songs, and proverbs or sayings. For example, farmers use the color of the sky, the shape and color of the clouds, the direction of the winds, the appearance of certain insects or migratory birds, and so on, to update the probability that the monsoon has arrived (Fein and Stephens, 1987).

households living in the same village, at least to the extent that those households are not *also* affected by the same shock).

- Government assistance (e.g. government work programs, drought assistance programs etc.).
- Formal insurance arrangements, like government crop insurance, or the rainfall insurance product considered here.

If these mechanisms are insufficient, households affected by a drought or other adverse weather events will experience a decline in consumption, or be forced to make costly adjustments in labor supply, production, family planning and migration decisions (e.g. moving to an urban area to find work if the monsoon crops fail). Each of these responses involves a potentially significant welfare cost for the household. In addition, as emphasized by Morduch (1995), households that are vulnerable to risk may also engage in a variety of costly ex-ante “income smoothing” activities that reduce income variability, but at the cost of lower average income. For example, a household with low savings concerned about monsoon risk may under-invest in fertilizer or hybrid seeds at the start of the monsoon season, because of a desire to maintain a stock of liquid savings in case the harvest fails.

We note that monsoon variation may be more difficult for households to smooth than other adverse events, because a bad monsoon affects virtually every household in a local rural geographic area. This makes several of the risk-sharing mechanisms described above less effective. For example, informal risk-pooling arrangements amongst neighbors will not work, because every household will have experienced a decline in agricultural income. Asset sales may also be less effective as a way to compensate for lost income, simply because all households will be seeking to sell assets at the same time. This in principle could push down prices in the local asset market, due to a “cash in the market” or “fire sale” effect, an idea that is modeled formally in Shleifer and Vishny (1992).

Previous research suggests that the mechanisms listed above do play an important role in reducing the effects of income shocks on consumption and welfare. For example, Townsend (1994) tests the benchmark of complete risk-sharing at the village level amongst rural households in three villages in India. Under this benchmark, consumption of each household

commoves only with aggregate consumption of the village, and is not disproportionately affected by idiosyncratic income shocks of the household. Consumption patterns are found to be surprisingly close to the complete risk-sharing benchmark, although insurance is found to be somewhat less complete for poorer households. Focusing on rainfall shocks, Paxson (1992) finds that saving and dissaving by Thai households absorbs a large fraction of movements in transitory household income due to rainfall variation. Yang and Choi (2007) and Miller and Paulson (2007) find that remittance income responds significantly to rainfall shocks, ameliorating the effects of income fluctuations on household consumption.

Despite these encouraging findings, a range of evidence also suggests many households remain significantly underinsured against weather risk and other related shocks. Maccini and Yang (2009) presents empirical evidence using Indonesian data that for females, local rainfall variation around the time of birth significantly affects schooling, health and socioeconomic status measured in adulthood, inconsistent with the notion that households are diversified against rainfall risk. Duflo and Udry (2004) reject the null of perfect risk-sharing with respect to rainfall shocks even *within* households. They show that rainfall-induced relative income shocks to female-tended crops cause changes in the relative expenditure share of goods favored by women, such as child education. Dercon and Outes (2009) present evidence that rainfall shocks generate plausibly exogenous variation in income that can lead to poverty traps.

Furthermore, Rosenzweig and Binswanger (1993) present evidence that households do engage in costly ‘income smoothing’ in response to rainfall risk, activities which they estimate significantly reduce average income. These authors estimate using Indian data that a one-standard deviation increase in average rainfall volatility is associated with a statistically significant reduction in risk-taking and profits, equivalent to 15% of average profits for the median farmer, and 35% of average profits for the bottom wealth quartile. Less directly focused on rainfall shocks, Morduch (1995) and Townsend (1994) present evidence that poor households are further from the full risk-sharing benchmark than wealthy households.

Household responses to qualitative surveys conducted by us in Andhra Pradesh are also consistent with the proposition that households are not fully insured against rainfall shocks. In a 2004 survey, we ask households to list the three most important sources of risk they face.

Notably, 89% of farmers cite drought as the most significant source of risk they face. (See Giné et al., 2008, for a table summarizing results of this survey question.) In addition, in surveys conducted in Andhra Pradesh and Gujarat, households who chose *not* to purchase insurance against rainfall risk were asked why. Only a very small fraction of these households (between 2% and 25% depending on the sample) cite “do not need insurance” as an explanation for non-purchase. See Section 7 of this chapter for more details.

We conclude this section by noting our view that, despite the significant body of research cited above, the literature studying the effect of monsoon quality on consumption, health, savings, labor supply, and so on, is still very much incomplete. Much more needs to be understood about exactly how rural households respond to an event like a severe drought, how large the welfare consequences are, and how those costs are distributed amongst households. We believe that further careful, systematic research on these questions would be very valuable, especially given the potential for climate change to amplify weather variation in future years and decades.

#### **4. Contract features**

In India, formal rainfall insurance contracts were first developed by the general insurer ICICI Lombard, with technical assistance from the World Bank (Hess, 2003). The ICICI Lombard product was piloted in 2003 in the Mahabubnagar district of Andhra Pradesh, a semi-arid region in south-central India; this pilot was expanded to also include villages in Ananthapur in 2004. These pilot areas are also the study area for field research conducted by us, which has involved a series of household surveys and field experiments conducted since 2004. Over time, rainfall insurance has become more available across many parts of India, and policies are also now underwritten by competing firms, including IFFCO-Tokio General Insurance Company, and the government company Agricultural Insurance Company of India (AIC). Total amounts sold each year remain relatively modest however (see Section 5 for a more detailed discussion of the market structure and growth).

In this section we describe institutional features of these rainfall insurance contracts. We focus on policies sold by ICICI Lombard, but also discuss competing products. At the end of the section, we describe the distribution networks used to sell policies to households.

#### *4.1 Coverage period and contract basis*

Policies cover rainfall during the primary monsoon season, known as the “Kharif”. This is the prime cropping season, which runs from approximately June to September. (Some farmers also plant a second irrigation-fed “Rabi” crop during the winter season).

For purposes of contract design, the Kharif is divided into three contiguous, sequential phases, each 35-45 days in length, intended to correspond to the agricultural phases of sowing, vegetative growth and harvest. Insurance payouts in the first two phases are linked to deficient rainfall. That is, the policy provides a positive payout if rainfall during the phase is below a particular threshold or ‘strike’ level. In the third phase, corresponding to harvest, this is reversed; the insurance provides a high payout if rainfall is higher than the threshold. This is meant to protect farmers against heavy rains causing damage to mature crops.

#### *4.2 How is rainfall measured?*

Each policy is linked to rainfall at a particular rain gauge during a phase or phases of the monsoon. ICICI Lombard policies are linked either to gauges maintained by the Indian Meteorological Department (IMD), or to automatic gauges maintained by private vendors. Policies are then marketed to households who live in areas close to the gauge. (For each study village in Andhra Pradesh, the insurance product offered to households is based on a gauge located no more than 20km from the village, generally significantly less).

#### *4.3 Contract design*

For each phase, the underlying index variable used to calculate payouts is accumulated rainfall between the start date and end date of the phase, measured at a given reference weather station.<sup>4</sup> The start of the first phase, rather than being a fixed calendar date, is set based on the monsoon rains. Namely, it begins on the first date on which accumulated rain since June 1 exceeds 50mm, or on July 1 if accumulated rain since June 1 is below 50mm.

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<sup>4</sup> Some adjustments are made to accumulated rainfall when constructing the rainfall index used to calculate payouts. If daily rainfall exceeds 60mm, only 60mm is counted towards the cumulative rainfall index. Also, rainfall <2mm is ignored. These adjustments reflect that heavy rain may generate water runoff, resulting in a less than proportionate increase in soil moisture, while very light rain is likely to evaporate before it soaks into the soil.

As an example, consider the contract linked to rainfall in phase 2 of the 2006 monsoon, measured at the Narayanpet Indian Meteorological Department (IMD) weather station. The structure of this contract is presented in Figure 3 below [source: Cole et. al., (2009)]. Although contracts differ, the basic structure shown in Figure 3 is broadly representative of the contracts underwritten by ICICI Lombard.

As the Figure shows, the policy pays zero if accumulated rainfall during the phase exceeds an upper threshold, or ‘strike’, which in this case is 100mm. Otherwise, the policy pays Rs. 15 for each mm of rainfall deficiency relative to the strike, until the lower threshold, or ‘exit’, is reached. If rainfall is below the exit value, the policy pays a fixed, higher indemnity of Rs. 2000. This exit level is meant to approximately correspond to crop failure. The choice of this non-linear payout structure was in part made based on the use of crop models, in an attempt to maximize the correlation between rainfall deficiency and loss of crop yield.

This example is for insurance on a single segment of the monsoon, in this case the second phase, corresponding to vegetative growth. In general, households may choose to purchase policies for an individual phase of the monsoon, or a single policy covering all three phases.

Rainfall index contracts offered by other underwriters differ somewhat from this structure. For example, Cole et al. (2009) also discusses insurance offered to households in the state of Gujarat, which is underwritten by IFFCO-Tokio. These policies have a simpler structure covering cumulative rainfall over the entire monsoon.

#### *4.4 Distribution networks*

ICICI Lombard and other Indian rainfall insurance underwriters do not generally sell insurance policies directly to farmers. Instead they use brokers, or partner with local financial institutions in each rural area, which have well-established networks for the provision of financial services to rural households. In our study areas, product marketing and distribution is performed by BASIX, a large microfinance institution. In areas where it is active, BASIX has a network of local agents, known as Livelihood Services Agents (or LSAs) who market a range of credit, savings and insurance products to rural households. (See Cole and Tufano, 2007, for a discussion of the business environment facing BASIX.)

BASIX receives a commission for each sale to cover marketing costs and payout disbursements. At the end of the rainfall insurance coverage period, ICICI Lombard calculates payouts based on measured rainfall, and provides funds to BASIX. BASIX then distributes payouts to households through their LSA network, such as by setting up a meeting or collection station in each village to distribute payouts once they become available.

To date, payouts have generally been made available to farmers by ICICI Lombard only some months after the end of the monsoon season. This in part reflects delays in certifying weather records by the IMD. However, we believe that this process could in principle be sped up significantly, given that rainfall can in principle be measured almost in real time. Reducing the delay between the realization of rainfall shocks and the settlement of claims should significantly improve the attractiveness of the product, particularly for households facing liquidity constraints. For example, payouts relating to Phase 1 (sowing) of the monsoon could be made during the monsoon season itself, providing funds to help with the replanting of crops in the wake of crop failure.

## **5. Market structure and growth**

Even before weather insurance became available in 2003, Indian farmers seeking to protect their crops could in principle attempt to do so through government crop insurance. India began to pilot crop insurance in a limited way between 1972 and 1978. These early pilots were succeeded by the Pilot Crop Insurance Scheme (PCIS) of 1979-1984 and after, the Comprehensive Crop Insurance Scheme (CCIS) of 1985-1999. Both PCIS and CCIS were targeted to farmers with loans from financial institutions. While the PCIS was voluntary, purchase of a CCIS policy was compulsory if a loan was taken from a formal financial institution. In 1999, the National Agricultural Insurance Scheme (NAIS) was introduced, replacing the CCIS. NAIS is available to borrowers and non-borrowers, although the vast majority of clients remain those forced to buy insurance as a condition of receiving a loan.

Each of the schemes described above employs an “area approach”. An insurance payout is triggered if measured crop yields from the area fall below a certain threshold, based on crop cutting experiments conducted on a sample of monitored selected plots. Distinct from the earlier

schemes, NAIS is based on an area approach for widespread calamities such as drought, but also includes an “individual approach” for localized weather events, such as landslides, floods and so on.

Premiums for crop insurance depend on the crop grown and are subsidized by 50% for small and marginal farmers. The subsidy is shared equally between the central and state government. In 2007, NAIS covered close to 20 million farmers in 23 Indian states and spanned over 30 different crops for the Kharif and 25 crops during Rabi season. Annual premia collected are around \$150m USD, covering 10 per cent of sown area and 7 per cent of farmers.

Despite the high subsidies and a resulting high ratio of claims to premia (Sinha, 2004; Raju and Chand, 2007; Nair, 2010), *voluntary* purchase of government insurance by farmers is very low. This likely reflects in part a number of limitations in product design, which are discussed in detail in Kalavakonda and Mahul, (2004), and also in the online Appendix S1 of Giné et al. (2008). In particular: (1) NAIS applies a uniform premium for each crop type, leading to mispricing and adverse selection, (2) understanding of the insurance is limited, and purchasing and claiming payouts involves significant administrative costs, (3) not all crops are covered by the scheme, (4) in some areas the geographic unit over which a crop cutting experiments are conducted is large, generating excessive basis risk, (5) claims take on average a year to be settled after the end of the growing season, (6) crop cutting experiments are expensive to conduct, and may produce noisy results if not conducted in large enough samples.

Following initial pilot tests of ICICI rainfall insurance in 2003, IFFCO-Tokio General Insurance developed its own rainfall insurance product, offered in Andhra Pradesh, Karnataka and Gujarat in 2004. The same year, AIC introduced “Varsha Bima” (rainfall insurance) in 20 gauges of Andhra Pradesh, Karnataka, Rajasthan and Uttar Pradesh. Since then, ICICI has expanded its portfolio to cover 11 states with contracts in over 200 locations and up to 13 crops per location. Other insurance companies have similarly expanded sales of the product.

Even before the introduction of ICICI Lombard rainfall insurance, some observers had argued that traditional crop insurance could be successfully replaced by other index insurance products (Skees, Hazell and Miranda, 1999). In the 2007 union budget speech, the Indian finance minister

stated that “AIC’s [...] pilot weather insurance scheme [...] appears to be a more promising risk mitigation scheme” and allocated USD \$25m to insurance companies to further develop weather based insurance schemes on a pilot basis as an alternative to NAIS. AIC launched the first pilot of the Weather-Based Crop Insurance Scheme (WBCIS) in Karnataka for Kharif 2007. For Rabi 2007-08 the scheme was expanded to 4 states, and for Kharif and Rabi 2008-09 to 10 states.

Similar to NAIS, WBCIS also operates on an area approach, except that area payouts are linked to a rainfall gauge, rather than measured crop yields. Although insurance companies charge actuarial rates, the farmers only pay a premium at par with NAIS. The remainder is borne equally by the central and implementing state governments. All insurance companies (both private and public) are invited to submit proposals for specific policies, and if approved are entitled to this premium subsidy support. At present, despite AIC having the largest market share, both ICICI Lombard and IFFCO-Tokio do participate in WBCIS in various states.

## 5.2 BASIX

In this section we present information on trends in policies sold by the MFI BASIX since 2003, using administrative data generously provided to us by them. BASIX was the vendor for ICICI Lombard’s original pilots of rainfall insurance in 2003. After an initial two year launch with several hundred policy holders in Andhra Pradesh, BASIX expanded into five states in 2005. In that year, 6,694 households purchased over 20,000 phases of insurance, including 43 distinct contracts.

Trends in sales of rainfall insurance by BASIX in Andhra Pradesh are presented in Figure 4 and Table 1.<sup>5</sup> This data shows that there has been a secular increase in the number of phases of insurance sold, as well as the number of customers served. The number of purchasers increases from 194 households in 2003 to 14,542 policies in 2009, held by 7,567 different households. Note that in the table we draw a scored line below 2004. This is because from 2005 onwards, households were able to purchase individual phases of insurance. (In 2003 and 2004, farmers could only buy a policy covering all three phases of the monsoon – we count that as three phases of coverage for the purposes of calculating figures in Table 1). Note that these trends are not due

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<sup>5</sup> Although we have also data on BASIX insurance sales in other states also, we focus on Andhra Pradesh for this analysis, to avoid confounding effects associated with the introduction of subsidized insurance by AIC under WBCIS in some other states. Policies sold in Andhra Pradesh are not subject to government subsidies.

to any government subsidies, since WBCIS is not active in Andhra Pradesh. Policies are priced and sold on a purely commercial basis.

The “sum insured” in Table 1 is the maximum payout of the insurance, meant to correspond to cases of crop failure. As shown by the final column of the table, this amount is generally more than 10 times as large as the policy premium in each year of the sample. Thus, the policy provides a very high rate of return in the worst case scenario when rainfall is very low.

A contributing factor to the specific types of policies sold that is perhaps generally overlooked is the role of insurance agents. In Andhra Pradesh, policies are sold through BASIX LSAs, who are responsible for client education and the sale of other microinsurance, savings and credit products. There are on average 13 LSAs in each location (rainfall station) which roughly corresponds to a BASIX branch. Each of these LSAs has on average 22 microinsurance customers (median is 15) and each customer buys on average 2.7 phases (median is 3, which coincides with the bundle policy). Interestingly, our data suggests that around half of the LSAs sell the exact same number and type of phases to each of his or her clients (e.g. 1 unit of phase 1 and 1 unit of phase 2), even though there is significant variation *across* LSAs selling in a given location. This suggests the suggestions of the LSA are a significant influence on household insurance demand.

While the popularity of rainfall insurance has increased over this period, growth has been steady rather than spectacular. As a point of comparison, Figure 5 plots growth in rainfall insurance and livestock insurance sold by BASIX since 2005. Over this period, livestock insurance coverage has grown five-fold, compared to about a 50% increase in coverage for rainfall insurance. This is not simply due to a difference in value, since as we discuss below, payouts on rainfall insurance are if anything greater relative to premia than is the case for livestock insurance. Section 7 describes some of the barriers to household participation in rainfall insurance products.

## **6. Distribution of payouts**

How often should a household expect rainfall insurance to pay out? How large is the expected return relative to premiums? In this section we present evidence on the distribution of insurance

payouts, based on a long span of historical rainfall data, combined with contract specifications from a previous paper by us. We also present information on actual payouts on policies sold in recent years, again based on administrative data generously provided to us by BASIX.

### *6.1 Putative historical distribution*

In a previous paper, Giné, Townsend and Vickery (2007), we use approximately three decades of daily historical rainfall data to estimate a putative distribution of insurance returns, based on 11 different contracts offered to farmers in Andhra Pradesh in 2006. Namely, we estimate payouts for each year of our rainfall data, assuming the 2006 contracts had been available during that year. Each of the 11 contracts we study is linked to rainfall data from the Indian Meteorological Department (IMD). The history of past rainfall data also comes from the IMD.

The estimated distribution of returns is presented in Figure 2 below. The x-axis for the graph is ‘payout rank,’ which ranks payouts in increasing order of size, expressed on a scale from 0 to 1. Figure 2 plots payout amount against payout rank. (The minimum payoff is zero, the maximum payoff is Rs. 1000). The calculated distribution presented in the Figure suggests that returns on the rainfall insurance are highly skewed. The payout is zero up to a payout rank of 0.89 (i.e. the 89<sup>th</sup> percentile), indicating that an indemnity is paid in only 11% of phases. The 95<sup>th</sup> percentile of payouts is around Rs. 200. In about 1% of phases, the insurance pays an indemnity of Rs. 1000, which is the maximum payout for each of these 11 contracts. Thus, the policies appear primarily to insure against extreme tail events, with around half of the value of indemnities being generated by the highest-paying 2% of phases.

Giné et al. (2007) also calculates the ratio of expected payouts on rainfall insurance relative to premia. We estimate that this ratio is around 30% on average across the 11 weather stations. This relatively low payout rate likely reflects a number of factors, amongst them a lack of economies of scale given the small initial market for the product, and limited competition amongst insurance providers. Payout ratios would likely converge to a higher value in a mature market. Interestingly, in Cole et al. (2009), we estimate using a simple theoretical model calibrated to empirical estimates that the insurance may still be valuable to Indian households even at low payout ratios such as 30%.

One limitation of Giné et al. (2007) is that the historical record of rainfall may be an imperfect guide to the future distribution of monsoon events, for example because global warming has led to a higher probability of extreme outcomes. While some preliminary hypothesis tests fail to find evidence of structural change, these tests are likely not to be very powerful, given our short history of rainfall data and the skewed return distribution. Below we present some additional evidence on actual payouts relative to premia on policies sold by BASIX since 2003.

## 6.2 *Recent payouts*

We again use administrative data provided by BASIX to calculate the ratio of total insurance payouts to total premia each year since 2005. We do the same for livestock insurance policies sold by BASIX. Results are presented in Figure 7.

Two facts are apparent from the Figure. First, average payouts on rainfall insurance are much more volatile, reflecting aggregate variation in the quality of the monsoon. In particular, the severe drought conditions of 2009 corresponded to a surge in payouts, which exceed 350% of premia collected.

The second fact is that average returns on the insurance product are actually quite high over this period, and in fact are better than actuarially fair based on a simple average of payout ratios across these years. This return is significantly higher than the 30% calculated in Giné et al (2007). This may reflect some unusual shocks over the past few years, particularly the record drought in 2009. Alternatively, it may be due to structural change in weather conditions, such as an increase in the volatility of the monsoon, which mean that the calculations in Giné et al., which are based on historical data, underestimate expected payouts. Notably, returns on livestock insurance are significantly less volatile than for rainfall insurance, and average around 60% of premia collected over this period.

## **7. Who buys rainfall insurance?**

In this section we discuss evidence from two of our original research papers studying factors determining rainfall insurance participation. In Giné et al. (2008), we estimate a simple regression model of the determinants of insurance demand, based on household characteristics like wealth, landholdings, risk aversion and so on. Cole et al. (2009) presents results of a series

of randomized trials, in which households in Andhra Pradesh and Gujarat are either visited by insurance educators, or presented with promotional material such as flyers and videos. Various aspects of these interventions are randomized across households (e.g. the price of the insurance or the amount of financial education provided). These field experiments provide direct *causal* evidence of the determinants of rainfall insurance demand, free of identification problems.

Evidence from these two papers relates to a fundamental research question: Why aren't financial products that help pool important sources of idiosyncratic risk (such as rainfall) widely available and widely used? A first potential answer to this question is simply that these products are too expensive to be attractive to households. Section 6 presents some evidence that rainfall insurance expected payouts on average appear to be significantly smaller than average premia, presumably reflecting a combination of transaction costs, limited product market competition, or a lack of scale economies. High costs are a persistent feature of financial services offered to the rural poor in India and other developing economies, even for financial products that are widely used. For example, Cull, Demirguc-Kunt and Morduch (2009) estimate that *annual* operating costs for nonbank microcredit loans are equal to 17-26% of loan value, far higher than corresponding ratios for consumer credit in the developed world.

An alternative view is that, while price is an important factor, other frictions, such as financial constraints, trust and financial literacy are equally important barriers to increasing market penetration of index insurance products. A more complete selection of potential determinants of rainfall insurance demand is presented below:

1. **Price relative to expected payouts.** All else constant, a higher insurance policy price should clearly be associated with lower insurance demand amongst households.
2. **Availability of alternative risk-sharing arrangements.** Some households may have limited need for formal rainfall insurance, because of the availability of other informal insurance arrangements, remittances, government and bank assistance during times of drought, and so on. While these other channels may certainly ameliorate demand, as described in Section 3, however, there is significant evidence that households are far from being fully insured against rainfall risk.

3. **Risk aversion, and basis risk.** Any standard model of insurance demand will predict that demand is increasing in the degree of household risk aversion. (In the limit, a household that is perfectly risk-neutral has no demand for insurance whatsoever.) In addition, demand will be declining in the level of *basis risk*, or equivalently, will be increasing in the correlation between the insurance payoffs and the risk being insured. For example, if the reference rain gauge is located far away from the household, measured index rainfall may be poorly correlated with the amount of rain that falls on the household's crops. The noisier the insurance payoffs relative to the household's marginal utility of consumption, the lower will be household demand.
4. **Ex-ante liquidity constraints.** Insurance premia must be paid at the start of the monsoon, while payouts are not generally received until the end of the monsoon season. A liquidity constrained household may thus have a high willingness-to-pay for insurance, but not have sufficient liquid assets at the start of the monsoon to purchase it, given competing uses for those funds, such as investment in fertilizer or other agricultural inputs.
5. **Understanding of the product, and learning.** Most target rural households have relatively limited education, and may simply not understand the main features of the product, or be able to accurately estimate the probability of different payoffs. Given some ambiguity aversion, this lack of understanding is likely to reduce demand. Households may also learn over time about the product, by observing whether it pays out in response to different monsoon seasons.
6. **Trust.** Related to the above point, households who do not fully understand the product may put significant weight on their trust in the insurance provider or the individual who markets the product to them. They may also rely on product endorsements from a trusted friend, village leader or family member. Guiso, Sapienza and Zingales (2007) argue trust has important effects on financial market participation.
7. **Framing and behavioral influences.** Research in psychology and behavioral economics suggests households are affected by subtle changes in the way a product is presented to them. For example, in a field experiment in South Africa, Bertrand et al. (2009) find subtle advertising cues significantly influence credit demand; for example, including the picture of a man rather than a woman on an advertising flyer for a consumer loan shifts loan demand by as much as a change of up to 2.2% in the *monthly* interest rate.

### 7.1 *Empirical evidence*

Our research has sought to identify the relative importance of the different demand factors described above. As a first simple type of evidence, Giné et al. (2009) presents results of household surveys from our study areas in Andhra Pradesh and Gujarat. These surveys ask households to describe in open-ended fashion why they did or did not purchase insurance. Responses are classified into one of a number of categories. Households who purchase insurance generally cite reasons relating to “security” or “risk reduction”. Reasons cited by households who do not purchase insurance are presented in Table 2.

In 2006, the most common single reason cited by households in both samples is ‘insufficient funds to buy insurance’. This response is particularly common in Andhra Pradesh, where it is cited by over 80% of households as the most important reason for non-purchase. This response is suggestive of the role of liquidity constraints in retarding demand for the product. Explanations relating to product quality, such as “it is not good value” and “it does not pay out when I suffer a loss”, are much less frequently cited, and only a small fraction of households cite “do not need insurance” as a reason for non-purchase (2.8% in Andhra Pradesh and 25.2% in Gujarat). This low fraction appears consistent with the evidence cited in Section 3 that households are not fully insured against rainfall risk. Notably, in 2004, a significant fraction of Andhra Pradesh households, 21%, cite “do not understand insurance” as the primary reason why they did not purchase any policies. This fraction falls to only 2% by 2006, as households become more familiar with the product.

Cole et al. (2009) also conducts a series of formal field experiments to provide causal evidence on several of the demand factors listed above. In Andhra Pradesh, this is done through household visits by an insurance educator. A random subset of our sample receives a household visit. Various aspects of the visit are then randomized across households. In Gujarat, treatments consist of either a flyer given to the household, or a video about the product that is shown to the farmer using a mobile video player. Content of the flyer and video are randomized across households. (Households are tracked via a registration number on each flyer, which the household presents when they buy insurance in return for a small discount on the product.) The main findings of Cole et al. are summarized below:

**Price.** In Gujarat, households receive a discount on insurance by presenting the flyer they were given by the insurance survey team. In a subset of the cases, the size of this discount is randomized across flyers. We find that takeup of insurance is significantly affected by the size of the discount offered.

A summary of these results is presented in Table 3. In each district where discounts were offered, an increase in the size of the discount offered to households significantly increases the take-up rate of the insurance product. (In Cole et al., it is shown that this change is statistically significant at the 1% level.) Given the initial insurance premia, our calculations imply that a 10% decrease in price increases product participation by 6.6 to 8.7 percent, suggesting demand is significantly price sensitive.

This observed price sensitivity underlines the importance of achieving economies of scale and maximizing competition amongst providers of insurance. However, Table 3 also shows that many households do not purchase insurance even when the product is better than actuarially fair. This suggests other frictions are also important constraints on demand.

**Liquidity constraints.** In household visits in Andhra Pradesh, households are given a monetary reward for their time from the insurance educator. The size of this payment is randomized across households. The payment size has a very significant effect on insurance demand; a payment of Rs. 100 rather than Rs. 25 increases the probability of insurance purchase by 34.7 percentage points, and thus more than doubles demand compared to an average takeup rate of 27%. Interestingly, this effect is strongest among poorer households.

This finding suggests liquidity constraints may be an important determinant of insurance demand. Consistent with this finding, Cole et al. (2009) and Giné et al. (2008) find in cross-sectional regressions that insurance participation is positively correlated with wealth, even though the benefits of insurance are likely to be stronger for the poorest households. It is also consistent with the survey evidence presented above (i.e. that insufficient funds are the most common explanation cited by households for non-purchase of insurance).

**Trust.** In Andhra Pradesh, it is found that insurance demand is significantly higher when the insurance educator, who is a village outsider, is endorsed by a trusted third party, namely, the local BASIX representative, who visits the village regularly and is known to locals. This endorsement increases takeup by 6.2 to 6.5 percentage points across the whole sample. Notably, this is entirely due to an effect amongst households that are familiar with BASIX. Amongst this subset of households, endorsement increases takeup by 10.9 percentage points. For households unfamiliar with BASIX, the effect is economically small and statistically insignificant.

Gujarat experiments also provide some evidence consistent with trust and endorsement effects. Namely, each flyer contains a written product endorsement from an individual identified by their name and setting as being Muslim, Hindu or a neutral figure. Amongst a subset of flyers, it is shown that takeup is higher when the religious affiliation of the figure in the flyer matches the affiliation of the household.

Together these results provide direct causal evidence that trust influences financial system participation, consistent with Guiso et al. (2007).

**Financial education.** In our Andhra Pradesh experiments, some household visits involve the insurance educator presenting a more extended education module about the product. This additional financial education is shown to have no statistically significant effect on takeup. While it is quite possible that this simply reflects a poor design of the education module, this result suggests some types of financial literacy training may not be useful to households, also consistent with the results of Cole, Sampson and Zia (2009).

**Framing and saliency.** Saliency of the product appears to significantly affect takeup, in the sense that Andhra Pradesh households who receive a visit from an insurance educator are more likely to purchase insurance, even if the household visit is not combined with any of the other treatments. In Gujarat, we test a number of behavioral biases and framing effects. These in general are not found to significantly influence takeup (see Cole et al. for full details).

### 7.3 *Summary and implications*

These field experiments suggest that insurance demand is significantly price sensitive, but also that other barriers, particularly liquidity constraints and trust, are significant barriers to higher household participation in index insurance products.

### **8. Does insurance provision affect behavior?**

Despite tremendous increases in global agricultural productivity brought about by the Green Revolution, traditional farming practices still predominate in many parts of India and in other developing countries. This holds despite high expected rates of return from switching to more productive technologies such as higher-yielding seeds and fertilizer (see Duflo, Kremer and Robinson, 2008, and Suri, 2009, for evidence from sub-Saharan Africa).

Credit constraints and limited access to information are often proposed as explanations for low investment and technology adoption in the developing world (Feder, Just and Zilberman, 1985). An additional explanation may be that low agricultural investment is a constrained-optimal response to the riskiness of these investments. Although key farm inputs increase average agricultural profitability, there is significant variation in their return on investment. For example, the application of fertilizer in semi-arid areas in India relies on sufficient rainfall for it to be effective. Thus, the return on fertilizer investments is very dependent on weather conditions, which are beyond the household's control. Consequently, risk averse households may be unwilling to bear consumption fluctuations associated with these investments, and may decide not to adopt them, or instead to shift towards lower-risk, lower-return alternatives.

Dercon and Christiaensen (2007) provide evidence of this hypothesis using panel data on rural households from Ethiopia. Fertilizer purchases are lower among poorer households due to both liquidity constraints and their inability to cope ex-post with adverse shocks. Thus, lack of insurance leads to underinvestment in fertilizer (see also Lamb, 2003 and Horowitz and Lichtenberg, 1993).

Some additional supportive evidence is presented in Cai et al. (2009), who examine changes in incentives of insurance sales staff to study the impact of insurance on livestock rearing in southwestern China. These authors present evidence that increased insurance provision increases

investment in livestock. Shapiro (2009) presents evidence from Mexico that participation in a government disaster relief program leads to an increase in the use of more expensive capital inputs and in the probability of sending a migrant abroad. Laboratory experiments by Lybbert et al. (2009) and Hill and Visceisza (2009) also suggest that over time, subjects learn the benefits of insurance and capitalize on it.

For the 2009 Kharif, we have designed an experiment to study whether the provision of formal insurance leads to higher adoption rates of fertilizer and other productive agricultural investments. Before planting, participating households were offered a (randomly determined) discount on fertilizer, as well as one of two financial products: rainfall insurance (similar to those sold in previous years) sufficient to cover the input costs of planting for one hectare of the main cash crop in the region; or the promise of a cash payment equivalent to the expected payout of these policies, to be paid at harvest time. Our preliminary results suggest the effects of insurance provision on fertilizer purchase and application are limited, although our research is still ongoing.

## **9. The future of rainfall insurance**

Rainfall insurance and other index insurance products present a promising way to insure a key source of idiosyncratic risk faced by rural households in rain-sensitive areas. While growing over time, rainfall insurance takeup is still modest. In part this reflects several barriers identified in our research, including high prices driven by transaction costs and a lack of economies of scale, as well as liquidity constraints, and factors related to trust and learning about the product.

These research findings suggest some possible practical innovations to the way the product is delivered to households. For example, the importance of liquidity constraints suggests policies should be paid out as quickly as possible, especially during the monsoon season when our data suggests households are particularly credit constrained. This has not always occurred in the past, at least in our study areas. (Related, it is also likely helpful to be as explicit as possible up-front with the farmer about the timing of the payment of any payouts.) A further possible design change would be to combine the product with a short-term loan, or equivalently, originate loans with interest rates that are explicitly state-contingent based on rainfall outcomes, to help alleviate credit constraints.

As another example of ongoing financial innovation, insurance companies are partnering with weather data providers, such as NCMSL, which are installing automated rainfall gauges throughout India. The use of these automated gauges can help ameliorate basis risk and reduce the delay before payouts can be calculated and paid. Historical data are not available for these new gauges, however, complicating the process of setting a fair premium. A promising alternative in areas that lack good rainfall data is the NDVI index, which measures vegetation greenness in a pre-specified grid using satellite imagery. This satellite data exists for several years; this approach may also have less basis risk than a rainfall index. The Centre for Insurance and Risk Management in Chennai is currently involved in a pilot of this product in Andhra Pradesh.

In some cases where household financial literacy is low, or other barriers to takeup are too high, insurance policies could be targeted to groups, such as an entire village, a producer group or cooperative. The group could then decide or pre-arrange how best to allocate funds amongst its members in case of a payout. Policies could also be sold to input companies. For example, during the 2005 monsoon season, Monsanto bought a bulk weather insurance policy so that it could attach free weather insurance coupons for a minimal level of drought coverage to its cottonseed packets which were sold to 100,000 farmers in Maharashtra.

The 11th Indian five-year plan (2007-2012) asks the government to earmark USD 7000 million for insurance, so that 40 percent of farmers will be insured by 2011-12. Developments in rainfall insurance and other micro-insurance markets are already contributing towards this ambitious goal. As these insurance markets mature, they are likely to significantly improve risk management opportunities amongst Indian households and entrepreneurial firms.

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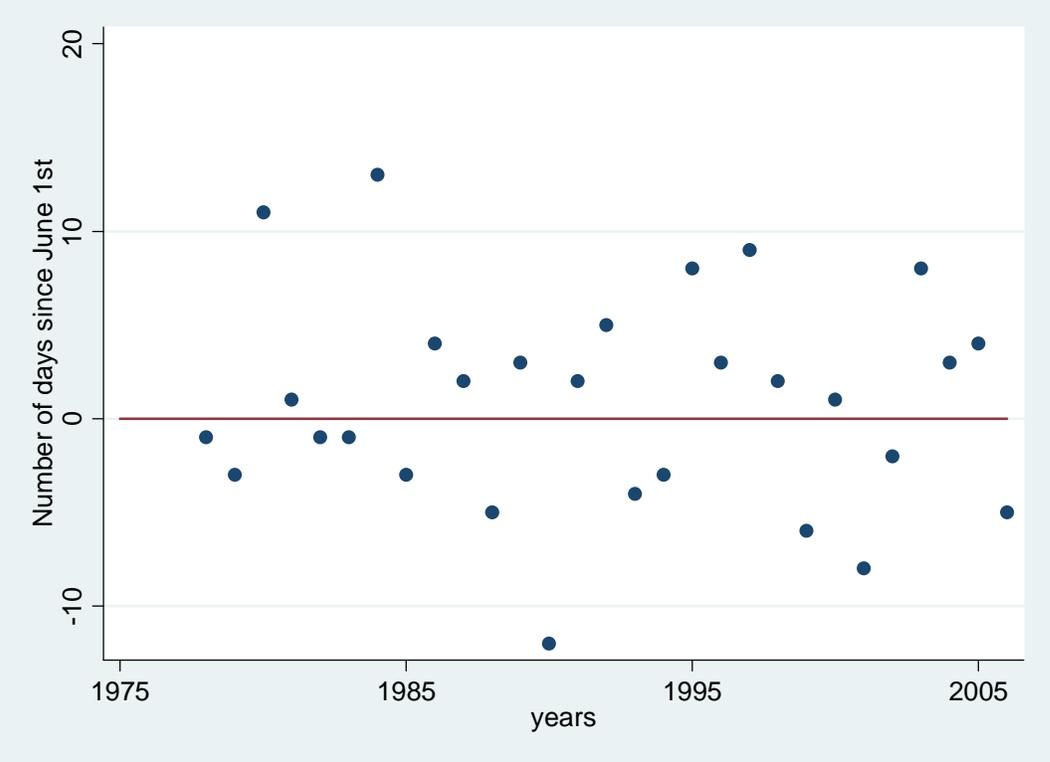
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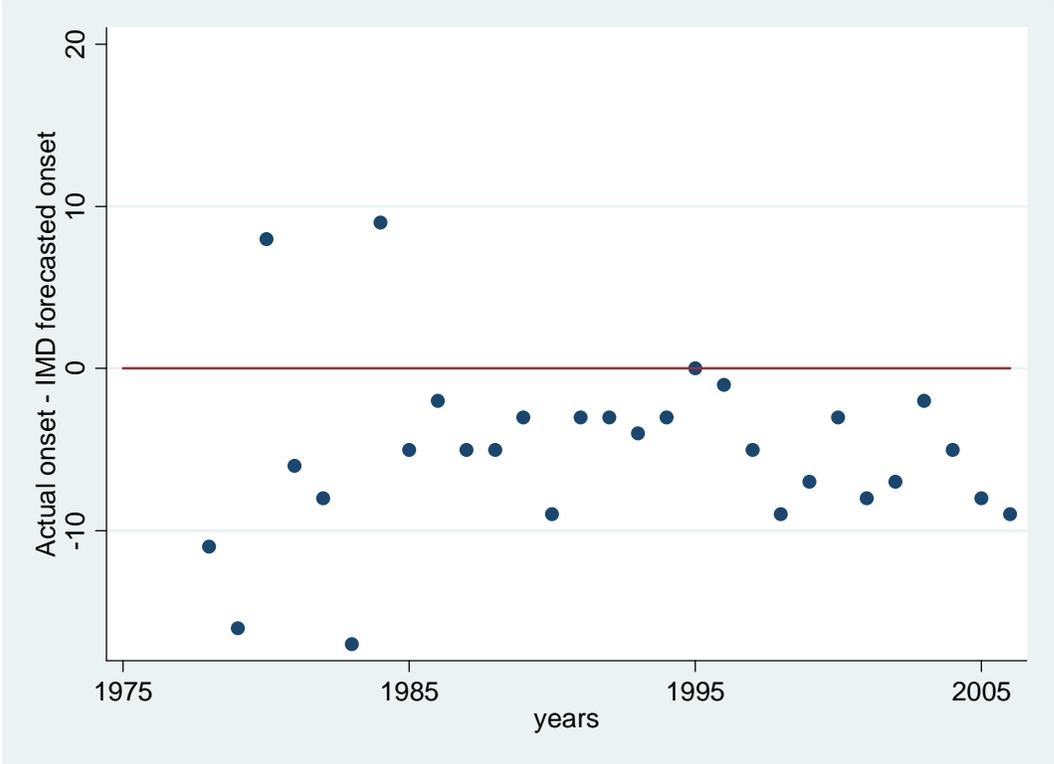
**Figure 1: Actual Onset over Kerala as deviations from June 1<sup>st</sup> (1978-2006)**

Data for this Figure come from Indian Meteorological Department (<http://www.imdpune.gov.in/>)



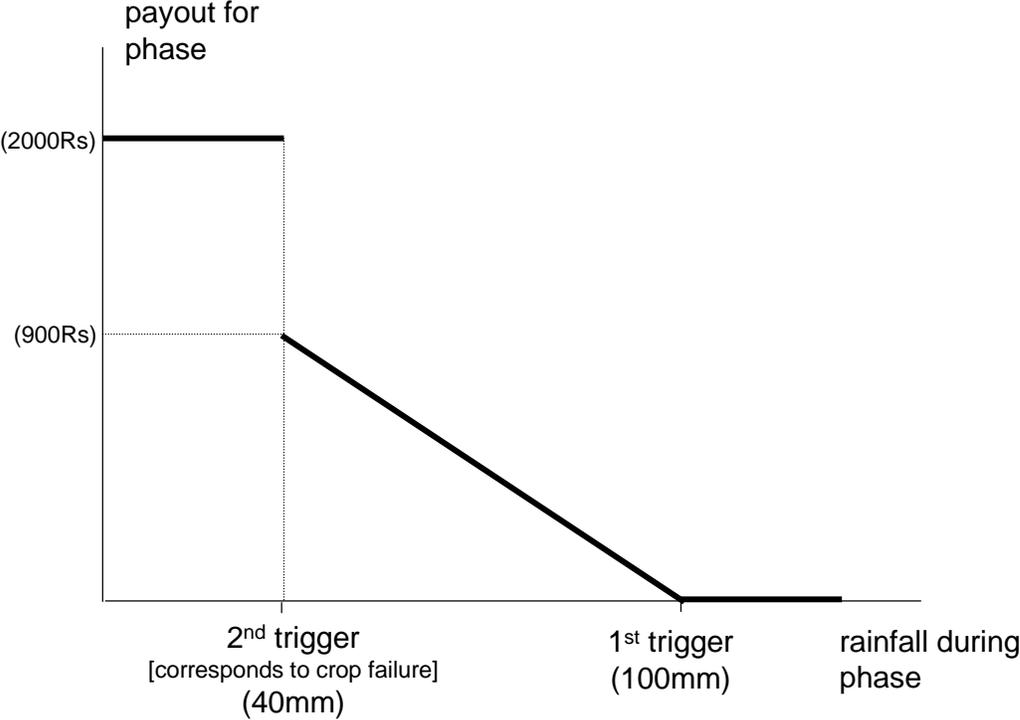
**Figure 2: Difference in days between onset and IMD long-range forecast of monsoon (1978-2006)**

Data for this Figure come from Indian Meteorological Department (<http://www.imdpune.gov.in/>)



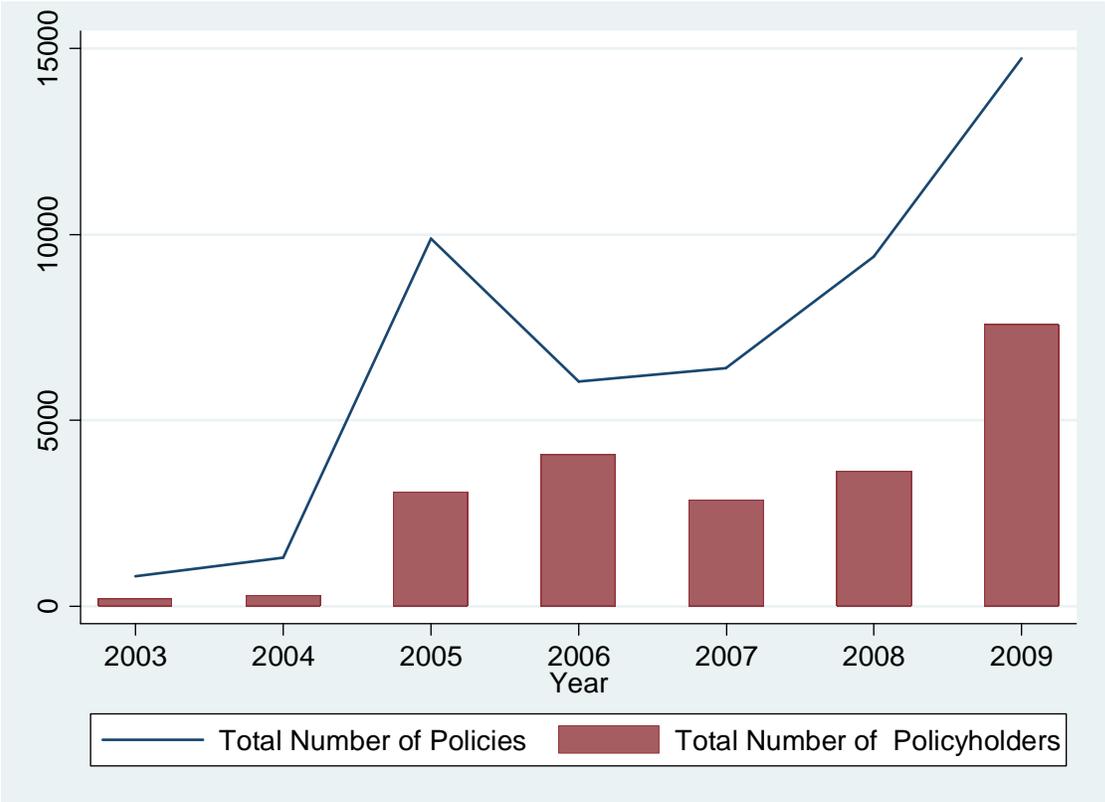
**Figure 3: Payout structure, Narayanpet Phase 2 insurance contract**

Figure plots the relationship between rainfall insurance payouts and phase rainfall. Source: Cole et al. (2009).



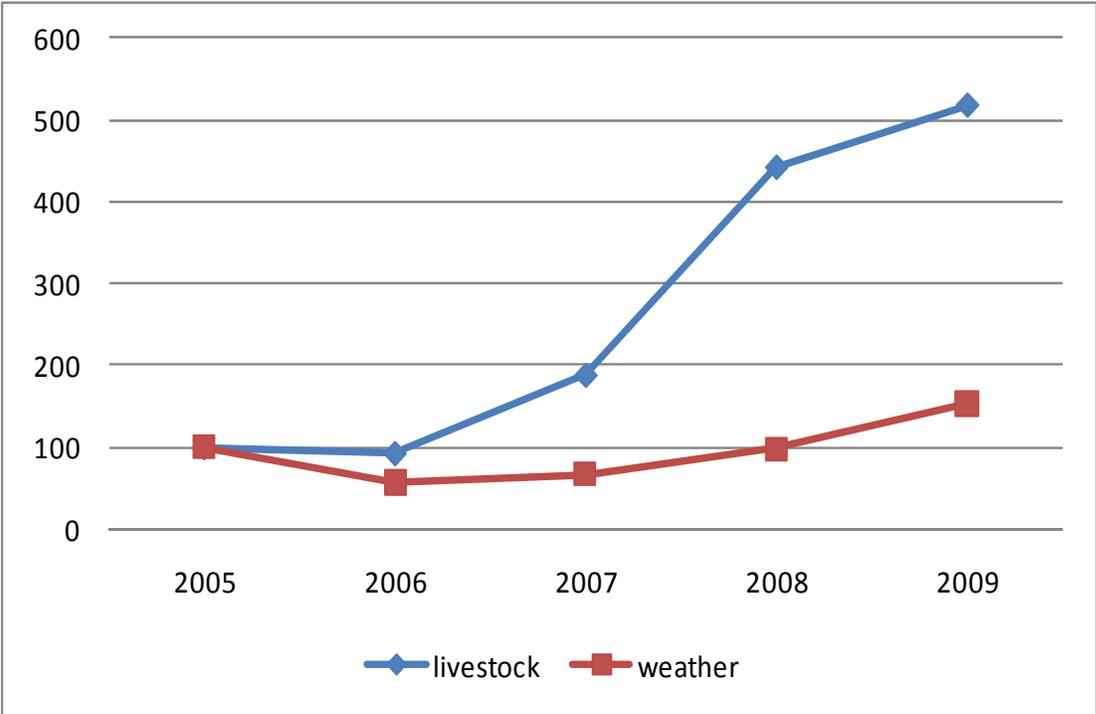
**Figure 4. Sales of rainfall insurance by BASIX, Andhra Pradesh**

Trends in sales of ICICI Lombard rainfall insurance in Andhra Pradesh. Figure plots the number of phases of policies sold, as well as the number of distinct policyholders. Source: BASIX.



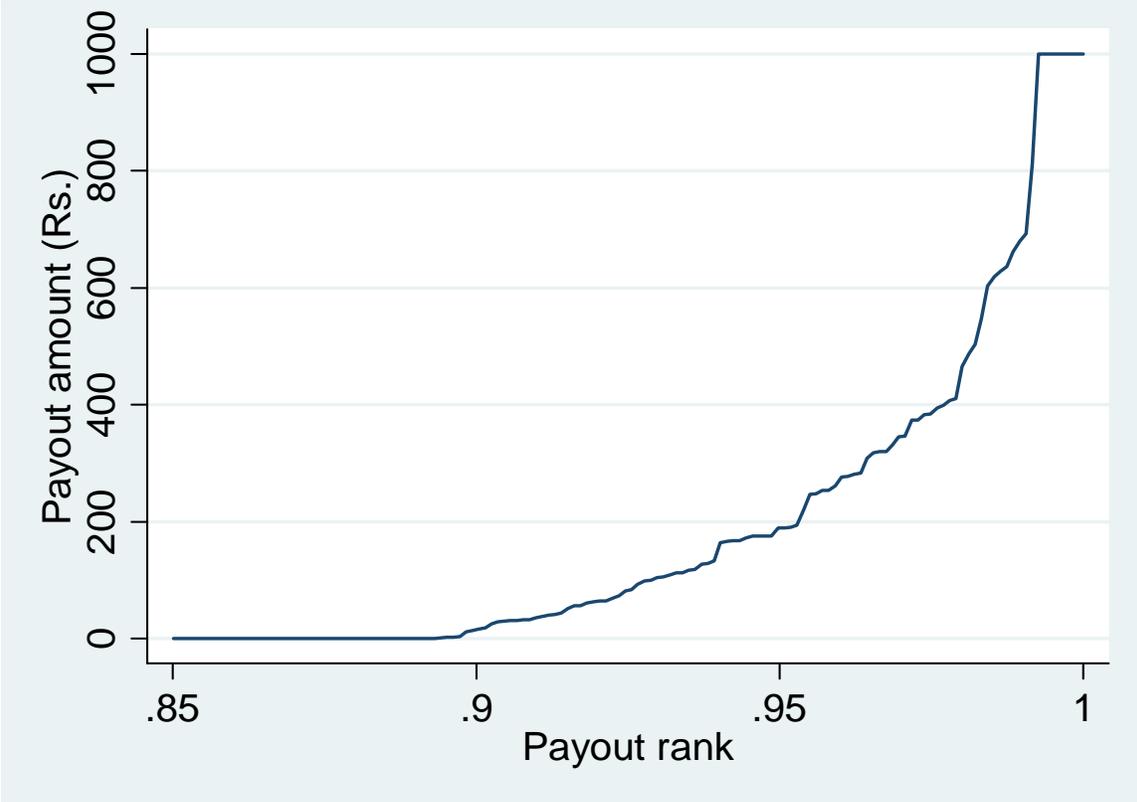
**Figure 5. Growth in livestock and weather microinsurance in Andhra Pradesh**

Figure presents total nominal premia (in Rs.) paid on livestock and weather microinsurance policies since 2005. Data for rainfall insurance is for Andhra Pradesh only, while data for livestock insurance is for all states. Indexed so that 2005 = 100. Source: BASIX.



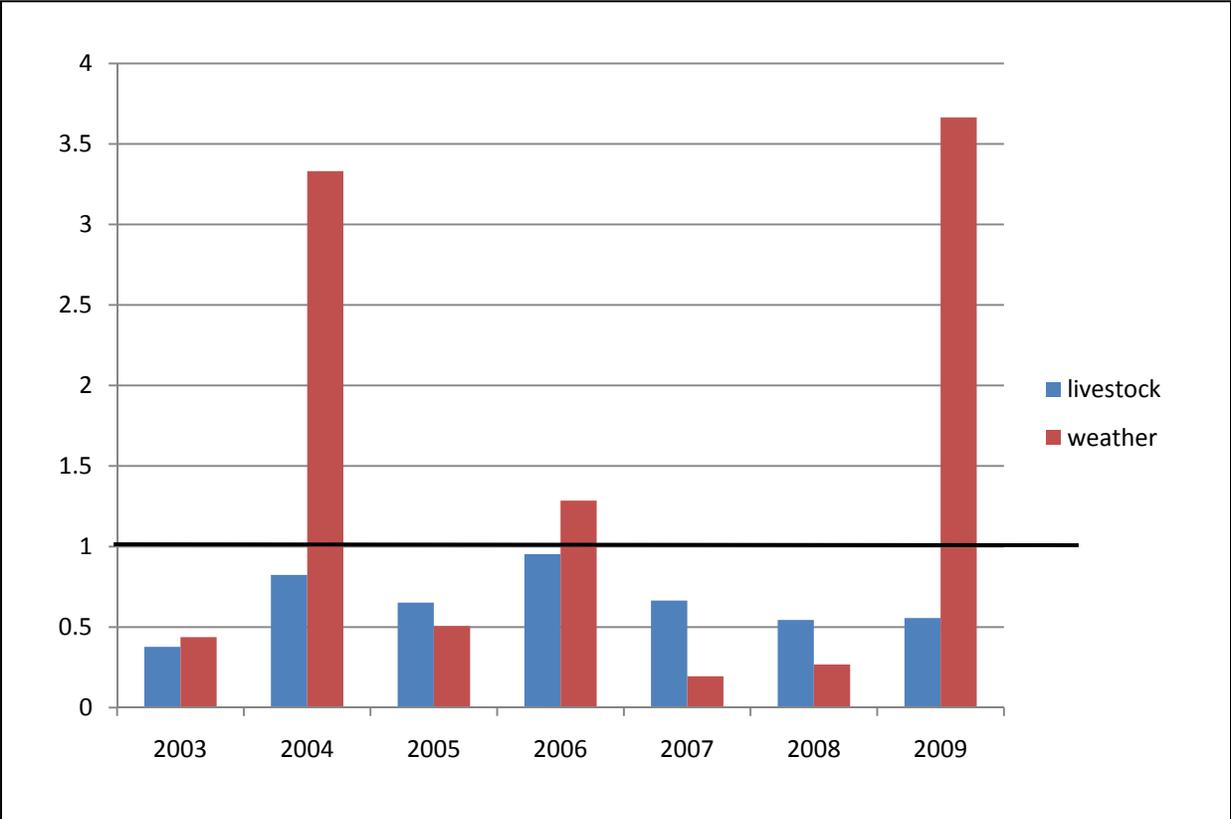
**Figure 6: Estimated distribution of insurance payouts**

Figure plots payout amount against payout rank, sorting all putative payouts in increasing order of size. Source: Giné et al. (2007).



**Figure 7. Payouts relative to premia for rainfall and livestock insurance**

Figure plots the ratio of total payouts to total premia paid for livestock insurance and rainfall insurance policies sold by BASIX across all states. Source: BASIX administrative data.



**Table 1: Summary Statistics on Insurance Policies Sold in Andhra Pradesh**

In some cases BASIX sold combined policies covering all three monsoon phases. These are counted as three policies (one per phase). Figures are also adjusted for 2003-2004. Source: BASIX administrative data.

<b>Year</b>	<b>Number of Policies</b>	<b>Number of Policy Holders</b>	<b>Policies per Policy Holder*</b>	<b>Premiums Collected (Rs)</b>	<b>Sum Insured (Rs)</b>	<b>Premium per phase (Rs)</b>	<b>Premium / Sum Insured</b>
2003	792	194	4.08				
2004	1,305	281	4.64				
2005	9,895	3,062	3.23	927,285	9,894,000	93.71	9.37%
2006	6,039	4,070	1.48	534,734	6,038,000	88.55	8.86%
2007	6,396	2,852	2.24	628,265	6,436,000	98.23	9.76%
2008	9,411	3,619	2.60	910,165	9,411,000	96.71	9.67%
2009	14,765	7,567	1.95	1,421,190	14,749,000	96.45	9.64%

**Table 2. Self-reported reasons for rainfall insurance non-purchase**

Non-purchasing households in the study areas Andhra Pradesh and Gujarat analyzed in Cole et al. (2009) are asked to explain why they did not buy insurance. In Andhra Pradesh, non-purchasing households were asked the top three reasons why they didn't buy insurance. Only the primary reason cited by the household for non-adoption of insurance is reported. This table is reproduced from Cole et al. (2009).

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

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**Table 3: Discounts and insurance demand**

The table below shows how rainfall insurance take-up rates in three districts of Gujarat, Ahmedabad, Patan and Anand, are affected by the size of the discount offered to households. “Return” indicates the estimated ratio of payoffs to premia, based on historical rainfall data (this calculation was not possible for Anand due to data limitations). Take-up indicates the fraction of treated households who purchase insurance. Reproduced from Cole et al. (2009).

<b>Discount</b>	<b>Ahmedabad</b>		<b>Patan</b>		<b>Anand</b>	
	“Return”	Take-Up	“Return”	Take-Up	“Return”	Take-Up
5	64%	25%	54%	22%	n.d.	36%
15	87%	37%	61%	22%	n.d.	37%
30	181%	47%	78%	30%	n.d.	44%