

Compound-Risk Aversion, Ambiguity and the Demand for Microinsurance

Ghada Elabed and Michael R. Carter*

February 19, 2014

Abstract

Index insurance has been faced with an unexpectedly low uptake, despite efforts to promote it as a tool for poverty alleviation. This paper offers new insights into the behavioral impediments to the uptake of index insurance, and proposes an alternative approach to designing insurance contracts. Beginning from the observation that an index insurance contract appears to the farmer as an ambiguous, compound lottery, this paper argues that the expected utility perspective may systematically overstate the desirability of index insurance and its expected impacts (given the presence of substantial basis risk). Using framed field experiments with 334 cotton farmers in Southern Mali, we elicit the coefficients of risk aversion and compound risk aversion. In the sample, 57% of the surveyed farmers reveal themselves to be compound-risk averse to varying degrees. Using the distributions of compound-risk aversion and risk aversion in this population, we simulate the magnitude of the impact of basis risk on the demand for an index insurance contract. If basis risk were as high as 50% (a not unreasonably high number under the kind of rainfall index insurance contracts that have been utilized in a number of pilots), expected demand would only be 35% of the population as opposed to the 60% of the population that would be expected to demand insurance if individuals were expected utility maximizers. Our results highlight the importance of designing contracts with minimal basis risk under compound-risk aversion. Such a reduction in basis risk would not only enhance the value and productivity impacts of index insurance, but would also assure that the contracts are popular and have the anticipated impact.

JEL Codes: D81, G22, O12, O16, Q12, Q13

Keywords: Index Insurance, Risk and Uncertainty, Compound Risk, Ambiguity, Field Experiments

1 Introduction

Behavioral economics has flourished over the past 30 years, providing compelling evidence that individuals systematically deviate from the predictions of the classical economic model of rationality. Despite their

*Respectively, PhD candidate and Professor, Agricultural and Resource Economics, University of California, Davis (elabed@primal.ucdavis.edu).

seemingly rich implications for the design of [economic development] interventions and policies (Datta and Mallainathan (2014)), policy reliance on behavioral insights has been modest, especially in the rapidly expanding area of microinsurance. Drawing on the related literatures on ambiguity and compound-risk aversion, and using parameter values estimated from framed field experiments in Mali, this paper offers new insights regarding behavioral constraints to the uptake of microinsurance. The findings of the paper justify the proposal for an alternative approach to designing insurance contracts. By increasing insurance uptake, these new kinds of contracts would have greater impacts on poor and rural populations in Africa and elsewhere in the developing world.

Uninsured risk impoverishes people and oftentimes keeps them poor by leading to suboptimal decision-making and forgone income (Alderman and Paxson 1992; Carter et al. 2007). Formal insurance contracts would seem to have a promising role to play in risk-prone regions of the developing world. Conventional individual indemnity insurance contracts are burdened by moral hazard and adverse selection problems that seem to guarantee their failure in rural regions of the developing world. In contrast, index insurance contracts—in which payments are based on an easily verifiable index correlated with, but not identical to, individual losses—appear as a promising solution to the long-standing problems of costly, uninsured risk, even though the insurance they offer is partial or incomplete.

Much of the work on index insurance operates the implicit expected utility perspective that although index insurance coverage is partial (i.e., it exhibits what is called basis risk), some insurance is better than no insurance. Therefore, it implies that index insurance contracts will be demanded and have their expected impacts. This paper takes a novel approach, rooted in the observation that an index insurance contract appears to the farmer as an ambiguous, compound lottery. We argue that the expected utility perspective may systematically overstate the desirability of index insurance and its expected impacts. If correct, this behaviorally informed view suggests that an index insurance contract’s design must prioritize the reduction of basis risk and ambiguity to succeed.

We begin our analysis by looking at index insurance from the farmer’s perspective. Compared to conventional indemnity insurance with individual loss verification, index insurance is itself a probabilistic investment: payouts are not perfectly correlated with the farmer’s loss. This feature makes index insurance a compound lottery: the first stage lottery determines the individual’s outcome, and the second stage determines whether or not the insurance index triggers an indemnity payout. When individuals satisfy the Reduction of Compound Lotteries axiom of expected utility theory, they are able to reduce this compound lottery structure to a corresponding simply lottery structure and insurance valuation is uninfluenced by the compound lottery structure per se. However, there is ample behavioral evidence that this axiom is in reality violated by large numbers of people. This paper examines the valuation of demand for microinsurance what happens when this axiom is violated.

A large body of literature examines alternatives to expected utility models of decision making under uncertainty; we focus here on the interrelated concepts of ambiguity and compound risk aversion. Ambi-

guity aversion was first demonstrated by Ellsberg (1961), who showed that individuals react much more cautiously when choosing among ambiguous lotteries (with unknown probabilities) than when they choose among lotteries with known probabilities. While the individual probabilities under index insurance are knowable, individuals who cannot reduce a compound lottery to a single lottery are faced with unknown final probabilities as in the Ellsberg experiment. Halvey (2007) corroborates this intuition by experimentally establishing a relationship between ambiguity aversion and compound-risk aversion, showing that those who are ambiguity averse are also compound-risk averse.

To explore further these ideas, we employ the smooth model of ambiguity aversion developed by Klibanoff, Marinacci, and Mukerji (2005) to analyze the index insurance problem. Following Maccheroni, Marinacci and Ruffino (2010) derive an ambiguity premium that can be attached to a microinsurance contract. Using this premium, we derive an expression for the willingness to pay (WTP) for index insurance. We define this WTP as the maximum amount of money that a farmer would pay while being indifferent between buying index insurance and having no insurance. We then show how this measure varies with compound-risk aversion, risk aversion and basis risk. Compound-risk aversion decreases the demand for index insurance relative to what it would be if individuals had the same degree of risk aversion but were compound-risk neutral. In addition, as basis risk increases, demand for actuarially unfair index insurance declines. This decline in demand is steeper under compound-risk aversion.

To estimate the magnitude of the impact of basis risk on the demand of index insurance, we implemented framed field experiments with cotton farmers in Southern Mali and elicit the coefficients of compound-risk aversion and risk aversion. In this sample, 57% of the surveyed farmers revealed themselves to be compound-risk averse to varying degrees. We then simulate the impact of basis risk on the demand for an index insurance contract, whose structure mimics the structure of an actual index insurance contract distributed to this population in Mali. If basis risk were as high as 50%, only 35% of the population would demand index insurance, in contrast to the 60% who would be willing to purchase the product if individuals were simply maximizing expected utility and behaved according to the axiom of the Reduction of Compound Lotteries.

The remainder of the paper is structured as follows. In Section 2, we frame our discussion by reviewing the existing literature and presenting our basic theoretical model. Using this model, we then derive the willingness to pay in Section 3. In Section 4, we describe the experimental design. In section 5, we present our main findings. Section 6 concludes with policy implications.

2 The microinsurance problem

To frame the discussion of the microinsurance problem, Figure 1 provides a stylized representation of an agricultural insurance contract under the simplifying assumption that there are only two states of the world. In the good state of the world (which occurs with probability p), the individual receives high production

income, Y_0 . In the bad state of the world (which occurs with probability $1 - p$), the individual suffers a loss $L > 0$, and receives production income of $Y_0 - L$.

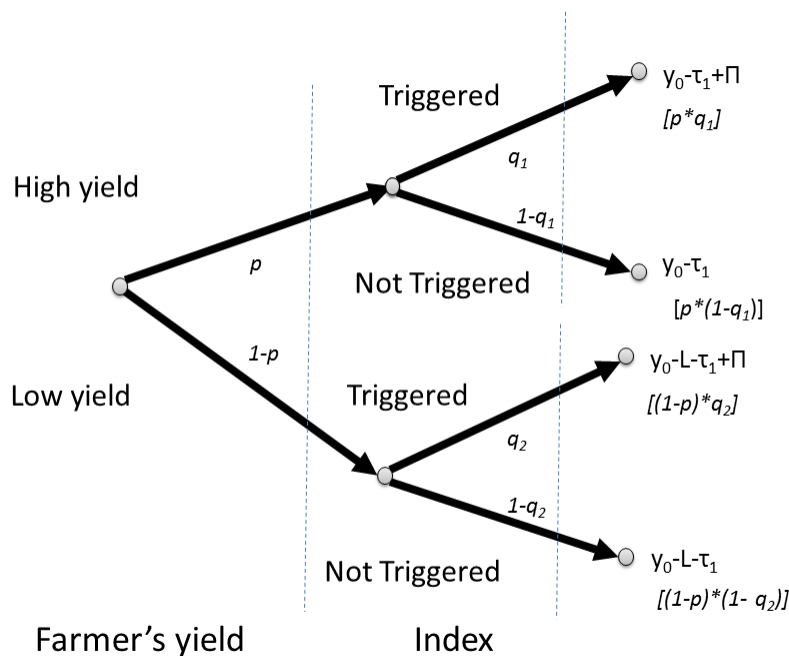


Figure 1: The micro insurance problem

Because we want to consider the possibility that microinsurance contracts do not always perfectly indemnify producers for losses, we define $q_2 \leq 1$ as the probability that the insurance pays off when the individual has experienced a loss. In this case, the individual's net income will be $Y_0 - L - \tau_1 + \Pi$, where Π is the insurance payment and τ_1 is the insurance premium. Conditional on a loss, the contract fails with $1 - q_2$. In this case, the individual receives a net income of $Y_0 - L - \tau_1$. The probability $1 - q_2$ is the false negative probability (FNP) because the insurance contract falsely signaled no loss when in fact a loss occurred.

We also want to consider the symmetric possibility that microinsurance may pay off when the insured does not actually experience a loss. Define $q_1 \geq 0$ as the probability that the individual receives the insurance payment in the good state of the world, resulting in a net income of $Y_0 - \tau_1 + \Pi$. Conditional on the good state of the world, the probability is $1 - q_1$ that no insurance payout is made and the individual experiences net income of $Y_0 - \tau_1$. The probability q_1 is the false positive probability (FPP). Figure 1 illustrates this full payoff structure, with the unconditional payoff probabilities shown in parentheses under each possible payoff amount.

Under an idealized insurance contract that never incorrectly signals losses, $q_1 = 0$ and $q_2 = 1$ and Figure 1 simplifies accordingly. However, in the world of microinsurance, in which sums insured and premium are often small relative to the costs of loss verification, such idealized insurance is unlikely to be found. In the

specific case of agricultural microinsurance, the failure of conventional insurance with loss verification (Hazell and Valdes (1985)) motivated the development of parametric or index insurance. Under index insurance, individual losses are not verified and payouts are instead made based on the level of an index (*e.g.*, rainfall, or average production levels in a locality) that is correlated with, but not identical to, individual losses.¹ It is this imperfect correlation that creates the prospect for non-zero false negative and false positive probabilities. Together, these two probabilities constitute what the literature on index insurance often refers to as a basis risk.

While other types of insurance may offer this type of partial protection or be probabilistic, it is more likely to be a feature of microinsurance in general, and agricultural microinsurance in particular. But how important is this partial or probabilistic feature of microinsurance? That is, how does the individual's perceived value of, and demand for, insurance change when q_1 and q_2 deviate from their relevant corner values of 0 and 1, respectively?

2.1 Partial or Probabilistic Insurance through the Lenses of Expected Utility and Cumulative Prospect Theory

Standard expected utility theory offers surprisingly rich insights into what happens to the demand for insurance as q_2 drops below 1, meaning that the insurance only covers some losses. As is well known, an expected utility maximizer faced with an actuarially fair insurance contract will insure the entire amount at risk. If the risk can only be partially insured (as with an index insurance contract with $q_2 < 1$), an expected utility maximizing agent will still purchase whatever partial insurance is available if it is priced at an actuarially fair level. However, when insurance is not actuarially fair (as happens when its price is marked up to cover capital, transaction and other administration costs²), standard theory predicts that the expected utility maximizer will leave part of the risk uninsured. In our simple binary outcome case, a risk averse agent will examine the 4 payouts and their associated final or unconditional probabilities, and purchase insurance only if the FNP or basis risk is small enough compared to the fraction of total risk to which the individual is exposed.

In a study specifically on the impact of basis risk on the demand for agricultural microinsurance, Clark (2011) analyzes the theoretical relationship between basis risk and the demand for actuarially unfair index insurance within the expected utility framework.³ His main finding is that increasing risk aversion does not necessarily lead to an increase in the demand for index insurance; the predicted demand follows an inverted U-shape (zero-increasing-decreasing) as the coefficient of risk aversion increases. These results are a direct consequence of a non-zero FNP. With $FNP > 0$, the worst that can happen to the individual is worse with

¹For further discussion on the logic of agricultural index insurance, see the discussion in Carter, 2013.

²In the context of US agricultural insurance, Smith and Glauber (2012) report that index insurance contracts are typically marked up by 20% over the actuarially fair price. In developing country context, the rate of mark-up is often substantially higher (Carter 2013).

³Clark (2011) defines basis risk as the joint probability of experiencing a loss and the index failing to trigger. Using the notation of figure 1, this corresponds to the FNP $1 - q_2$ multiplied by $1 - p$,

insurance ($Y_0 - L - \tau_1$) than without ($Y_0 - L$). With probability $(1 - q_2) * (1 - p)$ the household end up without payouts in the worst state of the world and yet still must pay premiums.

An alternative perspective on the aversion of the risk averse to partial or probabilistic insurance emerges from the behavioral economics literature. Wakker et al.(1997) show that the magnitude of experimental participants' aversion to probabilistic insurance exceeds the predictions of expected utility theory. In their experiments, the sample of respondents demand an almost 30% reduction in the premium to compensate for a modest 1% FNP. Expected utility theory cannot explain these findings. Under reasonable assumptions, they show that an expected utility maximizer would be expected to demand only a 1% decrease in premium to compensate them for the 1% FNP. To explain their findings, Wakker et al. (1997) make recourse to the probability weighting function of cumulative prospect theory. In particular, note that the probability of the worst outcome $((1 - q_2) * (1 - p))$ will be an extremely small number for q_2 close to 1. If people in fact overweight small probabilities as suggested by the standard probability weighting function of cumulative prospect theory, then respondents extreme response to a small FNP can be explained.⁴

While the Clarke (2011) and Wakker et al. (1997) work offer different perspectives on the importance of making insurance probabilistic or partial, both studies begin from the assumption that only the final payoffs and probabilities shown on the right side of Figure 1 matter. That is, they implicitly invoke the reduction of compound lotteries axiom, which states that a decision maker reduces a compound lottery to its equivalent simple lottery. Doing so allows them to ignore the fact that that probabilistic or partial insurance confronts the individual with a compound lottery structure. The goal of this paper is to explore the demand for probabilistic microinsurance when the reduction of compound lotteries axiom is violated.

2.2 Reconsidering the Demand for Insurance without the Reduction of Compound Lotteries Axiom

Although the reduction of compound lotteries axiom is attractive, behavioral experiments have found that decision makers often violate it (see Budescu and Fisher(2001) for an extensive list of these experiments). Dillenberger (2010) and Abdellaoui et al.(2011) call this particular behavior compound-risk aversion. Dillenberger (2010) go on to formally define a decision maker is compound-risk averse (seeking) if the certainty equivalent for the compound lottery is below (above) the certainty equivalent of the simple lottery.

A possible explanation for compound risk aversion is suggested by psychological studies find that the length and complexity of compound lotteries impact a decision maker emotionally and psychologically (Budescu and Fischer 2001). From this perspective, multiplying out the different probabilities to reduce a compound to its equivalent simple lottery may be cumbersome or simply not doable for some individuals. In this case, a compound lottery may present itself as unknown or ambiguous probabilities to the decision maker. The classic Ellsberg (1961) paradox, and many other subsequent experiments, have provided ev-

⁴Kahneman and Tversky (1979) examine the particular case of a probabilistic insurance in which the premium is paid back in case of a loss. They show that aversion to this specific type of probabilistic insurance is consistent with risk seeking over the loss domain.

idence that decision makers tend to be averse to ambiguous events with unknown or imprecisely known probabilities.

The notion that compound lotteries confront individuals with ambiguity is corroborated by Halevy’s (2007) experiments which demonstrate a strong link between ambiguity aversion and compound-risk attitudes. He finds that ambiguity neutral participants are more likely to reduce compound lotteries, behaving according to expected utility theory. Conversely, those who are ambiguity averse are also compound risk averse.

Interestingly, a growing body of literature explicitly models a la Ellsberg ambiguity as a compound lottery. Segal (1987) pioneered this method by representing the Ellsberg problem as a compound lottery. In the first stage, the decision maker assigns the probability of getting the various lotteries in the second stage. Using the recursive non expected utility model, Segal (1987) models ambiguity aversion as aversion to compound lotteries. Several other studies of ambiguity aversion rely on the violation of the reducibility assumption (Klibanoff et al. 2005; Ergin and Gul 2009; Nau 2006; Seo 2009).⁵

Following the lead of this literature, we here reconsider the compound lottery microinsurance contract shown in Figure 1 using the theoretical tools developed for the study of ambiguity. Specifically, we use the Smooth Model of Ambiguity Aversion formalized by Kilbanoff, Marinacci and Mukerji (2005) (here the *KMM model*). This model captures risk preferences by the curvature of the utility of wealth function, and ambiguity preferences by a second-stage utility functional defined over the expected utility of wealth. It therefore allows the separation of attitudes towards risk and compound-risk, and makes it possible to derive them in an experiment.

For the simple case of discrete outcomes in Figure 1, the objective function of the decision maker under the KMM model is evaluated by an increasing function v that captures compound risk preferences, and the farmer’s objective function is the expected value of v given the probability distribution of the yield

$$\begin{aligned}
 & p * v [(1 - q_1) * u(Y_0 - \tau_1) + q_1 * u(Y_0 - \tau_1 + \Pi)] + \\
 & (1 - p) * v [q_2 * u(Y_0 - L - \tau_1 + \Pi) + (1 - q_2) * u(Y_0 - L - \tau_1)]
 \end{aligned} \tag{1}$$

where the utility function u defined over final wealth captures the individual’s risk preferences. We assume that the farmer is risk averse by imposing concavity of u (u is as usual also increasing).

Notice that when $q_1 = 0$ and $q_2 = 1$, which is the case with an insurance contract that never incorrectly signal losses, the insurance contract becomes a simple lottery. In this situation, the farmer evaluates the contract by maximizing his expected utility:

⁵Other theories of decision making under ambiguity include the seminal work of Gilboa and Schmeidler (1989) who developed the max min expected utility theory: a decision maker has a set of prior beliefs and the utility of an act is the minimal expected utility in this set.

$$p * u(Y_0 - \tau_1) + (1 - p) * u(Y_0 - L - \tau_1 + \Pi) \quad (2)$$

Applying the increasing transformation v to the expression (2) does not change the objective function, but has the advantage of making the expressions (1) and (2) comparable. Therefore, the utility function of the farmer when facing the indemnity insurance contract is the following:

$$v [p * u(Y_0 - \tau_1) + (1 - p) * u(Y_0 - L - \tau_1 + \Pi)] \quad (3)$$

Similar to how risk aversion is imposed by the concavity of u , compound-risk aversion is obtained by imposing concavity of v : i.e. $v' > 0$ and $v'' \leq 0$ in the KMM model. In the compound-risk neutral case (i.e., when v is linear), expression (1) reduces to the conventional Von Neumann-Morgenstern expected utility maximization represented by expression(3).

We apply the KMM model in the more general case of multiple states of the nature. Let f_Y and f_X be the respective pdfs of the farmer's yield Y and the index X . Denote the final wealth of the farmer after all payments are made and premium paid under the index insurance contract by ρ , with pdf $f_\rho(Y, X)$. Here, Y is the farmer's yield, $I(X)$ is the insurance indemnity payment and τ_1 is the index insurance premium. The objective function of an expected utility maximizer is the following:

$$v [\mathbb{E}_{f_\rho} [u(\rho)]] \quad (4)$$

Under the KMM model, the farmer's objective function is given by:

$$E_{f_Y} [v (E_{f_{X|Y}} u(\rho))] \quad (5)$$

where E_{f_Y} denotes the expectation with respect to f_Y . The expectation $E_{f_{X|Y}}$ is taken with respect to $f_{X|Y}$, the probability distribution function of the index conditional on the realization of the yield.

Section 3 studies the implication of compound-risk aversion on insurance decisions. The results rely on the concept of compound lottery premium. This premium was derived by Maccheroni et al. (2010) and is an extension of the classical Arrow-Pratt premium, where the preferences are characterized by the KMM model.

3 Index insurance and the KMM Model

Maccheroni, Marinacci and Ruffino (2010) (MMR) derive an ambiguity premium under the KMM model. This premium is the analogue of the classic Arrow-Pratt approximation under the presence of ambiguity. We interpret this entity as a compound lottery premium, and use it to study the willingness to pay for index insurance.

3.1 The compound lottery premium

Let's define the compound lottery premium P_X of index insurance such that the farmer is indifferent between receiving the net revenue ρ from the index insurance contract and the certain average revenue $\rho^* = E_{f_\rho}(\rho)$. By definition, this premium solves the following equation:

$$E_{f_Y} v E_{f_{X,Y}} u(\rho) = v(u(\rho^* - P_X)) \quad (6)$$

If the farmer is compound risk neutral, then v is linear, and the compound lottery premium P_X^n is the regular Pratt premium defined by $E_\rho u(\rho) = u(\rho^* - P_X^n)$. Using Jensen's inequality, we have:

$$P_X \geq P_X^n \quad (7)$$

Proof. Since u is concave, using Jensen's inequality:

$$\begin{aligned} v(u(\rho^* - P_X)) &= E_{f_Y} v E_{f_{X,Y}} u(\rho) \\ &\leq v E_{f_Y} E_{f_{X,Y}} u(\rho) \\ &= v E_{f_\rho} u(\rho) \\ &= v(u(\rho^* - P_X^n)) \end{aligned}$$

□

This finding means that compound-risk aversion should increase the compound lottery premium for index insurance relative to what it would be if individuals had the same degree of risk aversion but were compound-risk neutral. In other words, index insurance appears riskier for a compound-risk averse farmer than to his compound-risk neutral counterpart, for the same level of risk aversion.

Intuitively, the compound lottery premium should be a function of the farmer's preference (levels of risk aversion and compound-risk aversion) and the basis risk characterizing the contract. The approximation of the compound lottery premium derived by MMR confirms this intuition. They show that it is the sum of a compound-risk premium and the classical Pratt risk premium:

$$P_X \simeq -\frac{1}{2}\sigma_\rho^2 \frac{u''(\rho^*)}{u'(\rho^*)} - \frac{1}{2}\sigma_{\rho^*}^2 \frac{v''(u(\rho^*))}{v'(u(\rho^*))} (u'(\rho^*)) \quad (8)$$

where the first term, $P_X^n \equiv -\frac{1}{2}\sigma_\rho^2 \frac{u''(\rho^*)}{u'(\rho^*)}$, is the classical Pratt premium, and the second term,

$P_X^c \equiv -\frac{1}{2}\sigma_{\rho^*}^2 \frac{v''(u(\rho^*))}{v'(u(\rho^*))} (u'(\rho^*))$, is the compound risk premium. Note that P_X is a function of two variances.

The first variance, σ_ρ^2 , is the variance of the final net wealth when purchasing the index insurance :

$$\sigma_\rho^2 = E_{f_y} \left[E_{f_{X|Y}} (\rho - \rho^*)^2 \right] \quad (9)$$

For every realization of the first stage lottery (the yield lottery), the farmer faces a second stage lottery (index lottery) that yields a given expected net wealth. The second variance is the variance of this net wealth measured with respect to the probability distribution of the yield:

$$\sigma_{\rho^*}^2 = E_{f_Y} \left[E_{f_{X|Y}} (\rho)^2 - E_{f_Y} E_{f_{X|Y}} (\rho) \right]^2 \quad (10)$$

$\sigma_{\rho^*}^2$ reflects the uncertainty on the expected net wealth of the farmer due to the compound structure of the prospect he faces. Therefore, $\sigma_{\rho^*}^2 = 0$ for a conventional indemnity insurance (a simple lottery). By the law of total variance, we have the following relationship between σ_ρ^2 and $\sigma_{\rho^*}^2$:

$$\begin{aligned} \sigma_\rho^2 &= E_{f_Y} [var(\rho | Y)] + Var E_{f_{X|Y}} (\rho | Y) \\ &= E_Y [var(\rho | Y)] + \sigma_{\rho^*}^2 \end{aligned}$$

The first component, $E[var(\rho | Y)]$, is called the expected value of conditional variances, which is the weighted average of the conditional variances. It is the “within” component of the variance: the expected variance of the net wealth realized in the secondary lottery. The second term, $\sigma_{\rho^*}^2$, is the “between” component of the variance. It is the variance of the conditional means, which represents the additional variances as a result of the uncertainty in the realization of the yield.

From Equation 8 note that:

1. For a compound-risk neutral individual, $P_X^c = 0$. The compound-lottery premium reduces to the classical Pratt premium:

$$P_X = P_X^n$$

2. For conventional indemnity insurance with $\sigma_{\rho^*}^2 = 0$, the compound lottery premium also reduces to the classical Pratt premium, whether the farmer is compound-risk averse or not.
3. A compound-risk averse individual is willing to pay an extra premium to eliminate basis risk compared to his compound-risk neutral counterpart, who has the same level of risk aversion. This extra premium is denoted P_X^c , and it is a function of the curvature of v , u and of $\sigma_{\rho^*}^2$.

3.2 Defining an increase in basis risk and its impact on the compound lottery premium

This section aims at studying the impact of an increase in basis risk on the compound lottery premium. First, this section defines an increase in basis risk. Then, it studies the impact of such an increase on σ_ρ^2 and $\sigma_{\rho^*}^2$. The result follows immediately.

First, define the random variable q as the probability that the index is triggered. q yields q_1 with probability p , and q_2 with probability $1 - p$. The index insurance contract presented in Figure 1 yields a payment with a probability \bar{q} given by:

$$\bar{q} = p * q_1 + (1 - p) * q_2 \quad (11)$$

Let's define an increase in basis risk as a mean preserving spread in the probability of payment \bar{q} such as the FNP $(1 - q_2)$ increases. Define q' as the random variable yielding either $q_1 + \frac{h(1-p)}{p}$ or $q_2 - h$, with probabilities p and $1 - p$ respectively:

$$q'(h) = \begin{cases} q_1 + \frac{h(1-p)}{p} & , p \\ q_2 - h, & 1 - p \end{cases} \quad (12)$$

Define the random variable ϵ as follows:

$$\epsilon = \begin{cases} (1 - p) * (q_1 - q_2 + \frac{h}{p}) & , p \\ p * (q_2 - q_1 - \frac{h}{p}), & 1 - p \end{cases} \quad (13)$$

Then, the variable q' can be written as the sum of \bar{q} and ϵ :

$$q' = \bar{q} + \epsilon$$

Note also that $E(\epsilon | \bar{q}) = 0$. Therefore, q' is a mean preserving spread of \bar{q} .

Lemma 1. Defining $\sigma_{\rho'}^2$ as the variance of the farmer's wealth under the new probability distribution q' , $\frac{\partial \sigma_{\rho'}^2}{\partial h} \geq 0$.

Proof. Using the notations defined in Section 2, we have:

$$\begin{aligned}
\sigma_\rho'^2 &= p \left(q_1 + \frac{h * (1-p)}{p} \right) (y_0 - \tau_1 + \Pi - \rho^*)^2 + p \left(1 - q_1 - \frac{h * (1-p)}{p} \right) (y_0 - \tau_1 - \rho^*)^2 \\
&+ (1-p) * (q_2 - h) (y_0 - L - \tau_1 + \Pi - \rho^*)^2 + (1-p) * (1 - q_2 + h) (y_0 - L - \tau_1 + \Pi - \rho^*)^2 \\
&= \sigma_\rho^2 + h * (1-p) * (y_0 - \tau_1 + \Pi - \rho^*)^2 - h * (1-p) * (y_0 - \tau_1 - \rho^*)^2 \\
&+ (1-p) * (-h) (y_0 - L - \tau_1 + \Pi - \rho^*)^2 + (1-p)h((y_0 - L - \tau_1 - \rho^*)^2) \\
\frac{\partial \sigma_\rho'^2}{\partial h} &= (1-p)(2\Pi L) \\
&\geq 0
\end{aligned}$$

since $L \geq 0$ and $\Pi \geq 0$. □

Lemma 2. Define $\sigma_{\rho^*}'^2$ as the analogous of σ_ρ^2 under the probability of payment q' . Then $\frac{\partial \sigma_{\rho^*}'^2}{\partial h} \geq 0$

Proof. Define $\bar{\rho}_1'$ and $\bar{\rho}_2'$ as the conditional means of the net wealth under the high yield and low yield, respectively. The variance $\sigma_{\rho^*}'^2$ can be written in the following way:

$$\begin{aligned}
\sigma_{\rho^*}'^2 &= p * (\bar{\rho}_1' - \rho^*)^2 + (1-p) * (\bar{\rho}_2' - \rho^*)^2 \\
&= p * \left(\bar{\rho}_1 + \frac{h(1-p)}{p} \pi - \rho^* \right)^2 + (1-p) * (\bar{\rho}_2 - h\pi - \rho^*)^2 \\
\frac{\partial \sigma_{\rho^*}'^2}{\partial h} &= 2 \frac{h(1-p)^2}{p} \pi^2 + 2(1-p)h\pi^2 + 2(1-p)(\bar{\rho}_1 - \bar{\rho}_2) \\
&\geq 0
\end{aligned}$$

since $\bar{\rho}_1' > \bar{\rho}_2'$. □

Lemma 1 & 2 imply two important results:

1. As basis risk increases, the compound lottery premium P_X for the index insurance contract increases.
2. Compound-risk aversion exacerbates the impact of an increase in basis risk on the compound-lottery premium.

3.3 Willingness to pay for index insurance

This section studies the willingness of a farmer to pay for index insurance (WTP_X) accounting for his compound-risk attitudes, and using the compound lottery premium defined in Section 2.2. WTP_X is defined as the difference between the certainty equivalent of the index insurance contract CE_X , and the certainty equivalent of the income lottery he faces in the autarkic situation, i.e. if he does not purchase any insurance CE_A . The certainty equivalent of the index insurance contract CE_X is defined by:

$$CE_X \equiv \rho^* - P_X$$

The certainty equivalent of the autarkic option is defined by:

$$CE_A \equiv \rho_A^* - P_A$$

where $\rho_A^* = E_{f_\rho}(\rho)$ is the expected final net wealth the farmer gets without insurance, $P_A \equiv \frac{1}{2} \sigma_{\rho_A}^2 \frac{u''(\rho_A^*)}{u'(\rho_A^*)}$ is the Arrow Pratt premium corresponding to the autarkic situation, and $\sigma_{\rho_A}^2$ is the variance of the farmer's final net wealth without insurance. Therefore, WTP_X is given by:

$$WTP_X = (\rho^* - \rho_A^*) + P_A - P_X \quad (14)$$

Thus, the magnitude of the willingness to pay for index insurance depends on the farmer's risk aversion, compound-risk aversion and on basis risk. If the farmer is compound-risk neutral, then his willingness to pay reduces to:

$$WTP_X^n = (\rho^* - \rho_A^*) + P_A - P_X^n \quad (15)$$

By equation 7, for a given level of basis risk $WTP_X \leq WTP_X^n$. Using lemma 1 & 2, it is straightforward to show the following two main results:

1. As basis risk increases, the WTP for the index insurance contract decreases.
2. Compound-risk aversion exacerbates the impact of an increase in basis risk on the WTP for index insurance.

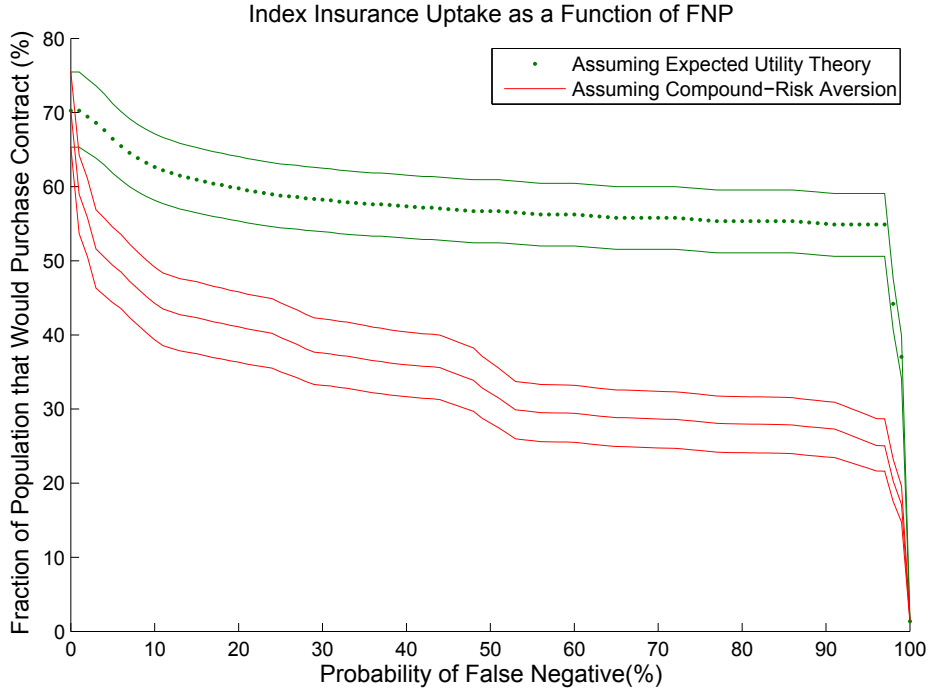


Figure 2: Impact of basis risk on the demand for index insurance

Figure 2 illustrates points 1 and 2 above. The X- axis represents the FNP, and the Y- axis represents the hypothetical demand for index insurance for a given level of FNP. The solid line represents this demand under expected utility theory, and the dotted line represents this demand under compound-risk aversion. As FNP increases, the demand decreases whether the individual is compound-risk averse or not. However, the dotted curve is steeper than the solid one, reflecting the fact that compound-risk aversion exacerbates the impact of an increase in basis risk. To simulate the real magnitude of the impact of FNP on the demand for index insurance, we have to derive the coefficients of risk aversion and compound-risk aversion from a sample of farmers. Deriving the coefficients of risk-aversion is a classic problem. The next section describes a methodology to characterize the compound-risk attitudes of the participants. The idea is to give the participants a choice between the index insurance and some equivalent conventional indemnity insurance. The outcome of this procedure is the elicitation of WTP to eliminate basis risk.

3.4 A method to derive the coefficient of compound-risk aversion

Compared to index insurance, conventional indemnity insurance does not have basis risk. The farmer receives a payment whenever he experiences a loss in his farm. Therefore, a measure of his willingness to pay to eliminate basis risk WTP_B can be obtained by comparing his attitude towards index insurance and conventional indemnity insurance. Let us imagine the situation where a farmer has to choose between the index insurance contract and a conventional indemnity insurance contract. This latter contract yields a net

wealth δ and pays for sure when the farmer's yield is low. What is the amount of money that makes the farmer indifferent between the two contracts? By definition, WTP_B is the maximum amount of money the farmer is willing to give up in order to be indifferent between the index insurance contract, and the individual insurance contract. Equivalently, WTP_B is defined as the difference between the certainty equivalent of the index insurance contract CE_X , and the certainty equivalent of the income lottery he faces if he purchases the individual insurance CE_I .

The certainty equivalent of the individual insurance CE_I contract is by definition:

$$CE_I \equiv \delta^* - P_I$$

where $\delta^* = E_{f_y}(\delta)$ is the expected final net wealth the farmer gets with the individual insurance, $P_I \equiv -\frac{1}{2}\sigma_\delta^2 \frac{u''(\delta^*)}{u'(\delta^*)}$ is the Arrow Pratt premium corresponding to the individual insurance contract, and σ_δ^2 is the variance of the farmer's final net wealth with individual insurance. Therefore, WTP_B is defined by:

$$WTP_B \equiv CE_X - CE_I$$

or equivalently,

$$WTP_B = (\rho^* - \delta^*) + (P_I - P_X^n - P_X^c) \tag{16}$$

Using the same reasoning as in section 3.2, we can verify that a compound-risk averse individual has a higher WTP compared to his compound-risk neutral counterpart, for the same level of risk aversion. WTP_B is a measure that can be derived in an experiment. For a given level of basis risk and risk aversion, this measure depends only on compound-risk aversion. Therefore, combining the finding of a game that derives WTP_B with the findings of a game that derives the coefficients of risk aversion allows the derivation of the coefficients of compound-risk aversion. Section 4 describes such games.

4 Experimental Design and Data

In summary, Section 3 implies that taking into account farmers' attitudes towards compound risk is essential for accurate prediction of their willingness to pay for index insurance. The theoretical model also provides the testable prediction that compound-risk neutral agents have a lower willingness to pay for index insurance than those who are compound-risk averse, for the same level of risk aversion. To examine this conjecture, we designed an artefactual field experiment that follows our theory.⁶

⁶According to Harrison and List (2004), artefactual field experiments are similar to laboratory experiments but with non-students (i.e., a non-standard subject pool).

The experimental technique consists of two games. The risk aversion game is designed to identify the coefficient of risk aversion by mapping from experimental choices to a constant relative risk aversion utility model. The willingness to pay game measures the additional premium the subject is willing to pay and be indifferent between a conventional indemnity insurance contract and an index insurance contract. We interpret this measure as the WTP to eliminate basis risk as defined in 16 since the conventional indemnity insurance contract does not present basis risk. This WTP is measured to identify the coefficient of compound risk aversion, potentially confounded by the risk aversion coefficient. The findings of the first game identify those of the second game by providing the information on the risk aversion coefficient.

4.1 Experimental procedure

Three rural area trainers translated the experimental protocol from French to Bambara, the local language, and ensured that it was accessible to a typical cotton farmer. Game trials were conducted with graduate students in Davis, CA, and with high school students and cotton farmers who were not part of the final experimental sample in Bougouni, Mali.

The participants were 331 cotton farmers selected at random from 34 cotton cooperatives in Bougouni, Mali. These cooperatives are part of the ongoing project "Index insurance for Cotton farmers in Mali", and launched by the Index Insurance Innovation Initiative (I4). More details about this project and the structure of the distributed contract can be found in Elabed et al. (2013). Local leaders (secretaries of cotton cooperatives and/or village chiefs) assisted us in recruiting the eligible participants from a list of names that we provided. In addition, a survey gathered detailed information on various socio-economic characteristics of the participating farmers such as demographic characteristics, wealth, assets owned, agricultural production and shocks. Data collection for the survey took place in December 2011 through January 2012, and the experiments took place in January and February 2012.

The actual sessions took place in a classroom on weekends and in the village chief's office on weekdays. The sessions took place with members of the same cooperative, and they lasted around two and a half hours. Since literacy rates are very low in the area, we presented the games orally with the help of visual aids. In addition, two rural trainers assisted the players with the various materials.

We divided the sessions into two parts with a short break between each. Each participant played two main games. Each game started with a set of "low stakes" rounds aimed at familiarizing the participants with the basic idea of the game, which were followed by a set of "high stakes" rounds. We told subjects that based on the decisions they made, and luck they could receive payment at the end of the experiment. These payments represented a fraction of the amount of game money won during the experiments. The gains from a high stake round were 5 times higher than the gains from a low stake round. In addition, we told the participants that we would choose one high stake and one low stake decision per game as the decisions that matter and their choices will be implemented.⁷We used this random incentive device in order to encourage

⁷When the different games were explained, we told the subjects that we will pick the decision that matters by rolling a die

the players to choose carefully. To incentivize the players to think more carefully about their decisions, we repeated the following sentence "There is no right or wrong answer. You should do what you think is best for you and your family whether it is choice #1, choice #2, etc." The full instructions are provided in the Appendix.

At the end of the session, participants received their game winnings in cash, in addition to a show up fee of 100 CFA. Minimum and maximum earnings, excluding show up fee, were 85 CFA and 2720 CFA and mean earnings was 1905 CFA. The daily wage for a male farm labor in the areas where we ran the experiments were between 500 CFA (0.93 USD) and 2000 CFA (3.75 USD) and on average 1040 CFA (1.95 USD).

4.2 The games

The subjects, endowed with one fictitious "hectare of land", had to take decisions framed in terms most familiar to them: their decisions were centered on cotton -their main cash crop. First, the participants learned how to determine their yields by drawing a block from a "yield sack". This sack contains several colored blocks that represent the probability distribution of the cotton yield. This distribution is calibrated using historical data from the area. Using actual input cost and cotton price per kg, farmers learned how to determine the revenue corresponding to a given yield realization.

Next, they learned how to determine their revenues with a hypothetical conventional insurance contract. Once we made sure they became familiar with this contract, they played the risk aversion game. This game consists in deciding between buying a conventional insurance contract or not, and if so choosing among five different coverage levels. By observing a participant's choice, we are able to derive his risk aversion coefficient.

After a short break, we introduced a hypothetical index insurance contract. Farmers practiced determining their revenues if they decided to purchase this contract. Farmers then played the WTP game. By combining the finding of the two games, we derive the coefficients of compound-risk aversion.

4.2.1 Determining the yield and the corresponding revenue

Based on historical yield distributions and pooling all the available data across years and cooperatives, we discretized the density of cotton yields into six sections with the following probabilities (in percent): 5, 5, 5, 10, 25 and 50, respectively. The individual yield values corresponding to the mid-point of those sections are (in kg/ha): 250, 450, 645, 740, 880 and 1530, respectively. Table 1 shows the yield distribution and the corresponding revenue in Dorome (d), the local rural currency.⁸

(six sided for the risk aversion game, and 10 sided for the willingness to pay game).

⁸1 Dorome equals 5 CFA.

Yield range (kg/ha)	Mid point	Probability	Revenue (in d)
<300	250	5%	2400
300-600	450	5%	10400
600-690	645	5%	18200
690-790	745	10%	22000
790-780	880	25%	27600
>980	1530	50%	53600

Table 1: Yield distribution and corresponding revenues

Understanding the notion of probability associated with the yield determination is a challenge that we addressed by using the randomization procedure used by Galarza and Carter (2011) in Peru to simulate the realizations of the individual yields. Every participating farmer drew his yield realizations from a bag containing 20 blocks (1 black, 1 yellow, 1 red, 2 orange, 5 green and 10 blue) which reproduce the probability distribution represented in 1 , going from the lowest to the highest yield. Figure 3 shows the visual aid provided to farmers to help them understand the game better. Equation 17 computes the individual farmer's per hectare profits in d without any insurance contract:

$$profit_i = p * y_i - Inputs \tag{17}$$

where the price (p) of a kg of cotton is set at d40, the cost of the inputs is set at d7600 in order to guarantee that the players never incur a real loss in the games with the different contracts.

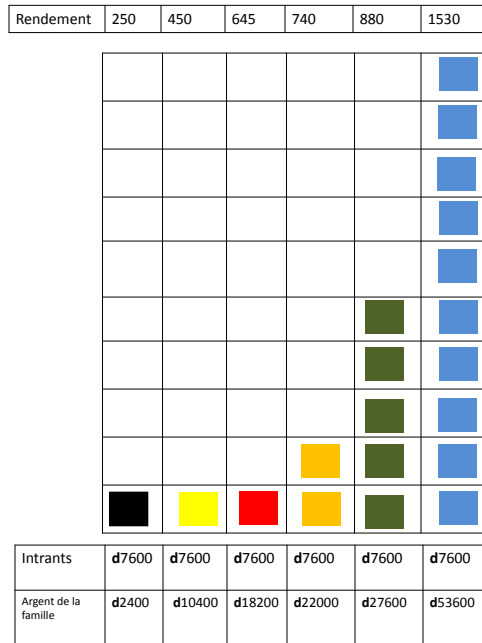


Figure 3: Visual aid for yield distribution

4.2.2 The risk aversion game

Introducing the conventional indemnity insurance contract

Once we made sure the participants understood how to determine their yields and the corresponding revenue, we introduced a hypothetical indemnity insurance contract. The contract is linear and the payment occurs if the yield falls below a strike point T set at 70% of the median historical yield. In other words, a farmer gets an insurance payment if he draws either the black, yellow or red block. The strike point T represents the yield level below which the farmer feels that he experiences a loss. In case the farmer is eligible for an insurance payment, the insurance reimburses the difference between the individual yield and the strike point such that the farmer is guaranteed to have an income corresponding to yield T . The premium is set to include a markup of 20%, such that the amount paid is 120% the amount received on average. Thus, the payment schedule for a player indexed by i is the following:

$$payment(y_i) = \begin{cases} p * (T - y_i), & y_i \leq T \\ 0 & y_i > T \end{cases} \quad (18)$$

The risk aversion game as a choice between different indemnity insurance contracts

This game is designed to obtain an experimental measure of the risk aversion coefficient. In particular, subjects performed an insurance choice task after having practiced determining their revenues with the insurance contract. Each subject had six different possibilities: don't purchase a conventional insurance contract, or choose among five different insurance contracts that differ in their strike points, which were 100%, 80%, 70%, 60%, and 50% of the median historical yield (980 kg/ha). In terms of actual yields, this corresponds to 980 kg/ha, 790 kg/ha, 690 kg/ha, 600 kg/ha, and 300 kg/ha, respectively. The net revenue of farmer i if he purchases contract j is given by the following formula:

$$profit_{ij} = p * y_i + Indemnity_j - premium_j \quad (19)$$

where *indemnity* is an indicator function for the insurance payment, and *premium* is the premium of the insurance contract. Table 2 shows the different revenues associated with each choice.

Contract	Trigger (% ybar)	Premium (d)	Net Profit (d)					CRRA range	
			250	450	645	740	880		1530
Yield (kg/ha)			5%	5%	5%	10%	25%	50%	
0	0	0	2400	10400	18200	22000	27600	53600	(∞ ; 0.08)
1	50	600	4280	10280	18080	21880	27480	53480	(0.08; 0.16)
2	60	1200	15200	15200	17000	20800	26400	52400	(0.16; 0.27)
3	70	1740	18260	18260	18260	20260	25860	52860	(0.27; 0.36)
4	80	2700	21300	21300	21300	21300	24900	50900	(0.36; 0.55)
5	100	6180	25420	25420	25420	25420	25420	47420	(0.55; ∞)

Table 2: Individual insurance contracts and risk aversion coefficient

The variance of the final revenue decreases with the coverage level, which is measured by the trigger as percentage of the median yield. Under the assumption of risk aversion, the subject prefers a contract with a lower variance to a contract with a higher variance. Therefore, the subject's contract choice carries information on his risk attitude. The last column of Table 2 exhibits the constant relative risk aversion (CRRA) ranges corresponding to every contract choice, assuming a CRRA utility function. Let's assume that the subject chose the third contract. Assuming monotonic preferences, this implies that he preferred this contract to contracts 2 and contract 4. The upper (lower) bounds of the CRRA range is found by equalizing the expected utility that the farmer derives from contract 2 and 3 (3 and 4). In this case, as Table 2 shows, the CRRA range of the player is (0.27; 0.36).

The last column of Table 3 below shows the distribution of the levels of CRRA of the participants, based on the results of Game 1. The majority of the farmers (78%) chose an insurance contract, and 30% of them chose the highest level of coverage which corresponds to a coefficient of risk aversion of more than 0.55. The median player chose the third insurance contract, which corresponds to a coefficient of risk aversion between 0.27 and 0.36.

Contract	CRRA range	%
0	(∞ ; 0.08)	22.56
1	(0.08; 0.16)	7.32
2	(0.16; 0.27)	9.76
3	(0.27; 0.36)	10.67
4	(0.36; 0.55)	17.99
5	(0.55; ∞)	31.71

Table 3: Distribution of the CRRAs in the sample

4.2.3 The WTP to eliminate basis risk game

Introducing the index insurance contract

The index insurance contract is characterized by a strike point T at the individual level, and by an index X defined at an aggregate level. Thus, compared to the regular indemnity insurance, in order to be eligible for a payment, the farmer has to satisfy an extra condition. The payment schedule is the following:

$$payment(y_i) = \begin{cases} p * (T - y_i) & : y_i \leq T \text{ and } y_z \leq X \\ 0 & \text{otherwise} \end{cases} \quad (20)$$

Thus, from the player's point of view, once he suffers a loss (i.e. his yield is below the individual strike point), he risks not getting a payment with positive probability. This FNP is set at 20%, which is a rough calibration related to the level of FNP in the contract distributed in the index insurance project described in Elabed et al. (2013). Further, the individual-level trigger is set at 70% of the median historical yield, and the contract was priced with a markup of 20%. If a farmer decides to purchase an index insurance contract, then he faces a two-stage game. First, he determines his own yield by drawing a block from the yield sack.

Then, if the yield is below the individual strike point, he draws another block from a second sack which contains 4 brown blocks (i.e. the index triggered) and one green block (i.e. the index is not triggered).

The WTP game

After having practiced determining his revenue under the index insurance contract, every participant played a game that aimed at eliciting the WTP to eliminate basis risk defined in Section 3.4. Specifically, we wanted to see whether the player, whom we call Mr. Toure, preferred the indemnity contract to the index contract as we increase the price of the individual contract from its base price (d1340) to d3540, by increments of d200.

The session leader presented players with the following scenario: Mr. Toure's friend, Mr. Cisse, is going to Bamako (the capital of Mali, 90 miles away). Mr. Toure asks Mr. Cisse to buy an insurance contract for Mr. Toure. Mr. Toure knows that the price of the individual contract can vary depending on the day, but the price of an index contract is always the same. After highlighting the fact that at the price of d1340, it is always more profitable to buy the individual insurance contract, Mr. Toure was asked to tell Mr. Cisse at which price Mr. Toure should switch to favoring the index insurance contract over the individual insurance contract. Thus, by the end of the game, we have the switching price for every player from which we deduce his willingness to pay to eliminate basis risk.

The game reduces to ten choices organized into a Switching Multiple Price List (sMPL) in order of increasing price of the indemnity insurance contract.⁹ The sMPL method was first used by Gonzalez and Wu (1999). This method extends the MPL method by asking the participant simply to choose at which price he will switch to the index insurance contract. We adopt this method for its simplicity relative to the standard MPL procedure.¹⁰

The first two columns of Table 4 show the array of paired choices the subject faces. Notice that the price of the index insurance contract does not vary, whereas the price of the individual insurance contract increases by d200 as we move down the table. The point where a participant switches from preferring the indemnity insurance contract to the index insurance contract carries information on his willingness to pay to eliminate basis risk. For example, a participant switchings at the second row has a WTP equal to 200. At the end of the session the session leader randomly selected one row , and the subject's choice for that row is implemented.

⁹The MPL design has been used in experimental economics to elicit risk attitudes, willingness to pay, and individual discount rates. In this design the subject faces a list of paired choices and decides which one to choose at each row. Therefore, the subject is allowed to switch back and forth. Andersen et al. (2006) examine the properties of this method.

¹⁰sMPL imposes a strict monotonicity of the underlying preferences. The goal of the experiment is not to test the monotonicity assumption of utility theory, but to elicit a consistent measure of the willingness to pay to eliminate basis risk (Andersen et al. (2006)). Therefore, imposing this assumption does not invalidate the results.

Index Insurance contract	Indemnity insurance contract	Implied WTP	Implied CRRA under EUT
d1450	d1740	0	(0; 0.49)
d1450	d1940	d200	(0.49; 0.71)
d1450	d2140	d400	(0.71; 0.87)
d1450	d2340	d600	(0.87; 0.99)
d1450	d2540	d800	(0.99; 1.09)
d1450	d2740	d1000	(1.09; 1.18)
d1450	d2940	d1200	(1.18; 1.25)
d1450	d3140	d1400	(1.25; 1.32)
d1450	d3340	d1600	(1.32; 1.37)
d1450	d3540	d1800	(1.37; $+\infty$)

Table 4: Game 2: Eliciting WTP measure.

To deduce an analytical expression of the willingness to pay to eliminate basis risk as defined in 16, we impose a functional form on the function v defined in Section 2. For computational convenience, we impose constant relative compound-risk aversion. Thus, the function v is given by:

$$v(y) = \begin{cases} \frac{y^{1-g}}{1-g} & \text{if } g \in [0, 1) \\ \log(y) & \text{if } g = 1 \end{cases} \quad (21)$$

where g is the coefficient of constant relative compound-risk aversion, and y is measured in d.

Pinning down the compound-risk aversion coefficient

Table 5 below lists the predicted coefficients of compound-risk aversion based on the player's choices in the two games. To simplify the calculations, these measures are made after taking the midpoint of every risk aversion range. For example, if the player chose contract 4 in the risk aversion game, then the corresponding CRRA is 0.45. The corresponding g is obtained using the definition of WTP_B expressed in equation 16.

WTP (d)	Contract choice in Game 1:					
	0	1	2	3	4	5
0	0.01	0.00	0.00	0.00	0.00	0.00
200	0.08	0.07	0.06	0.05	0.01	0.00
400	0.14	0.14	0.14	0.13	0.10	0.00
600	0.21	0.21	0.21	0.21	0.20	0.00
800	0.27	0.28	0.29	0.29	0.29	0.00
1000	0.34	0.35	0.36	0.38	0.39	0.00
1200	0.40	0.42	0.44	0.46	0.48	0.13
1400	0.47	0.49	0.51	0.54	0.58	0.29
1600	0.53	0.56	0.59	0.62	0.67	0.46
1800	0.59	0.62	0.66	0.70	0.76	0.63

Table 5: Predictions of the coefficients of compound-risk aversion.

5 Results

In this section we first describe the sample of participants. We then describe subjects' characteristics by compound-risk attitudes as revealed from the experimental choices. Next we describe the distribution of the revealed compound-risk aversion coefficients by risk aversion range. We finally investigate whether the measured coefficient of risk aversion are meaningful by testing the hypothesis that farmers are compound-risk neutral.

5.1 Summary statistics

All the participants are male, which is not surprising given the division of labor in the area of study: cotton production is mainly a male responsibility. 71% of the participants are the head of their households, and almost all of them had heard of the cotton insurance contract distributed in the field. The first column in Table 6 provides the descriptive statistics for the experiment participants. The average participant is approximately 47 years old, has limited formal education (four years of schooling), and belongs to a household with almost 19 members. The average household head has been a member in the cooperative for almost 9 years. The average household economic status is represented by a total livestock value of 1.8 million CFA, a house worth 400,000 CFA and a total land area of 9.62 ha.

Variable ^a	(1) All	(2) Compound-risk neutral	(3) Compound-risk averse	(4) Difference
Years of schooling	4.45	5.56	3.55	-2.01**
	[6.50]	[7.12]	[5.82]	(-2.40)
Age	46.87	46.66	47.03	0.38
	[15.22]	[12.20]	[13.73]	(0.23)
Cooperative experience	8.62	7.87	9.19	1.33*
	[6.28]	[5.04]	[7.04]	(1.81)
Household size	18.93	17.68	19.94	2.26*
	[11.90]	[10.62]	[12.78]	(1.79)
Livestock owned in 2012 (CFA)	1,822,602	1,421,806	2,124,324	702,517
	[5,634,664]	[2,002,009]	[7,249,888]	(1.23)
Agricultural assets 2012 (CFA)	204,200	188,693	215,874	27,181
	[164,468]	[136,508]	[182,227]	(1.39)
House value (CFA)	396,951	332,744	445,197	112,453
	[1,042,061]	[540,782]	[1,296,799]	(1.03)
Land owned (ha)	9.62	9.66	9.59	-0.06
	[7.81]	[7.99]	[7.70]	(-0.06)
Observations	321 ^b	136	185	321

Table 6: Descriptive Statistics of the Participants

^aColumns (1), (2) and (3) show means with standard deviations in brackets. Column (4) shows the coefficient on compound-risk aversion from regressions of each characteristic on compound-risk aversion clustering standard errors at the cooperative level with t-statistics in parenthesis.

***Significant at the 1 percent level. **Significant at the 5 percent level. *Significant at the 10 percent level.

^bThis number excludes the 13 participants who left the session before the end of the experiment

We examine our data based on subjects' revealed compound-risk preferences in the experiments described in Section 4. We find that 57% of the players are compound-risk averse. Columns (2) and (3) of Table 6 summarize the different characteristics by compound-risk attitude. Column (4) shows mean comparisons of compound-risk averse participants to the compound-risk neutral ones and a t-test from individual regression of each covariate on the compound-risk aversion variable, with standard errors clustered at the cooperative level. Compound-risk averse individuals are significantly less educated, and belong to larger households than their compound-risk neutral counterparts.

5.2 Distribution of compound-risk attitudes by risk aversion

The model presented in Section 3 implies that compound-risk aversion is identified for a given level of risk aversion. Therefore, it is useful to disaggregate the distribution of compound-risk aversion by risk aversion range. Figure 4 below displays such disaggregation. The compound-risk aversion coefficient ranges from the value of 0 (compound-risk neutral) to the value of 0.7. Attitudes towards compound-risk and attitudes towards risk seem to be independent from each other.

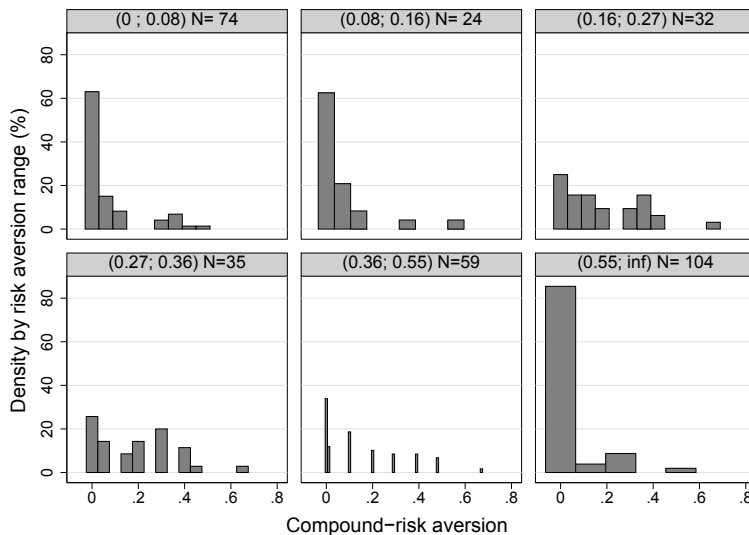


Figure 4: Compound-risk aversion by risk aversion range

5.3 Can we formally reject compound-risk neutrality?

While the revealed coefficients of compound-risk aversion allows to simulate the impact of FNP on the willingness to pay for index insurance, it is important to first verify that they are significant. Under the hypothesis that the participants are compound-risk neutral, the two games provide two alternative measures of constant relative risk aversion. Therefore, comparing the distributions of the risk aversion coefficients implied by each game allows us to test whether participants are compound-risk neutral or not. The last column of Table 4 presents the risk aversion ranges implied by the measured WTP_B if the player is compound-risk neutral. For example, if a player's i WTP_B is d800, then the expected utility he derives from the index insurance contract is larger than the expected utility of the individual contract priced at d2340 and smaller than the expected utility he derives from the individual contract priced at d2540: $EU(\pi + 600) \leq EU(\rho) \leq EU(\pi + 800)$.

5.3.1 Suggestive evidence against compound-risk neutrality:

Figure 5 plots the empirical probability distributions of the risk aversion coefficients implied by each game among the participants. The solid line in Figure 5 shows the CDF of the risk aversion coefficients derived from the first game, while the dashed line shows the CDF of the risk aversion coefficients derived from the second game, assuming compound-risk neutrality. As this figure shows, the empirical CDF of the coefficients derived from the willingness to pay game is more to the right of the CDF of the coefficients derived from the risk aversion game. The participating farmers seem to behave much more cautiously when faced with the index insurance contract. Therefore, the conventional measure of risk aversion is not enough to represent the farmer's attitude towards index insurance.

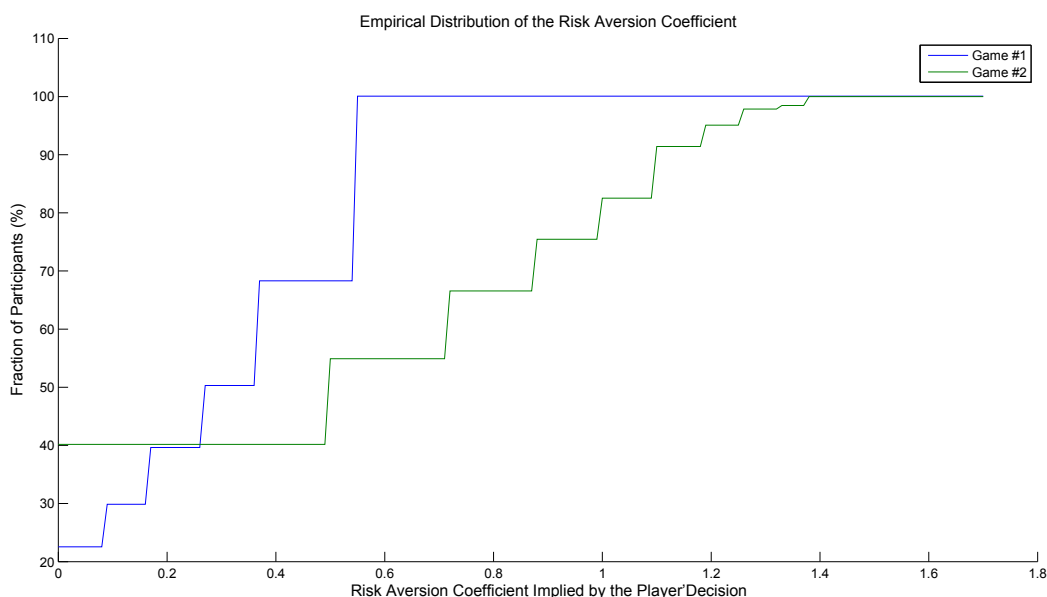


Figure 5: CDFs of CRRAs elicited from Game 1 and Game 2

5.3.2 Testing compound-risk neutrality

In this section we formally compare the distributions of the coefficients of risk aversion implied by player's choices in both games. By design, the two games do not elicit the actual constant relative risk aversion coefficients, but provide constant relative risk aversion ranges that are not directly comparable. Therefore, we begin by fitting a continuous probability distribution to the coefficients of risk aversion elicited from both games.

Instead of conducting an exhaustive search of every possible probability distribution, it is more practical to fit a general class distribution to the data. Ideally, this distribution will be flexible enough to reasonably

represent the underlying parameters. This section uses the Beta of the first kind (B1), a three-parameter distribution, as the continuous model that represents the data. The Beta distribution of the first kind is one member of a class of distributions called Generalized Beta distributions (GB), a family of five-parameter distributions that encompasses a number of commonly used distributions (Gamma, Pareto, etc.). The GB is a flexible unimodal distribution and is widely used when modeling bounded continuous outcomes, such as income distribution. Since the B1 distribution is defined for bounded variables, one should make assumptions about the range of the CRRAs. The participants are assumed to be risk-averse. We allow the upper bound of the elicited CRRA to be 1.7. We conducted robustness checks and showed that the result does not change with the upper bound being either 2 or 3.

Let $B1(b, p_1, q_1)$ and $B1(b, p_1, q_1)$ be the probability distribution functions of the CRRAs derived from the risk aversion game and the WTP game respectively. The parameter b is the upper bound of the CRRAs and is set at the value 1.7. As explained in the appendix, we use maximum likelihood method to estimate the parameters p_1, q_1, p_2 , and q_2 . Table 7 presents the results of the estimation method. We estimate the confidence intervals for the different parameters using the bootstrap method. Table 7 shows the confidence intervals of parameters p_1, q_1, p_2 and q_2 at the 5% significance level, obtained after 10000 simulations. It is clear that the bootstrap parameters are consistent estimates for the actual ones.

	Game 1	Game 2
p parameter	0.67	2.07
95% confidence interval	(0.63; 0.84)	(1.92; 2.57)
q parameter	1.98	4.37
95% confidence interval	(1.92; 2.57)	(4.16; 5.09)

Table 7: Bootstrap confidence intervals for the parameters.

The test of equality of the distributions of the risk aversion derived from the games is performed using 10 000 bootstrapped simulations of the data. We reject the hypothesis that the parameters of the two distributions are the same at the 5% level. Therefore, the distributions of risk aversion implied by the two games are different. While the existence of compound-risk aversion is important in and of itself, we will study its impact on the demand for index insurance in the next section.

6 Simulating the impact of FNP on the uptake of index insurance under compound-risk aversion

It is not immediately clear from the theoretical model the extent to which compound-risk aversion matters for the uptake of index insurance. To answer this question, we numerically simulate the impact of FNP on the uptake of index insurance under compound-risk aversion and under compound-risk neutrality. To do so we count the number of participants who would purchase an index insurance contract that has the same structure as the contract presented in Section 4 for every value of the FNP. A decision maker purchases an

insurance contract if the expected utility he derives from the index insurance contract is higher than then expected utility he derives without it. Using the notation of Section 2 this is equivalent to:

$$(1 - FNP) * v E_{f_{x,y}} u(\rho|high\ yield) + FNP * v E_{f_{x,y}} u(\rho|low\ yield) \geq v E_{f_y} u \rho^{No} \quad (22)$$

where ρ^{No} is the farmer's revenue without insurance. Equation 22 is calibrated to the population of cotton farmers who participated in the games.

The dotted curve of Figure 2 illustrates the impact of FNP on the demand for index insurance with 95% confidence interval using equation 22 and assuming that:

1. Individuals are expected utility maximizers,
2. The price of index insurance is 20% above the actuarially fair price, and
3. The distribution of risk aversion in the population of farmers matches the distribution revealed by the experimental games played in Mali.

As the FNP increases under this contract structure, the probability of a payout decreases, and the price of the insurance contract in turn declines. However, because the contract is not actuarially fair, a number of agents drop out of the market as FNP increases. As can be seen in Figure 2 , increasing FNP in an index insurance contract will discourage demand. For a contract with zero FNP, i.e. one that pays off for sure in case of a loss, moderately and highly risk averse farmers (70% of the population in the Mali experiment) ask for index insurance. As FNP increases, the farmers with the highest risk aversion coefficient are the first to stop demanding the contract. This drop in demand reaches as high as 15% for extremely high levels of FNP (90%). Despite this decrease in demand, the demand for the partial insurance provided by this index insurance contract remains relatively robust even as FNP increases (assuming that individuals maximize expected utility).

FNP matters even more when people are compound-risk averse. The solid line in Figure 2 shows, using equation 22 and the distribution of compound-risk aversion in the population of the farmers, the impact of FNP on demand for index insurance. As expected, compound risk aversion decreases the demand for index insurance relative to what it would be if individuals had the same degree of risk aversion but were compound-risk neutral. In addition, as can be seen in the figure, demand declines more steeply as FNP increases under compound-risk aversion. If FNP were as high as 50% (a not unreasonable high number under the kind of rainfall index insurance contracts that have utilized in a number of pilots), demand would be expected to be only 35% of the population as opposed to the 60% demand that would be expected if individuals were simply expected utility maximizers. In short, under compound-risk aversion, designing contracts with minimal FNP is important, not only to enhance the value and productivity impacts of index insurance, but also to assure that the contracts are demanded.

7 Conclusion

In the absence of formal insurance markets, poor rural households in developing countries may rely on costly risk-management mechanisms, including income smoothing strategies that entail avoiding riskier technologies with higher expected returns. Although the partial coverage provided by index insurance would appear to provide a good alternative to these households in theory, demand has been surprisingly low. This paper draws on insights from behavioral economics and framed field experiments to provide an explanation for the low uptake.

We begin our analysis by examining the farmer’s perspective of index insurance. To the farmer, index insurance appears as a compound lottery with two stages: the first stage lottery determines the individual farmer’s yield, and the second stage determines whether or not the index triggers an indemnity payout. Drawing on the literature on compound risk aversion and ambiguity aversion, we derive an expression of the willingness to pay for index insurance. This measure depends on two parameters: the coefficients of risk aversion and compound-risk aversion.

In Mali, we designed a set of framed field experiments with 334 cotton farmers to elicit the two parameters that define an individual’s attitude toward index insurance. We framed the first game in terms of insurance decisions to elicit risk aversion coefficients. The second game elicited the excess willingness to pay of farmers to get rid of the second stage lottery of the index insurance contract. Fitting an expected utility model to this measure allows us to elicit another set of coefficients of risk aversion. Using both graphical evidence and a statistical test, we find that the distributions of these two parameters are different. This finding suggests that farmers are not neutral to compound-risk. Using the smooth model of ambiguity aversion of KMM, we combine the findings of the two games to pin down the coefficients of compound-risk aversion. We find that 57% of game participants revealed themselves to be compound-risk averse to varying degrees. In fact, the willingness to pay to avoid the secondary lottery of those individuals who demand index insurance is on average considerably higher than the predictions of expected utility theory. Using the distribution of compound-risk aversion and risk aversion in this population, we simulated the impact of changes in basis risk on the demand for index insurance. As we expected we found that compound risk aversion decreases the demand for index insurance relative to what it would be if individuals had the same degree of risk aversion but were compound-risk neutral. In addition demand declines more steeply as basis risk increases under compound-risk aversion.

Our results highlight the importance of designing contracts with minimal basis risk under compound-risk aversion. Reducing basis risk would not only enhance the value and productivity impacts of index insurance, but would also assure that the contracts are popular and have the anticipated impact.

References

- ABDELLAOUI, M., P. KLIBANOFF, AND L. PLACIDO (2011): “Ambiguity and compound risk attitudes: an experiment,” .
- ALDERMAN, H. AND C. PAXSON (1992): *Do the poor insure?: a synthesis of the literature on risk and consumption in developing countries*, vol. 1008, World Bank Publications.
- ANDERSEN, S., G. W. HARRISON, M. I. LAU, AND E. E. RUTSTRÖM (2006): “Elicitation using multiple price list formats,” *Experimental Economics*, 9, 383–405.
- BUDESCU, D. V. AND I. FISCHER (2001): “The same but different: an empirical investigation of the reducibility principle,” *Journal of Behavioral Decision Making*, 14, 187–206.
- CARTER, M. R., P. D. LITTLE, T. MOGUES, AND W. NEGATU (2007): “Poverty Traps and Natural Disasters in Ethiopia and Honduras,” *World Development*, 35, 835–856.
- CLARKE, D. (2011): “A theory of rational demand for index insurance,” *Economics Series Working Papers*, 572.
- DATTA, S. AND S. MULLAINATHAN (2014): “Behavioral Design: A New Approach to Development Policy,” *Review of Income and Wealth*, 60, 7–35.
- DILLENBERGER, D. (2010): “Preferences for One-Shot Resolution of Uncertainty and Allais-Type Behavior,” *Econometrica*, 78, 1973–2004.
- ELABED, G., M. BELLEMARE, M. CARTER, AND C. GUIRKINGER (2013): “Managing Basis Risk with Multi-scale Index Insurance Contracts for Cotton Producers in Mali,” .
- ELLSBERG, D. (1961): “Risk, ambiguity, and the Savage axioms,” *The Quarterly Journal of Economics*, 643–669.
- ERGIN, H. AND F. GUL (2009): “A theory of subjective compound lotteries,” *Journal of Economic Theory*, 144, 899–929.
- GALARZA, F. B. AND M. R. CARTER (2011): “Risk Preferences and Demand for Insurance in Peru: A Field Experiment,” .
- GILBOA, I. AND D. SCHMEIDLER (1989): “Maxmin expected utility with non-unique prior,” *Journal of mathematical economics*, 18, 141–153, 2.
- GONZALEZ, R. AND G. WU (1999): “On the Shape of the Probability Weighting Function,” *Cognitive Psychology*, 38, 129–166.
- HALEVY, Y. (2007): “Ellsberg revisited: An experimental study,” *Econometrica*, 75, 503–536, 2.

- HARRISON, G. W. AND J. A. LIST (2004): “Field Experiments,” *Journal of Economic Literature*, 42, 1009–1055.
- HAZELL, P. B. R. AND A. VALDES (1985): *Crop insurance for agricultural development: Issues and experiences*, Baltimore, Maryland, USA: John Hopkins University Press, International Food Policy Research Institute, Washington, DC USA.
- KAHNEMAN, D. AND A. TVERSKY (1979): “Prospect theory: An analysis of decision under risk,” *Econometrica: Journal of the Econometric Society*, 263–291.
- KLIBANOFF, P., M. MARINACCI, AND S. MUKERJI (2005): “A smooth model of decision making under ambiguity,” *Econometrica*, 73, 1849–1892, 6.
- MACCHERONI, F., M. MARINACCI, AND D. RUFFINO (2010): “Alpha as Ambiguity: Robust Mean-Variance Portfolio Analysis,” *Working Papers*.
- MCDONALD, J. AND Y. XU (1995): “A generalization of the beta distribution with applications,” *Journal of Econometrics*, 66, 133–152, 1.
- NAU, R. F. (2006): “Uncertainty Aversion with Second-Order Utilities and Probabilities,” *Management Science*, 52, 136–145.
- SEGAL, U. (1987): “The Ellsberg paradox and risk aversion: An anticipated utility approach,” *International Economic Review*, 28, 175–202, 1.
- SEO, K. (2009): “Ambiguity and Second-Order Belief,” *Econometrica*, 77, 1575–1605.
- SMITH, V. H. AND J. W. GLAUBER (2012): “Agricultural Insurance in Developed Countries: Where Have We Been and Where Are We Going?” *Applied Economic Perspectives and Policy*, pps029.
- WAKKER, P., R. THALER, AND A. TVERSKY (1997): “Probabilistic insurance,” *Journal of Risk and Uncertainty*, 15, 7–28, 1.

A Appendix:

A.1 Fitting a B1 distribution to the CRRA

In this section, we estimate the probability density function f of the coefficient of constant relative risk aversion r we elicited from an experiment.

We use Maximum Likelihood estimation assuming that r follows a Generalized Beta distribution of first kind (GB1). The GB1 distribution is defined by the following pdf:

$$f(r; b, p, q) = \frac{r^{p-1} (1 - \frac{r}{b})^{q-1}}{b^p B(p, q)}$$

for $0 < r < b$ where b, p and q are positive. The scaling factor $B(p, q)$ is the Beta function: $B(p, q) = \frac{\Gamma(p)\Gamma(q)}{\Gamma(p+q)}$ where $\Gamma(p) = (p-1)!$.

By construction, our data is partitioned in 6 intervals. Therefore, we do not observe the continuous variable r . Following McDonald and Xu (1995), we obtain the parameters of interest (p and q) using a Maximum Likelihood estimator based on a multinomial with an underlying density $f(r; b, p, q)$ and cumulative function $F(r; b, p, q)$.

We now derive the log-likelihood function. Let j denote the risk aversion interval $[r_j, r_{j1}]$. Player i 's true risk aversion coefficient r has a probability $p_i = F(r_{j+1}; a, b, p, q) - F(r_j; a, b, p, q)$ of being in interval j . Denoting m_j the number of observations in interval j , the likelihood function L_N is the joint probability function:

$$L_N = \prod_{i=1}^N p_i$$

Maximizing L_N is equivalent to maximizing the log-likelihood function:

$$\begin{aligned} \mathcal{L}_N(b, p, q) &= \log L_N(b, p, q) \\ &= \sum_{j=1}^6 m_j \log(p_j) \end{aligned}$$

Where m_j is the number of observations in the interval $[r_j, r_{j1}]$. The probability p_j of being in that interval is

$$p_j = F(r_{j+1}; a, b, p, q) - F(r_j; a, b, p, q)$$

Since r is a Beta distribution of the first kind, its cumulative F is:

$$\begin{aligned} F(r; b, p, q) &= \int_0^{\frac{r}{b}} \frac{t^{p-1} (1-t)^{q-1}}{B(p, q)} dt \\ &= I_{(\frac{r}{b})}(p, q) \end{aligned}$$

where $I_{(\frac{r}{b})}(p, q)$ the regular beta function is the cumulative distribution function of the Beta variable with parameters p and q evaluated at $\frac{r}{b}$.

Proof. By definition:

$$F(r; a, b, pq) = \int_0^r \frac{t^{p-1} (1 - \frac{r}{b})^{q-1}}{b^p B(p, q)} dt$$

using the change of variable $x = \frac{t}{b}$, we obtain the result. □

A.2 Goodness of fit of the fitted distribution

Figure 6 demonstrates that the parameters follow a normal distribution with mean close to the observed values. Therefore, the estimation strategy provides a good fit for the data.

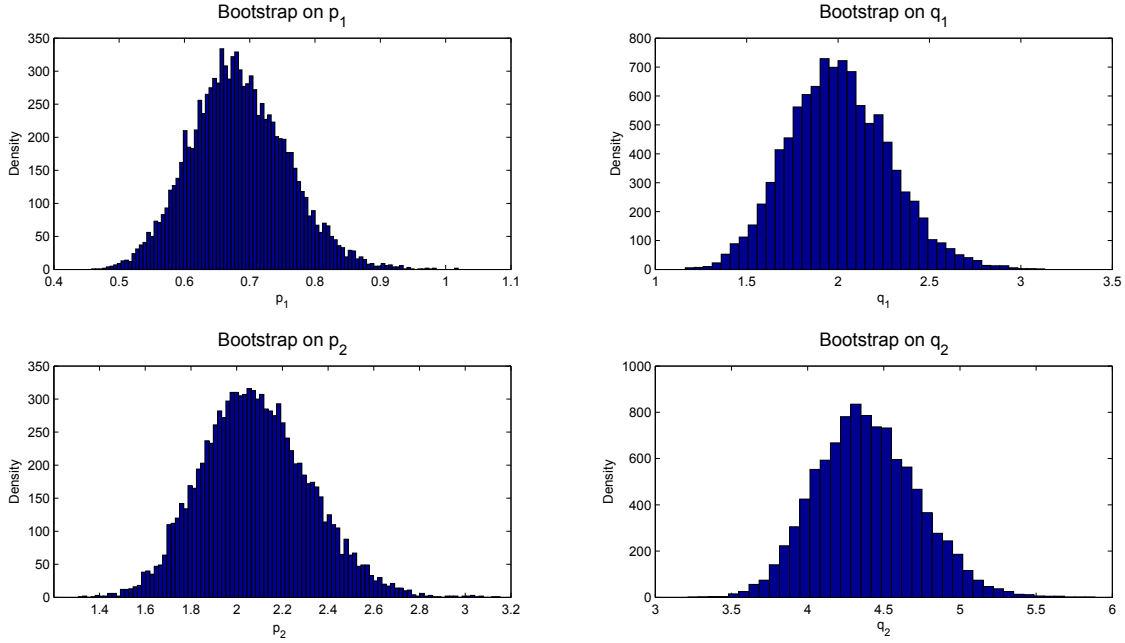


Figure 6: Histogram of bootstrap for parameter p and q .

A.3 Individual Characteristics

In this section we explore the possible determinants of the heterogeneity in compound-risk aversion by examining whether individual characteristics such as age, education or wealth can predict the level of compound-risk aversion. We also compare these results with the determinants of the coefficients of risk aversion. Since the elicited coefficients are intervals, we run an ordered probit estimation:

$$y_{ic}^* = X'_{ic}\beta + \varepsilon_{ic}$$

where y_{ic}^* is the latent variable of interest (either compound-risk aversion or risk aversion) of individual i from cooperative c .

In Table A.3 we analyze the correlation between the individual characteristics and risk aversion. We find that educated farmers are significantly more risk averse than less educated farmers. This result is counter

intuitive, but confirms the finding of Galarza (2009). Since the risk elicitation game is framed in terms of insurance decisions, farmers who are more educated and more experienced in cotton production are more likely to buy an insurance contract than their counterparts. There is also evidence that experience in cotton growing as proxied by the number of years spent in the cotton cooperative is significantly positively correlated with risk aversion.

Next, we analyze the correlation between the individual characteristics and compound-risk aversion. We perform this analysis in two different ways. First, as Table 9 shows, we classify individuals by compound-risk attitudes. Here, the compound-risk aversion variable is set at the value of 0 if the farmer is compound-risk neutral, and 1 if he is compound-risk averse. Contrary to the case of risk aversion, education is negatively correlated with compound-risk aversion. One year of education decreases the likelihood of being compound-risk averse by 0.036. In addition, the value of agricultural assets is significantly correlated with compound-risk aversion. Farmers who have spent more time in their cooperatives are also more averse to compound-risk.

In Table 10, we present another way of studying the relationship between individual characteristics and compound-risk aversion. As suggested by the theory, compound-risk aversion is defined for a given level of risk aversion. Therefore, we control for the risk aversion coefficient, and run the following ordered probit:

$$cra_{ic}^* = X'_{ic}\beta + r_{ic} + \varepsilon_{ic}$$

where cra_{ic}^* is the latent coefficient of compound-risk aversion, and r_{ic} is the coefficient of constant relative risk aversion. As shown in Table 10, education is still negatively correlated with compound-risk aversion as well as wealth measured by land owned.

	(1)
	risk_aversion
risk_aversion	
age	0.0016 (0.0046)
education	0.0262* (0.0140)
livestock_2012	-0.0000 (0.0000)
ag_value	0.0000 (0.0000)
assets_value	-0.0000 (0.0000)
house_value	0.0000 (0.0000)
land_owned	0.0017 (0.0094)
coop_years	-0.0314* (0.0179)
nbre_exp_cf	0.0037 (0.0055)
knowledge_ins	-0.2457 (0.3855)
<i>N</i>	248
adj. R^2	

Standard errors in parentheses

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 8: Determinants of risk aversion

	(1)
	cra
cra	
age	0.0014 (0.0064)
education	-0.0354* (0.0183)
livestock_2012	0.0000 (0.0000)
ag_value	0.0000* (0.0000)
assets_value	0.0000 (0.0000)
house_value	0.0000 (0.0000)
land_owned	-0.0103 (0.0157)
coop_years	0.0365** (0.0168)
nbre_exp_cf	-0.0057 (0.0059)
knowledge_ins	0.0530 (0.3252)
<i>N</i>	251
adj. R^2	

Standard errors in parentheses
* p<.1, ** p<.05, *** p<.01

Table 9: Determinants of compound-risk aversion

	(1)
	compound_risk_aversion
compound_risk_aversion	
risk_aversion	0.0986* (0.0507)
age	0.0061 (0.0050)
education	-0.0279** (0.0141)
livestock_2012	0.0000 (0.0000)
ag_value	0.0000*** (0.0000)
assets_value	-0.0000 (0.0000)
house_value	0.0000* (0.0000)
land_owned	-0.0289*** (0.0102)
coop_years	0.0143 (0.0127)
nbre_exp_cf	-0.0074 (0.0059)
knowledge_ins	-0.2595 (0.3319)
<i>N</i>	247
adj. <i>R</i> ²	

Standard errors in parentheses

* p<.1, ** p<.05, *** p<.01

Table 10: Determinants of compound-risk aversion