Policy Research Working Paper 5459

Microinsurance

A Case Study of the Indian Rainfall Index Insurance Market

Xavier Giné
Lev Menand
Robert Townsend
James Vickery

The World Bank
Development Research Group
Finance and Private Sector Development Team
October 2010

Policy Research Working Paper 5459

Abstract

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. This paper describes basic features of rainfall insurance contracts offered in India since 2003, and documents stylized facts about market demand and the distribution of payouts. The authors summarize the results of previous research on this market, which provides evidence that price, liquidity constraints, and trust all present significant barriers to increased take-up. They also discuss potential future prospects for rainfall insurance and other index insurance products.

This paper—a product of the Finance and Private Sector Development Team, Development Research Group—is part of a larger effort in the department to understand the weather based index insurance market in India. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The author may be contacted at xgine@worldbank.org.

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

Xavier Giné, World Bank

Lev Menand, Yale Law School

Robert Townsend, Massachusetts Institute of Technology

James Vickery, Federal Reserve Bank of New York

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 cited 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.[1]

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, 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.[2] 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 "microinsurance" products gaining popularity in the developing world. Other 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 microinsurance in some form and estimates a potential final market size of 1.5 billion to 3 billion households. Growth in these markets reflects a broadening of efforts toward greater financial access for the poor to include insurance and savings products in addition to microcredit.

A key challenge for microinsurance, as for other microfinance products, is to design it so as to minimize transaction costs and ameliorate incentive problems—factors which can otherwise 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 on the basis of a *publicly observed* and *exogenous* variable: 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 are observed in close to real time, this also means that claims can in principle be calculated and disbursed quickly to affected 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.[3]

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, for example, when the distance between the insured household and the rain gauge is larger 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 with 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 (Giné et al. 2008). Among 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 take-up. Our previous research shows, however, that other frictions—such as financial constraints and the level of trust of the household in the insurance provider—are also important for take-up. 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 land used for agriculture 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 macrodata from 1951 to 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 6.1 here]

Figure 6.1 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 1. 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, since if they were, farmers could use them to adapt their agricultural 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 6.2 shows the difference in days between the forecast and the actual onset for each year. (For example, in 2005 the IMD forecast that the monsoon would arrive in Kerala on June 13; as

it actually arrived on June 5, 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.[4]

[Figure 6.2 here]

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% had abandoned the crop at least once in the past ten years due to insufficient rain after the sowing period. Respondents report that the extra expense borne by those that replant is large, equivalent to 20% of average total production expenses. This suggests that farmers would benefit from having accurate prior information 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 prior information. In particular, when farmers with less access to risk-coping mechanisms had more accurate prior information, the increased accuracy led to average income gains of 8% to 9% of agricultural production.

3. Do Households Need Formal Rainfall Insurance?

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

- Drawing on accumulated savings of liquid assets (cash, bank account balances, etc.).
- Selling other assets (jewelry, land, livestock, etc.).

- Borrowing from moneylenders, microfinance institutions (MFIs), banks, or other financial institutions.
- Informal risk-sharing arrangements with neighbors, friends, or family. For example, if the household suffers an adverse shock, there may be an increase in remittance income sent by family members living abroad or in financial assistance provided by other households living in the same village, at least to the extent that those households are not themselves affected by the same shock.
- Government assistance (government work programs, drought-assistance programs etc.).
- Formal insurance arrangements (e.g. 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 involving labor supply, production, family planning, or 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 vulnerable to risk may also engage in a variety of costly ex ante "income smoothing" activities that may reduce income variability but also lower the average income. For example, a household with low savings concerned about monsoon risk may underinvest 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 (Gautam, Hazell, and Alderman 1994; Sakurai and Reardon 1997).

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 among 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 (Hazell and Ramasamy 1991). 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 among 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) present 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. Using Indian data, these authors estimate 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 asked households to list the three most important sources of risk they face. Notably, 89% of farmers cited drought as the most significant source of risk. (See Giné et al. [2008] for a table summarizing results of this question.) In addition, in surveys conducted in Andhra Pradesh and Gujarat, households that 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) cited “do not need insurance” as an explanation for nonpurchase. (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 among 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; Bryla and Syroka 2007; Hazell et al. 2010). The ICICI Lombard product was piloted in 2003 in the Mahabubnagar district of Andhra Pradesh, a semiarid 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 crop, called the Rabi, during the winter season).

For purposes of contract design, the Kharif is divided into three contiguous, sequential phases, each 35 to 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 such as NCMSL. Policies are then marketed to households that 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 20 kilometers 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.[5] 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 50 millimeters or on July 1 if accumulated rain since June 1 is below 50 millimeters.

As an example, consider the contract linked to rainfall in phase 1 of the 2006 monsoon, measured at the Mahabubnagar Indian Meteorological Department (IMD) weather station. The structure of this contract is presented in Figure 6.3, below (source: Giné et. al. 2007). Although contracts differ, the basic structure shown in Figure 6.3 is broadly representative of the contracts underwritten by ICICI Lombard.

[Figure 6.3 here]

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 70 millimeters. Otherwise, the policy pays 10 rupees for each millimeter of rainfall deficiency relative to the strike, until the lower threshold, or "exit," is reached. If rainfall is below the exit value, which in this case is 10 millimeters, the policy pays a fixed, higher indemnity of 1,000 rupees. This exit level is meant to approximately correspond to crop failure. The choice of this nonlinear 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 first phase, corresponding to sowing. 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 discuss 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 they partner in each rural area with local financial institutions which have well-established networks for the provision of financial services to rural households. Thanks to the 2005 Insurance Regulatory and Development Authority (IRDA) regulations, nongovernmental organizations, microfinance institutions, and self-help groups are legally recognized as microinsurance agents, thus increasing the potential for coverage (IRDA, 2005). In our study areas, product marketing and distribution is performed by the company Krishna Bhima Samruddhi Local Area Bank of BASIX, a large microfinance institution. In areas where it is active, BASIX has a network of local agents, known as Livelihood Services Agents (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, typically 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 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 the 1979–1984 period and, afterward, 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 nonborrowers, 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 drought and similar widespread calamities but also includes an “individual approach” for localized weather events, such as landslides, floods and the like.

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

Despite the high subsidies and a resulting high ratio of claims to premiums (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 involve significant administrative costs; (3) not all crops are covered by the scheme; (4) in some areas the geographic unit over which crop-cutting experiments are conducted is large, generating excessive basis risk; (5) claims take on average a year to be settled after the growing season; and (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 US$25 million 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, or rainy season crops (2007). For Rabi, or winter season crops (2007/08) the scheme was expanded to four states, and for Kharif and Rabi seasons (2008/09) to ten 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—ranging from 25% to 80%, depending on the crop (Hazell et al. 2010)—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, they are entitled to this premium subsidy support, which is meant as a temporary measure in the hope that the subsidy will promote adoption of index insurance and create a long-lasting insurance culture among farmers. At present, despite AIC having the largest market share, both ICICI Lombard and IFFCO-Tokio participate in WBCIS in various states.

5.2 BASIX

In this section we present information on trends in policies sold by BASIX through its company Krishna Bhima Samruddhi Local Area Bank 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 policyholders 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.

[Figure 6.4 here]

[Table 6.1 here]

Trends in sales of rainfall insurance by BASIX in Andhra Pradesh are presented in Figure 6.4 and Table 6.1.[6] These data show 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 7,567 households in 2009, accounting for 14,542 policies. 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 6.1.) Note that these trends are not due 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 6.1 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 ten 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 suggest that around half of the LSAs sell exactly the same number and type of phases to each of his or her clients (e.g. one unit of phase 1 and one unit of phase 2), even though there is significant variation across LSAs selling in a given location. This suggests that households follow the LSA's suggestions when deciding how much insurance to buy.

[Figure 6.5 here]

While the popularity of rainfall insurance has increased over this period, growth has been steady rather than spectacular. As a point of comparison, Figure 6.5 plots growth in rainfall insurance and livestock insurance sold by BASIX since 2005. Over this period, livestock insurance coverage has grown fivefold, compared with 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 premiums 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 et al. (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. 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 6.6, 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 6.6 plots payout amount against payout rank. (The minimum payout is zero, the maximum payout is 1,000 rupees.) 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 89th percentile), indicating that an indemnity is paid in only 11% of phases. The 95th percentile of payouts is around 200 rupees. In about 1% of phases, the insurance pays an indemnity of 1,000 rupees, 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.

[Figure 6.6 here]

Giné et al. (2007) also calculate the ratio of expected payouts on rainfall insurance relative to premiums. 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, among them a lack of economies of scale given the small initial market for the product and limited competition among insurance providers. Payout ratios would likely converge to a higher value in a mature market. 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 premiums 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 premiums each year since 2005. We do the same for livestock insurance policies sold by BASIX. Results are presented in Figure 6.7.

[Figure 6.7 here]

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 exceeded 350% of premiums 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 means that the calculations in Giné et al. (2007), which are based on historical data, underestimate expected payouts. (In that paper, we conducted some simple tests suggesting this is not the case; however, those tests were only preliminary in nature.) Notably, returns on livestock insurance are significantly less volatile than those on rainfall insurance and average around 60% of premiums collected over this period.

7. Who Buys Rainfall Insurance?

In this section we discuss evidence from Giné et al. (2008) which studies factors determining rainfall insurance participation. In particular, we estimate a simple regression model of the determinants of insurance demand, based on such household characteristics as wealth, landholdings, and risk aversion.

Evidence from this paper 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 premiums, presumably reflecting a combination of transaction costs, limited product market competition, and 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% to 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 factors, 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 being constant, a higher insurance policy price should clearly be associated with lower insurance demand among 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 on the like. While these other channels may certainly ameliorate demand, as described in Section 3, there is, however, 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 to the level of basis risk or, equivalently, will be increasing in the correlation between the insurance payoffs and the risk being insured (see, e.g. Clarke 2010). 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. While basis risk may contribute to a modest level of uptake, there is no rigorous evidence quantifying its magnitude for products studied in this chapter. A few arguments suggest,

however, that basis risk may be small. First, rainfall policies insure against near-catastrophic events (e.g. drought) that are systemic in nature. As a result, if a payout is triggered in one location, the probability of a payout in other locations is high. The insurance purchaser may be subject to other perils, such as pests, that affect crop yield but are not covered by the rainfall insurance policy, but insofar as these perils are idiosyncratic, they can be diversified away using existing risk-sharing networks. In addition, uptake of earthquake and flood insurance in the United States has also been characterized by low uptake, although the policy covers damages directly and hence there is no basis risk (Kunreuther and Roth 1998).

4. **Ex ante liquidity constraints**. Insurance premiums 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**. As with the previous point, households that do not fully understand the product may place 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. Similarly, households may perceive a risk of default of the insurance company (Doherty and Schlesinger 1990). Guiso, Sapienza, and Zingales (2008) argue that 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. (2010) 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 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 we present results of household surveys from our study areas in Andhra Pradesh. The survey 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 that purchase insurance generally cite reasons relating to “security” or “risk reduction.” Reasons cited by households that do not purchase insurance are presented in Table 6.2.

[Table 6.2 here]

In 2006, the most common single reason cited by households in both samples is "insufficient funds to buy insurance." This response is cited by over 80% of households as the most important reason for nonpurchase. 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 nonpurchase (2.8%). This low fraction appears consistent with the evidence cited in Section 3 that households are not fully insured against rainfall risk. Notably, in 2004, 21% of Andhra Pradesh households cited "do not understand insurance" as the primary reason why they did not purchase a policy. This fraction fell to only 2% by 2006, as households became more familiar with the product.

Cole et al. (2009) conduct 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 randomized household visits by an insurance educator, where various aspects of the visit were also randomized across households. In Gujarat, treatment consists of either a paper flyer or a video about the insurance product; the content of the flyer and video were randomized across households. 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.

Giné et al. (2008) also find evidence of liquidity constraints. In cross-sectional regressions insurance participation is positively correlated with wealth, even though the benefits of insurance are likely to be stronger for the poorest households. This finding 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).

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 [2011] 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 semiarid 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 toward 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 facto 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 by 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 designed an experiment to study whether the provision of formal insurance led to higher adoption rates of fertilizer and other productive agricultural investments. Before planting, participating households were offered, randomly, one of two financial products: rainfall insurance policies (similar to what was sold in previous years), or the promise of a cash payment equivalent to the expected payout of these policies, to be paid at harvest time. This research is still ongoing.

9. Recommendations

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 take-up 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.

9.1 Role of government

In order to ensure that weather insurance is used as an effective poverty reduction tool, the government could play an active role by (i) increasing the density of rainfall gauges, (ii) creating

a regulatory environment that fosters new product development and consumer protection, and (iii) fostering competition in the market.

Historical data are only available from approximately 550 IMD weather stations. These are insufficient to adequately cover the 150 million hectares of arable land, and they are rarely located in rural areas. In areas underserved by private weather providers, such as NCMSL, the government could help increase the density of automated rainfall gauges, which can help ameliorate basis risk and reduce the delay before payouts can be calculated and paid.[7]

By reforming the regulatory environment, the government could also improve the ability of the industry to underwrite contracts, thereby lowering reinsurance costs.[8] It could also devote resources to agronomic research to improve crop models that could lower basis risk by maximizing the correlation between the weather index and crop production.

Finally, the government could foster competition in the sector by scaling up WBCIS while providing incentives to insurance companies to lower the premiums. In areas where the correlation between rainfall and yields are well established or where basis risk is not a concern, WBCIS could be offered alone, but in other areas WBCIS could be perhaps combined with the modified NAIS. This way WBCIS would absorb weather risk, while NAIS could cover the residual production risk from other perils (pests, etc).

Although traditional financial markets do not allow households in developing countries to fully smooth out fluctuations in their living standards, the state and central governments could use weather insurance to hedge against fluctuations in the cost of social programs caused by weather events.[9] For example, relief aid and principal or interest waivers are likely to increase after a drought or a flood. Similarly, participation in the National Rural Employment Guarantee Act increases during bad monsoons as many of the rural poor decide to leave their land fallow to

work as laborers instead (Johnson 2009). The government could therefore purchase in international markets drought insurance that would pay precisely when the costs of welfare programs are higher.

In 2006, Ethiopia participated in one of the first government-level index-based insurance products, a project spearheaded by the UN's World Food Program (WFP) with technical assistance from the World Bank. Twenty-six weather stations throughout the country monitored rainfall daily, providing data to the French reinsurance company Axa Re. In the event of a drought, Axa Re would have paid US$7.1 million, to be disbursed in cash to as many as 300,000 farmers. The stations thus served as an early-warning system to trigger aid in the initial stages of a drought—up to four months sooner than traditional crisis aid—which would have enabled farmers to smooth their consumption by planting alternative crops and/or avoid selling off assets to survive. In 2007 the WFP and the World Bank developed software based on weather data to enhance this early-warning and monitoring system, and several donors, including the bank, the UK Department for International Development, and the U.S. Agency for International Development, are pledging resources earmarked for distribution in case these early-warning systems indicate a drought (World Bank 2010).

9.2 Role of the private sector

Our research findings also 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 suggest households are particularly credit constrained. This has not always occurred in the past, at least in our study areas. (On a related matter, it is also likely to be 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 experimenting with alternative indexes, like the NDVI, for areas that lack good rainfall data. The NDVI index measures vegetation greenness corresponding to the level of photosynthesis in a prespecified grid using satellite imagery. These satellite data exist for several years, are difficult to tamper with and can be accessed online in real time; this approach may also have less basis risk than a rainfall index. In 2005 AIC introduced an NDVI-based insurance product for wheat in Haryana and Punjab, but it faced problems due to cloud cover during critical growth periods. The Centre for Insurance and Risk Management in Chennai is currently involved in another pilot program in Andhra Pradesh.

In some cases where household financial literacy is low or other barriers to take-up are too high, insurance policies could be targeted to a group, such as an entire village, a producer group, or a cooperative.[10] The group could then decide or prearrange how best to allocate funds among 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.[11]

The 11th Indian five-year plan (2007–2012) asks the government to earmark US$7 billion for insurance, so that 40% of farmers will be insured by 2011/12. Developments in rainfall insurance and other microinsurance markets are already contributing toward this

ambitious goal. As these insurance markets mature, they are likely to significantly improve risk management opportunities among Indian households and entrepreneurial firms.

Acknowledgments

We thank BASIX for their generous provision of data and technical advice. We also express particular gratitude to K. P. C. Rao for his efforts in coordinating field experiments and collecting survey data in Andhra Pradesh; to an anonymous referee, Mangesh Patankar; to the editor, Chetan Ghate; and to our coauthors, especially Shawn Cole, for their insights. The views expressed in this chapter are those of the authors; they do not reflect the opinions of the Federal Reserve Bank of New York or the World Bank.

References

A. Our academic research on rainfall insurance

Cole, Shawn, Xavier Giné, Jeremy Tobacman, Petia Topalova, Robert Townsend, and James Vickery. 2009. Barriers to Household Risk Management: Evidence from India. Harvard Business School Working Paper 09–116. http://ssrn.com/abstract=1374076.

Giné, Xavier, Robert Townsend and James Vickery. 2007. Statistical Analysis of Rainfall Insurance Payouts in Southern India. *American Journal of Agricultural Economics* 89: 1248–1254. http://ssrn.com/abstract=1100218.

———. 2008. Patterns of Rainfall Insurance Participation in Rural India. *World Bank Economic Review* 22: 539–566. http://ssrn.com/abstract=1318107.

———. 2010. Forecasting When It Matters: Evidence from Semi-Arid India. Mimeo, World Bank.

B. Other cited papers

Balk, Deborah, Thomas Buettner, Gordon McGranahan, Mark R. Montgomery, Christopher Small, Donghwan Kim, Valentina Mara, Megan Todd, S. Chandrasekhar, and Sandra Baptista. 2009. Mapping the Risks of Climate Change in Developing Countries. Unpublished manuscript, City University of New York.Bertrand, Marianne, Dean Karlan, Sendhil Mullainathan, Eldar Shafir, and Jonathan Zinman. 2010. What's Advertising Content Worth? Evidence from a Consumer Credit Marketing Field Experiment. *Quarterly Journal of Economics* 125(1): 263–305.

Bryla, Erin and Joanna Syroka. 2007. Developing Index-Based Insurance for Agriculture in Developing Countries. United Nations Sustainable Development Innovation Briefs, Issue 2.

Caballero, Ricardo. 2000. Macroeconomic Volatility in Latin America: A Conceptual Framework and Three Case Studies. *Economía* 1 (1): 31–88.

Cai, Hongbin, Yuyu Chen, Hanming Fang, and Li-An Zhou. 2009. Microinsurance, Trust and Economic Development: Evidence from a Randomized Natural Field Experiment. Working paper, University of Pennsylvania.

Clarke, Daniel. 2010. A Theory of Rational Hedging. Mimeo. Oxford University.

Cole, Shawn, Thomas Sampson, and Bilal Zia. 2009. Money or Knowledge? What Drives Demand for Financial Services in Emerging Markets? Harvard Business School Working Paper 09–117.

Cole, Shawn, and Peter Tufano. 2007. BASIX. Harvard Business School Case 207–099.

Cull, Robert, Asli Demirguc-Kunt, and Jonathan Morduch. 2009. Microfinance Meets the Market. *Journal of Economic Perspectives* 23 (1): 167–192.

Dandekar, V. M. 1977. Crop Insurance for Developing Countries. Teaching and Research Forum Paper no. 10. New York: Agricultural Development Council.

Dercon, S., and L. Christiaensen (2007). Consumption Risk, Technology Adoption and Poverty Traps: Evidence from Ethiopia. World Bank Policy Research Working Paper 4257.

Dercon, Stefan, and Ingo Outes. 2009. Income Dynamics in Rural India: Testing for Poverty Traps and Multiple Equilibria. Working paper, Oxford University.

Doherty, Neil, and Harris Schlesinger. 1990. Rational Insurance Purchasing: Consideration of Contract Nonperformance. *Quarterly Journal of Economics* 105 (1): 243–253.

Duflo, Esther, Michael Kremer, and Jonathan Robinson. 2008. How High Are Rates of Return to Fertilizer? Evidence from Field Experiments in Kenya. *American Economic Review Papers and Proceedings* 98 (2): 482–488.

Duflo, Esther, and Chris Udry. 2004. Intrahousehold Resource Allocation in Côte d'Ivoire: Social Norms, Separate Accounts and Consumption Choices. NBER Working Paper no. 10498.

Feder, Gershon, Richard Just, and David Zilberman. 1985. Adoption of Agricultural Innovations in Developing Countries: A Survey. *Economic Development and Cultural Change* 33 (2), pp. 255–298.

Fein, J., and P. Stephens. 1987. *Monsoons*. New York: Wiley.

Gadgil, Sulochana, and Siddhartha Gadgil. 2006. The Indian Monsoon, GDP and Agriculture. *Economic and Political Weekly*November 2006: 4887–4895.

Gadgil, S., P. R. Seshagiri Rao, and K. Narahari Rao. 2002. Use of Climate Information for Farm-Level Decision Making: Rainfed Groundnut in Southern India. *Agricultural Systems* 74: 431–457.

Gautam, M., P. Hazell, and H. Alderman. 1994. Rural Demand for Drought Insurance. Policy Research Working Paper no. 1383. Washington, DC: World Bank.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales. 2008. Trusting the Stock Market. *Journal of Finance* 63 (6): 2557–2600.

Halcrow, H. G. 1948. The Theory of Crop Insurance. Ph.D. diss., University of Chicago.

Hazell, P., J. Anderson, N. Balzer, A. Hastrup Clemmensen, U. Hess, and F. Rispoli. 2010. *Potential for Scale and Sustainability in Weather Index Insurance for Agriculture and Rural Livelihoods*. Rome: International Fund for Agricultural Development and World Food Programme.

Hazell, P. B. R., and C. Ramasamy. 1991. *The Green Revolution Reconsidered: The Impact of High-Yielding Rice Varieties in South India*. Baltimore and London: International Food Policy Research Institute (IFPRI) / Johns Hopkins University Press.

Hess, U. 2003. Innovative Financial Services for Rural India: Monsoon-Index Lending and Insurance for Small-holders. ARD Working Paper 9. World Bank, Washington, DC.

Hill, Ruth Vargas, and Angelino Viceisza. 2009. An Experiment on the Impact of Weather Shocks and Insurance on Risky Investment. Mimeo. IFPRI.

Hohl, R., and H. Kannan. 2007. Greenfield for Agriculture Insurance. *IRDA Journal* (December): 17–19.

Horowitz, J., and E. Lichtenberg. 1993. Insurance, Moral Hazard, and Chemical Use in Agriculture. *American Journal of Agricultural Economics* 75 (November): 926–935.

Insurance Regulatory and Development Agency. 2005. Micro Insurance Regulations in Gazette of India. Extraordinary. Part III, Sec 4: 8–14. New Delhi.

Johnson, Doug. 2009. Can Workfare Serve as a Substitute for Weather Insurance? The Case of NREGA in Andhra Pradesh. IFMR Working Paper, series 32.

Kalavakonda, Vijay, and Olivier Mahul. 2004. Crop Insurance in Karnataka. Working paper, World Bank.

Kunreuther, Howard, and Richard Roth Sr., eds. 1998. *Paying the Price: The Status and Role of Insurance against Natural Disasters in the United States*. Joseph Henry Press, Washington, DC

Lamb, R. 2003. Fertilizer Use, Risk and Off-Farm Labor Markets in the Semi-Arid Tropics of India. *American Journal of Agricultural Economics* 85 (2): 359–371.

Lim, Youngjae, and Robert Townsend. 1998. General Equilibrium Models of Financial Systems: Theory and Measurement in Village Economies. *Review of Economic Dynamics* 1 (1): 59–118.

Lloyd's. 2009. Insurance in Developing Countries: Exploring Opportunities in Microinsurance. Report produced in conjunction with the MicroInsurance Centre. http://www.microinsurancecentre.org/UI/DocAbstract.aspx.

Lybbert, Travis, Francisco Galarza, John McPeak, Christopher B. Barrett, Steve Boucher, Michael R. Carter, Pin Chantarat, Aziz Fadlaoui, and Andrew Mude. 2009. Dynamic Field Experiments in Development Economics: Risk Valuation in Morocco, Kenya and Peru. Working paper, University of California at Davis.

Maccini, Sharon, and Dean Yang. 2009. Under the Weather: Health, Schooling, and Economic Consequences of Early-Life Rainfall. *American Economic Review* 99: 1006–1026.

Miller, Douglas, and Anna Paulson. 2007. Risk Taking and the Quality of Informal Insurance: Gambling and Remittances in Thailand. Federal Reserve Bank of Chicago Working Paper 2007–01.

Miranda, M. J.. 1991. Area-Yield Crop Insurance Reconsidered. *American Journal of Agricultural Economics* 73: 233–242.

Morduch, Jonathan. 1995. Income Smoothing and Consumption Smoothing. *Journal of Economic Perspectives* 9 (3): 103–114.

Nair, R. 2010. Crop Insurance in India: Changes and Challenges. *Economic and Political Weekly*, February 6, 19–22.

Parchure, R. 2002. Varsha Bonds and Options: Capital Market Solutions for Crop Insurance Problems. National Insurance Academy Working Paper, Balewadi, India..

Paxson, Christina H. 1992. Using Weather Variability to Estimate the Response of Consumption to Changes in Transitory Income in Thailand. *American Economic Review* 82: 15–33.

Raju, S. S.. and Ramesh Chand. 2007. Progress and Problems in Agricultural Insurance. *Economic and Political Weekly*, May 2007, 1905–1908.

Rao, Narahari, S. Gadgil, P. R. Seshagiri Rao, and K. Savithri. 2000. Tailoring Strategies to Rainfall Variability: The Choice of the Sowing Window. *Current Science* 78 (10): 1216–1230.

Rosenzweig, Mark, and Hans Binswanger. 1993. Wealth, Weather Risk and the Composition and Profitability of Agricultural Investments. *Economic Journal* 103, 56–78.

Sakurai, T., and T. Reardon. 1997. Potential Demand for Drought Insurance in Burkina Faso and Its Determinants. *American Journal of Agricultural Economics* 79 (4) (November): 1193–1207.

Shapiro, Jeremy. 2009. Weather Insurance and Investment Choice. Mimeo. MIT Department of Economics.

Shleifer, Andrei, and Robert Vishny. 1992. Liquidation Values and Debt Capacity: A Market Equilibrium Approach. *Journal of Finance* 47: 1343–1366.

Sinha, S. 2004. Agriculture Insurance in India: Scope for Participation of Private Insurers. *Economic and Political Weekly,* June 19, 2605–2612.

Skees, J. R., J. R. Black, and B. J. Barnett. 1997. Designing and Rating an Area Yield Crop Insurance Contract. *American Journal of Agricultural Economics* 79: 430–438.

Skees, Jerry, Peter Hazell, and Mario Miranda. 1999. New Approaches to Crop Yield Insurance in Developing Countries. EPTD Discussion Paper 55. International Food Policy Research Institute.

Suri, Tavneet. 2011. Selection and Comparative Advantage in Technology Adoption *Econometrica*, 79 (1): 159-209.

Townsend, Robert. 1994. Risk and Insurance in Village India. *Econometrica* 62 (3): 539–592.

World Bank. 2005. *Managing Agricultural Production Risk: Innovations in Developing Countries*. World Bank Agriculture and Rural Development Department. Washington, DC.

———. 2006. *Overcoming Drought: Adaptation Strategies for Andhra Pradesh, India*. Washington, DC.

———. 2010. *Innovative Finance for Development Solutions: Initiatives of the World Bank Group*. Washington, DC.

Yang, Dean, and HwaJung Choi. 2007. Are Remittances Insurance? Evidence from Rainfall Shocks in the Philippines. *World Bank Economic Review* 21: 219–248.

[1] 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.

[2] World Bank (2005) examines ten index insurance case studies in countries as different as India, Malawi, Nicaragua, and Ukraine.

[3] Index insurance was first proposed by Halcrow (1948) and Dandekar (1977) in the context of area yield insurance, which has since been tried on a subsidized basis in Canada, India, Sweden, and the United States (Miranda 1991; Skees, Black, and Barnett 1997).

[4] 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 the like to update the probability that the monsoon has arrived (Fein and Stephens, 1987).

[5] Some adjustments are made to accumulated rainfall when constructing the rainfall index used to calculate payouts. If daily rainfall exceeds 60 millimeters, only 60 millimeters is counted towards the cumulative rainfall index. Also, rainfall less than 2 millimeters 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.

[6] Although we also have data on BASIX insurance sales in other states, 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.

[7] Historical data not being available for these new gauges, however, the process of setting a fair premium is complicated, since insurance companies typically add an uncertainty loading to the premium.

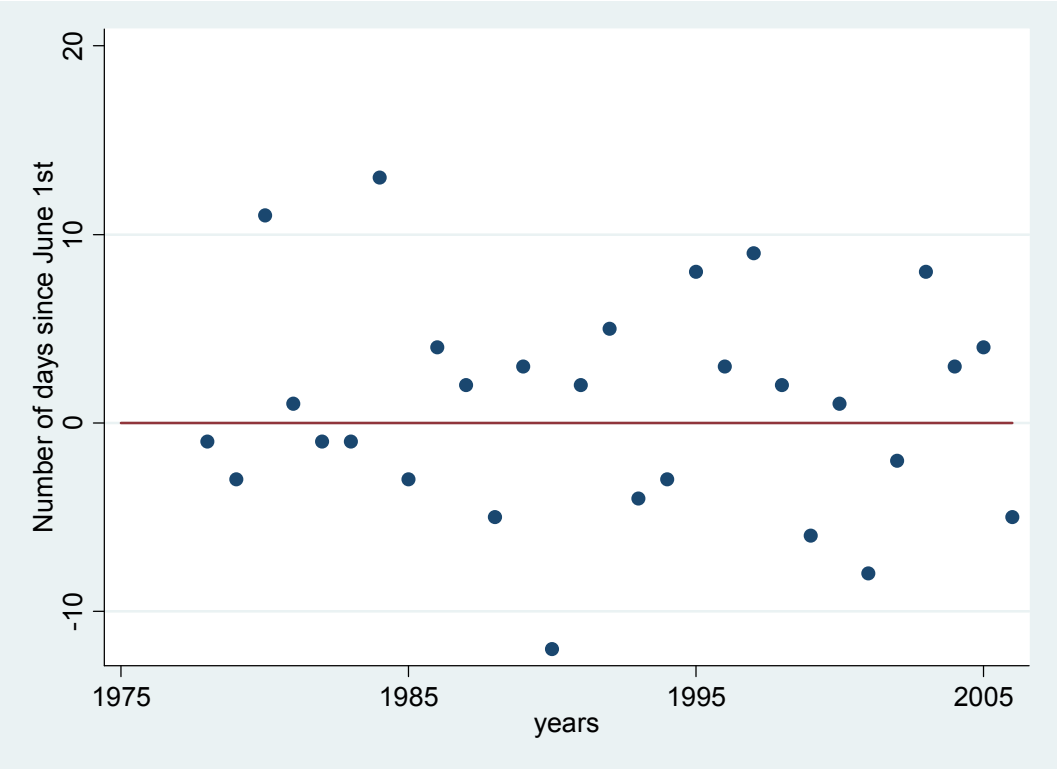
[8] The World Bank and other partners established in 2007 the Caribbean Catastrophe Risk Insurance Facility (CCRIF), the world's first regional insurance fund offering index-based insurance. Thanks to the CCRIF, member countries saved about 40% of premium costs (World Bank, 2010).

[9] Caballero (2000) shows evidence that Chile's GDP is sensitive to the world price of copper, more so than Australia's GDP is affected by the price of coal. Of course, it is important to smooth consumption, not GDP, and while this fact may reflect that financial markets are more developed in Australia than in Chile, copper represents a substantially higher share of Chile's economy than coal does in the Australian economy. Despite these criticisms, the point remains that Chile has not been able to use financial markets to fully smooth out the sensitivity of Chile's economy to fluctuations in copper prices.

[10] One of the reasons for comparing livestock to weather insurance in Section 5.2 was to emphasize differences in the level of understanding across insurance products. For example, farmers are far more familiar with livestock death than with a trigger of accumulated rainfall measured in millimeters at a nearby rainfall gauge.

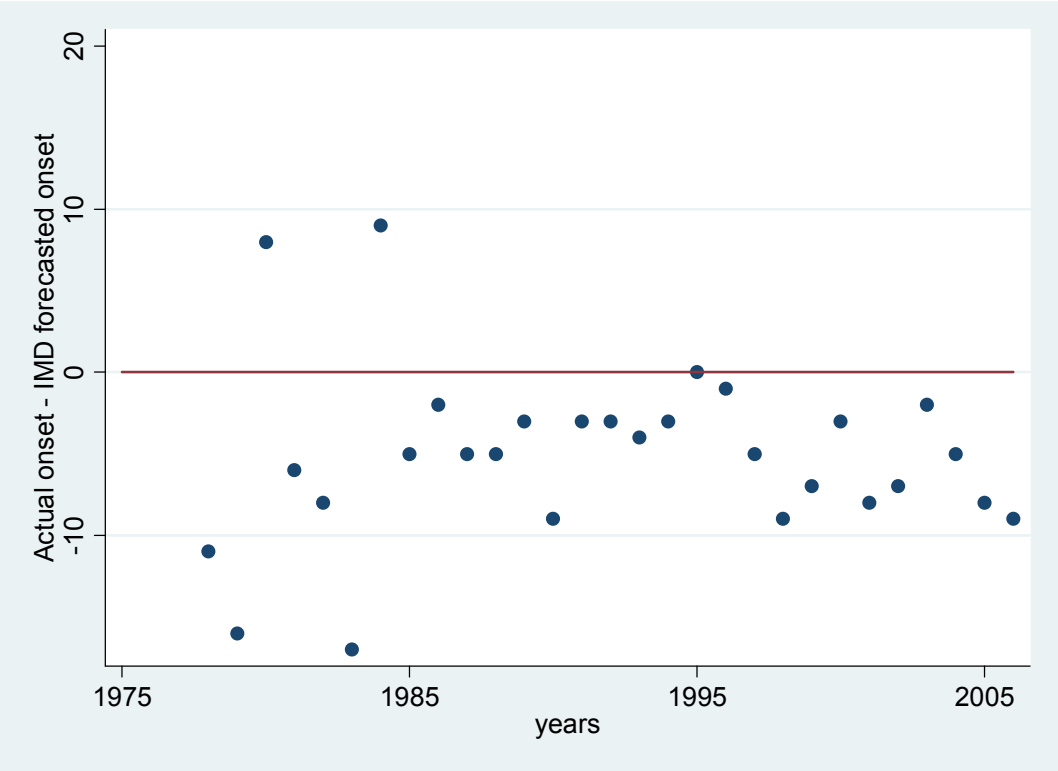
[11] See also the case study of PepsiCo potato farmers discussed in Hazel et al. (2010) and a pilot program similar to Monsanto's by Pioneer Seeds with paddy farmers in 2008.

Figure 1. Actual Onset over Kerala as deviations from June 1st (1978-2006)



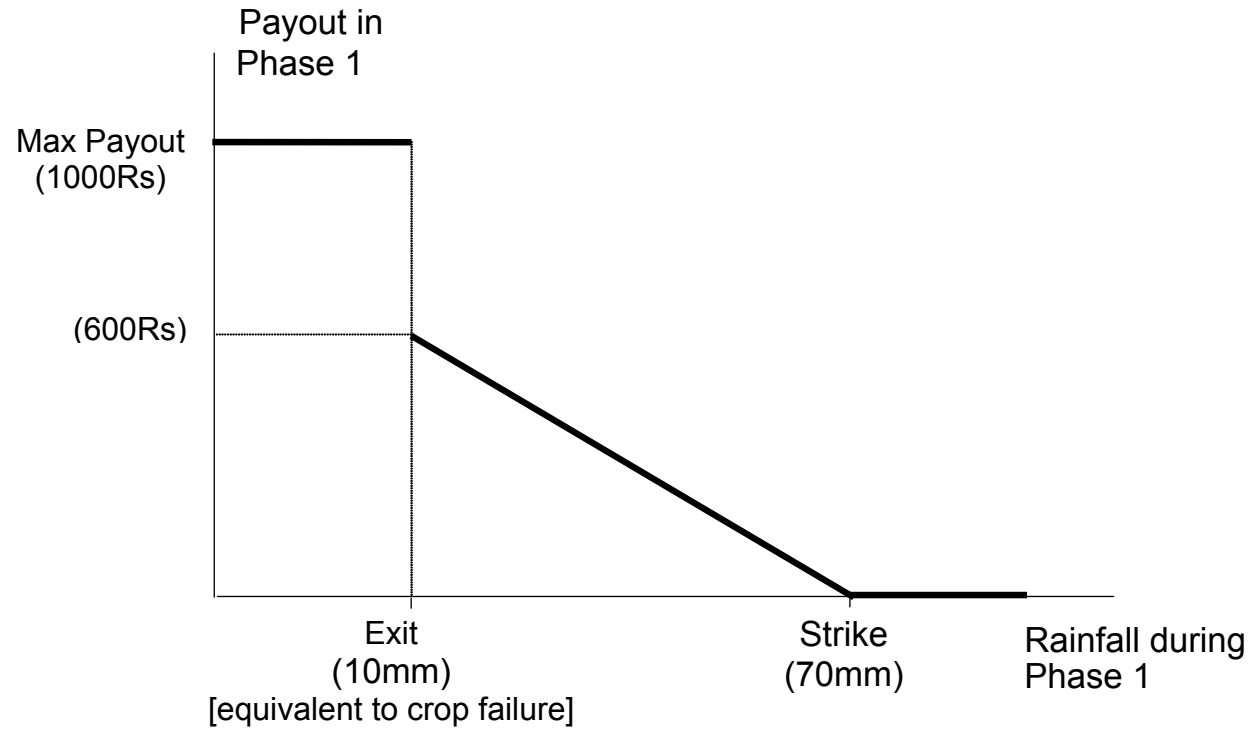
Note: Data for this Figure come from Indian Meteorological Department (http://www.imdpune.gov.in/)

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



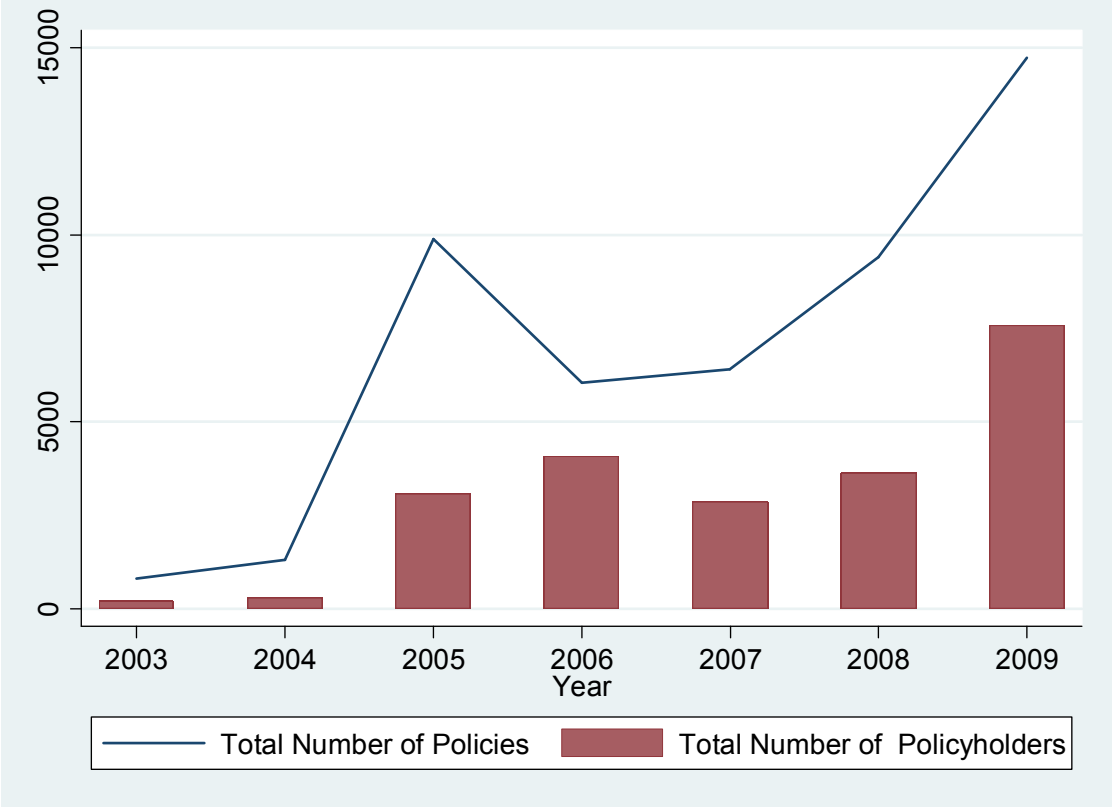
Note: Data for this Figure come from Indian Meteorological Department (http://www.imdpune.gov.in/)

Figure 3. Payout structure for rainfall insurance contracts



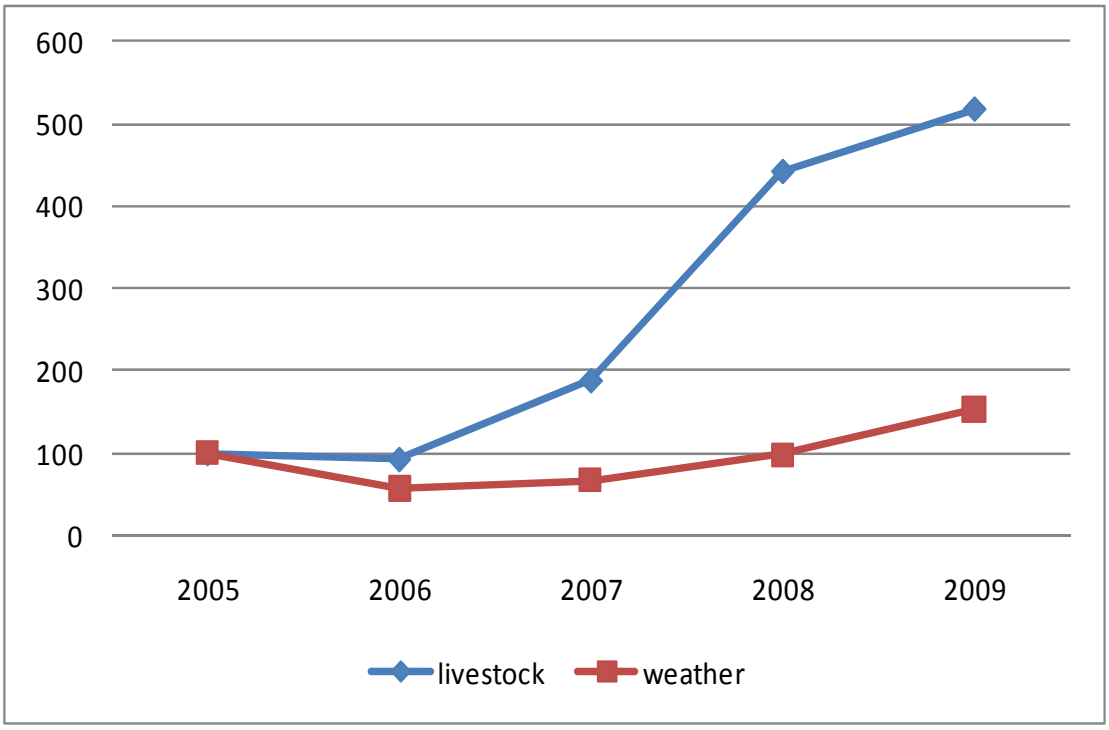
Note: Figure plots the relationship between insurance payouts and phase rainfall for an example insurance contract: the policy covering the first monsoon phase in 2006 for the Mahabubnagar mandal. Source: Giné et al. (2007).

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



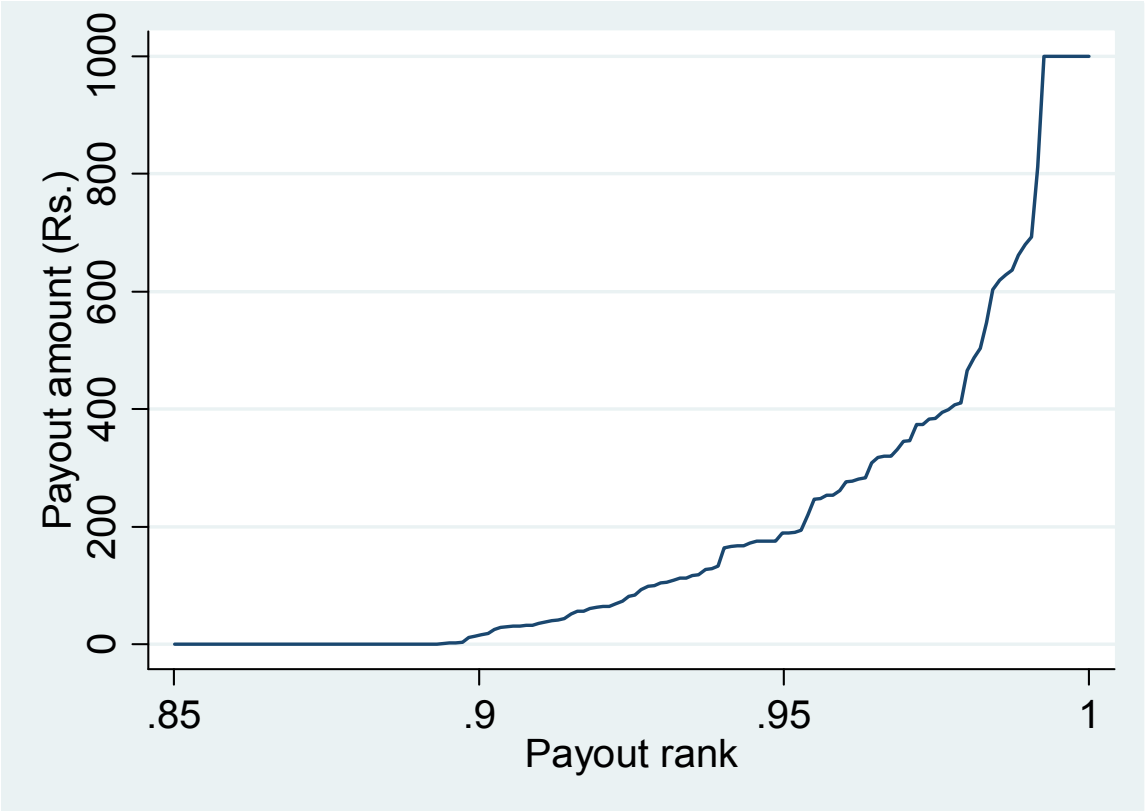
Note: Trends in sales of ICICI Lombard rainfall insurance in Andhra Pradesh. Figure plots the number of phases of policies sold, as well as the number of distinct policyholders. Source: BASIX.

Figure 5. Title: Growth in livestock and weather microinsurance in Andhra Pradesh



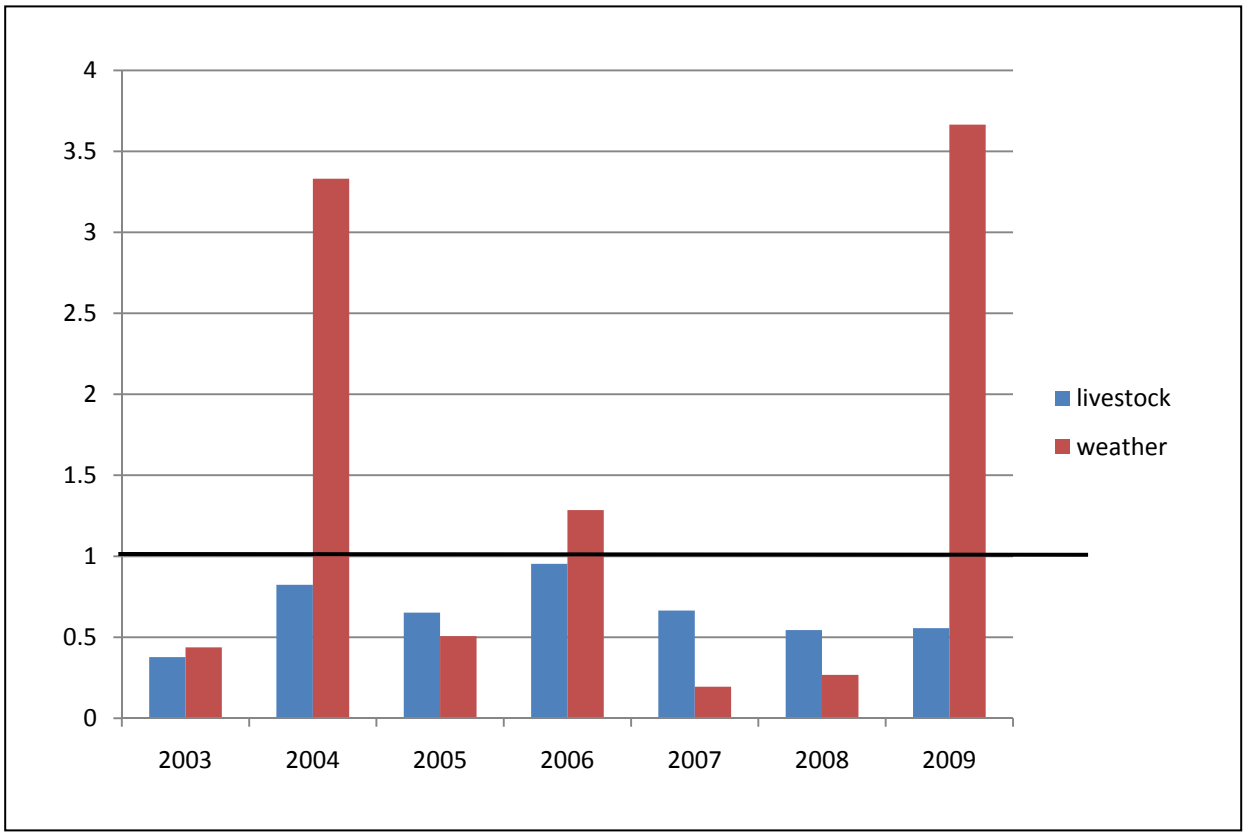
Note: Figure presents total nominal premia (in Rs.) paid on livestock and weather microinsurance policies since 2005. Data for rainfall insurance is for Andhra Pradesh only, while data for livestock insurance is for all states. Indexed so that 2005 = 100. Source: BASIX.

Figure 6. Estimated distribution of insurance payouts



Note: 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



Note: 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

Year	Number of Policies	Number of Policy Holders	Policies per Policy Holder*	Premiums Collected (Rs)	Sum Insured (Rs)	Premium per phase (Rs)	Premium/ Sum Insured
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%

Note: 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.

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

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

Note: 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).