Paying Premiums with the Insurer's Money: Insurance Decisions In a Repeated Interaction

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Abstract

Rainfall Index Insurance was introduced to India in 2003 with great fanfare, but has so far failed to gain much traction with consumers. This paper looks at the dynamic nature of rainfall insurance purchasing decisions, specifically looking at whether receiving an insurance payout induces a greater chance of purchasing insurance again the next year. Using customer data from the Indian microfinance institution BASIX, I find that receiving an insurance payout is associated with a 10-20% increased probability of purchasing insurance the following year. These empirical results conform with the predictions of a loss aversion model where premiums paid after receiving an insurance payout are perceived as decreasing these previous gains as opposed to a true loss. I do not find significant support for other potential mechanisms, such as previous weather directly affecting insurance decision or insurance payouts increasing trust in the insurance companies. Overall, low repurchasing rates even after payouts suggest that current rainfall index insurance products are likely to continue struggling in their current form.

1 Introduction

Roughly 60% of India's population are employed in agriculture, and over 50% of agricultural land is dependent on rainfall to nurture the crops.[1] But the Indian monsoon is notoriously unpredictable, prone to droughts and floods that can have devastating effects on the livelihood of rural Indians. In 2009 India was hit with a widespread drought which, according to Indian Finance Minister Pranab Mukherjee, would likely reduce farm production by 15-20% (Gora 2009). While Townsend (1994) argues that Indian villages do an effective job of providing informal consumption insurance against idiosyncratic shocks, a poor monsoon will hit whole villages and districts at once, likely rendering intra-village transfers ineffective. Beginning in the early 2000s, many economists had high hopes that

[1] CIA World Factbook: India; Indiastat.com

rainfall index insurance could play an important role in helping poor farmers deal with rainfall risk (Hess 2004). But despite its launch in many parts of India, rainfall index insurance has been struggling gain a critical mass of customers, especially when unsubsidized.[2]

Why has insurance been slow to take hold? Two field experiments, performed by Cole et al (2009) in Gujarat and Gine et al (2007) in Andhra Pradesh look at how various pricing schemes and marketing interventions affect insurance takeup. While some of their marketing experiments had minor effects, overall takeup was quite low (at around 15%) and increased only when the insurance policies were drastically discounted. While these results are discouraging for proponents of rainfall insurance, a common argument is that insurance simply needs time to take hold. For instance, Gine et al (2007) claims that "over time, lessons learned by insurance 'early adopters' will filter through to other households, generating higher penetration rates among poor households." Since it can be years until insurance customers experience their first payout, it may take a long time for people to become comfortable with insurance and understand its value. If this was true, it may be the case that insurers simply need to be persistent in their offerings of insurance. People will eventually receive or witness payouts, which would hopefully induce many to become regular customers.

This paper seeks to understand how previous insurance payouts can affect future insurance purchasing decisions, and what mechanisms can explain this behavior. I first test the prediction that recipients of an insurance payout will be more likely to purchase insurance again the following year. Using data on three years of insurance purchasers from the Indian MFI BASIX, I find that customers who received an insurance payout are 10-20% more likely to repurchase in the following year. Interpretation of this result is not obvious, since there could be many mechanisms behind this correlation. If it is driven by increased trust in the insurance company, this would indicate that insurance takeup is likely to increase over time as customers build up trust in the institution. But if it is instead due to psychological effects of the recent payout, the low insurance adoption rates are likely to endure.

I hypothesize that repurchases are indeed driven primarily by psychological effects, in that purchasers of insurance who receive insurance payouts will be more likely to purchase insurance in the future because their previous insurance 'profits' make future premiums seem like less of a loss. Building upon Thaler and Johnson (1990), I develop a dynamic choice model where customers exhibit loss aversion; it predicts that insurance customers will be more likely to purchase insurance after receiving a payout that is bigger than the premium they paid. This is because subjects will regard a premium paid after receiving a payout as a decrease in this previous gain rather than a true loss. Since loss aversion dictates that true losses are more painful than reduced gains, this makes insurance more attractive after receiving a payout.

I also explore the alternative hypothesis that payouts induce trust and learning about insurance,

[2]There have been some areas where there has been a lot of coverage, but this is generally due to heavy government subsidies or requiring insurance to obtain government loans. Sending a strong signal about the lack of confidence in rainfall index insurance, the government of India has decided not to expand its rainfall index insurance pilot (WBCIS) to all of India, and is planning to pilot a modified version of it's area-yield index product (NAIS).

and don't find convincing evidence for this explanation. Likewise, I look at whether there is actual autocorrelation in rainfall patterns, and whether this or other direct affects of weather could be driving insurance purchasing. I find no evidence of positive autocorrelation, and show that direct effects of weather are unlikely to account for increased insurance purchasing after a payout. Overall, the empirical analysis suggests that it is the physical reception of payout money that drives future purchases, which is consistent with the proposed model of loss aversion.

This paper makes a number of contributions to the field. First, it provides insight into the rainfall insurance decisions of Indian villagers, and sheds light on potential policies that may help the rainfall insurance industry succeed. The results suggest that people purchase insurance after receiving payouts due to psychological effects of the recent insurance payout as opposed to building trust in the institution of insurance, which implies that attracting long-term insurance customers by exposing them to payouts may be ineffective.

This work also contributes to the literature on choice under uncertainly by demonstrating behavior in the field that is consistent with the behavioral concepts of reference dependence and loss aversion. Seeing this behavior in real life is important, as most theoretical literature on these subjects relies on laboratory experiments to elicit preferences (for notable exceptions see Camerer [1998]). It also contributes by looking at how a dynamic setting can affect choices in a reference-dependent model. This was first tackled by Thaler and Johnson (1990), but this work builds on their conclusions by adapting their model to a real-world setting and testing its predictions on a large data set.

2 Context: BASIX Policies

In this analysis I study monsoon rainfall insurance policies underwritten by ICICI-LOMBARD and sold by BASIX. The policies insure against excess or deficient rainfall, and are calculated based on rainfall measured at a stated weather station. By basing payoffs on just rainfall, the policies should have low monitoring and verification costs, and also should be free of adverse selection and moral hazard. These attributes make policies inexpensive to create and administer, which allows them to be sold in small quantities and priced at levels affordable for poor farmers. BASIX's policies are designed pay out in situations where adverse rainfall would cause a farmer to experience crop loss, and are therefore calibrated to the water needs of local crops. Since they are designed to be affordable, one could consider the policies to be a form of disaster insurance; they only pay out for severe rainfall shortages.

BASIX policies are divided into three phases, which are meant to roughly capture the three phases of the growing season: planting, budding/flowering, and harvesting. If cumulative rainfall is too low or high in any of these phases, the crop's output is potentially damaged and the farmer could suffer a loss. The policies are designed to start around when farmers first start planing, which depends itself on rainfall. Therefore, the policies have a dynamic start date which means that Phase 1 begins on the day that cumulative rainfall since June 1 reaches 50mm or on July 1, whichever comes first. Each phase generally lasts 35-40 days. During this time, rainfall data is collected daily at a designated weather station, and payouts are calculated using the cumulative rainfall over the phase.

A phase of coverage is defined by three parameters: 'Strike', 'Exit', and 'Notional'. Deficit policies begin to pay out when the rainfall drops below the level of the Strike, and gives its full payout when it falls below the Exit. In between, it pays the Notional amount of rupees for each millimeter.

In 2006 and 2007, all rainfall insurance contracts sold by BASIX included three phases, with the first two protecting against deficit rainfall, and the third protecting against excess rainfall. In 2005 the policies all had three phases, but each phase protected only against deficit rainfall. Table 1 presents is a sample contract, from Nizamabad district in the state of Andhra Pradesh.

Phase	I	II	III
Duration (Days)	35	35	35
Type	Deficit	Deficit	Excess
Strike (mm)	135	125	730
Exit (mm)	40	40	820
Notional (Rs/mm)	10	10	10
Policy Limit (Rs)	1000	1000	1000
Premium (Rs)	110	110	90

Table 1: Example Insurance Policy

Given the policy parameters we can see how the payouts will evolve according to rainfall. Figure 1 shows the payout schedule for phase II of the above policy. There is no payout when rainfall is above the strike, which is 125mm. Then as rainfall decreases the payout increases linearly until rainfall reaches the exit of 40mm, then jumps to the policy limit of Rs 1000 once rainfall falls below 40mm.

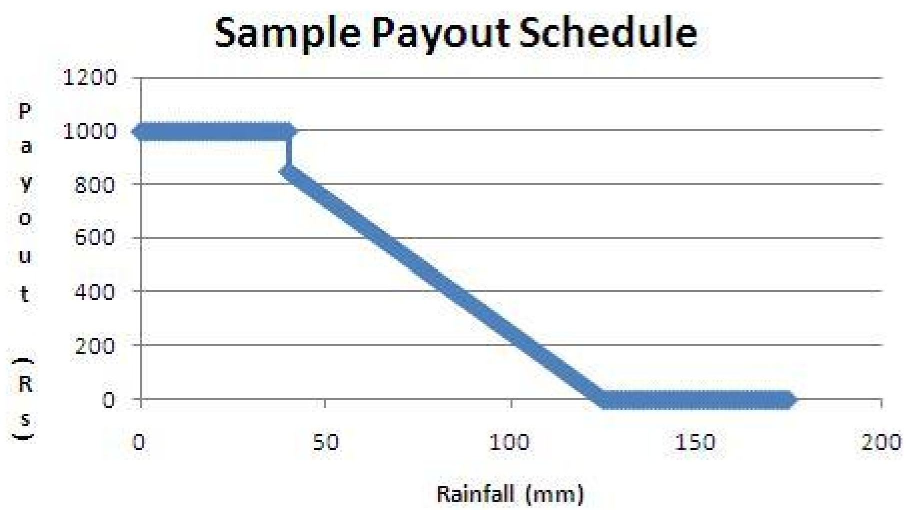

Figure 1: Example payout schedule

BASIX insurance policies are sold in April and May, which are the months the precede the monsoon in India. Insurance policies cover only one season, so if customers must purchase insurance again if they want coverage for the following year.

Year	2005	2006	2007
Number of Policies	34	42	28
Average Premium For Three Phases (Rs)	283	295	287
Expected Payout (Rs)	76	73	80
Average Loading	5.76	5.94	5.6
Percentage of Times Policy Paid out From 1961-2004	10.2	6.8	7

Table 2: Policy Summary Statistics

3 Data

The data set consists of the entire set of BASIX's purchasers of rainfall index insurance from 2005-2007, which covers six states.[3] Though it ran small pilots in 2003 and 2004, BASIX began to mass-market rainfall insurance starting in 2005. The data contains limited personal information about each customer including their location, how many policies they purchased, and what payouts they

[3]The states are, in descending order of number of buyers: Andhra Pradesh, Maharashtra, Jharkand, Karnataka, Madhya Pradesh, Orissa.

received during that season. The BASIX data covers 42 weather stations, and includes a total of 19,882 customers from 2005-2007.[4] After numerous rainfall shocks in 2006, BASIX realized that many customers who had purchased only a small amount of insurance were disappointed that they received small payouts. In response, BASIX instituted a rule in 2007 that required all customers to purchase insurance coverage with a maximum payout of at least Rs 3000. This was meant to encourage people to buy a level of coverage that would actually provide meaningful payouts in the event of a shock, but resulted in a sharp decrease in the number of customers in 2007.

For rainfall, I use a historical daily grid of rainfall, which is interpolated based on readings from thousands of rainfall stations throughout India. This data is provided by the Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation of water resources.[5] This data set has daily readings of rainfall from 1961-2004, at a precision of $.25^o$ x $.25^o$.[6] For each 25^o x $.25^o$ block, the data contains the amount of rainfall in millimeters and the amount of stations within the grid that contributed to the data. This historical data is used to evaluate how the insurance policies would have paid out historically, which can be used as a proxy for past rainfall shocks. Also, this allows us to calculate the expected payout of the insurance policy, which may have a direct effect on takeup.

The initial challenge in processing the BASIX administrative data was to turn it into a panel. Although BASIX had three years of data, there was no way to identify unique individuals that purchased in multiple years. In order to solve this problem I undertook a lengthy manual matching process, taking into account the customer name, father/husband name, location, and age in order to match names between years.[7] Also, as the data set contained husband names for female buyers, I could match a wife buying in one year and a husband purchasing the next as a single household unit.[8]

The potential for matching errors causes a serious concern about the validity of the data set. Since a crucial part of my analysis revolves around determining what causes buyers to re-purchase

[4] Note that BASIX also sold many policies in the district of Deogarh in Jarkhand, the those buyers are omitted from this analysis. The reason for this is that the policy for Deogarh is heavily subsidized, resulting in a policy that is completely different from all the others. For instance, the Deogarh policy for 2005 has an expected payout of Rs 1140 compared to an average of Rs 149, although the policy does not cost more than average. Following with its incredibly generous terms, the Deogarh policy has huge payouts for all years of the study, and therefore does not seem to be 'normal' enough to warrant inclusion in the main dataset. All the analysis below is performed excluding all buyers in Deogarh, though most results do not change substantially when it is included.

[5] APHRODITE's water resources project; http://www.chikyu.ac.jp/precip.

[6] $.25^\circ$ Latitude equals about 27.5km, while $.25^\circ$ longitude varies by latitude. Over the range of latitudes in this survey it equals roughly 26km.

[7] Also, as district, village, and customer names had highly variant spelling, it wasn't possible to match customers through the years using any automated means.

[8] Despite the meticulous care taken to match the data, there are certain to be some problems. For instance, within a household different family members could have purchased insurance in different years. Then although it would look like the original buyer did not re-buy, the household still purchased insurance. Also, it is possible that sometimes people with very similar names were thought to be the same person when in fact they weren't. If there were serious matching errors, it is possible that our estimates of the total repurchase rate could be biased. However, even though the matching is not perfect, there is no reason to think that any matching errors would be correlated with rainfall, insurance payouts, or insurance uptake. Therefore, we may expect our estimates to be biased downward due to classical measurement error.

insurance, determining who does so is extremely important. And despite a vast amount of effort which combined automated and manual matching methods, there are certain to be some errors in the dependent variable. However, there is no reason to believe that this measurement error is correlated with any independent variables in the regression. Given this assumption, OLS should still provide unbiased and consistent estimates, though the standard errors will be higher than if we were able to accurately measure the dependant variable.

A more serious problem with the data set is that it is not possible to observe the level of marketing that each person received, making 'marketing intensity' an important omitted variable. When BASIX markets rainfall insurance, it first calls a group meeting in a village, and shows the villagers a video about rainfall insurance (and other BASIX products). It then speaks with visitors and answers questions. The BASIX team then makes a follow-up visit where it goes door to door, trying to sell BASIX products including rainfall insurance. Unfortunately, I have no data on on the specific marketing practices of each village and don't even know for sure in which villages BASIX actively sold rainfall insurance in each given year. As marketing intensity is potentially correlated with previous insurance outcomes, this may bias our estimates. This needs to be taken into account when performing the analysis and interpreting the results.

Year	2005	2006	2007
Number of Villages	954	1426	432
Number of Weatherstations	34	42	28
Number of Buyers	6428	10077	3377
Average Sum Insured (Rs)	3055	1612	3547
Buyers Receiving Payouts	351	1346	529
Buyers Who bought the Following Year	453	364	

Table 3: Customer Summary Statistics

4 Payouts and Rainfall: An Initial Correlation

The first order of business is to answer the central question: does receiving an insurance payment make one more likely to purchase insurance the following year? To do this, I start by examining BASIX's customers in 2005 and 2006, and see whether those who receive a payout are more likely to repurchase the following year. The econometric specification is as follows:

$$y_{i,t+1} = \alpha + \beta_1 P_{i,t} + B_2 D_{2006} + \epsilon_{t,i} \tag{1}$$

Here $y_{i,t+1}$represents whether subject i purchases insurance at time $t+1$, and $P_{t,i}$ is a dummy variable that takes a value of 1 if person i receives an insurance payout at time t.[9] The sample is all buyers of insurance from 2005 and 2006, and I include a dummy (D_{2006}) for purchasers in the year 2006 to control for time effects. Also, I only include purchasers who have weather insurance contracts available in their area in the following year.[10] These results are presented in Table 4, and Column 1 reports the baseline OLS results. These results show that receiving a payout is associated with a 7.8% increased chance of repurchasing insurance the following year, and this result is significant at the 1% level. The dummy for 2006 is negative and significant, which is expected due to the minimum sum insured rules imposed in 2007. The increase in takeup is also significant economically, as people who receive payouts are more than twice as likely to re-purchase insurance than buyers who did not receive payouts. Column two adds state-level fixed effects, which ensures that the result is not being driven by some unobserved variables at the state level. There are six states in the analysis, and it is comforting to see that the results hold when looking within states.

	Dependent Variable is Customer Re-Purchasing Insurance			
	(1)	(2)	(3)	(4)
Received Payout	**0.0784*****	**0.0897*****	**0.169*****	**0.222*****
	(0.0224)	(0.0242)	(0.0394)	(0.0442)
Year 2006 Dummy	-0.0222**	-0.0251**	-0.0216	-0.0269
	(0.0107)	(0.0111)	(0.0271)	(0.0274)
Constant	0.0705***	0.0704***	0.171***	0.165***
	(0.00886)	(0.00901)	(0.0185)	(0.0172)
State Fixed Effects	NO	YES	NO	YES
Marketing Restricted Sample	NO	NO	YES	YES
Observations	11002	11002	4202	4202
R-squared	0.010	0.014	0.020	0.035

*** p<0.01, ** p<0.05, * p<0.1 — Observations are all insurance buyers in 2005 and 2006 `

Robust standard errors in parentheses — All errors clustered at the village level

Table 4: Insurance Repurchasing

One point of concern with these results is that there are many cases where there are multiple purchasers of insurance in a certain village in one year, and then zero in the next year. While this could be the result of people simply being unsatisfied with insurance, the large amount of villages that suddenly drop to zero purchasers is suspicious. As noted before, we don't know if BASIX marketed rainfall insurance in a particular village, or even if a certain village was visited by BASIX at all. For

[9]It makes sense to assume that the error $\epsilon_{t,i}$ is correlated for the same person across time, as well as across people in a given year. Ideally, we would like to include individual fixed effects to account for individual heterogeneity. However, in order to exploit this variation we would need to look at customers who purchased insurance in both 2005 and 2006, and received payouts in only one of those years. Unfortunately, due to the very low repurchase rate, this results in very little variation and is therefore an unsuitable method of analysis.

[10]Basix's insurance coverage area varied somewhat from year to year. Results do not change significantly is all areas are included in the regression.

all the villages that had purchasers in one year and then none in the next year, it is possible that no BASIX representative visited the village, and therefore the customer didn't really have a chance the purchase the insurance at all. If this was the case it would make sense to exclude these villages from the analysis, as the previous year's payout would have no way to possibly influence a customer's purchase decision.

In columns 3 and 4 I follow this route and exclude village that had no purchasers the following year from the analysis. For instance, say village A had 10 purchasers in 2005, 13 purchasers in 2006, and 0 in 2007. In this case, the buyers from 2005 would be included in the sample since they obviously had opportunity to purchase the next year. However, the 2006 buyers would be excluded because we are making the assumption that they didn't have the opportunity to buy in 2007. Restricting the sample this way results in a drop of the number of observation from 11002 to 4202, and causes the coefficient on receiving a payout to more than double to .169.

The reader may be suspicious of these results, as the decision to market to certain villages and not others is most likely not exogenous. If the marketing teams decided whether or not to market to certain villages based on the previous year's rainfall or experience with insurance then our results could be upward biased. For instance, let's imagine that there were a number of villages that experienced a rainfall shock but received very low payouts, making them unhappy with insurance. If the marketing team knew this they may have decided to not market to as many of these villages, therefore censoring villages that received a payout but were likely to have few repeat buyers. Regressions that use previous years' payout characteristics to try to predict whether insurance is sold in a village the following year do not reveal any patterns that would suggest selection bias, but they may miss more subtle selection patterns.[11]

It is possible that the coefficient for the marketing restricted sample is upward biased and it therefore would be reasonable to regard the coefficients in columns 3 and 4 as upper bounds, as opposed to those in columns 1 and 2, which could be regarded as lower bounds. Overall, the results indicate that receiving an insurance payout correlates with a roughly 10-20% higher chance of repurchasing the next year compared with someone who purchased insurance but did not receive a payout.

5 Theory

While the correlation between receiving an insurance payout and purchasing the following year is interesting, it isn't especially useful for policy making because a myriad of mechanisms could be in play. In order to think about what would cause people to re-purchase insurance, I find it useful to think about the reception of an insurance payout as actually consisting of three separate experiences.

First of all, a recipient of an insurance payout has most likely[12] experienced a rainfall shock, which

[11] Results Not Shown.

[12] I say 'most likely' since it is possible to receive a payout with actually experiencing a rainfall shock due to basis risk.

could directly affect insurance purchasing decisions. I will refer to this mechanism as The Weather Channel. Also, when receiving an insurance payout the subject also observes an insurance payout, giving them information about how insurance works. I will call this the Trust/Learning Channel. It may be helpful to take a look at each of the three channels in more detail and to think about how each of them may affect insurance purchases. Finally, the customer physically receives money from the insurance company, which could affect liquidity and also have psychological effects. In the following sections I will try to empirically separate the effects of these three channels, which are explained in more detail below.

1. **The Cash Flow Channel**. The Cash Flow Channel refers to the fact that the actual reception of money from the insurance company could drive future insurance decisions. The most obvious reason why one would think that receiving cash could affect future insurance decisions is through a direct effect on wealth or liquidity. If customers are cash-constrained, then they may not be able to purchase insurance even if that would be optimal; if receiving a payout eased this constraint, it may result in more insurance purchases. Cole et. al. (2009) have shown that liquidity constraints seem to be an important factor in a customer's decision to purchase rainfall insurance insurance.

However, there are a number of reasons to think that liquidity effects from previous payouts are unlikely to drive insurance purchases. As insurance payments are typically given around six months before the opportunity to re-purchase, it is hard to believe that the insurance payout would have a significant effect on the customer's liquidity far in the future. Also, insurance payouts are given in the context of a rainfall shock, which would most likely result in a loss of income. It may help to recall that the empirical results are being driven by variation in rainfall across locations, not by levels of insurance within a village. Therefore, for liquidity effects to be driving the results, one would need to think that experiencing an insurance payout in the context of a rainfall shock resulted in people having less cash constraints than those people who didn't experience a shock at all. Given the fact that most buyers bought a relatively low amount of insurance coverage, experiencing a rainfall shock, even when insured, would likely decrease future liquidity. Therefore, liquidity effects seem like a poor explanation as to why receiving payouts spur future insurance sales.

Instead, I propose that a more likely reason that The Cash Flow Channel could affect insurance is through the psychological effect of receiving a payout. If customers are loss averse, paying an insurance premium after receiving a payout could be considered as just taking away from their previous gain from the insurance company, as opposed to a real loss. This idea is explored in much more detail in the next section.

2. **The Trust/Learning Channel.** The Trust/Learning channel refers to any information customers can gain by simply witnessing an insurance payout. As rainfall insurance is a new product, farmers likely don't have a perfect understanding of what types of rainfall patterns will lead to an insurance payout. While they understand that the policy will pay out when there is a drought and they know what a drought is, they most likely will have difficulty tying the millimeter-based payout

structure to their own experiences with past rainfall. Therefore, when a farmer sees a specific payout amount tied to a specific amount of rainfall, he gains important information about how insurance works. Also, by verifying that the insurance company will provide money in the event that contract holders are owed a payout, he gains trust in the insurance company and the institution of insurance itself. While trust and learning could work in different ways, in this analysis they are going to be observationally equivalent so it makes sense to lump them together.

Alternatively, if people view insurance as an investment (as suggested in Slovik et al 1977), witnessing a payout could 'teach' people that insurance is a good investment, and would therefore be worthwhile purchasing the following year. This isn't necessarily rational, since if customers know that the insurance is offered by a for-profit firm (in this case the insurance company ICICI-Lombard), they should understand that purchasing insurance has a negative expected value. But customers may not understand this fact, so witnessing a payout may convince people that insurance is a good way to make money.

If insurance is actually a valuable product, it would be reasonable to assume that after receiving an insurance payout, The Trust/Learning Channel would increase a subject's propensity to purchase insurance again. But it could possibly work in the other direction as well. If a subject had inflated expectations about insurance, they may be unimpressed with they payout they receive, in essence learning that insurance isn't as useful as they thought.

3. **The Weather Channel**. In order for there to be an insurance payout, there has to be a rainfall shock (as defined in the insurance contract). It is possible that simply living through this shock will affect future insurance purchasing decisions, regardless of any actual experiences with insurance. There are a number of possible explanations as to why this may be the case. First of all, experiencing a bad shock might make the dangers of a drought more salient, spurring higher demand for insurance. A shock may also decrease cash on hand, making it more difficult for people to purchase insurance even if they wanted it.

A rainfall shock may also change peoples' beliefs about the probability of future rainfall events, which could affect insurance decisions. This could take three different forms.

- If there is actual autocorrelation in rainfall patterns, subjects may rationally update their beliefs about future rainfall shocks. Depending on the sign of the autocorrelation, this effect could go in either direction.

- Even without autocorrelation, people could still update their beliefs about rainfall events if shocks were rare and they therefore didn't have a great idea of their probability. The insurance policies BASIX introduced in 2005 would have paid out an average of 19% of the years from 1961-2004, so most people have lived through many shocks and therefore should have relatively accurate beliefs about a shock's frequency and repercussions. While it seems unlikely that people would be performing Bayesian updating on shock probabilities, it is still a possibility.

- People may update their beliefs on probability 'irrationally' if their behavior is consistent with the 'Hot Hand Fallacy' or 'Gambler's Fallacy'. The Hot Hand Fallacy (Gilovich 1995) refers to situations where people believe that experiencing a certain stochastic event makes the same event more likely in the future, even if the two events are independent. The classic case described by Gilovich shows that many people believe that a basketball player who has hit a few shots in a row is likely to keep making baskets, even if his run was simply due to luck. Applied to insurance purchases, a customer who experienced a rainfall shock would believe that a shock is more likely to occur the following year, and would therefore be more likely to purchase insurance the next year.

  The Gambler's Fallacy (Lee 1971) describes the opposite effect, where people who experience a stochastic event believe the event is less likely to happen in the future. For instance, a roulette player who has just witnessed five red finishes in a row may think that the wheel is 'due' to land on black. Applied to insurance, this would mean that someone who had experienced a rainfall shock would believe that a shock is less likely to occur in the following year, and therefore would be less likely to purchase insurance.

In order to understand which of these effects is truly driving the results, we need to examine some situations where people are exposed to some of the above channels in isolation from the others. I will present some of these cases in the following sections.

6 The Cash Flow Channel

The Cash Flow Channel refers to the hypothesis that receiving money from the insurance company could be directly driving people to purchase insurance again in the following year. As mentioned earlier, I do not believe this is due to liquidity or wealth affects, as the rainfall shock that accompanies an insurance payout is likely to decrease customers' future liquidity. Instead, I argue that customers purchase the next year due to psychological effects from receiving a payout. In this section, I develop this theory.

6.1 The Basic Framework

Consider a world where agents have a reference-dependent utility function that exhibits loss aversion. In other words, people compute their utility based on deviations from the 'status quo', but utility slopes more steeply for losses as opposed to gains in regard to the reference point . This idea is standard from prospect theory (Kahneman and Tversky 1979, 1991), but to incorporate this idea into a dynamic setting I allow the reference point to change over time while keeping the utility function normalized such that $u(c = 0) = 0$ regardless of the where the reference point lies. For simplicity, I assume a piecewise linear structure and restrict the reference point to $r \leq 0$. There is no discounting. Formally,

$$u(c, r) = \left\{ \begin{array}{cc} \alpha c \quad \text{if} & c > r \\ \beta c + (\alpha - \beta) r \text{ if} & c < r \end{array} \right\} \tag{2}$$

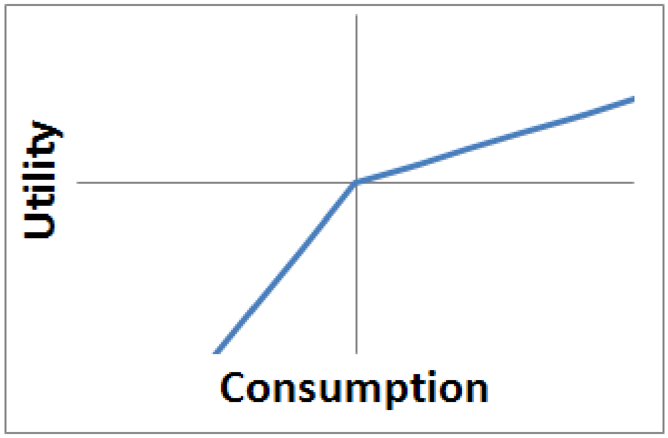

Figure 2: Sample utility function with r=0.

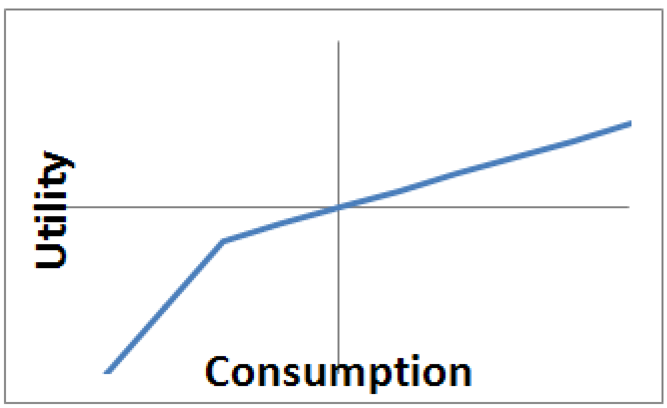

Figure 3: Sample utility function with r<0. Note that the agent is now risk averse for losses.

Agents live in a world with two periods. Each period they are subject to a rainfall shock, which causes a loss of X, which is a random variable distributed as $f(X)$. They have the option of purchasing insurance $I = \{1, 0\}$, which costs a premium $P = \lambda E(X)$. In actuarial parlance, $E(X)$is the expected loss of the insurance, and $\lambda$is the loading factor. Purchasing insurance completely protects customers from the shock. I assume that $r_1 = 0$.

Timing goes like this:

1. Agent starts with reference point $r_1 = 0$
2. Agent chooses insurance decision $I_1 = \{0, 1\}$.
3. State of the world $X_1$is realized, and agent receives period 1 utility.
4. Agent's reference point moves to r_2.
5. Agent chooses $I_2 = \{0, 1\}$
6. State of the world X_2 is realized, and agent receives period 2 utility.

The key question we want to ask is how a payout in the first period will affect the insurance decision in period 2. In this model, this effect will come from moving the reference point r. It should be clear from Figure 3 that if the reference point moves to $r < 0$, then the agent becomes more risk averse in period 2 than they were in period 1, and is therefore more likely to purchase insurance.

Proposition 1 *After an insurance payout in period 1, a subject's reference point moves from $r_1 = 0$ to $r_2 < 0$. If there was no insurance payout, $r_2 = r_1 = 0$.*

When agents receive an insurance payout, they take this gain into account when making decisions in the next period. After receiving an insurance payout in period 1, customers lose less utility when paying subsequent premium due to the fact the 'loss aversion' does not kick in right away. This is represented by the reference point decreasing after an insurance payout is received.

As long as this proposition holds[13], agents move from being risk neutral in period 1 to risk-averse in period 2, and are therefore more likely to purchase insurance after they have received a payout in period 1. Another way to think of it is that if an agent has received an insurance payout in period 1, his premium payout in period 2 is mentally accounted as simply decreasing this payout as opposed to being a true loss. Due to loss aversion this makes insurance in period 2 'cheaper' in terms of utility, and is therefore more attractive.

6.2 Full Model

While the above framework illuminates the basic mechanics of the theory, it has a few drawbacks that make it less attractive for detailed analysis. First of all, it is difficult to make predictions without explicitly spelling out the evolution of the reference point. I have justified that the reference point will decrease after receiving an insurance payout because agents who receive a payout think of themselves as 'in the money' with regard to the insurance company. Therefore, it makes sense that the reference

[13] And $r_2 > -X$

point should move by the amount of the agent's net gain from the previous year's insurance, which is $X_1 - \lambda E(X)$.[14]

Proposition 2 *If agents receive an insurance payout,* $r_2 = X_1 - \lambda E(X)$. *If there was no insurance payout,* $r_2 = r_1 = 0$.

Another issue with the basic model is that if an agent's reference point moves to $r < 0$, it makes him less sensitive to rainfall shocks, since now his utility function is shallower for for $c < 0$. For large shifts in the reference point, this would mean that the agent would not feel loss aversion to future rainfall shocks, which is an undesirable prediction. To solve this problem, I suggest the following change to the utility function.

Proposition 3 *Regardless of the reference point, an uninsured rainfall shock will cause a constant disutility of* $-\beta X$.

In other words, shifts in the reference point cannot affect the disutility caused by rainfall shocks. I justify this assumption by arguing that people have different mental accounts for different spheres of their lives (as in Thaler 1990), and that insurance transactions and losses due to rainfall occupy separate spheres. Therefore, these two separate phenomena may have different reference points, and only the insurance reference point moves after receiving an insurance payout. With these assumptions, it makes sense to think that a rainfall shock would cause a constant disutility regardless of the insurance reference point.

This assumption means that even if the reference point changes due to an insurance payout in period 1, this shift in the reference point cannot dull the effect of an uninsured rainfall shock in period 2. This also makes the predictions of the model less sensitive to the exact evolution of r. As shown below, as long $r_2 < -\lambda E(X)$, insurance will have constant (with respect to r_2) benefits in the second period.

Under these new assumptions (again restricting $r \leq 0$), the only thing that changes consumption as previously defined by the model is insurance premiums and payouts. But since we only allow full insurance in this model, and insurance payouts are exactly cancelled out by losses due to shocks, only the premium cost appears as consmption in the utility function. The utility function has two variant terms. The first is the disutility caused by paying an insurance premium, and the second is the disutility caused my an uninsured rainfall shock. The third term which appears in the case where $-I(\lambda E(X)) < r$ simply accounts for the kink in the utility function.

$$u(c, S, I; r) = \left\{ \begin{array}{cc} -I(\alpha\lambda E(X)) - (1-I)(\beta X) \quad \text{if} & -I(\lambda E(X)) \geq r \\ -I(\beta\lambda E(X)) + (1-I)(-\beta X) + (\alpha - \beta)r \quad \text{if} & -I(\lambda E(X)) < r \end{array} \right\} \tag{3}$$

[14] Note that tying down r is not necessarily for the main predictions of the model. As long as $r_2 < 0$ after an insurance payout, the buyer will be more likely to purchase insurance in the second period.

6.2.1 Naive Agents

First let's assume that agents are naive, and make decisions separately in each period without realizing that their reference points may change. In making his insurance decision, the agent compares his expected utility in the current period from insuring versus not insuring. Expected utility U in period 1 is as follows: (Recall that $r_1 = 0$.)

$$U(I_1 = 0) = -\beta E(X_1) \tag{4}$$

$$U(I_1 = 1) = -\beta\lambda E(X) \tag{5}$$

Define the expected benefits of insurance $B \equiv U(I = 1) - U(I = 0)$.

. The agent purchases insurance in period 1 if:.

$$B_1 = -\beta E(X_1)(1 - \lambda) > 0 \tag{6}$$

In period 2, the agent's reference point changes based on his experiences with insurance.

If the agent has received an insurance payout greater than the premium paid in period 1 ($X_1 > \lambda E(X)$), the reference point moves to $r_2 = -(X_1 - \lambda E(X))$, reflecting the fact that the agent perceives the premium payout in period 2 to not be a true loss. If the agent did not receive an insurance payout, $r_2 = r_1 = 0$. In the case that $r_2 = -(X_1 - \lambda E(X))$, the agent has the following decision process.

$$U(I_2 = 0) = -\beta E(X) \tag{7}$$

$$U(I_2 = 1) = \left\{ \begin{array}{ccc} -\alpha\lambda E(X) & \text{if} & X_1 \geq 2\lambda E(X) \\ -\beta\lambda E(X) - (\alpha - \beta)(X_1 - \lambda E(X)) & \text{if} & X_1 < 2\lambda E(X) \end{array} \right\} \tag{8}$$

He buys insurance in period 2 if the benefit from buying insurance $B_2 > 0$:

$$B_2 = \left\{ \begin{array}{ccc} -\alpha\lambda E(X) + \beta E(X) & \text{if} & X_1 \geq 2\lambda E(X) \\ -\beta\lambda E(X) - (\alpha - \beta)(X_1 - \lambda E(X)) + \beta E(X) & \text{if} & X_1 < 2\lambda E(X) \end{array} \right\} \tag{9}$$

Now we come back to the main question: does receiving an insurance payout in period 1 make agents more likely to purchase insurance in period 2 compared to other people who did not receive insurance payouts? A customer will be more likely to purchase insurance in period 2 if the benefits of insurance in period 2 are greater than the benefits they experienced in period 1. Comparing B_2

to B_1,we see that the answer is yes, as $B_2 - B_1 > 0$ when customers receive payouts in period 1. For people who did not receive a payout in period 1, their benefit $B_2 = B_1$. Therefore, the increased benefits of insurance in the second period for those who received a payout great than the premium they paid in phase 1 are:

$$B_2 - B_1 = \left\{ \begin{array}{ccc} (\beta - \alpha)\lambda E(X) & \text{if} & X_1 \geq 2\lambda E(X) \\ (\beta - \alpha)(X_1 - \lambda E(X)) & \text{if} & X_1 < 2\lambda E(X) \end{array} \right\} \tag{10}$$

Interpretation of these equations is straightforward. If the reference point moved by greater than the premium ($X_1 \geq 2\lambda E(X)$), the entire premium in period 2 is evaluated as a reduced gain instead of loss. Therefore, you gain the difference in slopes between gains and losses $(\beta - \alpha)$ times the amount of the premium ($\lambda E(X)$). If the reference point moved by less than the full premium ($X_1 < 2\lambda E(X)$),then you get the utility gain for only the portion of the premium you pay up until you reach the reference point($X_1 - \lambda E(X)$).

Since the benefit from purchasing insurance is greater in period two after an agent has received an insurance payout, the theory predicts that agents who receive an insurance payout are more likely to purchase insurance in the next period than those who have not received a payout. This result is driven by the fact that although the agents are loss averse, purchasing insurance after experiencing an insurance payout is not mentally calculated as a true 'loss', as the reference point is now below the zero level of consumption. Purchasing insurance in the second period after receiving an insurance payout is less 'costly' (in terms of utility) than is was in the first period, making the benefits of insurance greater.

When $X_1 < 2\lambda E(X)$, $B_2 - B_1$ increases linearly with the payout X_1. This is because as X_1 increases, it means that less of the premium is calculated as a true loss. When $X_1 \geqslant 2\lambda E(X)$, all the insurance premium payment takes place before the reference point, giving a constant benefit increase from the first period.

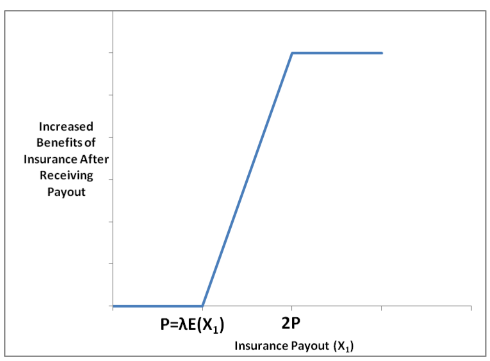

Figure 4: Extra Benefit of Insurance Induced by Previous Payout

6.3 Sophisticated Agents

In this section we assume that the agents are sophisticated, and therefore anticipate changes in their reference point and utility shock when taking decisions in period 1. While the math in this case gets a bit complicated it is easy to reason out the general conclusions.

The main change is that sophisticated agents will be more likely than unsophisticated agents to purchase insurance in period 1. If the reference point decreases in period 2 (which it will if the agent gets an insurance payout), then the agent is weakly better off under all conditions in period 2 than he would be if he hadn't received an insurance payout. Since this can only happen if the agent purchases insurance in period 1, it makes purchasing insurance in period 1 more attractive. As before, agents who receive an insurance payout in period 1 will be more likely to purchase insurance in period 2.

See Appendix 1 for more details.

6.4 Testing The Model

The model makes two main testable predictions

1. Subjects who received payouts that were larger than their premium should be more likely to repurchase insurance than those who received small or no payouts.

2. This effect should be strongest when payouts are larger than twice the premium.

Previously we saw that subjects who receive any sort of payout are more likely to purchase the next year than subjects who received no payout, which is consistent with Prediction 1. In order to test Prediction 2, I will have to test how purchasing behavior is related to different levels of payouts. In order to do this, I classify each of the payouts received according to their size, noting whether it is less than the paid premium, greater than the premium but less than twice the premium, or more than twice the premium. Similar to before, I regress a dummy indicating whether the subject re-purchased the next year on the three payout dummies and a year dummy. Results are presented in Table 5.

	Dependent Variable is Customer Re-Purchasing Insurance			
	(1)	(2)	(3)	(4)
Payout More Than Twice Premium	0.139***	0.140***	0.285***	0.287***
	(0.0309)	(0.0309)	(0.0516)	(0.0512)
Payout Greater Than Premium But < 2x	-0.000390	0.0107	-0.0372	0.0206
	(0.0171)	(0.0197)	(0.0431)	(0.0479)
Payout Smaller Than Premium	-0.0361***	-0.0261	-0.0464	0.0115
	(0.0132)	(0.0164)	(0.0484)	(0.0528)
2006 Dummy	-0.0343***	-0.0388***	-0.0339	-0.0430
	(0.0103)	(0.0109)	(0.0279)	(0.0284)
Constant	0.0753***	0.0757***	0.174***	0.168***
	(0.00879)	(0.00896)	(0.0185)	(0.0173)
State Fixed Effects	NO	YES	NO	YES
Marketing Restricted Sample	NO	NO	YES	YES
Observations	10997	10997	4201	4201
R-squared	0.024	0.028	0.037	0.053

Robust standard errors in parentheses — Observations are all insurance buyers in 2005 and 2006
*** p<0.01, ** p<0.05, * p<0.1 — All errors clustered at the village level
Omitted Category is not receiving a payout

Table 5: Magnitude of Payouts

Breaking down the payouts by magnitude, a far clearer picture emerges. Here we see that customers who received payouts less than two times the amount they paid in premiums are no more likely to purchase insurance the next year. In fact, there is some evidence that people with very low payouts may be less likely to purchase insurance than those who did not receive payouts, though this result is not robust across all specifications. However, people who received a payout of at least twice the premium they paid are 2.5-3 times more likely to purchase insurance next year than those who did not receive a payout. These results confirm the prediction of the model that payouts greater than two times the premium will have the most significant effect on purchasing.

The model also predicts that people with payouts greater than the premium but less than two times the premium should have a small but positive effect on repurchasing. The results find small coefficients that are not statistically different from zero, but also does not reject small positive coefficients, as would be predicted by the model.

While these results are consistent with the predictions of the Cash Flow Channel model, they could still be consistent with many other explanations. One important note is that in Table 5 we are still looking at the effects of people who have received insurance payouts, which means they have also been exposed to The Weather Channel and The Trust/Learning Channel. I will attempt to separate these effects in the following sections.

7 The Weather Channel

Since rainfall insurance payouts are always given when an area experiences a rainfall shock, it is possible that rainfall shocks as opposed to the insurance payouts lead people to purchase more insurance the following year. This would especially make sense if rainfall shocks were temporally correlated. For instance, if subjects knew that experiencing a rainfall shock meant that they were more likely to experience a shock the following year, one would expect their demand for insurance to increase after receiving a payout.[15]

To test autocorrelation of rainfall, I create a panel of various rainfall indicators from 1961-2004 for each weather station. For each indicator, I run a regression of six lags of the variable on the current value, including weatherstation-level fixed effects. These results are presented in column 1, with just the coefficient on the first lag shown. While a fixed effects regression with a lagged dependent variable is not generally consistent, it will converge to the true value as $T \to \infty$. As T is relatively large (38), these estimates are likely to suffer from little bias. However, just to be sure I also run a regression of the first lag using previous lags as instruments, using the methodology proposed by Arellano and Bond (1991). Results are presented in Table 6. The results from both specifications are similar, and show a surprising negative first-order autocorrelation in rainfall that appears to be driven by rains early in the season. The bottom two rows test for autocorrelation of rainfall shocks using the parameters of the 2005 insurance policy to determine shocks. By these measures, shocks to not appear to exhibit significant positive first-order autocorrelation.

[15] Assuming that the insurance company did not use this fact to adjust its premiums.

	Fixed Effects	Arenello-Bond
	(1)	(2)
Total Rainfall	-0.106***	-.086***
	(.030)	(.021)
Phase 1 Rainfall	-.090***	-.075***
	(.030)	(.029)
Phase 2 Rainfall	-.018	-.026
	(.030)	(.028)
Phase 3 Rainfall	-.029	.007
	(.030)	(.028)
Would Have Been Payout	.023	.017
	(.030)	(.022)
Total Insurance Payout	-.0353	.004
	(.030)	(.028)
Weatherstation Fixed Effects	YES	YES

Observation are years 1967-2004 for Fixed Effects Regression

Observation are years 1962-2004 for Arenello-Bond Regression

Fixed Effects regression contains six lags, Coefficient of First Lag Displayed

Arenello-Bond Regression contains one lag

Standard Errors are in Parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6: First Order Autocorrelation of Weather Variables

This evidence casts severe doubt on the hypothesis that positive autocorrelation of weather events is driving increased insurance purchasing. It appears that total rainfall is actually negatively autocorrelated, while shocks (which are proxied by the insurance contract giving a payout) do not appear to be correlated at all.

Even if there is no positive autocorrelation of rainfall, there may be other aspects about experiencing a shock that result in people having a higher propensity to purchase insurance. For instance, a rainfall shock may affect customers' liquidity or their perceived probabilities of a rainfall shock the next year. In order to look at the results of weather separately from the effects of insurance, I will analyze how previous weather events affected insurance purchase decisions in the first year that insurance was offered to BASIX customers, which was 2005. To accomplish this, I first aggregate the purchasing data to the village level and then test to see whether villages that experienced a rainfall shock in 2004, 2003, or 2002 had more insurance purchasers in 2005 than villages who did not experience a rainfall shock. I define a shock using each location's insurance policies in 2005: If insurance would have paid out in 2004 based on the structure of the 2005 weather policy, this is deemed a rainfall shock.[16]

[16]The APHRODITE weather data provides information about how many local weatherstations contributed to a certain rainfall reading. Since some of the rainfall observations likely to be more accurate than others, I weight them according to accuracy. If there are no rainfall stations contributing to the APHRODITE data within a $.75^o$x$.75^o$ grid around the desired BASIX rainfall station, the observation is given a weight of 1. If there is a least one rainfall station in this

The results of this regression are presented in Table 7.[17] Column 1 presents the baseline regression, which shows that villages that experienced a rainfall shock in 2004 actually had an average of 3.2 *fewer* purchasers in 2005, and this result only strengthens with the addition of state fixed effects in column 2. One worry with this regression may be that since the insurance policies and rainfall patterns of each location are different, the definition of a shock may vary from one place to another. Therefore, the estimates may be improved with the inclusion of location and policy-specific covariates. In columns 3 and 4 I add controls for the historical average rainfall, historical rainfall standard deviation, the policy premium in 2005, historical average payout of the policy, and the percentage of historical years there would have been a payout. Note that all the 'historical' data is calculated from 1961-2000. With the addition of these controls, the coefficient on having a rainfall shock in 2004 remains negative, though it is statistically insignificant when fixed effects are not included.

The estimated coefficients for the additional controls also shed some light onto insurance decisions. Places with lower historical rainfall and higher rainfall variability have more takeup, most likely indicating that drought-prone areas have more demand for insurance. The policy-specific characteristics are not statistically significant, but it is comforting to see that the point estimates indicate that people prefer cheaper policies with higher average payouts.

$.75^o$x$.75^o$ grid, the observation is given a weight of 1.5. If there is a rainfall station within the $.25^o$x$.25^o$ grid, the observation is given a weight of 2. The weighted results to not differ significantly from the unweighted results.

[17]Note that while it is reasonable to think that village-specific characteristics (such as village size) may have an effect on village-level insurance takeup, village-level co-variates are not included in the regression. In order to generate village-level characteristics we turned to the 2001 Indian census, which has data such as the village population, literacy rate, number of scheduled castes, etc. Unfortunately, villages in India have multiple names and multiple spellings, and it was not always possible to match the census data to the insurance buyer data- if fact, I was able to match only around 50% of the villages. When the regressions are run with the village characteristics included, our coefficients of interest do not change significantly. Also, most village-level characteristics had insignificant coefficients, with the exception that a more literate population was correlated with higher uptake.

	Dependent variable is number of buyers in 2005			
	(1)	(2)	(3)	(4)
Would Have Been Payout in 2004	-3.155***	-3.728***	-2.044	-3.572**
	(0.942)	(0.967)	(1.321)	(1.448)
Would Have Been Payout in 2003	1.436	1.717	0.0170	-0.765
	(1.592)	(1.306)	(1.261)	(1.037)
Would Have Been Payout in 2002	-2.329*	-0.406	0.0179	2.856*
	(1.226)	(0.987)	(1.292)	(1.414)
Historical Average Rainfall			-0.0143**	-0.0153**
			(0.00620)	(0.00590)
Historical Rainfall Standard Deviation			0.0447**	0.0834***
			(0.0171)	(0.0247)
Premium in 2005 (Rupees)			-0.0201	-0.0410*
			(0.0142)	(0.0215)
Historical Average Payout			0.0104	0.0403
			(0.0166)	(0.0302)
Percentage of Years With Payout			-16.76	-16.01
			(10.99)	(12.21)
Constant	8.456***	7.795***	18.91*	15.03*
	(0.859)	(0.735)	(9.869)	(8.107)
State Fixed Effects	NO	YES	NO	YES
Observations	734	734	733	733
R-squared	0.053	0.079	0.084	0.106
*** p<0.01, ** p<0.05, * p<0.1	Obervations weighted by quality of rainfall data			
Robust standard errors in parentheses	Errors Clustered at Weatherstation Level			

Table 7: Effect of Shocks on Purchasing

While controlling for the various policy-specific variables should make us feel a bit better about our definition of a weather shock, the heterogeneity of the policies may still be worrying. Plus, using a binary definition of a shock is quite crude, and may not be an accurate enough proxy. Therefore, it would be prudent to check how other measurements of recent rainfall might possibly affect insurance purchases. To do this, I create a continuous variable entitled 'Rainfall Deviation', which is the number of standard deviations from the historical mean of total rainfall over the monsoon season. At least with regards to drought, the higher this number the better the rains. Therefore, positive coefficients for rainfall deviation would mean that rainfall shocks are correlated with less insurance uptake, which is what we found in Table 7. Using the same specifications as were used in Table 7, results using rainfall deviations are presented in Table 8.

	Dependent variable is number of buyers in 2005			
	(1)	(2)	(3)	(4)
Rainfall Deviation in 2004	-0.429	3.712**	-1.798	0.286
	(1.666)	(1.453)	(1.880)	(2.276)
Rainfall Deviation in 2003	-1.586	-4.000***	-0.0740	-1.372
	(1.051)	(0.816)	(1.225)	(1.396)
Rainfall Deviation in 2002	1.323	0.679	0.0954	-0.0211
	(1.260)	(1.045)	(0.620)	(0.624)
Historical Average Rainfall			-0.0186***	-0.0142***
			(0.00450)	(0.00505)
Historical Rainfall Standard Deviation			0.0520***	0.0289
			(0.0171)	(0.0241)
Premium in 2005 (Rupees)			-0.0194	-0.00567
			(0.0188)	(0.0170)
Historical Average Payout			-0.0125	-0.00450
			(0.0249)	(0.0210)
Percentage of Years With Payout			-9.313	-9.205
			(10.07)	(10.42)
Constant	7.709***	12.17***	17.88*	17.15*
	(2.737)	(2.138)	(8.862)	(8.434)
State Fixed Effects	NO	YES	NO	YES
Observations	734	734	733	733
R-squared	0.028	0.082	0.086	0.095
*** p<0.01, ** p<0.05, * p<0.1	Obervations weighted by quality of rainfall data			
Robust standard errors in parentheses	Errors Clustered at Weatherstation Level			

Table 8: Rainfall Deviations as Shocks

The main message of Table 7 is that previous rainfall deviations do not generally have an effect on the number of insurance buyers in 2005. The one exception is in column 2, where the regression using state fixed effect and no extra covariates gives a positive and statistically significant coefficient for the rainfall deviations in 2004. While it is comforting that this is consistent with the results in Table 6, the fact that the point estimates on Rainfall Deviations are extremely erratic across specifications casts doubt on their validity.

Taking stock of these results, it appears extremely unlikely that The Weather Channel is driving people who receive payouts to purchase insurance again. If anything, it seems like poor weather alone has a negative effect on insurance uptake. One likely explanation for this is that people who have just experienced a shock are likely to be cash constrained the following year, so they may not have the money to purchase rainfall insurance.

8 The Trust/Learning Channel

It is also possible that the propensity to purchase insurance after receiving a payout results from learning about insurance and trusting the insurance company, as opposed to being a direct result of the payout. One point to note first is that the basic results in Table 5 already cast doubt on the importance on some mechanisms of The Trust/Learning Channel. These results showed that only people who received payouts greater than two times their premium were more likely to purchase insurance the following year. But experiencing a payout of any amount should give people an indication of how insurance works, and should also show that the insurance company will pay up when they are due. However, if people view insurance as an investment, witnessing higher insurance payouts could increase their propensity to purchase insurance the following year.

To separate the effect of the Trust/Learning Channel, we will need to take a look at a population of people who witnessed the workings of insurance but did not actually receive a payout themselves. Since the data only contains insurance purchasers, and generally all customers in village receive payouts if there is a shock, separating out The Trust/Learning Channel is not entirely straightforward.[18]

However, there is one group that was likely exposed to The Trust/Learning Channel without having received insurance payouts: people who purchased insurance in 2005 but decided not to purchase in 2006, even though there were insurance sales in their village. Since they purchased in 2005, these people were certainly aware of insurance, and would most likely be in a position to hear about insurance payouts in their village. Witnessing payouts should allow someone to learn about insurance and gain trust in the insurance company if if they didn't receive any payouts themselves. Therefore, if there was in insurance payout in their village they should have had the opportunity to experience the Trust/Learning Channel but not the Cash Flow Channel.

One point to note is that if this group witnessed a payout in 2006, then they also must have experienced a weather shock in 2006. Therefore, the following results will not reflect the pure effect of the Trust/Learning Channel, but instead measure the combined effects of The Trust/Learning Channel and The Weather Channel.

To test whether this group of non-purchasers were also affected by payouts in their village, I pool all insurance purchasers from 2006 with insurance purchasers in 2005 who lived in villages where there were insurance purchasers in 2006 but did not purchase themselves. I then test to see whether the non-buyers are affected by observing insurance payouts, and also whether the effect of payouts is different for buyers and non-buyers. These results are presented in Table 9.

[18]There are some cases where a person buys just one phase of an insurance product and another pays out, so that the person can witness others in the village receiving payouts. These people are far less likely to purchase insurance next year than people who simply received no payouts. (Results not shown.) While this could be interpreted as evidence of The Trust/Learning Channel, this interpretation is likely to be complicated by the fact that customers may be angry that they didn't receive a payout even though there was a shock.

Dependent Variable is Whether Customer Purchased Insurance in Following Year		
	(1)	(2)
Payout Less Than Premium in Village	-0.00761	-0.0591
	(0.0282)	(0.0522)
Received Payout Less Than Premium	-0.0349	-0.0441
	(0.0374)	(0.0726)
Payout > Premium but < 2X in Village	0.0572	0.0374
	(0.0743)	(0.113)
Received Payout > Premium but < 2X	-0.0757	-0.0745
	(0.0713)	(0.115)
Payout >2X Premium in Village	0.0121	0.0372
	(0.0357)	(0.0768)
Received Payout >2X Premium	0.144***	0.228***
	(0.0414)	(0.0811)
Constant	0.0412***	0.127***
	(0.00753)	(0.0187)
Marketing Restricted Sample	NO	YES
Observations	6,327	2,178
R-squared	0.057	0.083
Robust standard errors in parentheses	All Regressions Have State Fixed Effects	
*** p<0.01, ** p<0.05, * p<0.1	Errors Clustered at Village Level	

Table 9: Non-Buyers of Insurance

Following previous evidence that the size of the payout matters, I once again include dummies for the three separate levels of payouts: payout below the premium, payouts above the premium but less then two times the premium, and payouts greater than two times the premium. In this regression, for each of these levels I include a dummy for whether a payout occurred in the village and also whether the individual actually received the payout.[19]If someone received a payout then there must have been a payout in the village, so the coefficients on the 'Received Payouts' variables can be interpreted as an interaction between the 'Payout in Village' coefficients and a dummy for having actually purchased insurance. As expected from previous results, low level of payouts do not have statistically significant effects on purchasing the following year, either for purchasers of insurance or other people in the village. Receiving payouts greater than 2 times the premium result in a 14 or 23 percent increase in purchasing probability for the full and marketing restricted samples respectively. However, simply living in a village where people received large payouts does not result in a significantly significant effect on purchasing the next year. The point estimates are are positive (.01 and .04) and the standard errors are large, so I cannot reject the possibility of modest effects of witnessing a payout. However, receiving the payout clearly has a much larger effect than simply witnessing it.

While using people who purchased in 2005 but not in 2006 may give us the most direct test of the Trust/Learning Channel, one may be worried that this is too restrictive of a group (it consists of only

[19]In cases where there were multiple levels of payout among buyers in a village, I code the village based on which level of payout had the highest proportion of recipients.

1039 people.) If we are willing to assume that all people living in a village that received insurance payouts potentially will be exposed to the Trust/Learning Channel, then we can use village-level data to get another perspective. Do do this I test whether having any payouts in a village affects the number of new purchasers the following year. Note that as above, people living in a village where there were payouts also experienced a rainfall shock, so in essence I am measuring the combined effects of The Weather Channel and The Trust/Learning Channel. Results are presented in Table 10.

	Dependent Variable is the Number of Buyers in a Village the Following Year					
	All Villages			Villages With At Least 1 Repeat Buyer		
	Total Buyers	Repeat Buyers	New Buyers	Total Buyers	Repeat Buyers	New Buyers
	(1)	(2)	(3)	(4)	(5)	(6)
Payout Less Than Premium	1.536	-0.177	1.713	8.442***	-0.293	8.735***
	(2.477)	(0.210)	(2.308)	(2.713)	(0.425)	(2.552)
Payout Greater Than Premium but < 2X	0.724	0.156	0.568	-0.165	0.247	-0.412
	(1.145)	(0.202)	(1.133)	(2.274)	(0.588)	(2.360)
Payout Greater Than 2 Times Premium	2.373	1.380***	0.993	4.811*	3.932***	0.879
	(1.633)	(0.491)	(1.248)	(2.758)	(0.463)	(2.500)
Year 2006 Dummy	-2.768	-0.243	-2.526*	-5.608*	-0.00841	-5.600*
	(1.705)	(0.247)	(1.478)	(3.195)	(0.523)	(2.831)
Number of Purchasers Previous Year	0.106**	0.0588***	0.0473	0.196***	0.101**	0.0951
	(0.0481)	(0.0186)	(0.0353)	(0.0531)	(0.0432)	(0.0602)
Constant	3.374***	0.0730	3.301***	10.54***	0.480*	10.06***
	(1.184)	(0.150)	(1.099)	(1.594)	(0.253)	(1.617)
Observations	1,490	1,490	1,490	459	459	459
R-squared	0.048	0.125	0.037	0.098	0.279	0.080

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Errors Clustered at the Weatherstation Level. All Regressions Include State Fixed Effects
Data is aggregated to the Village Level
Includes all villages in 2005 and 2006 where there was insurance coverage the following year

Table 10: New Buyers In A Village

Table 10 uses village-level data to explore how payouts in a village affect the number of total, repeat, and new buyers in the following year. Columns 1-3 include all villages where insurance was available in their region the following year. In these estimates, we see that receiving a payout greater than two times the premium correlates with an average of 1.3 more repeat buyers than villages that did not see a payout. For new buyers, this coefficient is imprecisely estimated (with a point estimate of around 1) and not statistically different than zero. However, due to to large standard errors on the estimate I cannot reject the hypothesis that the effect of receiving payouts is the same for repeat buyers and new buyers.

Columns 4-6 include only villages where there was at least one buyer in the following year. Equivalent to the 'Marketing Restricted Sample' regressions in the individual-level data, this essentially makes the assumption that villages where there were no buyers the next year received no marketing and therefore didn't really have an opportunity to purchase insurance. Therefore, it makes sense to exclude them from the regression. In these estimates, a clearer picture emerges. In column 5 we see once again receiving large payouts correlates with more repeat buyers, with a higher point estimate of 3.9. In column 6 we see that now the same coefficient for new buyers is much smaller, and is statistically different from the coefficient on repeat buyers but is not statistically different from zero. This result is consistent with the theory that repeat buying is spurred by The Cash Flow Channel, as people who did not directly receive cash are not more likely to purchase insurance the next year.

However, column six also contains another, unexpected result. It shows that villages where there was a payout less than the premium have an average of 8.7 more new buyers the following year than other villages. This result does not hold for repeat buyers, nor for larger levels of payouts. At first glance, this looks like evidence in favor of the Trust/Learning channel, but upon further reflection it is more puzzling. If potential buyers were learning about insurance, why would this only apply to low levels of payout? And if low levels of payouts taught people about insurance, then why wouldn't this spur repeat buying as well? If people view insurance as an investment, certainly higher payouts would induce more new buyers. The finding that only small payouts in the village increases the amount of new buyers the next year does not seem to conform with any of our hypotheses about why payouts might induce insurance buying. However, it is worthwhile to note that the results are very large and statistically significant, so should not simply be ignored.

In any case, the taking all the results together casts serious doubt on the proposition that repeat buying by people who received insurance payouts could be caused primarily by the The Trust/Learning channel. While I cannot reject the possibility of some effects of the Trust/Learning Channel, the evidence is unclear, and therefore I believe that the Trust/Learning Channel could not be driving the main result that receiving insurance payouts makes customers more likely to become repeat purchasers.

One important caveat is to clarify that I was never able to look at The Trust/Learning Channel in isolation, only combined with The Weather Channel. Therefore, the results of this section actually show that the combined effect of The Trust/Learning Channel and The Weather Channel are not driving repeat buying. In the previous section, there was some weak evidence that The Weather Channel might have negative effects on takeup. If this is indeed true, it is possible that the non-results of this section are a result of a negative Weather Channel cancelling out a positive Trust/Learning Channel. Unfortunately, this data set does not allow me to test this hypothesis.

The results of this section point again toward the significance of The Cash Flow Channel in driving increased insurance purchases. If The Weather Channel and The Trust/Learning channel have insignificant effects on takeup, then the Cash Flow channel is likely driving the results.

9 Econometric Concern: Omitted Marketing Intensity

As the dataset has no information on marketing practices of the BASIX sales team, an omitted variable that may cause problems for the interpretation of our results is marketing intensity. For instance, let's assume that the marketing staff at BASIX think that people who have just received a payout are more likely to repurchase insurance. In this case, as the marketing team has limited resources, it may make sense for them to direct these resources towards the area of highest return, which would be people who have already received payouts. If this was the case, the increased takeup rates from people who received payouts could simply result from increased marketing attention from the BASIX team.

While the results could be picking up some of this effect, there are a couple of reasons I believe it is unlikely to be a significant factor. First of all, in conversations with the BASIX marketing staff they claim to not give any special marketing treatment to previous payout recipients.[20] As they are trying to build long-term business, BASIX claims that they do not change their marketing practices for villages that have recently received a payout. Next, if BASIX targeted payout recipients and they didn't really have a higher tendency to purchase, one would think that the marketing team would quickly learn that this strategy wasn't effective and would stop it. While it is true that we are only observing two marketing cycles and therefore erroneous beliefs could survive throughout the short time span, it is telling that the effect of payouts on takeup is greater in 2006 than 2005, suggesting that the effect is increasing over time.[21] If it was caused by erroneous expectations of the marketing team, we would expect the effect to decrease over time. Overall, while I must accept the possibility increased marketing is driving the results, I regard it as unlikely.

10 Discussion

The previous sections attempted to empirically separate out the effects of The Cash Flow Channel, The Trust/Learning Channel, and The Weather Channel. While I was not able to look at each of these channels independently, taking all the results together points to the Cash Flow Channel as driving the central result that people who receive insurance payouts are more likely to purchase insurance again the next year. Looking at the Weather Channel in isolation (section 8), I found that being exposed to a rainfall shock weakly decreases peoples' desire to purchase rainfall insurance. Taking a look at The Trust/Learning Channel along with The Weather Channel, I found small and insignificant effects on takeup. It seems unlikely that the combination of these two channels is driving repeat purchasing. Only when I looked at situations where people actually received insurance payouts did we see significant differences in the propensity to purchase insurance the next year. Therefore, I conclude that The Cash Flow channel is driving these purchasing decisions. While the proposed model of loss aversion is not the only model that could generate repeat decisions after receiving an insurance payout, its predictions are supported by the data.

This result does not bode well for the future of rainfall index insurance in India. If people are buying only due to psychological effects of recent payouts, they will not turn into long-term customers. However, the result man not be as negative as if first seems. This study looks at the first major scale-up of rainfall insurance in the world. Rainfall insurance is still a young product, and is still evolving to meet the needs of customers. One particular point of attention is the massive loading on most policies offered. As we saw in Table 2, the many BASIX insurance policies had premiums of up to six times the actuarialy fair rate. With premiums this high, it is unsurprising that people are not signing up. Also,

[20] Conversation with Sridhar Reddy, Assistant Manager for Insurance at Basix, Jan 09.

[21] Results not shown.

policies are constantly evolving to better correlate with crop outcomes and avoid basis risk. While this study predicts that rainfall insurance in the form of BASIX's policies from 2005-2007 is likely to fail, it is quite possible that innovations in products and pricing can create an insurance product that better meets the needs of Indian farmers.

11 Conclusion

After receiving an insurance payout, customers of rainfall insurance in India are 10-20% more likely to purchase insurance again the next year. This behavior seems to be driven by actually receiving the money from the insurance company, and is consistent with a loss aversion model where previous insurance gains shift the subject's reference point. After receiving an insurance payout, a subject views future insurance premiums as deductions from his previous gains, as opposed to a true loss. Therefore, after receiving an insurance payout future insurance purchases are more attractive.

This result is not entirely helpful in terms of policy prescriptions. If the propensity to purchase insurance after receiving a payout is truly due to the reception of money, in order maintain customers the insurance company would have to give out significant payouts each year. Since this would result in losses for the insurance company, such a scheme would not be sustainable in the long run.

One of the main arguments made for the slow adoption of insurance in India is that people do not understand insurance and do not trust the insurance companies. If trust and learning were the crucial determinant of insurance adoption, then over time as people witnessed and experienced payouts we would expect insurance adoption to grow. This paper fails to find any evidence of increased trust and learning driving insurance decisions, which suggests that insurance adoption is unlikely to grow quickly once these barriers are overcome.

This study brings to light a number of questions which would be ripe for future research. First of all, it would be interesting to understand whether insurance payouts have long-term effects on future purchases, and also whether payouts continue to have similar effects for people who have years of experience with insurance. To answer these questions one would need a data set with a longer time frame. Also, a longer data set could shed further light onto the question of whether customers learn about insurance over time. It is possible that people need a few years of experience with insurance to really learn about the product and gain trust in it, which would explain why we failed to see any effects of The Trust/Learning Channel.

With relation to the future of rainfall index insurance in India, one stark result is that the raw numbers of continuing customers of insurance are very low, calling into question the sustainability of the product. Even among people who received payouts in excess of twice their premium in 2006, only 18% bought again in 2007. With the proportion of repeat buyers so low, one would have to assume that many people are not satisfied with their experience of insurance, which does not bode well for the future success of the rainfall insurance industry in India. It seems like there will need to be some evolution of the product, price, or marketing strategy in order to turn rainfall index insurance into a viable product in the long run.

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Appendix 1: Insurance Decisions with Sophisticated Agents

NOTE THIS APPENDIX IS CURRENTLY OUT OF DATE. I NEED TO UPDATE IT TO REFLECT RECENT CHANGES TO THE THEORY

In this section assume that agents are sophisticated, which means that in their period 1 insurance decision they realize that their decision might cause their period 2 reference point to change and take this into account. I'll solve this problem using backward induction. In order to understand this task we will need to put some assumption on the distribution of the utility shocks ϵ. Assume $\epsilon_1 \sim N(0, \sigma)$ and $\epsilon_2 \sim N(\epsilon_1, \sigma)$. For simplicity, also assume $X \succeq 2P$. Looking forward to period 2, agents must take into account the distribution of ϵ_2 given ϵ_1. However, their future reference point is uncertain. They face the following problem in period 2:

If they received an insurance payout in period 1, $r_2 = -(X - P)$ agent will purchase insurance in period 2 if $B_2 > 0$

$$\epsilon_2 > \alpha P - p\beta X \tag{11}$$

As ϵ_2 is distributed as $N(\epsilon_1, \sigma)$, the probability of this occurring is

$$1 - \Phi(\frac{\alpha P - p\beta X - \epsilon_1}{\sigma}) \tag{12}$$

Therefore, the expected utility in period 2 given ϵ_1 is

$$U_2 = \Phi(\frac{\alpha P - p\beta X - \epsilon_1}{\sigma})(-p\beta X)) + (1 - \Phi(\frac{\alpha P - p\beta X - \epsilon_1}{\sigma}))(-\alpha P + \epsilon_1) \tag{13}$$

If they didn't receive an insurance payout in period 2, $r_2 = 0$. Again, the agent will purchase insurance in period 2 if $B_2 > 0$

$\epsilon_2 > \beta P - p\beta X$

The probability of purchasing insurance is

$1 - \Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma})$

Therefore, the expected utility in period 2 given ϵ_1 is

$U_2 = \Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma})(-p\beta X) + (1 - \Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma}))(-\beta P + \epsilon_1)$

Now we turn to the problem in period 1. Given ϵ_1, the agent must choose whether or not to purchase insurance. If he doesn't purchase insurance, there is no chance that his reference point will change so the calculation is straightforward.

$$U(I=0|\epsilon_1) = (-p\beta X) + (\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma})(-p\beta X) + (1-\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma}))(-\beta P + \epsilon_1))$$

If he does purchase insurance, he needs to take into account the fact that his reference point will change in period 2.

$$U(I=1|\epsilon_1) = -\beta P + \epsilon_1 + p(\Phi(\frac{\alpha P - p\beta X - \epsilon_1}{\sigma})(-p\beta X)) + (1-\Phi(\frac{\alpha P - p\beta X - \epsilon_1}{\sigma}))(-\alpha P + \epsilon_1)) + (1-p)(\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma})(-p\beta X) + (1-\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma}))(-\beta P + \epsilon_1))$$

Therefore, the expected benefits of insurance in period 1 are

$$B_1 = -\beta P + pBX + \epsilon_1 + p(\Phi(\frac{\alpha P - p\beta X - \epsilon_1}{\sigma})(-p\beta X)) + (1-\Phi(\frac{\alpha P - p\beta X - \epsilon_1}{\sigma}))(-\alpha P + \epsilon_1)) + (1-p)(\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma})(-p\beta X) + (1-\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma}))(-\beta P + \epsilon_1)) - ((-p\beta X) + (\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma})(-p\beta X) + (1-\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma}))(-\beta P + \epsilon_1)))$$

So, are sophisticated agents more likely to purchase insurance in period 1 than unsophisticated agents? The expectation of the differential benefit is:

$$B_{1S} - B_{NS} = p(\Phi(\frac{\alpha P - p\beta X - \epsilon_1}{\sigma})(-p\beta X)) + (1-\Phi(\frac{\alpha P - p\beta X - \epsilon_1}{\sigma}))(-\alpha P + \epsilon_1)) + (1-p)(\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma})(-p\beta X) + (1-\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma}))(-\beta P + \epsilon_1)) - (\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma})(-p\beta X) + (1-\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma}))(-\beta P + \epsilon_1)))$$

$$= (-p\beta X)(p\Phi(\frac{\alpha P - p\beta X - \epsilon_1}{\sigma}) + (1-p)\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma}) - \Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma})) - P(p\alpha(1-\Phi(\frac{\alpha P - p\beta X - \epsilon_1}{\sigma})) + (1-p)\beta(1-\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma})) - (1-\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma}))) + \epsilon_1(p(1-\Phi(\frac{\alpha P - p\beta X - \epsilon_1}{\sigma})) + (1-p)(1-\Phi(\frac{\beta P - p\beta X - \epsilon_1}{\sigma})))$$

This is greater than zero. Sophisticated agents will realize in that if they purchase insurance in period 1, there is some chance that their reference point will move in period 2 in a way that increases their utility. They take this into account when purchasing in period 1, therefore making them more likely to purchase.