Weather Insurance: Managing Risk Through an Innovative Retail Derivative

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Abstract

This paper presents the results of a series of randomized field experiments conducted in villages in rural Gujarat. Rainfall insurance, an innovative risk-management tool, was marketed to farmers and agricultural laborers. We first examine what factors affected take-up decisions. Wealth, education, risk-aversion, and the ability to understand probabilities are positively associated with take-up. We then conduct a series of marketing experiments, which reveal the following: framing risk dramatically affects take up, while other subtle cues do not. Finally, we measure the price elasticity of demand, finding a high sensitivity.

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1 Introduction

Rural households in India are exposed to substantial weather risks. Farmers' crops may fail when the monsoon is bad, agricultural laborers may not be able to find work, and demand for non-agricultural labor will fall. Households have of course developed a variety of coping mechanisms – savings, formal and informal insurance, borrowing, choice of economic activity, and choosing to work more hours – to cope with them.

Many of these coping strategies are far from ideal, however. Savings typically earn low rates of return. Borrowing from moneylenders may help smooth consumption, but these loans come at very high cost. Perhaps most importantly, weather shocks are aggregate shocks, meaning all households demand insurance at the same time. Global financial markets are well-suited to insure this consumption risk. While the growth rate of the Indian economy is related to the quality of the monsoons the country experiences, the value of global financial markets do not, and the basic capital asset pricing model suggests that markets should be willing to insure Indian agricultural consumption at nearly risk-free rates.

Rainfall insurance is a financial contract which pays policy holders a payout if accumulated rainfall during a period falls outside prespecified bands. The contract specifies a weather station at which rainfall is measured, along with start and finish dates, and the payout in case of shortfall (and, sometimes, excess).

In 2005, an Indian NGO, the Self-Employed Women's Association (SEWA), began offering rainfall insurance to its members. In 2006, they expanded marketing efforts, offering insurance to 33 villages, selected randomly from a list of 100. In 2007, 17 additional villages were added, bringing the total number of villages in which insurance was offered to 50. In offering the insurance, SEWA randomly varied the marketing messages, allowing a test of framing effects. Finally, marketers offered a range of discount coupons. This variation, combined with a panel survey of 1,500 households, allows us to answer questions about the demand for insurance, how psychological and social factors affect purchase decisions, and, in the longer-term, the causal impact of insurance on household investment decisions, consumption smoothing, employment decisions, and general welfare.

We find the following. Cognitive barriers to adoption may be important: both education,

and facility with numbers, are closely correlated with the decision to purchase insurance. Wealth and risk-aversion are also positively correlated with insurance purchase. Consumers are price sensitive: discounts on the price of insurance have large impact on the demand for insurance. Finally, psychological factors play a significant, but limited, role. Several manipulations do not affect purchasing decisions. These include whether the SEWA brand is emphasized, which religion is made salient, and whether focus is placed on individual vs. group well-being is stressed. In contrast, the use of negative language (e.g., 'Protect yourself from catastrophe') has a strong and positive effect on take-up of insurance, comparable in size to the largest discount offered.

This paper is closely related to Gine, Townsend, and Vickery (2007), which studies rainfall insurance in Andhra Pradesh, India. In the conclusion, we compare and contrast our findings with their work.

This paper proceeds as follows. The next section describes the context in which our work takes place, and describes the study design. The third section presents a description of the household characteristics and risk-coping mechanisms. The fourth explores what household characteristics are correlated with demand for rainfall insurance. The next two sections describes the marketing and pricing experiments. Finally, section seven concludes.

2 Agriculture in Gujarat

2.1 Environment

This work studies the behavior of households in 100 villages in rural areas of three districts of rural Gujarat (Ahmedabad, Anand, and Patan). Most of the population in our study area rely on subsistence agriculture, often combined with casual day labor. Subsistence crops include bajri (millet) and sorghum. Those with more land grow crops for sale, including cotton, castor, and cumin.

While the crop insurance is notionally available, very few individuals purchase it. (Sinha, 2004[1]) The reasons are many: first, it is primarily sold through government banks, which require agricultural borrowers to purchase the insurance. However, few farmers, and in particular very

[1] A more thorough discussion of agricultural insurance in India may be obtained from Sinha, 2004.

few poor farmers, are able to borrow from government banks. Many are not aware of the product. Even when the policy should pay out, the insurance companies may legally decline to pay, as their liability is limited by the amount of premiums they collected. In these cases, political considerations affect which farmers are paid.

In the absence of insurance, households have developed a variety of mechanisms – savings, formal and informal insurance, borrowing, choice of economic activity, and choosing to work more hours – to cope with them. Seminal work by Townsend (1994) demonstrates that there is substantial consumption insurance at the village level in southern India, as household consumption comoves closely with average (or aggregate) village income. However, much aggregate risk remains. Jayachandran (2006) shows that productivity shocks induced by low rainfall have heterogenous effects, and in particular push down the wage for laborers, exacerbating their vulnerability.

Indeed, many coping strategies are far from ideal. Savings typically earn low rates of return. Informal insurance is of limited value when the shock affects most people in the area, since all households will be in need of assistance at the same time. Borrowing from moneylenders may help smooth consumption, but these loans come at very high cost.

While local households are limited in their ability to cope with local shocks, larger financial markets can provide complete insurance against local shocks. Traditionally, several factors have limited the scope for micro-insurance products such as crop-insurance. First, moral hazard and adverse selection, present in any insurance market, may be particularly severe in crop insurance. Individuals have a good sense of the quality of their land, while the insurer typically knows very little. Second, transaction costs may be very high, as highly trained, incorruptible individuals are required to administer claims. Transactions costs are a particularly important concern when the size of the policy sold is very small.

Recently, a new model in which NGOs concerned about the welfare of their members cooperate with the insurance company to reduce transaction costs has led to the emergence of micro-insurance products. We describe the evolution of rainfall insurance in the next subsection.

2.2 Rainfall Insurance and Study Design

The arrival of rainfall insurance in India was spurred by two events. India has dramatically liberalized financial markets in the past decade, and in particular allowed new entrants into the field. Insurance companies, however, face a requirement to generate a certain share of revenue from rural areas. This has led to development in microinsurance, with companies offering health, life, property, and livestock insurance. Around the turn of the century, the International Task Force on Commodity Risk Management in Developing Countries conceived, and began to work out, the technical details for offering rainfall insurance.

The idea is relatively simple: an insurance contract agrees on a pre-specified amount of rainfall, usually the minimum needed to ensure successful growth of a given crop. If, during the growing season (which is also pre-specified), rainfall falls below a pre-specified threshold, the policy holder is eligible to receive a payment. The payment typically increases with the amount of the rainfall deficit, with a maximum payout at a threshold below which total crop failure is likely.

The World Bank / Commodity Risk Management Group first implemented rainfall insurance in the state of Andhra Pradesh, in India, in cooperation with BASIX, a microfinance corporation, and ICICI Lombard, a private insurance company (see Hess, 2003, and World Bank, 2005). Within several years, sales had grown to tens of thousands policies, and at least one other private insurer entered the market.

Before discussing the advantages and limitations of rainfall insurance, it may be useful to fix ideas. We describe two products, the first provided by ICICI, and sold by SEWA in 2006, the second provided by IFFCO-Tokio, and sold by SEWA in 2007.

2.2.1 ICICI Lombard's Product

The product design is given in Table 1. It was divided into three separate phases: the first two paid in case of rainfall deficit, while the third paid in case of excess rainfall. The amount of payout is determined as follows: in Phase I, if rainfall is above 100mm, no payout is made. For each mm of deficit below 100mm, the policy holder is paid Rs. 5 / mm of deficit. If total rainfall is below 10 mm, the policy-holder is paid a single payment of Rs. 500. In financial terms, the contract may be replicated by buying 5 puts on rainfall at a strike price of 100, selling 5 puts at

a strike price of 10, and buying a digital option that pays Rs. 500 if rainfall falls below 10mm.

	Phase I	Phase II	Phase III
Coverage	Deficit	Deficit	Excess
Target (Strike)	100	65	550
Rs/mm over target	5	5	5
Exit	10mm	5mm	650mm
Policy Limit	Rs. 500	Rs. 500	Rs. 500

Table 1: Ahmedabad Low Rainfall Policy, 2006

Phase II works similarly (though with different strike prices), while Phase III pays out only in the event that rainfall is above 550mm, with a maximum payout of Rs. 500 rainfall is above 650 mm. The price of the contract was Rs. 144, or about USD 3.

The start date of Phase I was dynamically determined, based on the first date in June in which cumulative rainfall exceeded 50mm. Farmers plant seeds only after the soil has received some moisture. If cumulative rainfall did not exceed 50 mm by June 1st, the first day of Phase I would be July 1st. Phases I and II last 35 days each, while Phase III lasts 40 days. Because the soil has only a limited capacity to absorb moisture, any rainfall occurring in Phase I or II that exceeded 50mm in a single day, would count as only 50mm. Similarly, any day with rainfall less than 2mm would count as zero, because such small amounts would not be absorbed in the soil.

2.2.2 IFFCO Tokio Product

Based on feedback received from the marketing team and consumers, SEWA elected to go with a simpler policy for 2007. This policy sets a target amount of rainfall over a four-month period, and pays out according to a schedule if the total cumulative rainfall falls short. The schedule is reproduced in Table 2.

% Deficiency	Claim Payout (% of SI)
0%	0
10%	0
20%	0
30%	10%
40%	15%
50%	25%
60%	35%
70%	45%
80%	75%
90%	100%

Table 2: IFFCO-Tokio Product

2.2.3 The Economics of Rainfall Insurance

One might reasonably ask why insurance companies are selling rainfall insurance, rather than crop insurance, as rainfall insurance suffers from substantially greater basis risk. In this subsection, we briefly discuss the advantages and limitations of rainfall insurance.

Rainfall insurance has at least two important advantages. First, relative to crop insurance, transaction costs are significantly lower. There is no need to hire individuals to verify crop production (nor to hire individuals to monitor the claims adjusters, etc.). This is a significant advantage, as it can be very costly to hire and monitor individuals with the requisite human capital to work in rural areas. In contrast, rainfall insurance pays out based on the reported index. The only cost is the weather monitoring station. Low transaction costs make it feasible to offer very small policies, particularly if a non-profit organization provides the marketing services.

Second, rainfall insurance avoids some problems of adverse selection. Crop insurance in India is not linked to individual farms: rather, the government selects (presumably at random) test farms, on which it measures output loss. Thus, there is no direct moral hazard or adverse selection. However, agricultural output is difficult to model. To the extent that the government

does not correctly price insurance (perhaps because of incomplete or incorrect price models, or possibly political pressure), farmers in underpriced areas may purchase more than in areas where it is relatively overpriced, exacerbating the cost of mispricing mistakes.

Third, rainfall risk may be easier to model, and therefore for insurers to reinsure. Historical rainfall data are generally of good quality, and much more plentiful than data on crop output.

Rainfall insurance also has several disadvantages. The first, and likely most important, is basis risk. Crop output is not perfectly correlated with rainfall. Moreover, households may experience different rainfall patterns than those measured at the weather station. (For this reason, insurance is typically not sold to households more than 30 km from the rainfall station). Finally, policy holders face all sorts of other risks, such as pests, flooding, etc., which are not covered by rainfall insurance.

Second, rainfall insurance is complicated: it is much easier to explain crop insurance or life insurance than rainfall insurance. Farmers may not have a good concept of what a millimeter of rain is, or what range of rainfall outcomes are likely to obtain. Many have limited numeracy skills, which makes even calculating a payout complicated. Some individuals may not trust private financial markets.

2.3 Study Design

We first describe the study design. In 2006, 100 villages were selected for inclusion in the study, based on the criteria that they be located fewer than 30 km from the nearest rainfall station, and that SEWA have a presence in the village. Fifteen households were interviewed in each village. Following this selection, however, two of the 100 villages were deemed to be so close that it would not be possible to treat one and not the other, so they were grouped together, and both assigned the same treatment status. Thirty households in this pair of villages were interviewed. The total sample size is therefore 1,500. The villages were divided roughly evenly across districts (see Table 3).

Households were surveyed in May of 2006. Following the survey treatment status was assigned, and rainfall insurance was offered to 30 of the 100 villages. In the first year, none of the rainfall insurance policies paid out. A follow-up survey was conducted in October of 2006.

In 2007, SEWA elected to continue to phase in the insurance product, offering it to an

additional 25 villages. These villages were randomly selected from the remaining villages.

We now turn to the household decision to purchase insurance. There are large fixed-costs associated with providing insurance: staff training, weather data subscription, etc. Take-up was relatively high for a new product: approximately 23% of the households offered insurance purchased a policy. In 2006, the insurance was offered in 33 villages, so overall approximately 114 surveyed individuals elected to purchase insurance.

Table 7 reports insurance take-up rates. Insurance take-up was highest in Patan, where 34% of those surveyed purchased insurance. Only 14% of those surveyed in Ahmedabad, and 18% in Anand, elected to buy insurance.

3 Household Characteristics and Risk-Coping Mechanisms

3.1 Summary Statistics: Agricultural Households in Gujarat

The decision to purchase rainfall insurance depends on a households circumstances (if it has enough assets, it may prefer to self-insure), as well as it's understanding of the product, and its attitude towards risk. In this section,we report on these household characteristics. The survey covered 15 households, in 100 villages. The sampling methodology for each village was: 5 households chosen at random from SEWA membership rolls; 5 households chosen at random from a list of households with financial savings; and 5 households thought likely by SEWA to purchase insurance.[2]

3.1.1 Composition, Wealth and Income

The first line panel of Table 4 gives the income source of the SEWA members surveyed. It is immediately clear that agricultural income is an important source of livelihood for respondents. Overall, 72% of the households reported agriculture as the main source of income. Many more households reported agricultural labor (45%) as their primary source of income, relative to

[2] All sample selection was done before villages were assigned treatment status, so we are not worried about any experimental bias. This non-random selection clearly limits the representativeness of our sample. However, in many villages a large share of households are members of SEWA. Moreover, this targeting was necessary to ensure statistical power.

own cultivation (19%). The average household size was 5.94 individuals, with a large share of respondents belonging to a "scheduled" caste: 35% overall, with minor variation by district.

To measure wealth, we construct an asset index, using 26, including such items as phones, clocks, television, bicycle, cart, and jewelry, and normalize the index to range from 0 to 1. Ahmedabad is the richest district (with an average asset index score of .33), followed by Anand (.25) and Patan (.23).

The households in our study are very poor. The average measured annual income of households in our sample was approximately Rs. 27,000 per year, which translates to a per capita income of roughly $110 USD per annum. Approximately fifty percent of the households owned some amount of land

3.1.2 Education, Financial Literacy, and Attitude Towards Risk

Rainfall insurance is complicated, and household characteristics may affect how individuals value the product. Only 17% of the sample, on average, reported being illiterate (the national illiteracy rate in India was 35% in 2001). Simply having completed school may be a poor indicator of an individual's ability to read, write, and solve math problems one encounters in everyday life. We thus administered math tests, as well as checks to see how the respondents understood probability problems and whether they could answer simple financial questions. To thank the respondents for their effort, and ensure they had an incentive to think about the questions, Rs. 1 reward was offered for each correct question.

The average math score was 64%. Almost all respondents could answer the simplest question ("what is 4+3") while many more had difficulty with multiplication ("3 times 6") and division ("one-tenth of 400"). Since respondents were not allowed to ask their friends or neighbors, it is reasonable to think that in the real world, they may perform better when answering these questions.

To measure financial literacy, we adapted three questions used by Lusardi and Mitchell (2006). The questions were: (i) if you borrow Rs. 100 at a money lender at a rate of 2 percent per month, with no repayment for three months. After three months, do you owe less than Rs.102, exactly Rs. 102, or more than Rs. 102. (ii) Suppose you need to borrow Rs. 500. Two people offer you a loan. One loan requires you to pay back Rs. 600 in one month. The second

loan requires you pay back in one month Rs. 500 plus 15% interest. Which loan represents a better deal for you? Finally, (iii) Is it riskier to plant multiple crops or one crop?

Measured financial literacy was very low: the average score was .34, or one correct question. (Three questions were asked). If people were guessing, we would expect a score of .44, (two questions were multiple choice with two answers, one was multiple choice with three answers.)

The decision to buy insurance is, to a large extent, shaped by what one believes the probability of a drought is. To test individuals understanding of probability, we showed them several diagrams. Each diagram was a pair of bags, in which a number of black and white balls were placed. We asked the households to name the bag in which a black ball was more likely to be drawn. Respondents did much better on these questions, answering on average 72% of the questions correctly.

Finally, we read (once) a description of a sample insurance product (temperature insurance), and tested household comprehension. After only one description, households answered 68% of the questions testing their knowledge of the product correctly.

Individuals' attitudes towards risk are important when deciding whether to purchase insurance—since the "expected return" of an insurance product is negative, the product has value only to the extent that households place a higher value on money in times of drought than times of good rainfall. Risk aversion is difficult to measure, because people often do not make the same decision in reality, as they do when answering hypothetical questions.

We follow Binswanger (1981) and measure risk aversion with actual lotteries, for real (and substantial) amounts of money. We gave individuals a choice of a set of lotteries, ranging from a perfectly safe lottery (that paid Rs. 50 for sure), to a lottery that paid Rs. 200 with probability $\frac{1}{2}$ and Rs. 0 with probability $\frac{1}{2}$. The detailed results are given in Table 6. Approximately 14% of the households chose the perfectly safe option. The most popular choice was Rs. 160 with probability $\frac{1}{2}$, and Rs. 20 with probability $\frac{1}{2}$. In general, subjects exhibited risk aversion, as the riskiest lotteries were chosen by relatively few households.

Table 5 also reports measures of the degree to which individuals depart from what is predicted by standard economic models. For example, we asked a question: "Would you prefer Rs. 8 today, or Rs. 10 in one month?" We also asked "Would you prefer Rs. 8 in six months, or Rs. 10 in seven months." Economic theory predicts that if one prefers Rs. 8 today to Rs. 10 in one month,

one should also prefer Rs. 8 in six months to Rs. 10 in seven months. Yet, nearly two-thirds of the population expressed "preference reversal," changing from patient to impatient depending on the horizon.

Finally, we surveyed the respondents subjective expectation of good rainfall. Approximately 63% thought that the monsoon would be good in the coming year.

3.1.3 Risk-Coping Mechanisms

How do households with low levels of income and assets cope with risk?

Risk-coping mechanisms can be classified as “ex ante” (those undertaken in anticipation of bad shock to reduce the suffering when income drops) and “ex post” mechanisms, which are changes in household behavior that may affect risk taking. Table 6 reports the frequency with which households report using these measures.

A forward looking method of smoothing risk is to save money (or wealth) when times are good, in anticipation of drawing on the resources during difficult times. Slightly more than half (56%) of households saved goods (farm output or input, or goods to trade), as a means of adapting to bad shocks. The average household had approximately 3,900 Rs. worth of goods saved.

Savings accounts were surprisingly common: this may well be due to the wide reach of SEWA financial services. Approximately 2/3rds of households reported holding a savings account. Interestingly, very few of these accounts were in a formal bank (12%). For households with savings accounts, the average amount of savings was Rs. 1,944.

Because households vary in size, we also asked a question about whether the household had enough savings to cover at least one month of household expenditures, if they were to receive no income in a month. Only 18% of households reported having sufficient savings.

Ex-post measures include borrowing, selling assets, or using formal or informal insurance. Borrowing is very popular among the households surveyed: 72% of the households have an outstanding loan. However, most of these loans are informal in nature. Only 9% of the households surveyed have a bank loan, while 10% receive credit from a Micro Finance Institution. For those who have a loan, the average reported loan size is large, at Rs. 52,000. The average is high because a few individuals report relatively large loan sizes.

Asset sales do not seem to be as important a risk-coping mechanism. The survey was conducted less than one year after floods damaged many households' crops: yet, only 9% of households reported having sold an asset in the previous year. Because shocks to agriculture affect almost everyone, assets may not be a useful way to protect against risk: when there is a drought, few seek to purchase them. This may push the price down, and households may be unwilling to sell. A similar share of households (7%) pawned an asset in the previous twelve months, and again only 9% of the households sold an animal in the previous year.

Informal insurance is, after savings, the most common risk-coping mechanism. Sixty-one percent of households report having made a gift to relatives or friends in the past twelve months. This number is high in Ahmedabad and Patan (ca. 75%), but very low in Patan (38%). Fewer households reported receiving gifts: 31% overall, with a higher share in Ahmedabad and Patan, and a lower share in Anand. The share of households giving gifts need not equal the share of households receiving gifts, since one household could give to many other households, and one household could receive gifts from many households. Nonetheless, the fact that most households reported giving gifts, while few reported receiving them, suggests that either the households surveyed were rich on average, and/or that individuals have a better recollection of gifts given than those received.

4 The Demand for Rainfall Insurance

4.1 Correlates of Take-Up

Who purchased insurance? Table 8 reports what household characteristics are correlated with insurance take-up. We focus on the binary variable of whether the household purchased any insurance policy, because few households purchased more than one policy.

Wealth appears to be an important determinant of a household's decision to purchase insurance. The reported coefficient (.52) is statistically significant. As a household's measured asset index increases by 10%, the probability that a household purchased insurance increases by 5.2%.

Log PCE is a measure of per capita expenditure. Households that reported greater monthly expenditure were also more likely to purchase insurance, as were households that owned more land. More educated households (those completing middle school or above) were 12% more

likely to purchase insurance than those that did not. Whether an individual was a member of a scheduled tribe or scheduled caste was not associated with an increased likelihood of purchasing insurance. Finally, Muslim households were 18% more likely to purchase insurance than Hindu households.

Panel B of the table examines how cognitive ability and attitudes towards risk correlate with purchase of insurance. Surprisingly, those who think the weather will be bad are no more likely to purchase insurance than those who expect the monsoon to be bad. (This may not be so surprising, however, if individuals realize they have little ability to predict the weather.) Probability skill is highly correlated with purchase: apparently those who are comfortable with probability felt more comfortable purchasing the insurance. Interestingly, the ability to understand insurance quickly did not seem to affect take-up.

Risk aversion is positively correlated with take up: those that chose less risky lotteries during the pre survey were more likely to purchase rainfall insurance. Finally, experience with an insurance product (that is, holding SEWA life and/or asset insurance), is positively correlated with take-up of weather insurance.

Table 8b examines all of these factors in a regression setting, and breaks the sample into landless and landed laborers. Wealth, PCE, education, religion, probability skill, and experience with insurance continue to be important correlates of take up, as does distaste for risk. These results are more pronounced among the sample of insurance purchasers who owned land, relative to landless laborers. Some of these results are consistent with evidence from developed countries. For example, Cole and Shastry (2007) show education and cognitive ability affect financial market participation in the U.S.

5 Marketing Manipulations

In 2007, SEWA used two primary methods to market rainfall insurance to its members. Insurance marketing in 2006 in the 30 villages that had been offered insurance encompassed visits from SEWA staff, who distributed flyers describing the rainfall insurance. In 2007, for those 30 villages, SEWA continued to offer insurance, and again distributed flyers. In the 25 villages which were first offered insurance in 2007, SEWA used personal video players (similar to a video

iPod) to deliver a sixty-second marketing message directly to household-decision makers.

To study the efficacy of various messages, different households received different marketing messages. In the 30 villages that were treated in 2006 and 2007, SEWA delivered 2,391 flyers in 2006. In the villages that were first treated in 2007, SEWA visited 1,415 households, showing each household a randomly selected video. To keep track of which households had received which messages, households were given a non-transferable coupon for a discount, which indicated the marketing message the household had received. The size of the discount was varied as well. In this section, we first describe the marketing manipulations used, and then describe results.

The use of video players had several advantages: first, it allows SEWA to explain the product to the households in a consistent manner. Second, it allows for a more careful experimental treatment, as it reduces the role of the individual delivering the marketing messages.

5.1 Manipulations

Previous research from marketing and economics suggest that many factors may affect an individuals decision to purchase insurance. In the video experiments, the following manipulations were used. They are summarized in Table 9; the phrases in parentheses below give the keyword used to identify each treatment in the table. The number of households in each treatment category is given in the final column of Table 9:

- SEWA Brand (Yes or No): SEWA has worked for years in the villages in the study, while ICICI Lombard, the insurance company, is virtually unknown to the rural population. In the 'Yes' treatment, the videos included clear indications that the product was being offered by SEWA. In the 'No' treatment, SEWA was not mentioned in the video. We hypothesize that including the SEWA brand will lead to higher take-up, as consumers will have greater levels of trust in the product. Trust has been shown to be an important determinant of financial market participation. (Guiso, Sapienza, and Zingales, 2007).

- Peer / Authority (Peer or Authority Figure): Individuals learn about new products from various sources. In the "Peer" treatment, an endorsement of the product was delivered by a local farmer. In the 'Authority' treatment, a teacher delivered the message.

- Payout (8/10 or 2/10): This framing treatment emphasized either the probability the

product would pay out, or the probability the product would not pay out. In the '8/10' treatment, households were told that = the product would not have paid out in approximately 8 of the previous 10 years. In the '2/10' treatment, households were told that the product would pay out in approximately 2 of the previous 10 years.

- Positive/Negative (Positive or Negative): The Positive treatment described the benefits of insurance, as something that will protect the household and ensure prosperity. The Negative treatment warned the household of the difficulties it may face if a drought occurs and it does not have insurance.

These treatments were crossed, though not all possible combinations were used. For the household surveys, four videos were used (A-D in Table 9). Because an important goal of the study is to measure the effect on take-up, the SEWA brand was included in all videos, due to our prior that it would have a positive impact. For the households that received marketing treatment, but were not surveyed, one of eight distinct videos was randomly assigned.

The flyer treatments tested two different manipulations:

- Individual or Group (Individual or Group): the 'Individual' treatment emphasized the potential benefits of the insurance product for the individual who purchases the policy. The Group flier emphasizes the value of the policy for the family of the purchaser.

- Religion: (Hindu, Muslim, or Neutral) A photograph on the flier depicted a farmer, who was either standing near a Hindu temple (Hindu Treatment), a Mosque (Muslim Treatment), or a nondescript building. The individual was also given a matching first name, that was either characteristically Hindu, characteristically Muslim, or neutral.

5.2 Results

Summary statistics from the marketing manipulations are presented in Table 10. For each treatment, we report the share of households receiving the treatment that purchased insurance. Stars report results from a t-test of difference of means.

In total, 29.3% of households who received video treatment purchased weather insurance, while 25.9% of households that received flyer treatments purchased insurance. This difference

is statistically significant. While SEWA marketers reported that the video marketing was very effective, it would not be correct to conclude that videos were more effective than flyers: the difference in take-up reflects both the difference in media, and the fact that the villages that received the fliers had already been exposed to weather insurance (recall that in 2006, the policies did not pay out).

Only one of the marketing manipulations has a statistically significant effect: households that receive negative language are significantly more likely to purchase weather insurance than those that received negative language. This effect is very large, increasing the probability of purchase by almost 16 percentage points. Neither of the flier treatments have measurable effects.

Table 11 presents the analysis of flyer treatment in a regression format, controlling for all manipulations in one regressions:

$$Purchase_i = \alpha + \pi_1 \text{Muslim} + \pi_2 \text{Hindu} + \pi_3 \text{Group} + \varepsilon_i. \tag{1}$$

Note that since the treatments were assigned at the individual level, point estimates and coefficients are invariant to clustering standard errors at village level or including a village fixed effect. The regressions confirm the results of the t-tests, that the flyer manipulations did not affect the take up rate.

Table 12 presents analysis of the videos in a regression format.

$$Purchase_i = \alpha + \beta_1 SEWA + \beta_2 Peer + \beta_3 Two/Ten + \beta_4 Postiive + \beta_5 Discount + \varepsilon_i \tag{2}$$

Again, only the language manipulation has an effect.

6 Price Elasticity of Demand

Discount coupons for the insurance policy were distributed with the marketing videos. Each household was randomly assigned a coupon with value Rs. 5, Rs. 15, or Rs. 30. Forty percent of households received the Rs. 5 coupon; forty percent received the Rs. 15 coupon; and 20% of households received the Rs. 30 coupon. The coupon was non-transferable, and the name and address of the respondent were written on the coupon.

Equation 2 estimates the effect of the discount on demand, with results presented in Table 12. The point estimate is .005, with a t-statistic of 5, indicating a very strong response. Moving from a Rs. 5 discount to a Rs. 30 increases the probability of purchase of insurance by 12.5 percentage points, from a base of 26.25%. The t-tests in table 10 indicate that variation comes mainly from the Rs. 30 discount coupon: the Rs. 15 coupon has a small, statistically insignificant effect on take-up.

We calculate the price elasticity of demand in the following manner. We estimate β_5 from equation 2 separately for each district. Denote P as price and Q as quantity. Taking β_5 for ΔQ, the average take-up rate in the district for Q, 1 for ΔP, and then weighted average price to which households were exposed, we calculate the price elasticity of demand for all three districts.[3] The elasticity of demand is highest in Ahmedabad and Anand, at .83, and .875, respectively, but much lower in Patan, at .66.

7 Conclusion

Morduch (2004) identifies several practical challenges that can limit the success of microinsurance: the need for reinsurance, the need for data on which to base premiums, and the need to limit transaction costs. Rainfall insurance fulfills all of these criteria, and is gaining commercial acceptance throughout India. Whether it will grow into a mature product remains to be seen. Expanding into areas where no weather station exists (perhaps 2/3 of the area of India) is not as simple as installing a new weather station, as insurers and reinsurers will require historical data to price policies.

This work suggests that there are substantial challenges at the retail level as well. While the percentage of households that purchased insurance was relatively high, so were marketing costs. Moreover, few households purchased more than one unit of insurance, suggesting that they are experimenting with the product, rather than heavily exploiting its risk-management properties. While this learning behavior may well be rational for the households, it limits the scale economics of those selling insurance.

[3] The base price of the insurance product varied across districts, as each had different historical rainfall patterns. In 2007 the price was Rs. 72 in Anand, 44 in Ahmedabad, and 86 in Patan. The coupons, which were 5, 15, and 30 in all three districts.

While it does not play a central role in this paper, an important aspect of the research project is the random assignment of treatment status to villages. As households gain greater familiarity with rainfall insurance, we expect some will elect to use it as a substantive risk management tool. Ongoing household surveys will measure households investment decisions, risk-sharing activity, and consumption. The study was designed to span three districts, with three separate rainfall stations, with the goal of measuring the beneficial effects of insurance in case of adverse weather.

This paper presents results from a large-scale randomized field experiment that offered weather insurance to farmers in over 50 villages. Our findings are as follows. First, education, wealth, and risk aversion are strong predictors of the decision to purchase weather insurance. While financial literacy per say did not predict take-up, facility with probabilities was strongly correlated with the decision to purchase insurance.

It is useful to compare these results with those reported in Gine, Townsend, and Vickery (2007). They too find that education, income, and risk aversion are correlated with the decision to purchase weather insurance, though perhaps surprisingly, they find that more risk-averse households are less likely to purchase insurance.

Our second set of findings relate to the effects of subtle marketing manipulations. We find, at least in this context, that they have relatively few effects. The use of negative language had a significant effect on household decisions to purchase insurance, increasing take-up by twelve percentage points. However, other manipulations had no effect: emphasis of a trusted brand name, the identity of an authority figure, the salience of religion, and the framing of the probability of payout appear to have had no influence on households decisions to purchase insurance. These results stand in contrast to Bertrand et al. (2006), who find that a host of psychological manipulations have large effects on consumers decision to borrow from a commercial bank.

Third, demand for insurance is very price sensitive, with discounts (reducing the cost from \$1.80 to \$1.20) having large effects on households decision to purchase insurance.

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Table 3: Overview of Study Design

		Surveyed Households							
		Ahmedabad District		Anand District		Patan District		Entire Study	
		Villages	Households	Villages	Households	Villages	Households	Villages	Households
2006	Treatment	8	120	11	165	11	165	30	450
	Control	20	315	29	435	20	300	69	1050
	Total	28	435	40	600	31	465	99	1500
2007	Treatment	14	210	24	360	17	255	55	825
	Control	14	225	16	240	14	210	44	675
	Total	28	435	40	600	31	465	99	1500

Table 4. Household Characteristics

	Ahmedabad	Anand	Patan	All
Income Sources	(1)	(2)	(3)	(4)
Main income is from agriculture	61%	75%	81%	72%
Main income is from own cultivation	19%	13%	28%	19%
Main income is from agricultural labor	34%	57%	39%	45%
Demographic Characteristics				
Household Size	5.70	5.63	6.57	5.94
	(2.24)	(2.47)	(2.64)	(2.49)
Scheduled Caste	42%	37%	26%	35%
Scheduled Tribe	16%	7%	3%	8%
Muslim	5%	10%	11%	9%
Wealth and Income				
Household has electricity	84%	77%	56%	72%
Household has Tap water	71%	52%	19%	47%
Wealth index (0-1)	0.33	0.25	0.23	0.26
	(0.14)	(0.12)	(0.11)	(0.13)
Has any livestock, cattle, birds etc.	54%	56%	78%	62%
Monthly Per Capita Expenditures	1,275	1,075	1,416	1,239
	(1,354)	(1,399)	(2,023)	(1,612)
Total Annual Income	33,536	22,123	29,989	27,877
	(39,963)	(19,922)	(24,553)	(28,852)
Total Annual Income - Cultivators	52,826	32,777	34,911	39,409
	(73,441)	(30,257)	(24,534)	(45,727)
Total Annual Income - Agricultural Workers	19,653	16,067	22,217	18,515
	(16,212)	(14,344)	(16,068)	(15,453)
Total Annual Income - Wage workers (casual & regul	36,212	29,942	28,718	32,445
	(29,738)	(21,310)	(22,785)	(25,723)
Own Land	53%	31%	64%	48%
Amount of Land owned (bigha=.5 acres)	4.75	2.01	9.56	6.03
	(10.21)	(2.50)	(8.64)	(8.72)
Number of plots	1.90	1.29	1.66	1.64
	(1.43)	(0.73)	(1.03)	(1.13)

Table 5. Factors That May Affect Household's Decision-Making

	Ahmedabad	**Anand**	**Patan**	**All**
	(1)	(2)	(3)	(4)
Education				
Highest edu achievement-illiterate	10%	8%	35%	17%
Highest edu achievement-literate	8%	5%	12%	8%
Highest edu achievement-primary	12%	14%	25%	17%
Highest edu achievement-middle	31%	36%	16%	29%
Highest edu achievement-highschool or above	38%	36%	12%	29%
Demonstrated Ability				
Score-math questions	0.68	0.56	0.64	0.62
	(0.28)	(0.32)	(0.27)	(0.30)
Score-financial literacy questions	0.40	0.30	0.39	0.36
	(0.28)	(0.32)	(0.30)	(0.31)
Score-Probability knowledge questions	0.76	0.70	0.70	0.72
	(0.36)	(0.40)	(0.40)	(0.39)
Score-Insurance questions	0.75	0.59	0.74	0.68
	(0.34)	(0.41)	(0.34)	(0.38)
Risk Aversion				
Prefer Rs 2 for sure vs lottery with expected value of 2.5	76%	83%	84%	81%
Prefer Higher Risker / Higher Return Lottery (Biswanger)	0.38	0.51	0.46	0.46
	(0.30)	(0.29)	(0.34)	(0.32)
Discount Rates - Impatience				
Do you prefer 8 Rs. today vs X Rs 1 month from today	0.60	0.67	0.70	0.66
	(0.34)	(0.35)	(0.32)	(0.34)
Rain Forecast				
Number of Beans placed on Good Rains	0.64	0.62	0.64	0.63
	(0.30)	(0.30)	(0.31)	(0.30)

Table 6. Risk Coping Mechanisms

	Ahmedabad	Anand	Patan	All
	(1)	(2)	(3)	(4)
Tools for smoothing consumption ex ante				
Precautionary Savings				
Share of hh who store farm output, inputs, goods to trade	74%	28%	75%	56%
Value of goods stored	5,023	3,030	3,312	3,909
	(11,139)	(7,098)	(12,904)	(11,283)
Share of hh that have a savings account	63%	60%	69%	63%
Share of hh that have a savings account in a bank	22%	7%	9%	12%
Value of Savings (for those who have a savings account)	3,520	1,587	1,141	1,994
	(13,700)	(2,904)	(2,426)	(7,749)
Share of HH with value of stored goods+savings can cover at least 1 month of hh expenditure	31%	14%	10%	18%
Choice of economic activity				
Number of income sources	2.12	1.73	2.17	1.98
	(0.79)	(0.79)	(0.87)	(0.84)
Use HYV varieties	44%	45%	66%	53%
Tools for smoothing consumption ex post				
Credit				
Share of hh who have an outstanding loan	73%	67%	77%	72%
Share of hh who have a BANK loan	8%	8%	10%	9%
Share of hh who have a MFI loan	10%	8%	11%	10%
Value of Loans (for those who have a loan)	41,258	63,984	48,544	52,164
	(74,831)	(700,142)	(92,707)	(433,261)
Asset sales				
Share of hh who sold an asset in past 12 months	9%	6%	14%	9%
Share of hh who pawned an asset in past 12 months	12%	5%	6%	7%
Share of hh who sold an animal in past 12 months	10%	5%	13%	9%
Informal insurance				
Share of hh who gave a gift to relatives/friends in past 12 months	75%	38%	77%	61%
Share of hh who received a gift from relative/friends in past 12 months	47%	15%	37%	31%
Formal insurance				
Share of hh who have crop insurance	4%	0%	14%	7%

Table 7. Insurance Take-Up

	Ahmedabad	Anand	Patan	All
	(1)	(2)	(3)	(4)
Share of surveyed hh who bought insurance	14%	18%	34%	23%
Share of Landless who bought insurance	7%	17%	32%	18%
Share of Landowners who bought insurance	21%	19%	35%	27%

Table 8a. Correlates of Take-Up

PANEL A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Targeted Marketing	0.083							
	(0.055)							
Wealth Index		0.592 ***						
		(0.211)						
Log PCE			0.048 *					
			(0.028)					
Number of plots				0.059 **				
				(0.025)				
Highest education<middle					0.122 **			
					(0.054)			
Highest education>=middle					0.130 ***			
					(0.045)			
Scheduled Caste						0.015		
						(0.050)		
Scheduled Tribe						0.012		
						(0.090)		
Muslim							0.179 *	
							(0.098)	
Number of Observations	0.18	0.20	0.18	0.19	0.18	0.17	0.18	
R2	480	480	479	480	480	479	480	
PANEL B								
Respondent's Probability Rain	0.000							
	(0.059)							
Probability Skill		0.121 **						
		(0.050)						
Insurance Skill			0.016					
			(0.054)					
Tolerance for Risk				-0.101 *				
				(0.055)				
Impatience					-0.039			
					(0.061)			
Has Loan						0.019		
						(0.044)		
Has SEWA Insurance							0.086 **	
							(0.043)	
Has Savings Account								0.048
								(0.045)
Number of Observations	0.17	0.19	0.17	0.17	0.18	0.17	0.18	0.18
R2	478	479	468	479	478	479	480	479

Table 8b. Correlates of Take-Up

	All		Landless		Land Owners	
	1		2		3	
Targeted Marketing	0.059		0.030		0.073	
	(0.052)		(0.036)		(0.080)	
Wealth Index	0.499	*	0.319		0.496	
	(0.257)		(0.289)		(0.345)	
Log PCE	0.050	*	0.065		0.047	
	(0.026)		(0.043)		(0.048)	
Highest education<middle	0.110	*	0.117		0.086	
	(0.061)		(0.077)		(0.105)	
Highest education>=middle	0.074		0.137	**	-0.057	
	(0.058)		(0.057)		(0.107)	
Scheduled Caste	0.039		0.009		0.073	
	(0.050)		(0.061)		(0.086)	
Scheduled Tribe	0.019		-0.067		0.166	
	(0.079)		(0.091)		(0.143)	
Muslim	0.193	**	0.097		0.266	***
	(0.097)		(0.158)		(0.085)	
Respondent's Probability Rain will be good	0.026		-0.033		0.034	
	(0.061)		(0.094)		(0.090)	
Probability Skill	0.121	**	0.157	**	0.112	
	(0.055)		(0.065)		(0.090)	
Insurance Skill	-0.078		-0.044		-0.009	
	(0.052)		(0.075)		(0.080)	
Risk Loving	-0.134	**	-0.104		-0.199	*
	(0.057)		(0.083)		(0.106)	
Impatience	-0.105	*	0.019		-0.239	***
	(0.062)		(0.081)		(0.090)	
Has Loan	0.039		-0.002		0.063	
	(0.043)		(0.055)		(0.053)	
Has SEWA Insurance	0.077	*	-0.025		0.159	**
	(0.045)		(0.060)		(0.077)	
Has Savings Account	0.035		0.037		0.000	
	(0.045)		(0.065)		(0.078)	
Number of Observations	0.24		0.37		0.30	
R2	458		234		224	

Table 9: Design of Marketing Experiment

Videos for Surveyed Households

Video ID	Sewa Brand	Peer/Authority	8/10 or 2/10	Positive/Negative Frame	Number of HH Visited
A	Yes	Peer	8/10	Positive	75
B	Yes	Peer	8/10	Negative	81
C	Yes	Peer	2/10	Positive	78
D	Yes	Peer	2/10	Negative	81

Videos for Non-Surveyed Households

Video ID	Sewa Brand	Peer/Authority	8/10 or 2/10	Positive/Negative Frame	Number of HH Visited
1	Yes	Peer	8/10	Positive	124
2	No	Peer	8/10	Positive	126
3	Yes	Authority Figure	8/10	Positive	150
4	No	Authority Figure	8/10	Positive	131
5	Yes	Peer	2/10	Positive	137
6	No	Peer	2/10	Positive	135
7	Yes	Authority Figure	2/10	Positive	147
8	No	Authority Figure	2/10	Positive	150

Flyers for Households in Villages Offered Insurance in 2006 and 2007

Flyer ID	Individual / Grou	Religion	Number of HH Visited
F1	Individual	Neutral	378
F2	Individual	Muslim	438
F3	Individual	Hindu	416
F4	Group	Neutral	368
F5	Group	Muslim	398
F6	Group	Hindu	393

Table 10: Take-up Rates Under Marketing Treatments, Year 2

Video Treatments		
Sewa Brand		
Strong	30.58%	
	(N=873)	
Weak	27.31%	
	(N=542)	
Social Distance		
Peer	30.70%	
	(N=837)	
Authority	27.34%	
	(N=578)	
Information		
Pays 2/10	28.02%	
	(N=728)	
Doesn't pay 8/10	30.71%	
	(N=687)	
Language		
Positive	27.53%	**
	(N=1253)	
Negative	43.21%	**
	(N=162)	
Discount		
Rs. 5	26.25%	
	(N=598)	
Rs. 15	28.78%	
	(N=542)	
Rs. 30	37.36%	**
	(N=273)	

Flyer Treatments		
Religion		
Muslim	23.56%	
	(N=836)	
Hindu	23.98%	
	(N=809)	
Neutral	23.86%	
	(N=746)	
Beneficiaries		
Group	24.76%	
	(N=1159)	
Individual	22.89%	
	(N=1232)	

Totals		
Video Treatments	29.33%	*
	(N=1415)	
Flyer Treatments	23.88%	*
	(N=2391)	
Overall	25.91%	
	(N=3806)	

Notes: **- p-value < .01 *- p-value < .05. Stars indicate significant differences between treatment conditions. Flyer treatments were offered to individuals in villages that first received access to weather insurance in Year 1. Villages receiving video treatment and coupon discounts were receiving access to weather insurance for the first time.

Table 11: Effects on Insurance Take-up of Flyer Marketing Treatments

	OLS	Probit	OLS	Probit	OLS	Probit
	(1)	(2)	(3)	(4)	(5)	(6)
Muslim	-0.003	-0.002	-0.002	-0.002	-0.004	-0.001
	(0.021)	(0.021)	(0.023)	(0.023)	(0.021)	(0.021)
Hindu	0.001	0.001	0.001	0.001	0.006	0.008
	(0.022)	(0.021)	(0.019)	(0.019)	(0.020)	(0.018)
Group	0.018	0.019	0.019	0.019	0.013	0.016
	(0.017)	(0.017)	(0.019)	(0.018)	(0.016)	(0.018)
Cluster (Village)			X	X		
Village Dummies					X	X
Constant	0.229 **		0.229 **			
	(0.017)		(0.034)			
N	2391	2391	2391	2391	2391	2391
R^2/pseudo R^2	0.00	0.000	0.000	0.000	0.105	0.096

Notes: Standard errors are in parenthesis. **- p-value < .01 *- p-value < .05

This table reports effects of randomly assigned flyer marketing treatments on the probability of weather insurance purchase. OLS Columns represent linear probability models. The mean of the dependent variable is 23.9%. Columns labelled Probit report marginal effects (generated with Stata's dprobit command). Flyer treatments were implemented in villages that first received access to weather insurance in Year 1.

Regression(3)-(4) clusters observations into 32 villages.

Columns (5) and (6) include a full set of village dummies.

Table 12: Effects on Insurance Take-up of Video Marketing Treatments

	OLS		Probit		OLS		Probit		OLS		Probit	
	(1)		(2)		(3)		(4)		(5)		(6)	
Strong Sewa Brand	0.004		0.004		0.005		0.004		0.004		0.004	
	(0.025)		(0.026)		(0.030)		(0.031)		(0.024)		(0.027)	
Peer	0.003		0.004		0.003		0.004		0.017		0.021	
	(0.025)		(0.026)		(0.033)		(0.034)		(0.024)		(0.027)	
Pays 2/10 Years	-0.027		-0.028		-0.027		-0.028		-0.034		-0.034	
	(0.024)		(0.024)		(0.023)		(0.023)		(0.023)		(0.025)	
Positive Language	-0.156		-0.158		-0.156		-0.158		-0.165		-0.187	
	(0.044)	**	(0.045)	**	(0.053)	**	(0.053)	**	(0.043)	**	(0.047)	**
Discount (Rs.)	0.005		0.005		0.001		0.005		0.005		0.005	
	(0.001)	**	(0.001)	**	(0.001)	**	(0.001)	**	(0.001)	**	(0.001)	**
Cluster (Village)					X		X					
Village Dummies									X		X	
Constant	0.379				0.379							
	(0.057)	**			(0.067)	**						
N	1413		1413		1413		1413		1413		1413	
R^2/pseudo R^2	0.021		0.017		0.021		0.017		0.120		0.102	

Standard errors are in parenthesis. **- p-value < .01 *- p-value < .05

This table reports effects of randomly assigned video marketing treatments and discount coupons on the probability of weather insurance purchase. OLS Columns represent linear probability models. The mean of the dependent variable is 29.3%. Columns labelled Probit report marginal effects (generated with Stata's dprobit command).

Columns (3) and (4) cluster observations at the village level.

Columns (5) and (6) include a full set of village dummies.