# How might climate change influence farmers' demand for index-based insurance?

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**Abstract**

The low observed uptake of non-subsidised index-based insurance policies in developing countries has been puzzling researchers for about a decade. This paper analyses the role of drought frequency in farmers' demand for index-based insurance in developing countries. While it is typically assumed that an increase in exposure to risk would result in higher demand for index insurance, this paper finds the opposite: an increase in drought frequency may result in lower demand for index insurance under fairly standard conditions. In an expected utility model, we show that the demand for insurance is an inverted U function of drought frequency. We further show that downside basis risk decreases insurance demand under frequent drought conditions. It implies that insurance against similar but more frequent events cannot meet large demand from farmers. To check the empirical relevance of these effects, we conduct an insurance field experiment in Burkina Faso with 205 farmers. We analyse insurance demand for different drought frequencies, different levels of basis risks and different loading factors through incentivised lottery choices. This analysis confirms that for higher drought frequencies, insurance demand is lower. Insurance demand also decreases with basis risk and the loading factor.

Keywords: index-based insurance, extreme events, frequency, basis risk.
JEL codes: G22, O12, Q18.

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## 1 Introduction

In developing countries, index-based insurance schemes are becoming more widespread. Yet, despite growing interest among donors, insurers and banks, there is a low take-up rate of index-based insurance products among farmers (Cole et al., 2013; Giné and Yang, 2009). Substantial progress has been made in the economic literature in understanding the factors that may prevent farmers from purchasing index-based insurance in developing countries, such as cost and access to reliable information, and these factors are not easy to overcome (Platteau et al., 2017). But the nature of the risk itself may affect demand for insurance. And in this respect, the effect of drought frequency - and more generally damage frequency - on insurance take-up has not received much attention, apart from the literature on low probability risk problems (Slovic et al., 1977; Tversky and Kahneman, 1992; Kunreuther and Pauly, 2004).

Few climatologists have certainties about how climate change might influence precipitations in the Sahel, but one likely scenario is that drought may be more frequent. As mentioned by Panthou et al. (2018), there seem to be a recent recovery in annual cumulative rainfall, but this recovery is associated with an increase of rainfall intensity and a lower number of rainy days during the rainfall season, thus creating more frequent dry spells.

In this paper we look at the role of drought frequency on demand for index-based insurance in Burkina Faso. Rainfall season quality is critical for agriculture, and climate change may alter the frequency, severity, duration and timing of drought and the impact of such a change on demand for insurance is not known. We only consider here one dimension of climate change, namely the increase in drought frequency while we take severity, duration and timing as given. Several reactions of the insurer to this evolution could be considered, notably premium increase, or partial indemnification. We focus on the premium increase, for clarity, and because our focus is on the demand side of insurance[1]. However, we do not know *a priori* whether such change will favour or discourage insurance subscription, because both the price of insurance and the protection provided are greater.

Many factors contributing to the low demand for insurance in developing countries have been addressed in the economic literature.

A first set of factors is related to the demand side of index-based insurance products. Farmers may be liquidity constrained, especially in the absence of credit markets, and thus unable to afford insurance premiums (Cole et al., 2013; Carter et al., 2016). They also often experience a seasonality in their credit constraint (Dercon and Krishnan, 2000), the premium being generally paid before sowing, which corresponds to the end of the lean season when the credit constraint is particularly tied. Casaburi and Willis (2018) showed that interlinked insurance contracts deducting premiums from farmers revenues at harvest time significantly increase take-up rates. However, uncertainty in the payout also matters, Casaburi and Macchiavello (2019) show evidence that farmers are willing to incur sizable costs to receive infrequent payments as a commitment saving device. Alternatively, farmers may find index-based insurance too complex to understand

(Gaurav et al., 2011), for instance because of low financial literacy (Cai et al., 2015). They may not trust the insurance supplier to provide the promised payouts (Patt et al., 2010; Cai et al., 2009; Dercon et al., 2015). They may also already be insured through informal networks, through non-agricultural activities or through limited-liability credit contracts, which in turn limit their demand for a formal insurance product (Mobarak and Rosenzweig, 2013).

A second set of factors is related to the supply side and to the limitations of index-based insurance products, which may be too expensive or present technical deficiencies. Although satellite data may be used to overcome ground data limitations, it may be subject to biases and trust issues. The lack of quality historical data and infrastructures, such as dense networks of weather stations, remain significant obstacles to index insurance supply in many countries. Recent experiments carried out with different levels of subsidy argue in favour of a high elasticity of index-based insurance demand to insurance price (Mobarak and Rosenzweig, 2012; Karlan et al., 2014). Contract non-performance is another potential source of insurance product rejection (Doherty and Schlesinger, 1990). It is particularly relevant for index-based insurance contracts because of the imperfect correlation between the index and farmers yields. This discrepancy between insurance payouts and agricultural output, known as basis risk, may deter farmers from taking out index-based insurance (Giné et al., 2008; Giné and Yang, 2009; Cole et al., 2013; Tadesse et al., 2015; Dercon et al., 2014; Clarke, 2016). Basis risk can arise from different reasons (Leblois et al., 2014; Norton et al., 2013; Dalhaus et al., 2018) and frequenctly turns out to be a downside basis risk, that is a yield shock situation with no payout triggered by the index[2]. If this happens, the farmer finds herself in a worse situation with insurance after paying a premium than without insurance (Clarke, 2016).

A third set of factors may be due to the nature of climate risk itself. The probability of risk occurrence could be a potential obstacle to insurance subscription and to our knowledge, it has not been addressed in the specific literature on index insurance.

The literature on optimal insurance addresses the question of the property of risk on the optimal contract from the insurer's point of view, under the constraint that farmers subscribe (Chambers, 1989; Mahul, 2001). The farmers' demand is studied through the lens of the participation constraint. In their framework, a farmer participates to the insurance scheme if and only if her expected utility with insurance is greater than her expected utility without insurance. The sign of expected gains from insurance suffices to design optimal insurance contract, but if we want to address the demand side of existing index insurances, it is crucial to study also the size of expected gains.

Theoretical and empirical evidence about the potential impact of shock frequency on insurance demand have focused on low-probability events. Literature on disaster coverage in particular highlights low take-up for low-probability risks (Slovic et al., 1977). Behaviour in relation to probability-based insurance is used in Kahneman and Tversky (1979)'s seminal paper to explain the limited demand for insurance against low-probability risks (typically disaster insurances). Kunreuther and Slovic (1978); Hertwig et al. (2004); Kunreuther et al. (2001) argue that low probabilities are more difficult to perceive than high probabilities. Raschky et al. (2013); Kousky and Cooke (2012);

Grislain-Letrémy (2016) find empirical support for this hypothesis in various countries. However, some experimental results provide empirical evidence suggesting the inverse relationship and highlight the fact that insurance demand for low-probability risks may be higher than that for higher-probability risks. McClelland et al. (1993) and Laury et al. (2009) have conducted two experiments showing that demand for insurance decreases when the probability of the shock increases[3]. In most cases, authors simultaneously test an increase in shock probability, and a decrease in the damage magnitude to keep the premium constant (Slovic et al., 1977) or small enough (Laury et al., 2009). This implies that they compare different types of damage, not different frequencies of a same damage.

Furthermore, this literature has not really looked the effect of shock frequency for a broad range of probability events. The only paper we found that investigates the impact of shock frequency on insurance demand in the case of high-probability events is Norton et al. (2014). The authors demonstrate, using a choice experiment based on similar commercial insurance contracts sold locally, that insurance take up is much higher among Ethiopian farmers in the case of high frequency risks. Their main result is that insurance demand increases with the frequency of insured events, but again, in a setting where the frequent damage is not more expensive than the infrequent damage.

To measure the specific effect of frequency change and not the combined effect of a frequency change and a magnitude change, we propose an experiment and a theoretical model where the damage magnitude is constant as its frequency increases. The corollary is that the premium increases, as it would typically do when climate change occurs. Given that farmers already face zero-yield situations in the Sahel, and that climate change may increase the occurrence of such events, it seems relatively reasonable to bound damage magnitude.

We build an expected utility (EU) discrete choice model of insurance derived from Doherty and Schlesinger (1990)'s conceptual model to analyse the effect of shock frequency on insurance demand for the same damage. We establish that (1) the demand for insurance is an inverted U function of shock frequency indicating that there is an optimal frequency for farmers to take out insurance, (2) for high-frequency shocks, gains from insurance become negative (3) and both optimal frequency and maximal insurable frequency decrease with basis risk and loading factor levels.

To assess the empirical relevance of these effects, we conducted an insurance field experiment with 205 farmers in Burkina Faso. Farmers were asked to choose between insurance and no insurance, in 18 lottery choices representing insurance policies with different loading factors, different levels of basis risk and different drought frequencies. Three shock frequencies were used: 1/20 (low-probability shocks that occur on average once over a 20-year period), 2/20 (intermediate-probability shocks) and 7/20 (high-probability shocks). Three levels of downside basis risk were tested for each frequency: zero (no discrepancy between the index and the yield), 1/5 and 2/5, corresponding to the probability of not getting a payout conditional upon the occurrence of a shock. Finally, two loading factors were tested for each of the above combinations: the actuarially fair rate and a loading factor of 1.5. We find that an increase in basis risk or loading factor leads to lower demand for insurance, and, more originally, that an increase in drought frequency significantly reduces demand for insurance if the frequency is greater than 1/10. These experimental results are robust to different statistical specifications and consistent with the theoretical model, for frequencies beyond the optimal level.

The paper is organized as follows. In section 2 we build upon a conceptual model to account for the effect of shock frequency on insurance demand. In section 3, we present the field experiment that we conducted in Burkina Faso, and in section 4, we describe our empirical results.

## 2 An index-based insurance probability model

We adapt the formal framework proposed by Doherty and Schlesinger (1990) to the binary decision to get full insurance or no insurance in the context of basis risk. In theory two types of basis risk are possible: the "false alarm", i.e. the probability of a farmer receiving an indemnification while her production has not been impacted, and the "missed crisis" (or downside basis risk), i.e. the probability of a farmer receiving no indemnification while her production has been impacted by a random shock that is theoretically included in the contract. We focus here on downside basis risk because from the farmer's point of view, only the downside basis risk is an actual risk, whereas the "false alarm" is a risk for the insurer, which is not our perspective here. In the case of a continuous risk, a similar asymmetry exists and the downside risk is then typically defined by the semi-variance of profits (Turvey and Nayak, 2003; Conradt et al., 2015).

Downside basis risk can be formalized as a non performing contract (Doherty and Schlesinger, 1990), be it an imperfection in the insurance scheme or a default by the insurer. We note $p$ the frequency of drought and $r$ the downside basis risk, i.e. the probability of a farmer who has contracted an insurance receiving no indemnity conditional on the occurrence of the shock. It encompasses both imperfections in the index and insurer's failings. The probability of a farmer who has contracted an insurance suffering a shock without receiving any indemnity is thus $rp$.

In our model, a drought is an event of prolonged low rainfall leading to shortages in water availability, such as low cumulative rainfall or unusually long or frequent dry spells that are known to have a substantial impact on agriculture when they take place during the cropping season. This impact is summarized into the crop yield decrease relatively to a normal year, and in our simplified framework, it takes a unique value $L$, the loss in case of a shock. If $y$ is the farmer's income in a normal year, $y - L$ is the income in the case of a drought year. In the case of a drought, the insurer pays an indemnity $L$ with probability $1 - r$. Let $P$ denote the yearly premium, and $m \geq 1$ the loading factor applied by the insurer. The premium is then the average loss $pL$ multiplied by the probability of indemnification $1 - r$ multiplied by the loading factor, $P = mp(1 - r)L$. The insurance framework probability model is summarised in Table 1. Note that an increase in downside basis risk implies a lower rate of indemnification, thus a lower premium.

The farmer's expected utility gain from taking out insurance is the difference between her expected utility with insurance and her expected utility without insurance. This

Table 1: Insurance framework probability model

| | Payout (1-r) | No payout (r) |
|---|---|---|
| No yield shock (1-p) | 0 | $1-p$ |
| Yield shock (p) | $(1-r)p$ | $rp$ |

supposes that the decision to take out insurance is binary, which is a simplification with regard to Doherty and Schlesinger (1990) where the decision is about choosing an insurance rate between 0 and 1. This simplification is consistent with our field experimental framework.

$$\begin{aligned} \Delta EU = (1-p)u(y-P) + (1-r)pu(y-P) + rpu(y-P-L) \\ - [(1-p)u(y) + pu(y-L)] \end{aligned} \tag{1}$$

In this expression, the first term is the expected utility in the case of no drought if the farmer has contracted an insurance, resulting from the benefit of the harvest minus the cost of the premium (ie the probability of no drought times the utility with no drought). In case of drought, there are two sub-cases. Either the farmer gets reimbursed and her utility remains the same as in the case without drought, $pu(y-P)$, or the farmer does not get reimbursed and her utility is lower, $u(y-P-L)$. The expected utility in case of drought is a combination of these two sub-cases : probability of a drought that is indemnified times utility in this case (second term), and the probability of a drought that is not indemnified times utility in this case (third term).

The fourth term is the expected utility for a farmer who does not take up the insurance and there is no drought, and the fifth term is the expected utility for a farmer who does not take up the insurance and there is a drought.

The farmer is supposed to take the insurance if she expects a higher utility, in average, if she is insured than if she is not. Thus the demand for insurance is a binary decision that depends on the sign of $\Delta EU$. However, this decision is generally subject to individual idiosyncrasies, leading to individual heterogeneity in take-up decisions for a given set of parameters $(m, p, L, y)$. People do not all take the same choice, even if their farming activity is the same and face the same potential insurance contract. To account for these idiosyncrasies we define individual demand $x_i(p, y, L, m)$ as follows:

$$x_i(p, y, L, m) = \begin{cases} 0 & if \quad \Delta EU + \epsilon_i \leq 0 \\ 1 & if \quad \Delta EU + \epsilon_i > 0 \end{cases} \tag{2}$$

so that the probability that a farmer gets the insurance, $E(x_i|m, p, L, y)$, equals the probability that her expected gains of insurance plus the error term is strictly positive, $prob(\Delta EU + \epsilon_i > 0|m, p, L, y)$, where $\epsilon_i$ is the error term representing idiosyncrasies. Individual demands are added together to form a collective demand $n(m, p, L, y) =$

$\sum_{i \in [1,N]} x_i(m, p, L, y)$ where $N$ is the total number of farmers potentially concerned by the insurance contract.

## 2.1 Optimal shock frequency in the absence of basis risk

This subsection aims to provide understanding of the impact that drought frequency would have on expected gains from insurance in the absence of basis risk. To achieve this, we introduce $r = 0$ and thus $P = pmL$ into (1) and derive the two propositions:

Proposition 1.
*If the insurer's profit rate is beyond a certain threshold, expected gains from insurance are negative for all drought frequencies*

Proposition 2.
*If the insurer's profit rate is below a certain threshold, in the absence of basis risk, expected gains from insurance describe an inverted u-shaped curve as drought frequency increases*

Formal writings and proofs of all propositions are developed in the Appendix, section 6.2. As a consequence, there is a unique drought frequency (lower than 1) for which the gain from insurance is maximum.

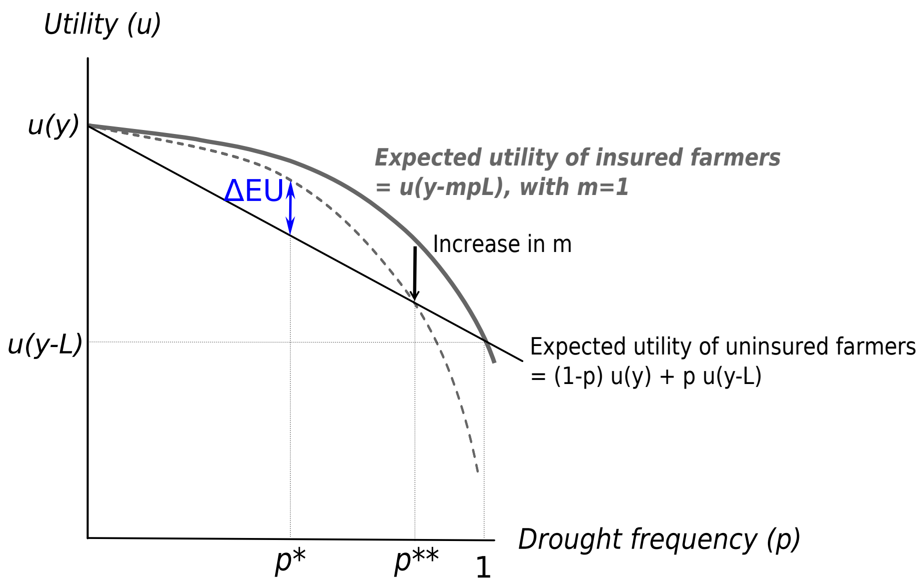


Figure 1: Expected gain from insurance (Δ EU), without basis risk. $p^*$ is the drought frequency that maximises the expected gain from insurance and $p^{*}*$ is the drought frequency for which the expected gain from insurance is nil.

Figure 1 provides some intuition of proposition 2. An increase in drought frequency impacts insured and uninsured farmers in a different way. For uninsured farmers the expected utility decreases linearly as $p$ increases, ie their marginal utility decrease is constant, $u(y) - u(y - L)$. For insured farmers utility decreases at an increasing rate, $mLu'(y - mpL)$, when $p$ increases.

At low drought frequencies, the marginal cost of an increase in $p$ is smaller for insured farmers than for uninsured farmers, but increasing for insured farmers and constant for uninsured farmers. As $p$ increases until $p^*$, it becomes more and more interesting to take out the insurance. At $p^*$, the marginal cost of an increase in $p$ for insured farmers is equal to the marginal cost of an increase in $p$ for uninsured farmers. At this point the benefit of being insured is maximal. And for higher values of $p$, the marginal cost of an increase in $p$ is greater for insured farmers. The expected utility of insured farmers decreases faster than the utility of uninsured farmers as $p$ increases. It is still profitable to be insured, but the gain from being insured decreases as $p$ increases. As $p$ approaches 1, the utility for insured farmers $u(y - mpL)$ becomes close to the utility for uninsured farmers $pu(y - L) + (1 - p)u(y)$, all the more as $m$ is also close to one.

The case where $p$ approaches 1 is implausible in practice, which tends to reduce the range of observable probabilities where $\Delta EU$ decreases with $p$. For instance if $p^* = 0.5$, it is unlikely that the decreasing side of the u-shaped curve can be empirically observed because farmers would stop considering drought as a risk if it occurs more often than every two years. This case of hyper-frequent droughts is useful only from theoretical point of view, to understand why farmers stop getting insurance before this upper limit. If $p^* = 0.1$, it is more likely that the decreasing side of the u-shaped curve can be validated empirically.

## 2.2 Optimal shock frequency with basis risk

This subsection aims to show that downside basis risk does not qualitatively alter the main result of the previous subsection.

Proposition 3

*If the insurer's profit rate is not too high, in case of downside basis risk, the gain from insurance is an inverted u-shape curve as drought frequency increases. For common utility functions, downside basis risk has a negative impact on insurance take up*

Proof is given in the Appendix, section 6.2.

The incentive to take out insurance first increases and then decreases with $p$. In other words, if shocks are too rare, gains from insurance are low and if shocks are too frequent, gains are low as well. Below we provide some intuition of this result. The principle is as above, except that the benefit of insurance is risky. Starting from a virtual situation where drought is very rare, the premium is cheap, but the indemnity is rare, so that the gain from insurance is low.

Figure 2 represents farmers' utility after the cropping season. Again, this utility is independent of $p$ for unisured farmers, and decreasing with $p$ for insured farmers, because the premium increases with $p$. Insured farmers in case of a non indemnified drought get the worse pay off, all the more as $p$ increases. the corresponding expected utilities are drawn on figure 3 in the case where the expected utility of insured farmers in the case of

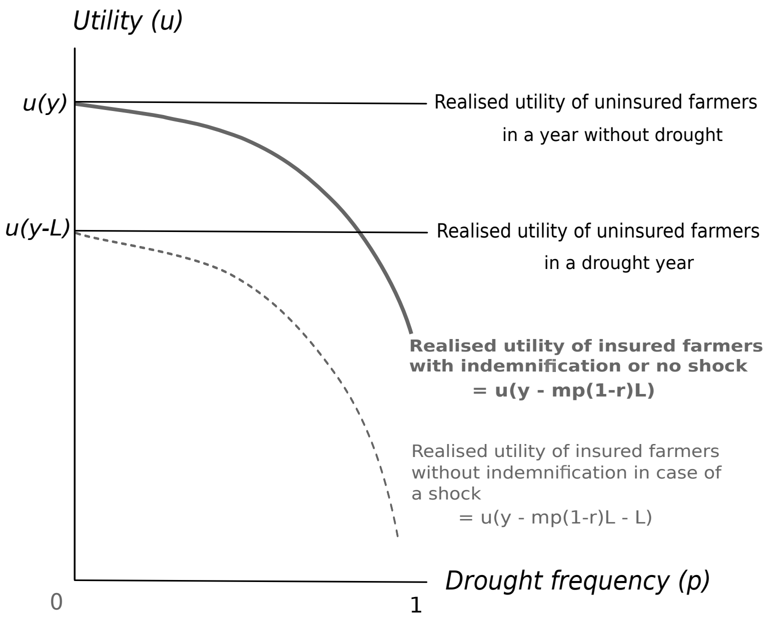


Figure 2: Realised utility of insured and uninsured farmers.

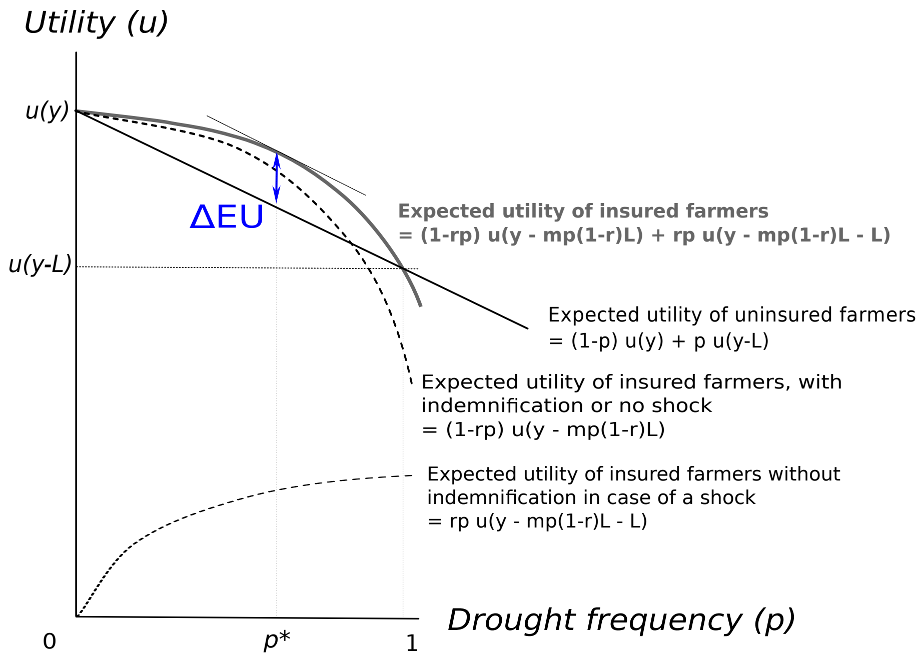


Figure 3: Gain from insurance: expected utility of uninsured and insured farmers, in the case where $L \in [\frac{2ry}{m(1-r)(2rp+\rho(1-rp))}; \frac{y}{mp(2-\rho)(1-r)+1}]$. $p^*$ is the drought frequency that maximises the expected gain from insurance.

a non indemnified drought, $rpu(y - mp(1-r)L - L)$, increases with $p$ and is concave on $[0, 1]$, while the expected utility of insured farmers in the case of indemnification, $(1 - rp)u(y - mp(1-r)L)$ decreases with $p$ and is concave on $[0, 1]$. This is the case for instance with a CRRA utility function of parameter $\rho$ if $L \in [\frac{2ry}{m(1-r)(2rp+\rho(1-rp))}; \frac{y}{mp(2-\rho)(1-r)+1}]$. Note that these restrictions are imposed for illustration in Figure 3 but they are not necessary for proposition 3. The expected utility of insured farmers (plein curve at the top) is the sum of the expected utility of insured farmers in case of a non indemnified drought (upward sloping dashed curve) and the expected utility of insured farmers in case of an indemnified drought (downward sloping dashed curve).

## 2.3 Expected impacts of drought frequency on insurance demand

If the loading factor is not too high, the expected impact of an increase in drought frequency is a decrease in the demand for insurance, provided drought frequency has reached a threshold value strictly inferior to 1. Furthermore, the demand for insurance is expected to decrease when the loading factor increases, and with some additional restrictions, the demand for insurance is expected to decrease when downside basis risk increases. See proofs in the appendix, section 6.2.

If the loading factor is not too high, basis risk tends to decrease subscription. This implies that the maximal insurable shock frequency decreases as basis risk increases. Figure 4 shows the expected effect of an increase in basis risk on expected utility.

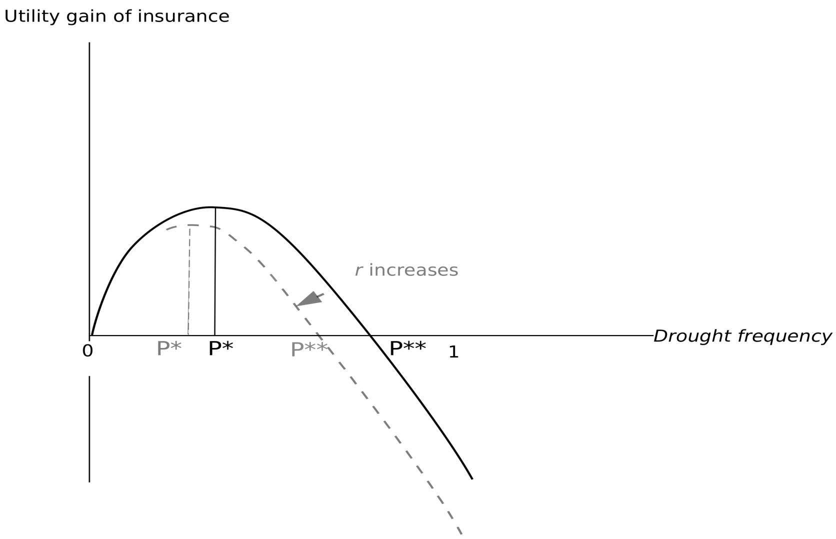


Figure 4: Expected effect of an increase in basis risk ($r$) on demand for index-based insurance.

# 3 Experimental design

In November 2015, we conducted a field experiment with 205 farmers in Burkina Faso to look at the influence of different drought insurance policies on farmers' insurance demand. The insurance policies varied in terms of shock frequency, basis risk and loading factor. Our experiment took place in the field which improves external validity of experimental results, and has been raised by Gneezy and Imas (2017) as a tool "to complement traditional Randomized Control Trials in collecting covariates to test theoretical predictions and explore behavioral mechanism" at limited costs.

Agriculture in Burkina Faso is dominated by grain and cotton production. Grain production tends to be oriented towards self-sufficiency strategies, especially for millet and sorghum. Maize is partly sold on domestic markets. Millet, sorghum and maize are rain-fed crops: grain yields are highly dependent on the occurrence of drought. Our experiment took place after the end of the rainy season, which ends in Octobre in Burkina Faso, where the dry season then runs until April.

## 3.1 Sample description

Nine villages were randomly selected in two different administrative units (*départements*) of Burkina Faso: Yako and Komsilga (see Fig. 5 in Appendix, section 6.1 for their location). An exhaustive list of villages in each unit, among which were randomly selected 4 and 5 villages, in Yako and Komsilga respectively, was provided by the *Conféderation Paysanne du Faso*, the main national producers organisation, regrouping over 36 thousands of cooperatives and producer groups across the country. We conducted field experiment sessions in each village, with 20 or 25 farmers. A total of 205 producers were surveyed in the 9 villages and participated in the insurance field experiment. The participants were arbitrarily selected by the village chief, who we asked for a representative sample of the village in terms of age, gender, income and ethnic group, provided that each participant was available for the entire half day, and was able to write a cross in the appropriate row and column identified by a figure. Nevertheless, we have no proof that our sample is representative of the villages, and there is certainly some selection bias. Our selection method was the only one we could find in order to avoid selecting too many people who were not able to respond or were not available, as random selection would have done. The survey aimed to characterise the respondents, their households and their agricultural activities. Table 2 presents the descriptive statistics of our sample.

## 3.2 The insurance field experiment

We held two main sessions to carry out the field experiment. As an introduction, we described drought index-based insurance to the farmers: its principles, the frequency of the insured droughts, the existence of basis risk, the premiums farmers would have to pay if they wanted to take out an insurance policy and the payouts they would receive from the insurer if a drought occurred and the indemnity was effectively being paid.

Table 2: Household characteristics

| Variable | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Sex (female=1) | 205 | .3 | 0.5 | 0 | 1 |
| Age | 204 | 40 | 12 | 17 | 72 |
| Ability to read | 204 | 0.5 | 0.5 | 0 | 1 |
| Number of household members | 204 | 9 | 5 | 1 | 30 |
| Total acreage (ha) | 198 | 3.2 | 2.3 | 0.25 | 15 |
| Sorghum acreage (ha) | 205 | 1.6 | 1.3 | 0 | 10 |
| Maize acreage (ha) | 205 | 0.5 | 0.8 | 0 | 5 |
| Millet acreage (ha) | 205 | 0.7 | 0.8 | 0 | 4 |
| Number of cattle | 202 | 1 | 3.3 | 0 | 40 |

Then, before the first session, we carried out hypothetical training using contextualized games involving insurance contracts where farmers had to choose to take out the insurance or not, on the basis of 18 examples of insurance contracts. In this training period, no money changed hands. Then we ran incentivised versions of the same contextualized games where farmers were presented with 18 insurance contracts. Two of the 18 games, randomly selected, resulted in payments being made to the farmers (one of each session).

Insurance contracts were calibrated on existing drought index-based insurance contracts in Burkina Faso. The assumptions were: a fixed surface of 0.5 ha of maize, and a revenue of 80,000 cfa Francs (cfaF) based on maize production of 800 kg in a normal year, and extreme damage of zero production in a dry year. For each of the 18 examples, the farmers were presented with a contract defined by the probability of drought, the basis risk, the premium, and the payout. The insurance premium differed for each of the 18 products, with a minimum of 2,000 cfaF (rare drought, high basis risk, no loading factor) and a maximum of 56,000 cfaF (frequent drought, no basis risk and high loading factor). Table 7 in Appendix 6.3 summarises these 18 insurance products. Insurance premiums increased mechanically with the loading factor, the frequency of the insured drought and decreased with basis risk. For each of the 18 insurance products, the farmers had to choose whether or not they wanted to take out the insurance. After the first session of nine such games without loading factor, a blindfolded child was asked to pick a ball at random in the weather lottery. If he or she picked a white ball, meaning no drought, real payouts for the first session were announced. If the child picked an orange ball, meaning drought, he/she ran a second lottery (basis risk) to determine whether or not the insurer would actually pay the indemnity. Real payouts were announced and games 10 to 18 were then similarly played (with loading factor), giving rise to another real payout.

*Weather lottery*

The occurrence of drought was determined by the result of a lottery, materialised by a transparent bowl with white and orange table tennis balls. The proportion of balls of each colour reflected the drought frequency. There was a total of 20 balls in the bowl, and the drought frequency varied from 1/20 to 7/20: the number of orange drought-balls varied from 1 to 7 and the number of white rain-balls varied from 13 to 19.

*Basis risk lottery*
The second lottery represented basis risk, and was played for contracts with basis risk (12 of the 18 games), i.e. only if a drought occurred in the first lottery. This second lottery was materialised by a transparent bucket with black and red table tennis balls. The proportion of black balls reflected the basis risk. There was a total of 5 balls and the basis risk varied from 0 to 2/5. When there was no basis risk, the basis risk lottery was not played. In the remaining cases, the number of black balls indicating risk varied from 1 to 2, while the number of red balls indicating absence of risk varied from 3 to 4.

### 3.2.1 Training sessions

The training sessions involved 18 examples calibrated on the actual harvest. The first nine examples corresponded to insurance contracts with an actuarially fair rate (m=1), while the next nine corresponded to contracts with a loading factor (m=1.5). For each subset of nine examples, those with no basis risk were played first, and corresponded to examples 1 to 3 and 10 to 12. Examples with basis risk corresponded to examples 4 to 9 and 13 to 18.

### 3.2.2 Incentivised sessions

The incentivised sessions were the same as the training sessions, except that the farmers are told that 2 of their 18 games would lead to a payment, and that this payment would be one percent of the above-mentioned amounts calibrated on the actual harvest. They had to decide whether they wanted to take out an insurance policy for 18 situations corresponding to the ones presented during the training sessions (revenue divided by 100), and 2 games were randomly selected after game 9 and 18 respectively. Payments were made at the end of the incentivised sessions. The average gains were around 700 cfaF for the first set of nine games and around 600 cfaF for the second set of nine games. The overall average gain was thus 1,300 cfaF (about 2.2 USD), corresponding to about 1 to 2 working days' wages in Burkina Faso.

Because of the existence of basis risks, some farmers could lose money. This situation could occur if the following four conditions were met: the randomly paid games corresponded to one with basis risk, i.e. 4 to 9 or 14 to 18; the farmer decided to take out insurance; a drought ball is picked in the first lottery; and a black ball is picked in the basis risk lottery. We attributed a fixed loan of 840 cfaF to each participant before beginning, so that liquidity was not a constraint on participation and no farmer could lose money during the experiment. For practical reasons, no cash was manipulated during the experiment, the payment was made at the end of the experiment. Table 3 details payments for the incentivised sessions, to be multiplied by 100 to obtain contextualized revenues (see Table 7). Table 4 describes the samples for both insurance sessions.

Table 3: Insurance contract characteristics and expected gains from lottery games

| game (#) | load. fact. $m$ | basis risk $r$ | drought freq. $p$ | premium (cfaF) $P$ | outcome (cfaF) | | | | | expec. gains (cfaF) | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | not insured | | insured | | | not insured | insured |
| | | | | | rain | drought | rain | drought | | | |
| | | | | | | | | indemn. | no indemn. | | |
| | | | | | $(1-p)$ | $p$ | $(1-p)$ | $(1-r)p$ | $rp$ | | |
| 1 | 1 | 0 | 1/20 | 40 | 800 | 0 | 760 | 760 | -40 | 760 | 760 |
| 2 | 1 | 0 | 2/20 | 80 | 800 | 0 | 720 | 720 | -80 | 720 | 720 |
| 3 | 1 | 0 | 7/20 | 280 | 800 | 0 | 520 | 520 | -280 | 520 | 520 |
| 4 | 1 | 1/5 | 1/20 | 30 | 800 | 0 | 770 | 770 | -30 | 760 | 760 |
| 5 | 1 | 1/5 | 2/20 | 60 | 800 | 0 | 740 | 740 | -60 | 720 | 720 |
| 6 | 1 | 1/5 | 7/20 | 220 | 800 | 0 | 580 | 580 | -220 | 520 | 520 |
| 7 | 1 | 2/5 | 1/20 | 20 | 800 | 0 | 780 | 780 | -20 | 760 | 760 |
| 8 | 1 | 2/5 | 2/20 | 50 | 800 | 0 | 750 | 750 | -50 | 720 | 720 |
| 9 | 1 | 2/5 | 7/20 | 170 | 800 | 0 | 630 | 630 | -170 | 520 | 520 |
| 10 | 1.5 | 0 | 1/20 | 80 | 800 | 0 | 720 | 720 | -80 | 760 | 720 |
| 11 | 1.5 | 0 | 2/20 | 160 | 800 | 0 | 640 | 640 | -160 | 720 | 640 |
| 12 | 1.5 | 0 | 7/20 | 560 | 800 | 0 | 240 | 240 | -560 | 520 | 240 |
| 13 | 1.5 | 1/5 | 1/20 | 60 | 800 | 0 | 740 | 740 | -60 | 760 | 730 |
| 14 | 1.5 | 1/5 | 2/20 | 130 | 800 | 0 | 670 | 670 | -120 | 720 | 650 |
| 15 | 1.5 | 1/5 | 7/20 | 450 | 800 | 0 | 350 | 350 | -450 | 520 | 290 |
| 16 | 1.5 | 2/5 | 1/20 | 50 | 800 | 0 | 750 | 750 | -40 | 760 | 730 |
| 17 | 1.5 | 2/5 | 2/20 | 100 | 800 | 0 | 700 | 700 | -100 | 720 | 670 |
| 18 | 1.5 | 2/5 | 7/20 | 340 | 800 | 0 | 460 | 460 | -340 | 520 | 350 |

Table 4: Insurance contracts offered by villages

| Sessions | games | N villages | N prod | N obs. |
|---|---|---|---|---|
| Actuarially fair (m=1) | 1 to 9 | 9 | 205 | 1,841 |
| Loading factor (m=1.5) | 10 to 18 | 6 | 130 | 1,168 |

Note: insurance with m=1.5 could not be played in 3 out of 9 villages

The sequence could imply a potential effects of learning on insurance adoption (Vasilaky et al., 2019): because lottery games were not randomised, it is possible that, by increasing their understanding of the task, farmers may have improved their choices as they played one game after another, which would interfere with exogenous changes in parameters. Since the games with a loading factor were always played after the games without a loading factor, we cannot exclude the possibility that the effect attributed to the loading factor *vis à vis* take-up actually reflects the fact that farmers play better in the second session. Although we cannot rule out the possibility of a remaining learning effect in our experiment, we played multiple hypothetical training sessions before the incentivized sessions to limit such an effect. Plus, we use session and game fixed effects and session clustering in our econometric models to control for this learning effect.

### 3.3 Estimation strategy

Since each farmer has to make 18 binary choices, we have a typical panel structure of 205 time series and 18 sets of data.

$$x^*_{it} = \alpha_i + Z_{it}.\beta + \mu_{it} \qquad i \in [1, 205] \quad t \in [1, 18] \tag{3}$$

$$x_{it} = 1(x^*_{it} > 0) \tag{4}$$

where $x^*_{it}$ is the latent variable of insurance uptake and $x_{it}$ is the binary variable of insurance uptake; $\alpha_i$ is the individual effect of farmer $i$ and $Z_{it}$ is the vector of explanatory variables. Let $\Phi$ be the cumulative distribution function of observations,

$$p(x_{it} = 1 | Z_{it}, \alpha_i) = \Phi(\alpha_i + Z_{it}.\beta) \tag{5}$$

Given the experimental nature of our data, the variables of interest are exogenous and uncorrelated with fixed effects. Because linear estimations provide converging and unbiased estimators (Angrist and Pischke, 2008), we show the results of linear regressions in section 4 and provide robustness checks under nonlinear specifications, in the Appendix, section 6.4.

## 4 Empirical results

### 4.1 Overall insurance demand

Table 5 shows the summary statistics of the insurance games.

Table 5: Descriptive statistics of the insurance games

| Sessions | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Take-up if m=1 | 1,841 | 0.81 | 0.39 | 0 | 1 |
| Take-up if m=1.5 | 1,168 | 0.67 | 0.47 | 0 | 1 |

Overall, we obtain high insurance take-up rates, on average 80% for the actuarially fair rate and 67% with a loading factor of $m = 1.5$ (Table 5), comparable with other similar real earnings games involving contextualized agricultural insurance among farmers (Petraud et al., 2014; Norton et al., 2014) or non-farmers (Laury et al., 2009; Slovic et al., 1977). McIntosh et al. (2013) compared a survey-based hypothetical willingness to pay for insurance with actual uptake and found that stated and actual demand are very poorly correlated. Although our experiment is incentivised, it cannot be used to determine the magnitude of the effect of drought frequency on insurance take up in real life. The relatively high adoption rate in our experiment, required to increase the precision of marginal effects, should not be used as an indicator of real life insurance attractiveness. Take-up rates for all values of the parameters of interest ($m$, $r$ and $p$), i.e. in each of the 18 games, are available in Table 7.

These take-up rates are much higher than in empirical non-experimental survey pilots[4]. Higher take-up in experiments than in pilots of real insurance supply seem to be a rather general feature, found in comparable studies with high take-up or willingness to pay, such as Petraud et al. (2014); Norton et al. (2014) and Serfilippi et al. (2016). This discrepancy may be due to the fact that many practical issues such as seasonal liquidity constraint or mistrust in the insurer are ignored in experimental set-ups.

## 4.2 Individual insurance demand

We estimate the relative role of the determinants of index-based insurance demand using different linear panel estimations: with random and fixed effects (Table 6). Fixed effects allows to control for the specificity of each village (column 2), individual (column 3), game (18 per individual, column 4) and session (2 per individual, column 5).

Because there may be longitudinal effects, for instance if a learning effect exists, wealth effects or any psychological effect due to pay off announcement, we introduce game fixed effects in addition to individual fixed effect. In particular, if a learning effect exists at each step of the experiment, its average value should be embedded in game fixed effects. Session fixed effects were introduced to control for individual specific learning across sessions. Similarly, although payments occurred at the end of the experiment, farmers could mentally compute their gain after the first session, and play the second one with greater wealth. We cannot exclude the possibility that this wealth effect is linked to loading factor increases. The session effect tends to decrease this bias.

We control for heteroscedasticity by clustering at the individual and session level. In the case of session clustering (column 5 of Table 6), because the number of clusters was low (9), we use the Wild bootstrap method for a small number of clusters proposed by

Table 6: Drivers of insurance take up : linear panel estimations

| | (1) RE | (2) RE | (3) FE | (4) FE | (5) FE |
|---|---|---|---|---|---|
| $m$ | $-0.211^{***}$ | $-0.208^{***}$ | $-0.208^{***}$ | $-0.418^{***}$ | |
| | (0.0491) | (0.0518) | (0.0504) | (0.098) | |
| $p$ | $-0.235^{***}$ | $-0.236^{***}$ | $-0.235^{***}$ | $-0.431^{**}$ | $-0.248^{**}$ |
| | (0.0542) | (0.0592) | (0.0584) | (0.177) | (0.110) |
| | | | | | [0.0240] |
| $r$ | $-0.0909^{**}$ | $-0.0908^{**}$ | $-0.0909^{**}$ | 0.154 | $-0.0809$ |
| | (0.0437) | (0.0400) | (0.0396) | (0.115) | (0.0664) |
| | | | | | [0.2382] |
| Constant | $1.066^{***}$ | $0.976^{***}$ | $1.059^{***}$ | 0.787 | $0.811^{***}$ |
| | (0.0637) | (0.0965) | (0.0662) | (0.715) | (0.0319) |
| Fixed-effects | No | Village | Ind. | Ind. & game | Ind. $\times$ session |
| Observations | 3009 | 3009 | 3009 | 3009 | 3009 |

Bootstrapped standard errors in parentheses, with individual (columns 1 to 4) and session (column 5) clustering. P-values from the distribution of Wild bootstrap t-statistics in brackets, with session clustering (column 5).
$^{*}$ $p < .1$, $^{**}$ $p < .05$, $^{***}$ $p < .01$

Cameron et al. (2008). With this model, the effect of the loading factor ($m$) change is included in the session fixed effect and is thus not reported.

Our main empirical result is that increasing drought frequency significantly decreases insurance take-up, this result being robust to different specifications (columns 1 to 5). The negative effect of $p$ indeed holds both for random and fixed effects models and stands for specifications with individual (column 1 to 4) and sessions clustering (column 5). As robustness checks, we ran additional nonlinear model specifications, available in Appendix (Table 8 section 6.4), including both probit and logit regressions. Linear panel regressions, as well as nonlinear panel estimations, validate the theoretical predictions that increasing the loading factor or the basis risk significantly reduces insurance take-up, in accordance with previous studies (Mobarak and Rosenzweig, 2012; Karlan et al., 2014; Clarke, 2016; Giné et al., 2008; Giné and Yang, 2009; Cole et al., 2013).

The amplitude of the negative estimated impact of $m$ should be treated with caution when considering the potential effect of learning during the experiment. Although training sessions were played before incentivised sessions, it may be that farmers' understanding was deeper during the second session with a higher loading factor, potentially altering their attitudes and notably their sensitivity to parameter changes.

We establish that the demand for insurance decreases with drought frequency, this result being robust to all specifications. In the trade-off between smoothing income and maintaining a higher income average, our result indicates that the second effect tends to dominate the first one as the drought frequency increases. It is consistent with the right side of the inverted U curve. Moreover, the amplitude of the negative effect of $p$ is high and overpasses the impact of basis risk.

We have attempted to check whether drought frequency had a positive impact on insurance take up for lower values of drought frequency (in addition to their negative impact for greater values of drought frequency), as predicted in the theoretical model. Unfortunately, this attempt does not lead to a clear conclusion, in particular in the longitudinal effects specifications (see Table 10 of section 6.4 in Appendix).

Basic individual characteristics of farmers (i.e. sex and age) and households (members, number of cattle) were found to be non-significant (see Appendix, section 6.4).

To sum up our empirical results, demand for index-based insurance decreases with the probability of drought for high-probability droughts. This extends existing results on low-probabilities of shocks (Slovic et al., 1977; McClelland et al., 1993) to higher risk probabilities. The fact that the demand for index-based insurance depends on the probability of the insured risk challenges future index-based insurance contracts. Insurers willing to develop index-based drought insurance products in developing countries should bear in mind that : (1) drought insurance is only attractive to farmers under certain climatic contexts, with relatively low drought frequency (in a context of climate change, the attractiveness of such insurance is reduced if drought becomes more frequent); and (2) the drought frequency of insurance products should be chosen as a function of both basis risk and loading factor.

# 5 Conclusion

In this article we highlight that the low uptake of index-based insurance in developing countries may be partly due to the high probability of shocks. For damages of a given magnitude, there is an optimal damage frequency for which farmers' willingness to take out insurance is maximal. Our analytical and empirical findings suggest that beyond a certain threshold, demand for drought insurance decreases when drought frequency increases, all the more so as loading factor and basis risk are high.

Therefore, in addition to the low probability risk issue observed by many authors (e.g. in the context of earthquakes or floods), there may be a high probability risk issue, in the case of shocks like droughts, where damage remains significant as droughts tend to be more frequent. In a nutshell, since climate change may increase the probability of a given shock, it could hinder future individual adoption of private drought insurance. The optimal drought frequency depends on the basis risk and the loading factor. In our model this optimal frequency is reduced under basis risk, but we could not provide empirical validation of this theoretical feature.

Our experimental results must be seen through the lens of experimental economics, often associated with limitations on external validity. The amounts at stake in the experiment are lower than the amounts at stake in real life, and take-up decisions in real life may be subject to more complex constraints and incentives. The main interest of our experiment is that the marginal effects of drought frequency on take-up, revealed in the experiment, could explain some of the real life observations of low adoption of insurance. Three parameter changes are introduced into our experiment, and we consider a unique magnitude of loss, which is fixed and corresponds to a unique drought type, fully covered by the insurance. Our work does not consider other factors limiting insurance take-up, such as liquidity constraint or income diversification and the inhibiting role of drought frequency on insurance demand should probably be confronted to competing factors. The role of subjective probabilities and ambiguity on insurance demand has also been tested by Visser et al. (2019) and Belissa et al. (2019). Combination of subjective weighted probabilities and perception of actual changes in drought probabilities could be a potential follow up to our work.

Moreover, climate change in the Sahel may also be accompanied by more severe, though still infrequent, droughts, which are not within the scope of our analysis. Future research could address such questions by comparing different types of droughts that may occur in the near future, considering the negative relationship between the probability and the magnitude of the damage.

## Notes

[1] If climate change increases the probability of occurrence of a shock, we expect the insurer to adjust insurance products to the raise of frequency by modifying the strike level (i.e. the threshold of the weather index) and/or by increasing insurance premiums and indemnifications).

[2] A risk of "missed crisis", as opposed to a "false alarm", corresponding to an indemnification in absence of a weather shock, see section 2.

[3] See also the literature review by Jaspersen (2015) on experimental evidence for insurance demand, for a discussion on the methods used.

[4] See section 1.

## References

Angrist, J. D. and J.-S. Pischke (2008): *Mostly harmless econometrics: An empiricist's companion*, Princeton university press.

Belissa, T. K., R. Lensink, and M. van Asseldonk (2019): "Risk and ambiguity aversion behavior in index-based insurance uptake decisions: Experimental evidence from Ethiopia," *Journal of Economic Behavior & Organization*.

Cai, H., Y. Chen, H. Fang, and L.-A. Zhou (2009): "Microinsurance, Trust and Economic Development: Evidence from a Randomized Natural Field Experiment," Working Paper 15396, National Bureau of Economic Research.

Cai, J., A. De Janvry, and E. Sadoulet (2015): "Social Networks and the Decision to Insure," *American Economic Journal: Applied Economics*, 7, 81–108.

Cameron, A. C., J. B. Gelbach, and D. L. Miller (2008): "Bootstrap-based improvements for inference with clustered errors," *The Review of Economics and Statistics*, 90, 414–427.

Carter, M. R., L. Cheng, and A. Sarris (2016): "Where and how index insurance can boost the adoption of improved agricultural technologies," *Journal of Development Economics*, 118, 59–71.

Casaburi, L. and R. Macchiavello (2019): "Demand and supply of infrequent payments as a commitment device: evidence from Kenya," *American Economic Review*, 109, 523–55.

Casaburi, L. and J. Willis (2018): "Time versus state in insurance: Experimental evidence from contract farming in Kenya," *American Economic Review*, 108, 3778–3813.

Chamberlain, G. (1984): "Panel data," in *Handbook of Econometrics*, ed. by Z. Griliches and M. D. Intriligator, Elsevier, vol. 2, chap. 22, 1247–1318, 1 ed.

Chambers, R. G. (1989): "Insurability and moral hazard in agricultural insurance markets," *American Journal of Agricultural Economics*, 71, 604–616.

Clarke, D. J. (2016): "A theory of rational demand for index insurance," *American Economic Jounal: Microeconomics*, forthcoming.

Cole, S., X. Giné, J. Tobacman, P. Topalova, R. Townsend, and J. Vickery (2013): "Barriers to Household Risk Management: Evidence from India," *American Economic Journal: Applied Economics*, 5, 104–35.

Conradt, S., R. Finger, and M. Spörri (2015): "Flexible weather index-based insurance design," *Climate Risk Management*, 10, 106–117.

Dalhaus, T., O. Musshoff, and R. Finger (2018): "Phenology information contributes to reduce temporal basis risk in agricultural weather index insurance," *Scientific reports*, 8, 46.

Dercon, S., J. W. Gunning, and A. Zeitlin (2015): "The demand for insurance under limited trust: Evidence from a field experiment in Kenya," Tech. rep., Oxford, Centre for the Studies of African Economies.

Dercon, S., R. V. Hill, D. Clarke, I. Outes-Leon, and A. S. Taffesse (2014): "Offering rainfall insurance to informal insurance groups: Evidence from a field experiment in Ethiopia," *Journal of Development Economics*, 106, 132–143.

Dercon, S. and P. Krishnan (2000): "Vulnerability, seasonality and poverty in Ethiopia," *The Journal of Development Studies*, 36, 25–53.

Doherty, Neil, A. and H. Schlesinger (1990): "Rational Insurance Purchasing: Consideration of Contract Nonperformance," *Quarterly Journal of Economics*, 55, 243–253.

Funk, C., P. Peterson, M. Landsfeld, D. Pedreros, J. Verdin, S. Shukla, G. Husak, J. Rowland, L. Harrison, A. Hoell, et al. (2015): "The climate hazards infrared precipitation with stationsa new environmental record for monitoring extremes," *Scientific data*, 2, 150066.

Gaurav, S., S. Cole, and J. Tobacman (2011): "A Randomized Evaluation of the impact of Financial Literacy on Rainfall insurance Take up in Gujarat," Tech. rep., ILO/EUDN.

Giné, X., R. Townsend, and J. Vickery (2008): "Patterns of Rainfall Insurance Participation in Rural India," *World Bank Econ Rev*, 22, 539–566.

Giné, X. and D. Yang (2009): "Insurance, credit, and technology adoption: Field experimental evidence from Malawi," *Journal of Development Economics*, 89, 1–11, 0304-3878.

Gneezy, U. and A. Imas (2017): "Lab in the field: Measuring preferences in the wild," in *Handbook of economic field experiments*, Elsevier, vol. 1, 439–464.

Grislain-Letrémy, C. (2016): "Natural disasters: Exposure and underinsurance," Mimeo.

Hertwig, R., G. Barron, E. U. Weber, and I. Erev (2004): "Decisions from experience and the effect of rare events in risky choice," *Psychological science*, 15, 534–539.

Jaspersen, J. G. (2015): "Hypothetical Surveys and Experimental Studies of Insurance Demand: A Review," *Journal of Risk and Insurance*.

Kahneman, D. and A. Tversky (1979): "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, 47, 263–91.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry (2014): "Agricultural Decisions after Relaxing Credit and Risk Constraints," *The Quarterly Journal of Economics*.

Kousky, C. and R. Cooke (2012): "Explaining the failure to insure catastrophic risks," *The Geneva Papers on Risk and Insurance Issues and Practice*, 37, 206–227.

Kunreuther, H., N. Novemsky, and D. Kahneman (2001): "Making low probabilities useful," *Journal of risk and uncertainty*, 23, 103–120.

Kunreuther, H. and M. Pauly (2004): "Neglecting disaster: Why don't people insure against large losses?" *Journal of Risk and Uncertainty*, 28, 5–21.

Kunreuther, H. and P. Slovic (1978): "Economics, psychology, and protective behavior," *The American Economic Review*, 68, 64–69.

Laury, S. K., M. M. McInnes, and J. T. Swarthout (2009): "Insurance decisions for low-probability losses," *Journal of Risk and Uncertainty*, 39, 17–44.

Leblois, A., P. Quirion, and B. Sultan (2014): "Price vs. weather shock hedging for cash crops: Ex ante evaluation for cotton producers in Cameroon," *Ecological Economics*, 101, 67–80.

Mahul, O. (2001): "Optimal insurance against climatic experience," *American Journal of Agricultural Economics*, 83, 593–604.

McClelland, G. H., W. D. Schulze, and D. L. Coursey (1993): "Insurance for low-probability hazards: A bimodal response to unlikely events," *Journal of Risk and Uncertainty*, 7, 95–116.

McIntosh, C., A. Sarris, and F. Papadopoulos (2013): "Productivity, credit, risk, and the demand for weather index insurance in smallholder agriculture in Ethiopia," *Agricultural Economics*, 44, 399–417.

Mobarak, A. M. and M. R. Rosenzweig (2012): "Selling formal insurance to the informally insured," Yale Economics Department Working Paper.

——— (2013): "Informal Risk Sharing, Index Insurance, and Risk Taking in Developing Countries," *American Economic Review*, 103, 375–80.

Mundlak, Y. (1978): "On the pooling of time series and cross section data," *Econometrica*, 69–85.

Norton, M., D. Osgood, M. Madajewicz, E. Holthaus, N. Peterson, R. Diro, C. Mullally, T.-L. Teh, and M. Gebremichael (2014): "Evidence of Demand for Index Insurance: Experimental Games and Commercial Transactions in Ethiopia," *The Journal of Development Studies*, 50, 630–648.

Norton, M. T., C. Turvey, and D. Osgood (2013): "Quantifying spatial basis risk for weather index insurance," *The Journal of Risk Finance*.

Panthou, G., T. Lebel, T. Vischel, G. Quantin, Y. Sane, A. Ba, O. Ndiaye, A. Diongue-Niang, and M. Diopkane (2018): "Rainfall intensification in tropical semi-arid regions: The Sahelian case," *Environmental Research Letters*, 13, 064–013.

Patt, A., P. Suarez, and U. Hess (2010): "How do small-holder farmers understand insurance, and how much do they want it? Evidence from Africa," *Global Environmental Change*, 20, 153 – 161, adaptive Capacity to Global Change in Latin America.

Petraud, J. P., S. Boucher, M. Carter, et al. (2014): "Competing theories of risk preferences and the demand for crop insurance: Experimental evidence from Peru," *document de travail, département de léconomie agricole et des ressources naturelles, Université de Californie à Davis.*

Platteau, J.-P., O. De Bock, and W. Gelade (2017): "The Demand for Microinsurance: A Literature Review," *World Development*.

Raschky, P. A., R. Schwarze, M. Schwindt, and F. Zahn (2013): "Uncertainty of governmental relief and the crowding out of flood insurance," *Environmental and Resource Economics*, 54, 179–200.

Serfilippi, E., M. Carter, and C. Guirkinger (2016): "Insurance Contracts when Farmers Greatly Value Certainty: Results from Field Experiments in Burkina Faso," Mimeo.

Slovic, P., B. Fischhoff, S. Lichtenstein, B. Corrigan, and B. Combs (1977): "Preference for insuring against probable small losses: Insurance implications," *Journal of Risk and insurance*, 237–258.

Tadesse, M. A., B. A. Shiferaw, and O. Erenstein (2015): "Weather index insurance for managing drought risk in smallholder agriculture: lessons and policy implications for sub-Saharan Africa," *Agricultural and Food Economics*, 3, 1–21.

Turvey, C. G. and G. Nayak (2003): "The semivariance-minimizing hedge ratio," *Journal of Agricultural and Resource Economics*, 100–115.

Tversky, A. and D. Kahneman (1992): "Advances in prospect theory: Cumulative representation of uncertainty," *Journal of Risk and uncertainty*, 5, 297–323.

Vasilaky, K., R. Diro, M. Norton, G. McCarney, and D. Osgood (2019): "Can Education Unlock Scale? The Demand Impact of Educational Games on a Large-Scale Unsubsidised Index Insurance Programme in Ethiopia," *The Journal of Development Studies*, 1–23.

Visser, M., H. Jumare, and K. Brick (2019): "Risk preferences and poverty traps in the uptake of credit and insurance amongst small-scale farmers in South Africa," *Journal of Economic Behavior & Organization.*

# 6 Appendix

## 6.1 Location of villages in Burkina Faso

Lab-in-the-field experiments took place in 9 villages in Burkina Faso, which location is shown on the following map (Fig. 5).

## 6.2 Propositions and proofs of the model

**Proposition 1**

*If* $m > \frac{u(y)-u(y-L)}{Lu'(y)}, \Delta EU \leq 0$ *(nil in* $p = 0$ *and increasingly negative as* $p$ *increases).*

**Proof**

First note that $\frac{\partial \Delta EU}{\partial p} = u(y) - u(y-L) - mLu'(y - mpL)$. In $p = 0$, $\frac{\partial \Delta EU}{\partial p} < 0$ if and only if $m > \frac{u(y)-u(y-L)}{Lu'(y)}$. Furthermore, it is clear from (1) that $\Delta EU = 0$, in $p = 0$. Finally, check that $\frac{\partial^2 \Delta EU}{\partial p^2} = m^2 L^2 u''(y - mpL) < 0$.

As a consequence, if $m > \frac{u(y)-u(y-L)}{Lu'(y)}$, $\Delta EU$ is nil and decreasing with $p$ in $p = 0$, concave in $[0, 1]$, this implies that $\forall p > 0, \Delta EU < 0$.

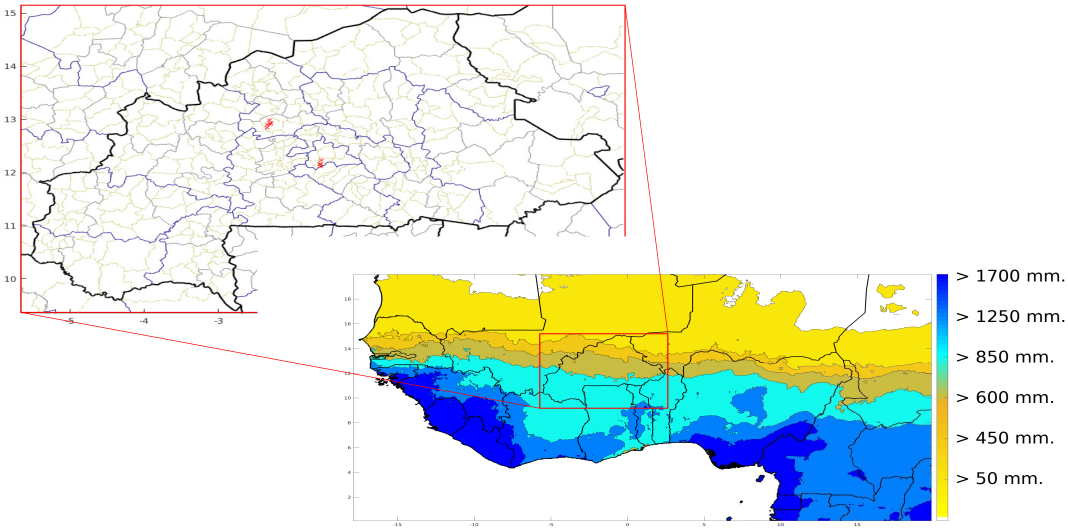


Figure 5: Average annual cumulative rainfall levels (50, 450, 600, 850, 1250 and 1700mm isohyets, CHIRPS data, 0.05 decimal degree resolution, 2000-2015, Funk et al. (2015)) and administrative units of Burkina Faso (*départments*: grey lines, *régions*: blue lines). The field experiment took place in nine villages (red crosses), 5 in Yako department (North Region) and 4 in Komsilga department (Center region).

**Proposition 2**

*If* $1 \leq m < \frac{u(y)-u(y-L)}{Lu'(y)}$ *and* $r = 0$*,* $\Delta EU$ *is an inverted u-shaped curve as* $p$ *varies, with the following properties:*

$\Delta EU$ *is nil in* $p = 0$*, increasing with* $p$ *in* $[0, p^* = \frac{y-u'^{-1}\left(\frac{u(y)-u(y-L)}{mL}\right)}{mL}]$*, decreasing with* $p$ *in* $[p^*; 1]$*, and negative in* $p = 1$ *if and only if* $m > 1$*.*

*As a corollary, if* $1 < m < \frac{u(y)-u(y-L)}{Lu'(y)}$*, there exists* $p^{**} \in ]p^*; 1[$ *such that expected gains are negative in* $[p^{**}; 1]$*, with* $p^{**} = \frac{u(y-mp^{**}L)-u(y)}{u(y-L)-u(y)}$

**Proof**

The proof of proposition 1 implies that if $m < \frac{u(y)-u(y-L)}{Lu'(y)}$, $\frac{\partial \Delta EU}{\partial p} > 0$ for $p = 0$.

In $p = 1$, $\Delta EU = u(y - mL) - u(y - L)$, which is strictly negative if and only if $m > 1$.

These three properties together (concavity on $[0, 1]$, positive slope in 0, $\Delta EU = 0$ in $p = 0$ and $\Delta EU < 0$ in $p = 1$) guarantee the inverted U-shape of $\Delta EU$ in $p$, and the existence of an optimal value of $p^* \in ]0; 1[$ such that $p^* = \frac{y-u'^{-1}(\frac{u(y)-u(y-L)}{mL})}{mL} < 1$.

**Proposition 3**

$\forall r \in [0;1[$, *if* $m < \frac{u(y)-u(y-L)}{Lu'(y)}$, $\Delta EU$ *is an inverted u-shape function of* $p$ *in* $[0,1]$

As a consequence, there is a unique $p^* \in \quad ]0;1[$ such that $p^* = argmax(\Delta EU)$.

**Proof**

First note that if $p = 0$, $\Delta EU = 0$. Furthermore, replacing $P$ by $mp(1-r)L$ in equation 1, and deriving with regard to $p$ leads to

$$\begin{aligned}\frac{\partial \Delta EU}{\partial p} &= u(y) - u(y-L) - r[u(y-mpL(1-r)) - u(y-mpL(1-r)-L)] \\ &\quad - (1-r)mL[pru'(y-mpL(1-r)-L) + (1-pr)u'(y-mpL(1-r))]\end{aligned} \tag{6}$$

In $p = 0$, $\frac{\partial EU}{\partial p} = (1-r)[u(y) - u(y-L) - mLu'(y)]$.

Given that $0 \leq r \leq 1$, $\Delta EU$ increases with $p$ in $p = 0$ if and only if $m < \frac{u(y)-u(y-L)}{Lu'(y)}$, as in the case with no basis risk.

We then check that $\Delta EU$ is concave in $p$

$$\begin{aligned}&\tfrac{\partial^2 \Delta EU}{\partial p^2} = rm(1-r)Lu'(y-mp(1-r)L) + \\ &rm(1-r)Lu'(y-mp(1-r)L) + (1-rp)m^2(1-r)^2L^2u''(y-mp(1-r)L) \\ &-m(1-r)Lru'(y-mp(1-r)L-L) - rm(1-r)Lu'(y-mp(1-r)L-L) \\ &+rpm^2(1-r)^2L^2u''(y-mp(1-r)L-L)\end{aligned} \tag{7}$$

Or after rearranging,

$$\begin{aligned}&\tfrac{\partial^2 \Delta EU}{\partial p^2} = 2rm(1-r)L\left[u'(y-mp(1-r)L) - u'(y-mp(1-r)L-L)\right] \\ &+(1-rp)m^2(1-r)^2L^2u''(y-mp(1-r)L) \\ &+rpm^2(1-r)^2L^2u''(y-mp(1-r)L-L)\end{aligned} \tag{8}$$

Concavity of $u$ ensures that $u'(y-mp(1-r)L) < u'(y-mp(1-r)L-L)$ and that $u'' < 0$. We thus have $\frac{\partial^2 \Delta EU}{\partial p^2} < 0$.

Then we show that in $p = 1, \Delta EU < 0$.

$\Delta EU = (1-r)u(y-P) + ru(y-P-L) - u(y-L)$.

If $L < P$, $u(y-L-P) < u(y-P) < u(y-L)$ and $u(y-L)$ is then greater than any weighted mean of $u(y-P)$ and $u(y-P-L)$, thus $(1-r)u(y-P) + ru(y-P-L) < u(y-L)$.

If $L \geq P$, $u(y-L-P) < u(y-L) < u(y-P)$ and because $u$ is concave, $u(y-L)$ is greater than any weighted mean of $u(y-L-P)$ and $u(y-P)$, thus $(1-r)u(y-P) + ru(y-P-L) \leq u(y-L)$.

Thus, $\Delta EU$ is nil in $p = 0$, increasing with $p$ in $p = 0$ provided $m > \frac{u(y)-u(y-L)}{Lu'(y)}$, and concave on [0,1], and reaches negative values before $p = 1$. This garantees that

$\forall p \in [0;1]$, if $m < \frac{u(y)-u(y-L)}{Lu'(y)}$, expected gain from insurance has an inverted U-shape as $p$ varies.

The global analysis of the variation of $\Delta EU$ when $r$ varies on $[0,1]$ is not trivial because $\Delta EU$ is not concave in $r$ without more assumptions. For instance $\Delta EU$ is decreasing in $r$ for $r = 0, \forall p$ but increasing in $r$ in $r = 1$, $p = 1$, which indicates a change in concavity of $\Delta EU$ with respect to $r$ for $p = 1$.

We can nevertheless provide a sufficient condition for $\Delta EU$ to be decreasing in $r$ on $[0;1]$. If $u$ is a CRRA function of parameter $\rho$, $\frac{\partial \Delta EU}{\partial r} < 0$ is equivalent to

$$\left(\frac{y-P}{y-P-L}\right)^{\rho} \frac{(1-\rho)rpmL + y - P - L}{(1-rp)(1-\rho)mL - y + P} < -1$$

a sufficient condition for this expression to be true is

$$m < \frac{1}{1-\rho}$$

**Expected effects**

*If $m < \frac{u(y)-u(y-L)}{Lu'(y)}$, three types of impact are expected:*
$\frac{\partial prob(\tilde{x}_i=1)}{\partial m} < 0$
$\frac{\partial prob(\tilde{x}_i=1)}{\partial p} < 0$ *iff* $p > p^*$
$\frac{\partial prob(\tilde{x}_i=1)}{\partial r} < 0$ *if $u(r,m,p,L)$ is a CRRA utility function of parameter $\rho$ and $m < \frac{1}{1-\rho}$*

The partial effect of $m$ is straightforward and the partial effect of $p$ simply derives from the fact that $prob(\tilde{x}_i = 1) = prob(\Delta EU + \epsilon_i > 0)$ which is decreasing with $p$ if and only if $\Delta EU$ is decreasing with $p$, i.e. when $p > p^*$.

## 6.3 Experimental protocol

**Introductory comments**

You have the opportunity to take part in a field experiment about risk and drought insurance. Drought insurance is an agreement between a farmer and an insurer whereby the farmer pays a premium in May and, if drought occurs, he receives an indemnity in November. We will describe 18 types of insurance, and for each one, you have to decide whether you want to take out the insurance and pay the premium. A the end of the experiment, you will get the amount of money that is defined in these contracts, depending on the choices you made in these games, and whether drought occurred or not. Of the 18 choices, two will be randomly selected, and these two choices will determine how much money you will receive. The amount you will receive will depend on your choices, but also on random factors, since the occurrence of drought or rain is random.

This money will be yours.
Do you have any questions?

If you have questions during the games, raise your hand and we will answer you. It is important that you do not talk with one another once the game has started. There is no right or wrong answer, the money you will obtain will depend upon your choices and the random draws. It is important that you do not try to look at your neighbour's sheet.

The games will last two hours. If you think that you cannot stay for two hours, please tell us now.

**Instructions given to farmers. Training examples**

Before starting the experiment, we will give you two examples. In this game, we consider that you produce maize and you have the choice whether or not to take out insurance against drought affecting your maize production.

In the example, you cultivate half a hectare of maize and your yield is 8 bags of 100 kg if the rainfall is good and 0 bags if there is a drought. Each bag you produce is sold for 10,000 cfaF. If the rainfall is good, you earn 80,000 cfaF and if there is a drought you earn zero.

In the first example, drought is rare. There is a drought once every 20 years. In May, you decide whether to take out the insurance, in which case you will pay a premium of 4,000 cfaF, or not to pay the premium. Then we must determine whether there is rain or drought. To do this, we put one orange ball and 19 white balls in a bowl. A blindfolded child will pick one ball.

If he picks a white ball, the season is rainy and the harvest is good. If you have paid the insurance premium (4,000 cfaF) the harvest value is 80,000 cfaF and your income is thus 76,000 cfaF. If you did not pay for the insurance, your income is 80,000 cfaF.

If the child picks the orange ball, the season is dry and the harvest is nil. If you have paid the premium (4,000 cfaF) you get an indemnity to compensate for your loss (80,000 cfaF), so that your income is 76,000 cfaF. If you did not pay the premium, you get zero.

The choice you have to make is: "do you want to take out this insurance?"

In the second example, the drought is still rare, but there is a small risk that the insurer makes a mistake and does not pay the indemnity. There is one drought every 20 years and the insurer can make a mistake on two occasions out of ten. This means that if there is a drought and if you have paid the premium, there is a 2 in 10 chance that the insurer does not pay the indemnity. This is because, for example, the insurer thinks that there has been rain but in reality, the rain has not fallen on your field or not during the useful period. The insurance premium is then cheaper (3,200 cfaF) because the insurer knows that he might make a mistake. First, you decide whether or not to pay the insurance premium, then the child picks a ball from the bowl to determine whether the weather is rainy or dry.

If he picks a white ball, there is rain. Everybody harvests 80,000 cfaF-worth of maize. The income of those who have paid the premium is 76,800 cfaF, whereas those who have not paid the premium receive 80,000 cfaF.

If the child picks an orange ball, there is a drought. The harvest is zero. Those who did not take the insurance get zero. The income of those who took the insurance depends on the result from the bucket, which contains two red balls and 8 black balls. If the child picks a red ball, those who have paid the insurance get zero from the insurer, so that they have lost 3,200 cfaF. If the child picks a black ball, the income of those who have paid the insurance is 76,800 cfaF.

The choice you have to make is: "do you want to take out this insurance?". Do you have any questions? Has everyone understood everything ?

**Instructions given to farmers. Incentivised insurance experiment**

Now, the game is for real money. For each type of insurance, we will tell you the amount of the premium, the frequency of drought, and the risk that the insurer makes a mistake. For each type of insurance, you decide whether you want to pay the premium or not. If you want to pay the premium, you make a cross in the blue column. If you do not want to pay the insurance, you make a cross in the yellow column. There are 18 choices in this serie, for 18 types of insurance. At the end of the series, a child will pick two of the 18 numbered balls from this cage. The numbers on these two balls will indicate the numbers of the choices for which you will receive money. Then, the child will pick one ball from the bowl to determine whether the rainfall was good, and one ball from the bucket to determine whether you get the indemnity from the insurer. You will then receive the amount of money corresponding to your decision whether or to to take out insurance. In the previous examples, the price of a bag was 10,000 cfaF. In the experiment, it is 100cfaF. In the first example above, this means that the harvest is 800 cfaF instead of 80,000 cfaF if there is rain, and the premium is 40 cfaF instead of 4,000 cfaF.

Do you have any questions? Has everyone understood everything ?

- Insurance 1. Drought occurs once every twenty years, and the insurer makes no mistakes. The premium is 40 cfaF. There are 19 white balls and 1 orange ball in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 760 cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who take the insurance get 760 cfaF, those who do not take the insurance receive zero. Do you want to pay the premium and take out the insurance?

- Insurance 2. Drought occurs twice every twenty years, and the insurer makes no mistakes. The premium is 80 cfaF. There are 18 white balls and 2 orange balls in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 720 cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who take the insurance receive 720 cfaF, those who do not take the insurance receive zero. Do you want to pay the premium and take out the insurance?

- Insurance 3. Drought occurs seven times every twenty years, and the insurer makes no mistakes. The premium is 280 cfaF. There are 13 white balls and 7 orange balls in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 520cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who take the insurance receive 520 cfaF, those who do not take the insurance receive zero. Do you want to pay the premium and take out the insurance?

- Insurance 4. Drought occurs once every twenty years, and the insurer makes 2 mistakes out of 10 cases. The premium is 30 cfaF. There are 19 white balls and 1 orange ball in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 770 cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who do not take the insurance receive zero and the income of those who take the insurance depends on the results from the bucket. If the child picks a red ball from the bucket, they lose their 30cfaF and if the child picks a black ball, they receive 770 cfaF. Do you want to pay the premium and take out the insurance?

- Insurance 5. Drought occurs twice every twenty years, and the insurer makes 2 mistakes out of 10 cases. The premium is 60 cfaF. There are 18 white balls and 2 orange balls in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 740 cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who do not take the insurance receive zero and the income of those who take the insurance depends on the results from the bucket. If the child picks a red ball from the bucket, they lose their 60cfaF and if the child picks a black ball, they receive 740cfaF. Do you want to pay the premium and take out the insurance?

- Insurance 6. Drought occurs seven times every twenty years, and the insurer makes 2 mistakes out of 10 cases. The premium is 220 cfaF. There are 13 white balls and 7 orange balls in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 580 cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who do not take the insurance receive zero and the income of those who take the insurance depends on the results from the bucket. If the child picks a red ball from the bucket, they lose their 220 cfaF and if the child picks a black ball, they receive 580 cfaF. Do you want to pay the premium and take out the insurance?

- Insurance 7. Drought occurs once every twenty years, and the insurer makes 4 mistakes out of 10 cases. The premium is 20 cfaF. There are 19 white balls and 1 orange ball in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 780 cfaF, and those who do not take insurance receive 800cfaF. If the child picks an orange ball, the harvest is nil, those who do not take the insurance receive zero and the income of those who take the insurance depends on the results from the bucket. If the child picks a red ball from the bucket, they lose their 20 cfaF and if the child picks a black ball, they receive 780 cfaF. Do you want to pay the premium and take out the insurance?

- Insurance 8. Drought occurs twice every twenty years, and the insurer makes 4 mistakes out of 10 cases. The premium is 50 cfaF. There are 18 white balls and 2 orange balls in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 750 cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who do not take the insurance receive zero and the income of those who take the insurance depends on the results from the bucket. If the child picks a red ball from the bucket, they lose their 50cfaF and if the child picks a black ball, they receive 750 cfaF. Do you want to pay the premium and take out the insurance?

- Insurance 9. Drought occurs seven times every twenty years, and the insurer makes 4 mistakes out of 10 cases. The premium is 170 cfaF. There are 13 white balls and 7 orange balls in the bowl. If the child picks a white ball, there is rain, and those who take insurance receive 630 cfaF, and those who do not take insurance receive 800 cfaF. If the child picks an orange ball, the harvest is nil, those who do not take the insurance receive zero and the income of those who take the insurance depends on the results from the bucket. If the child picks a red ball from the bucket, they lose their 170 cfaF and if the child picks a black ball, they receive 630 cfaF. Do you want to pay the premium and take out the insurance?

Nine similar choices are made in the case where the insurer makes a profit (loading factor $m = 1.5$). The 18 insurance products are summarised below.

Table 7: Premiums and loading factors, basis risks and drought frequencies

| Game number | Loading factor $m$ | Basis risk $r$ | Drought frequency $p$ | Premium (cfaF) $P$ | Outcome: not insured, Rain | Outcome: not insured, Drought | Outcome: insured, Rain | Outcome: insured, Drought, Indemnity | Outcome: insured, Drought, No indemnity | Average $\Delta$ Expected gain | Average take-up |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0 | 1/20 | 4,000 | 80,000 | 0 | 76,000 | 76,000 | -4,000 | 0 | 0.82 |
| 2 | 1 | 0 | 2/20 | 8,000 | 80,000 | 0 | 72,000 | 72,000 | -8,000 | 0 | 0.83 |
| 3 | 1 | 0 | 7/20 | 28,000 | 80,000 | 0 | 52,000 | 52,000 | -28,000 | 0 | 0.82 |
| 4 | 1 | 1/5 | 1/20 | 3,000 | 80,000 | 0 | 77,000 | 77,000 | -3,000 | 0 | 0.82 |
| 5 | 1 | 1/5 | 2/20 | 6,000 | 80,000 | 0 | 74,000 | 74,000 | -6,000 | 0 | 0.80 |
| 6 | 1 | 1/5 | 7/20 | 22,000 | 80,000 | 0 | 58,000 | 58,000 | -22,000 | 0 | 0.78 |
| 7 | 1 | 2/5 | 1/20 | 2,000 | 80,000 | 0 | 78,000 | 78,000 | -2,000 | 0 | 0.78 |
| 8 | 1 | 2/5 | 2/20 | 5,000 | 80,000 | 0 | 75,000 | 75,000 | -5,000 | 0 | 0.80 |
| 9 | 1 | 2/5 | 7/20 | 17,000 | 80,000 | 0 | 63,000 | 63,000 | -17,000 | 0 | 0.80 |
| 10 | 1.5 | 0 | 1/20 | 8,000 | 80,000 | 0 | 72,000 | 72,000 | -8,000 | -4,000 | 0.82 |
| 11 | 1.5 | 0 | 2/20 | 16,000 | 80,000 | 0 | 64,000 | 64,000 | -16,000 | -8,000 | 0.74 |
| 12 | 1.5 | 0 | 7/20 | 56,000 | 80,000 | 0 | 24,000 | 24,000 | -56,000 | -28,000 | 0.53 |
| 13 | 1.5 | 1/5 | 1/20 | 6,000 | 80,000 | 0 | 74,000 | 74,000 | -6,000 | -3000 | 0.68 |
| 14 | 1.5 | 1/5 | 2/20 | 13,000 | 80,000 | 0 | 67,000 | 67,000 | -13,000 | -6,000 | 0.71 |
| 15 | 1.5 | 1/5 | 7/20 | 45,000 | 80,000 | 0 | 35,000 | 35,000 | -45,000 | -23,000 | 0.55 |
| 16 | 1.5 | 2/5 | 1/20 | 5,000 | 80,000 | 0 | 75,000 | 75,000 | -5,000 | -2,000 | 0.70 |
| 17 | 1.5 | 2/5 | 2/20 | 10,000 | 80,000 | 0 | 70,000 | 70,000 | -10,000 | -5,000 | 0.70 |
| 18 | 1.5 | 2/5 | 7/20 | 34,000 | 80,000 | 0 | 46,000 | 46,000 | -34,000 | -17,000 | 0.58 |

## 6.4 Robustness checks

### Nonlinear estimations

We decline, as robustness checks, our analysis using two main econometric specifications in panel: a probit random effects model with bootstrapped standard errors (Table 8 columns 1 and 2) including Mundlak-Chamberlain's corrections and a logit model with individual fixed effects (Table 8 column 3). In column 2 of Table 8, village fixed effects are added to the estimation.

We first estimate a probit random effects panel regression as in Laury et al. (2009), with bootstrapped standard errors. The MLE of this model is the efficient-unbiased estimation method in case of no correlation between regressors and fixed effects. However, Hausman's test of no correlation between regressors and individual effects is significantly rejected and this rejection is robust to specification changes, which raises doubts about the random effect specification. Mundlak-Chamberlain's approach can be used to no longer apply the random effect assumption of no correlation between individual effects and regressors (Chamberlain, 1984). The correlation is supposed to have a given structure, for instance a linear function of the mean of the regressors for each time series, as in Mundlak (1978):

$$\alpha_i | Z_{it} \sim \mathcal{N}(\psi + \bar{Z}_i \xi, \sigma^2) \tag{9}$$

where $\bar{Z}_i$ is a vector of individual mean values of each regressor $Z_{it}$.

Secondly, we estimate a conditional logit model which eliminates the fixed effect terms in the estimate of covariates. The covariate estimates are then unbiased. This method works with a logistic functional form of the error term distribution and not with a normal one.

With both estimators, we estimate a linear model:

$$x_{it}^* = \alpha_i + \beta_0 + \beta_1 m_t + \beta_2 p_t + \beta_3 r_t + C_i.\gamma + \mu_{it} \tag{10}$$

$$x_{it} = 1 \quad (x_{it}^* > 0) \tag{11}$$

where $C_i$ is the vector of individual characteristics of farmer $i$, only used in the random effects estimations. When this vector is introduced in the fixed effect model, multi-colinearity makes estimation impossible.

### Household characteristics

The results of linear panel specifications show no stable impact of household characteristics on adoption rates (Table 9). We control for household characteristics and for productive assets, and notably for age and education (ability to read and secondary school attendance), number of members of the household, total acreage and number of cattle.

Table 8: Drivers of insurance take up : nonlinear estimations

| | (1)<br>Probit RE | (2)<br>Probit RE | (3)<br>Logit FE |
|---|---|---|---|
| $m$ | $-1.426^{***}$ | $-1.403^{***}$ | $-2.370^{***}$ |
| | (0.367) | (0.310) | (0.543) |
| $p$ | $-1.417^{***}$ | $-1.417^{***}$ | $-2.402^{***}$ |
| | (0.400) | (0.284) | (0.445) |
| $r$ | $-0.506^{**}$ | $-0.505^{**}$ | $-0.886^{**}$ |
| | (0.249) | (0.234) | (0.357) |
| Constant | $3.237^{***}$ | $2.751^{***}$ | . |
| | (0.396) | (0.568) | . |
| lnsig2u | $1.088^{***}$ | $0.942^{***}$ | . |
| | (0.146) | (0.170) | . |
| Observations | 3009 | 3009 | 1596 |
| Prob > chi2 | . | . | 0.0000 |
| Village fixed effects | No | Yes | No |

Bootstrapped standard errors in parentheses

$^{*}$ $p < .1$, $^{**}$ $p < .05$, $^{***}$ $p < .01$

**Drivers of insurance take up for low and high values of drought frequencies in a linear panel estimation**

The inverted u shape of the effect of $p$ on the take up, cannot directly be tested in our setting, but we can try to distinguish the effect of p for relatively low values of $p$ and for relatively high values of p. We constructed two binary variables, $p_1 = p$ when $p < 7/20$ and zero if $p = 7/20$, and $p_2 = p$ when $p > 1/20$ and zero if $p = 1/20$. The results are presented in Table 10. The effect of drought frequency on insurance take-up is not monotonic. The effect of $p_1$ is the shift from a high frequency (7/20) to lower frequencies and it appears to have no clear effect or a positive effect on take up, (especially after controlling for session-specific variance through session clustering (column 4, Table 10). By contrast, the shift from a low frequency (1/20) to higher frequencies ($p_2$) has a clearly negative impact on take up. This cannot be taken as a confirmation of our theory of a inverted u curve, but mostly a validation that the negative effect occurs for higher frequencies.

Table 9: Drivers of insurance take up : linear estimations, control for households characteristics

| | (1) RE | (2) RE | (3) RE | (4) RE | (5) RE |
|---|---|---|---|---|---|
| $m$ | $-0.117^{**}$ | $-0.0951^{**}$ | $-0.117^{*}$ | $-0.117^{*}$ | $-0.0951^{*}$ |
| | (0.0505) | (0.0468) | (0.0671) | (0.0683) | (0.0555) |
| $p$ | $-0.245^{***}$ | $-0.246^{***}$ | $-0.245^{**}$ | $-0.245^{**}$ | $-0.246^{**}$ |
| | (0.0540) | (0.0551) | (0.109) | (0.117) | (0.117) |
| $r$ | $-0.0852^{*}$ | $-0.0843^{*}$ | $-0.0852$ | $-0.0852$ | $-0.0843$ |
| | (0.0470) | (0.0478) | (0.0652) | (0.0696) | (0.0698) |
| Sex | 0.0491 | 0.0566 | 0.0491 | 0.0491 | 0.0566 |
| | (0.0500) | (0.0488) | (0.0499) | (0.0429) | (0.0381) |
| Age | $0.00338^{*}$ | 0.00260 | $0.00338^{***}$ | $0.00338^{**}$ | $0.00260^{**}$ |
| | (0.00174) | (0.00179) | (0.00126) | (0.00145) | (0.00124) |
| Ability to read | $-0.0170$ | $-0.0195$ | $-0.0170$ | $-0.0170$ | $-0.0195$ |
| | (0.0454) | (0.0457) | (0.0427) | (0.0395) | (0.0308) |
| Secondary school attendance | $-0.0976$ | $-0.108$ | $-0.0976$ | $-0.0976$ | $-0.108^{*}$ |
| | (0.0950) | (0.0930) | (0.107) | (0.0646) | (0.0624) |
| Household members | $-0.000466$ | 0.00115 | $-0.000466$ | $-0.000466$ | 0.00115 |
| | (0.00443) | (0.00453) | (0.00350) | (0.00385) | (0.00511) |
| Cultivated area | $-0.00797$ | $-0.0136$ | $-0.00797$ | $-0.00797$ | $-0.0136$ |
| | (0.00884) | (0.00964) | (0.00858) | (0.0128) | (0.0145) |
| Number of cattle | 0.00561 | 0.00386 | 0.00561 | $0.00561^{**}$ | $0.00386^{**}$ |
| | (0.0125) | (0.0159) | (0.0132) | (0.00263) | (0.00178) |
| Constant | $0.787^{***}$ | $0.699^{***}$ | $0.787^{***}$ | $0.787^{***}$ | $0.699^{***}$ |
| | (0.129) | (0.144) | (0.103) | (0.103) | (0.112) |
| Fixed Effects | *No* | *Village* | *No* | *No* | *Village* |
| Level of clustering | Individual | Individual | Village | session | session |
| Observations | 2928 | 2928 | 2928 | 2928 | 2928 |

Standard errors in parentheses, robust to clustering
$^{*}$ $p < .1$, $^{**}$ $p < .05$, $^{***}$ $p < .01$

Table 10: Drivers of insurance take up for low and high values of p: linear panel estimations

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | RE | RE | FE | FE | FE |
| $m$ | $-0.211^{***}$ | $-0.208^{***}$ | $-0.208^{***}$ | $-0.418^{***}$ | |
| | (0.0508) | (0.0489) | (0.0505) | (0.091) | |
| $p1$ | $0.232^{*}$ | $0.231^{*}$ | $0.230^{*}$ | 0.424 | 0.202 |
| | (0.138) | (0.134) | (0.129) | (0.324) | (0.159) |
| | | | | | [0.2162] |
| $p2$ | $-0.161^{***}$ | $-0.161^{***}$ | $-0.162^{***}$ | $-0.269^{*}$ | $-0.179^{*}$ |
| | (0.0487) | (0.0492) | (0.0557) | (0.138) | (0.0939) |
| | | | | | [0.0761] |
| $r$ | $-0.0909^{*}$ | $-0.0908^{**}$ | $-0.0909^{**}$ | 0.154 | $-0.0809$ |
| | (0.0477) | (0.0443) | (0.0390) | (0.137) | (0.0695) |
| | | | | | [0.2573] |
| Constant | $1.040^{***}$ | $0.950^{***}$ | $1.032^{***}$ | $0.786^{***}$ | $1.252^{***}$ |
| | (0.0652) | (0.0897) | (0.0622) | (0.0337) | (0.187) |
| Fixed effects | No | Village | Individual | Ind. & game | Ind. × session |
| Observations | 3009 | 3009 | 3009 | 3009 | 3009 |

Bootstrapped standard errors in parentheses, with individual (columns 1 to 4) and session (column 5) clustering.

P-values from the distribution of Wild bootstrap t-statistics in brackets, with session clustering (column 5).

$^{*}$ $p < .1$, $^{**}$ $p < .05$, $^{***}$ $p < .01$