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LOSS AVERSION AND THE DEMAND FOR INDEX INSURANCE

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Loss aversion and the demand for index insurance*

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Abstract

This work analyzes if reference dependence and loss aversion can explain the puzzling low adoption rates of rainfall index insurance. We present a model that predicts the impact of loss aversion on index insurance demand to vary with different levels of insurance understanding. Index insurance demand of farmers who are unaware of the loss-hedging benefit that insurance provides decreases with loss aversion. In contrast, insurance demand of farmers who are aware of the loss-hedging benefit increases with loss aversion. The model further predicts that farmers who are unaware of the loss-hedging benefit will not demand an even highly subsidized index insurance. Using data from a randomized controlled trial involving a sample of Indian farmers we provide empirical support for our core conjecture that insurance understanding mitigates the negative impact of loss aversion on index insurance adoption.

Keywords: Prospect Theory; Reference Dependence; Microinsurance; Farm Household

JEL-codes: D91, G22, Q12

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1 Introduction

The economies of most developing countries are highly dependent on agriculture. The agricultural sector in Africa, for example, accounts for more than 50% of the total employment on the continent (Patt et al., 2010). Furthermore, this sector faces inherent weather risks (Hyman et al., 2008; Cooper et al., 2008; Barrett and Santos, 2014; Hansen et al., 2018). Accordingly, formal financial hedges that smooth agricultural income between periods with good and bad weather conditions are regarded as a prerequisite for sustainable economic growth. One particular type of formal financial hedge offered in many developing countries is index insurance. Index rainfall insurance underwrites an indemnity payment depending on the realized rainfall at the farmer's nearest weather station. The advantages are, first, a low premium because of low administrative costs and, second, the absence of moral hazard and adverse selection (Giné et al., 2008; Carter et al., 2014). The main drawback of index insurance is that payouts are not perfectly correlated with farmer's harvest loss. This lack of correlation is known as basis risk. Basis risk is particularly pronounced if the weather stations are too far away from farmer's field (Würtenberger, 2017). Given the inherent riskiness of farming, the low and stagnating take-up rates of about 20% are puzzling and cannot be explained by standard expected utility models of insurance demand (Hellmuth et al., 2009; Patt et al., 2010; Karlan et al., 2014).[1]

This paper takes a behavioral economics approach to explain the low demand for index insurance. In particular, we incorporate two of the four ingredients of Kahneman and Tversky's (1979) Prospect Theory (hereafter PT); namely, reference dependence and loss aversion.[2] According to Barberis (2013), it is often unclear how to define precisely what a subjective gain or loss is. Therefore, the central challenge in the application of PT is the choice of appropriate reference points. In our index insurance demand

[1]If the index insurance is offered at an actuarially fair price, the estimated take-up rates range from 25% (Cole et al., 2013) to 11% (Karlan et al., 2014) and even 6.4% (Gaurav et al., 2011). Take-up rates increase to about 35% if the insurance is offered at a price equal to 50% of its actuarially fair value (Karlan et al., 2014; Mobarak and Rosenzweig, 2012). Previous research showing considerable welfare gains for farmers holding index insurance contracts (Cole et al., 2017; Carter et al., 2016) makes these low rates even more puzzling.

[2]According to Barberis (2013), PT consist of four aspects: reference dependence, loss aversion, diminishing sensitivity and probability weighting.

model we choose two reference points which we believe are reasonable choices for two different types of farmers: naïve and insurance-literate farmers.

The purpose of insurance is to alleviate the impact of losses. Therefore, the demand for insurance depends on how an individual assesses the benefit of alleviating the impact of losses versus the cost of the insurance premium (Brown and Finkelstein, 2008; Gottlieb and Mitchell, 2015). Additionally, it is likely that this assessment depends on the level of insurance understanding (Giné and Yang, 2009; Gaurav et al., 2011). Consistent with this view, we distinguish between naïve farmers who do not understand how insurance works and insurance-literate farmers who do. We assume that naïve farmers are not aware of the loss-hedging benefit that index insurance provides. Instead, they regard index insurance as an uncertain investment that is not related to the actual harvest loss. Thus, naïve farmers compare the outcomes of the index insurance to not investing at all, which constitutes a natural reference point for these farmers. This means if no loss occurs - and, thus, no indemnity is paid out - the premium is perceived as a pure loss. This view of 'insurance as investment' rather than a loss-hedging device is supported by Patt et al. (2009), who report that some farmers are upset if the indemnity payment is less than the premium paid for the insurance. In contrast, insurance-literate farmers are aware of the loss-hedging benefit of index insurance. Accordingly, these farmers only expect an indemnity payment in case of harvest loss. A natural reference point to model this situation is coverage of a (perfect) insurance which, if a loss occurs, always pays out. These two distinct reference points propose different influences of loss aversion on index insurance demand. Our PT model predicts that insurance demand of naïve farmers is decreasing with loss aversion, whereas it is increasing with loss aversion for insurance-literate farmers. Furthermore, our model suggests that naïve farmers whose preferences are characterized by median values of the PT parameters do not demand index insurance even if it is highly subsidized.

We take the predictions of our model to the data, revisiting Cole et al.'s (2013) evidence on index insurance demand of farmers in a rural region of India. Cole et al. (2013) randomly assigned an insurance education module to a subsample of 350 out of 1,042 farmers. We utilize this treatment as an exogenous variation of farmers' level of insurance understanding and, therefore, awareness of the loss-hedging benefit that insurance provides. The dataset captures measures of insurance demand, information on financial socialization and information on the socio-economic background. Furthermore, farmers were asked to choose among lotteries varying in risk and expected return. Following Binswanger (1981), Cole et al. (2013) interpret lottery choices as indicators of risk aversion. The payouts of the experimental choice task are small relative to farmers' real world income.[3] Accordingly, lottery choices are only suitable to elicit risk attitudes if farmers are assumed to isolate the income from the choice task from lifetime income (Rabin, 2000). We follow other experimental studies (Fehr and Goette, 2007; Gächter et al., 2007) and assume that farmers integrate the experimental income with their lifetime income. Imposing further strict assumptions we show that lottery choices may also indicate loss aversion. We document substantial differences in the impact of loss aversion on insurance demand between farmers in the treatment and in the control group. Insurance demand of farmers in the control group decreases with loss aversion. An increase in loss aversion by one standard deviation decreases the likelihood to demand at least one insurance contract by between 2.6 and 3.5 percentage points. Given an overall take-up rate of 30.2%, these effects are economically meaningful. The negative effect vanishes for farmers in the treatment group.[4] Due to its specific design, the education module positively affects the awareness of the loss-hedging benefit that insurance provides. Furthermore, it is unlikely that the insurance education treatment impacts the relationship between loss aversion and insurance demand other than by increasing the overall awareness of the loss-hedging benefit. Thus, our findings support our conjecture that the impact of loss aversion on insurance demand varies systematically with the level of product understanding.

Our paper contributes to three main strands of literature. First, we add to the recent literature on the impact of economic preferences on the demand for index insurance products. Clarke (2016) presents a rational demand model that assumes imperfect correlation between insurance net transfer

[3]The payoffs of the choice task range between Rs. $0 - 110$ whereas farmers' mean (median) yearly income is Rs. $57,991$ $(34,116)$. Thus, the maximum income from the choice task amounts to 2.3% (= 12 · 110/57,991) of the average monthly income. Accordingly, stakes are much smaller than in the high-stake decision task of Binswanger (1981) with stakes amounting to a month's average income.

[4]In some specifications, the effect turns positive and an increase in loss aversion by one standard deviation increases the likelihood to demand at least one insurance contract by between 2.2 and 3.7 percentage points.

and farmers' net loss (basis risk). This model only explains the observed low insurance take-up of the most risk-averse farmers (Giné et al., 2008) as a rational response to the risk of contract non-performance. In contrast to Clarke (2016), we focus on loss instead of risk aversion.[5] To the best of our knowledge, the impact of loss aversion on index insurance demand has not yet been analyzed. Thus, we add to this literature by highlighting the role of loss aversion.

Second, we contribute to the research on the role of PT preferences in insurance demand decisions. Most of the literature focuses on probability weighting (Sydnor, 2010; Barseghyan et al., 2013) and neglects loss aversion. Recent studies by Gottlieb and Mitchell (2015) and Hwang (2016) include loss aversion and present similar models to ours and empirically find a negative impact of narrow framing and loss aversion on the demand for long-term care insurances in the US. To the best of our knowledge, we are the first to analyze the impact of loss aversion on insurance demand within a setting that includes a contract non-performance risk.

Third, we contribute to the literature on the role of loss aversion as well as product understanding for technology adoption. Liu (2013) finds that loss aversion is one of the main drivers for the sluggish adoption of a new and superior crop among Chinese farmers. Emerick et al. (2016) find that adoption of a new seed variety among farmers in rural Indian villages is increasing with understanding of the product. The assumption that the decision to adopt a familiar product might require a different reference point than the decision to adopt an unfamiliar product seems tautological. However, to the best of our knowledge, there is not extant research that combines loss aversion and product understanding. We contribute to this literature by documenting that product understanding mitigates the negative impact of loss aversion on technology adoption.[6]

The remainder of this paper is organized as follows. Section 2 introduces our behavioral index insurance demand model. Section 3 presents the data and the empirical test of our core hypothesis. Section 4 discusses shortcomings of the model and the empirical specification. Section 5 concludes.

[5]The scenario in which a farmer buys an insurance and still suffers a loss without indemnity payment is a natural starting point to include loss aversion.

[6]Given the high level of loss aversion (Liu, 2013; Holden and Quiggin, 2017) accompanied by the low level of education in developing countries (Cole et al., 2013), we offer meaningful new insights to explain the low technology adoption rates (Brick and Visser, 2015; Abay et al., 2017) in the developing world.

2 Behavioral insurance demand model

We focus on a model with only four states of the world. A loss L occurs with probability p. In a classical insurance setting the loss would trigger an indemnity payment I. To account for the specific feature of an index insurance, the basis risk, we assume that, given a loss, there is a probability $q_1 > 0$ that the insurance does not pay out the indemnity payment. We refer to this state as the downside basis risk. Similarly, to include the upside basis risk, we assume that, given no loss, there is a probability $q_2 > 0$ that the insurance does pay out the indemnity payment. Table 1 illustrates the four states and the associated probabilities.

Table 1: Four state framework (probabilities)

	Indemnity	No Indemnity
Loss	$p(1-q_1)$	pq_1
No Loss	$(1-p)q_2$	$(1-p)(1-q_2)$

We assume that the probabilities the insurance under- or overestimates the actual loss are the same, i.e., $pq_1 = (1-p)q_2$.[7] We denote these probabilities by r. We label farmer's initial wealth level with W and, finally, assume that the premium Π is actuarially fair, i.e., $\Pi = pI$. Table 2 assigns labels $((1)-(4))$ to the different states and summarizes the outcomes for a farmer who does not demand and a farmer who does demand the insurance.

Table 2: Four state framework (probabilities and outcomes)

	Loss		No Loss	
State	Indemnity	No Indemnity	Indemnity	No Indemnity
	(1)	(2)	(3)	(4)
Probability	$p(1-q_1)$	r	r	$(1-p)(1-q_2)$
Wealth, No Insurance	$W-L$	$W-L$	W	W
Wealth, Index Insurance	$W-pI-L+I$	$W-pI-L$	$W-pI+I$	$W-pI$

We assume that farmers do not obey asset integration. Instead, they evaluate monetary outcomes in terms of gains and losses with respect to

[7]Under this assumption the probability that the index insurance pays out is p. Thus, the index insurance indemnity payment is an unbiased approximation of the indemnity payment of an insurance without the existence of basis risk. This assumption is supported by the empirical findings of Clarke et al. (2012).

some reference point. According to PT, farmers' value function equals

$$v(x) = \begin{cases} (x - R)^{\alpha} & \text{, if} \quad x \geq R \\ -\lambda(R - x)^{\alpha} & \text{, if} \quad x < R. \end{cases} \tag{1}$$

In the value function (1), R is the reference point, α the coefficient of diminishing marginal sensitivity for gains and losses and λ the coefficient of loss aversion.[8] The crucial issue within the application of PT is the choice of an appropriate reference point. Wakker et al. (1997) and Sydnor (2010) use initial wealth W as a reference point. However, the main problem with this reference point is, as Sydnor (2010) argues, the fact that the decision to demand insurance is then entirely determined in the loss domain. Thus, initial wealth is a questionable choice.[9] In many other applications of PT in economics, the reference point is set as the status quo. In the index insurance context the status quo (= no coverage) is state dependent. It equals either W or $W - L$. Consequently, a possibly reasonable choice of the reference point might be $W - L$ for the state in which the loss L occurs and W for the state in which no loss occurs. We refer to this reference point as 'No Insurance Coverage' and analyze the implications of its choice in Section 2.1.[10] Several empirical findings suggest that the status quo might not necessarily be an appropriate choice. Instead, it seems that individuals often choose risk-free outcomes as the reference point (for a review see Schmidt (2016)). Accordingly, Schmidt (2016) proposes full insurance coverage as an alternative reference point. The index insurance setting is special in the sense that, although a farmer is insured, he might, because of the basis risk, still suffer from an unsecured loss. Thus, index insurance coverage is not a risk-free outcome. Accordingly, we choose full coverage of a perfect insurance that always pays out in the case of a loss but never pays out in case of no loss as a second reference point. We refer to this reference point as

[8]For the sake of simplicity, we assume that the diminishing marginal sensitivity for gains and losses are equal, i.e., $\alpha \approx \beta$. This assumption is supported by Tversky and Kahneman (1992) who find a median value of $\alpha_m = \beta_m = 0.88$.

[9]For a further discussion on this issue see Schmidt (2016).

[10]PT as proposed by Kahneman and Tversky (1979) assumes that the reference point is a fixed value. Accordingly, our model is actually embedded in the so-called Third-generation PT which is proposed by Schmidt et al. (2008) and allows endogenous and state dependent reference points.

'Perfect Insurance Coverage' and analyze the implications of its choice in Section 2.2.

2.1 No insurance coverage

We first analyze insurance demand with a state-dependent reference point given by wealth without any insurance. Hence, the reference point equals either $W - L$ in the states (1) and (2) in which a loss occurs or W in the states (3) and (4) in which no loss occurs. Therefore, if the subject does not demand the insurance, there is neither a gain nor a loss in all four states. If the farmer demands the insurance, there is a gain of $-pI + I$ if the insurance pays out (state (1) and (3)). Furthermore, there is a loss of the insurance premium pI if the insurance does not pay out (state (2) and (4)). Table 3 presents a summary of the encoded outcomes and their probabilities.

Table 3: No insurace coverage as reference point

	Loss		No Loss	
State	Indemnity	No Indemnity	Indemnity	No Indemnity
	(1)	(2)	(3)	(4)
Probability	$p(1-q_1)$	r	r	$(1-p)(1-q_2)$
Gains/Losses, No Insurance	0	0	0	0
Gains/Losses, Index Insurance	$(1-p)I$	$-pI$	$(1-p)I$	$-pI$

A farmer demands the insurance if the PT Value of demanding is at least as large as the PT Value of not demanding. Neglecting probability weighting, the condition that needs to be fulfilled equals[11]

$$-\lambda(1-p)(pI)^{\alpha} + p((1-p)I)^{\alpha} \geq 0. \tag{2}$$

From condition (2) we can observe that an increase in the loss aversion coefficient λ negatively impacts the likelihood to demand the index insurance. Furthermore, the basis risk probability r is not included in the condition. Hence, a possible in- or decrease in basis risk does not impact the insurance demand decision. Both predictions hold independently of the value of α and, thus, under risk neutrality, i.e., $\alpha = 1$, as well as under risk aversion, i.e., $\alpha < 1$. The following proposition summarizes these predictions.

[11]Within our model set up we assume that the probability of upside and downside basis risk are the same. Therefore $p(1-q_1)+r = p(1-q_1)+pq_1 = p$. Similarly $r+(1-p)(1-q_2) = 1-p$.

Proposition 2.1. *Given the reference point 'No Insurance Coverage', insurance demand is independent of basis risk and decreasing with loss aversion.*

Rearranging of inequality (2) shows that a farmer only demands the insurance, if

$$\lambda \leq \left(\frac{p}{1-p}\right)^{1-\alpha}.$$

Accordingly, as also stated by Gottlieb and Mitchell (2015), scenarios in which the probability that a loss occurs is smaller than 0.5, i.e., $p < 0.5$, require the loss aversion parameter to be smaller than 1, i.e., $\lambda < 1$. This implies that losses do not loom larger than gains and therefore contradicts one of the most tested assumptions of PT. Furthermore, using the median PT parameter $\alpha_m = 0.88$ and $\lambda_m = 2.25$ shows that a loss probability of $p > 0.99$ is required such that a farmer demands the insurance.[12] Thus, it is very likely that farmers using the reference point 'No Insurance Coverage' never demand an actuarially fair priced insurance.[13] We further analyze insurance demand if the premium is lower than its actuarially fair value. We denote $s > 0$ as the subsidy factor and assume that $\Pi = (1-s)pI$ holds. Proposition 2.2 states subsidy requirements.

Proposition 2.2 (Requirement for the subsidy)**.** *A farmer with reference point 'No Insurance Coverage' demands the subsidized insurance only if the inequality*

$$s \geq 1 - \frac{1}{p\left(\left(\lambda\frac{1-p}{p}\right)^{1/\alpha} + 1\right)}$$

is fulfilled. The subsidy requirement is increasing with loss aversion.
Proof: Appendix B.1.

[12]The median values $\alpha_m = 0.88, \lambda_m = 2.25$ of Kahneman and Tversky (1979) were estimated in experiments with a small number of students. These populations are among the least representative on a lot of dimensions (Henrich et al., 2010). However, using PT parameters estimated by Liu (2013) and Holden and Quiggin (2017) in a closer context lead to similar strict conditions.

[13]This implication is straightforward since the farmer regards the insurance as an investment and the decision to demand the insurance as being independent of crop risk. Hence, he does not demand a zero expected return, positive risk insurance contract.

Using the median PT parameters $\alpha_m = 0.88$, $\lambda_m = 2.25$ and assuming that the loss probability lies between 5% and 50%, i.e. $0.05 < p < 0.5$, Proposition 2.2 predicts that a subsidy between 55% and 85% is required such that a farmer with reference point 'No Insurance Coverage' demands the insurance.

2.2 Perfect insurance coverage

We now analyze insurance demand with a state-dependent reference point equal to wealth with full coverage of an insurance that always - and only - pays out in case of a loss. Under full coverage the indemnity payment equals the loss (i.e., $I = L$). Accordingly, the reference point is $W - pI$ in all four states.[14] Therefore, if the farmer does not demand the insurance and a loss occurs (state (1) and (2)), there is a loss of $I - pI$. Furthermore, there is a gain of the premium pI if no loss occurs (state (3) and (4)). If the farmer demands the insurance, the existence of basis risk leads to a loss of the indemnity payment I in state (2) and a gain of I in state (3). Both states occur with the same probability r. Table 4 presents a summary of the encoded outcomes and their probabilities.

Table 4: Perfect insurance as reference point

State	Loss		No Loss	
	Indemnity	No Indemnity	Indemnity	No Indemnity
	(1)	(2)	(3)	(4)
Probability	$p(1-q_1)$	r	r	$(1-p)(1-q_2)$
Gains/Losses, No Insurance	$(p-1)I$	$(p-1)I$	pI	pI
Gains/Losses, Index Insurance	0	$-I$	I	0

A farmer demands the insurance if the PT Value of demanding is at least as large as the PT Value of not demanding. Neglecting probability weighting, the condition that needs to be fulfilled is

$$r(1-\lambda)I^\alpha > -p\lambda\left((1-p)I\right)^\alpha + (1-p)\left(pI\right)^\alpha . \tag{3}$$

[14] In the states (1) and (2) in which a loss occurs the reference point is $W - pI - L + I = W - pI$. In the states (3) and (4) in which no loss occurs farmers do not receive any indemnity payment but still have to pay the insurance premium pI. Thus, the reference point is also $W - pI$.

From condition (3) we can see that an increase in the basis risk probability r negatively impacts the likelihood to demand the index insurance. Furthermore, rearranging leads to

$$\lambda(p(1-p)^{\alpha} - r) + r - (1-p)p^{\alpha} > 0.$$

Thus, the likelihood to demand the insurance is increasing with loss aversion exactly if $p(1-p)^{\alpha} > r$. An increase in the basis risk probability r makes it less likely that this condition is fulfilled. Recalling from our model set up described at the beginning of Section 2, $r = pq_1$ holds, where q_1 denotes the probability that, given a loss, the insurance does not pay out. Hence, the condition simplifies to $(1-p)^{\alpha} > q_1$. The left side of the inequality is decreasing with α. Thus, it is sufficient to analyze the case $\alpha = 1$. Assuming that the loss probability p is below 50%, this condition is fulfilled as long as $q_1 < 0.5$. We believe that an insurance with a non-performance probability of above 50% is an unlikely scenario. Accordingly, we conclude that the likelihood to demand the insurance is increasing with loss aversion under risk neutrality, i.e., $\alpha = 1$, and, therefore, also under risk aversion, i.e., $\alpha < 1$. Proposition 2.3 summarizes the predictions.

Proposition 2.3. *Given the reference point 'Perfect Insurance Coverage', insurance demand is decreasing with basis risk and increasing with loss aversion. Furthermore, the positive impact of loss aversion diminishes with an increasing basis risk.*

2.3 Model predictions

Our behavioral model contrasts insurance demand for two reference points: 'No Insurance Coverage' and 'Perfect Insurance Coverage'. We believe that these reference points are likely to be related to farmers' level of insurance understanding and, therefore, the awareness of the loss-hedging benefit that insurance provides. A farmer without further understanding of the insurance is not aware of the loss-hedging benefit. Instead, he regards the insurance as an investment whose payout is not related to harvest loss. Consequently, the farmer only evaluates a payout larger than the purchase price of the investment - i.e., the insurance premium - as a gain. This view of 'insurance as investment' rather than a loss-hedging device is supported by Patt et al. (2009), who report that some farmers are upset if the indemnity payment is less than the premium paid for the insurance. A farmer with further insurance understanding, however, is aware of the loss-hedging benefit. Accordingly, he regards the insurance as a loss-hedging device and exclusively expects an indemnity payment in case of harvest loss. The analyzed reference points capture these two scenarios. We, therefore, suggest that the reference point 'No Insurance Coverage' models the index insurance demand decision of a farmer who is unaware of the loss-hedging benefit that insurance provides, whereas the reference point 'Perfect Insurance Coverage' models the index insurance demand decision of a farmer who is aware of the loss-hedging benefit that insurance provides. We refer to these two types as naïve and insurance-literate farmers.

We can relate our interpretation of the reference points to models that endogenize expectations as the reference point (Kőszegi and Rabin, 2006, 2007; Gottlieb and Mitchell, 2015). These models suggest that if a farmer plans to be covered by an insurance, wealth under insurance coverage serves as the reference point. Farmers who are unaware of the loss-hedging benefit of insurance do most likely not plan to buy the insurance. Accordingly, their reference point should always be the status quo ('No Insurance Coverage'). Among the group of farmers that are aware of the loss-hedging benefit at least the ones with a sufficiently large aversion towards losses (risks) plan to be covered by an insurance that would, in the ideal case, pay out an indemnity whenever a loss occurs. Hence, 'Perfect Insurance Coverage' serves as the reference point for these farmers. We can further relate our interpretation of the reference points to recent work by Schmidt (2016). Several empirical studies suggest that individuals often use risk-free outcomes as the reference point. Transferring this to the insurance context, Schmidt (2016) proposes wealth under full insurance coverage as a reference point. However, if farmers are unaware of the loss-hedging benefit that insurance provides, they do not anticipate that full coverage of an insurance should imply a risk-free outcome. Thus, following the argumentation of Schmidt (2016), only the farmers that are aware of the loss-hedging benefit should use the reference point 'Perfect Insurance Coverage'.

Table 5 summarizes the predictions of our behavioral model and compares them to empirical findings from the literature. Columns (1) and (2) display the predictions, Columns (3) and (4) the empirical findings.

Table 5: Behavioral insurance demand model and empirical findings

	Behavioral Model		Empirical Findings	
	Naïve	Insurance-literate	Naïve	Insurance-literate
	(1)	(2)	(3)	(4)
Basis risk	0	–	0	–
Loss aversion	–	+	n.a.	n.a.

Following our PT model, basis risk is not related to the insurance demand of a naïve farmer, whereas it negatively impacts the insurance demand of an insurance-literate farmer. A recent study by Jensen et al. (2018) supports this prediction. Their results suggest that further understanding of the product considerably increases sensitivity to basis risk. Jensen et al. (2018) further find only very little relationship between basis risk and insurance demand among farmers that were not further educated about the index insurance. Our second prediction addresses the effect of loss aversion on index insurance demand. To the best of our knowledge, no research on the relationship between loss aversion and index insurance demand exists. We, therefore, state our core Hypothesis 2.1:

Hypothesis 2.1. *The impact of loss aversion on index insurance demand varies with the level of insurance understanding. While insurance demand is decreasing with loss aversion among farmers who are unaware of the loss-hedging benefit that insurance provides, it is increasing with loss aversion among farmers who are aware of the loss-hedging benefit that insurance provides.*

3 Empirical support

3.1 Assumptions

To identify the causal relationship between insurance understanding and the effect of loss aversion on index insurance demand, strict assumptions must be met. Understanding should be randomly distributed across a group of otherwise similar farmers. Furthermore, an identical insurance contract should be offered to all farmers at the same point in time. Finally, farmers should participate in choice tasks eliciting loss aversion. We did not conduct our own field experiment. Instead, we make use of the publicly available dataset of the randomized controlled trial (RCT) conducted by Cole et al. (2013) to provide empirical support for our core hypothesis.

Cole et al.'s (2013) field experiments featured real world index insurance take-up decisions for a relevant and representative subject pool. Next to these advantages the set up imposes one major limitation; Cole et al. (2013) did not elicit parameters for loss aversion. We need to impose strict assumptions to interpret farmers' choices in an experimental gamble as indicators of loss aversion. Farmers were asked to choose among lotteries varying in risk and expected return. Following Binswanger (1981), Cole et al. (2013) interpret lottery choices as indicators of risk aversion. As we discuss in Section 3.3, the payouts of the experimental choice task are small relative to farmers' real world income. Thus, lottery choices are not necessarily suitable to elicit risk attitudes (Rabin, 2000). Imposing strict assumptions, we show that lottery choices could also be interpreted as indicators of loss aversion. One might be critical of using lottery choices in Binswanger (1981) choice tasks as indicator of loss aversion. Accordingly, we are cautious to interpret any of our results in a causal manner but, instead, view this approach as a first step to test our core hypothesis. If we gave up our strict assumptions and interpret lottery choices as indicators of risk aversion, our empirical findings would suggest that insurance understanding mitigates the negative effect of risk aversion on index insurance demand. We explain how such a finding can be related to our model in the discussion section of this paper.

In the RCT of Cole et al. (2013), some members of a large group of farmers were randomly assigned to an insurance education module. We split farmers into two groups according to the assignment of the module. We then analyze if the relationship between loss aversion and index insurance demand varies systematically between these two groups. Succinctly put, we use the assignment of the insurance education module as a proxy for a higher likelihood that a randomly drawn farmer is aware of the loss-hedging benefit of insurance. Interpreting the results of this approach as empirical support for our core hypothesis imposes two key assumptions that deserve to be explained in detail. First, the insurance education treatment has an overall positive effect on farmers' awareness of the loss-hedging benefit that insurance provides (A1).[15] Second, the insurance education treatment does

[15]This assumption implicitly requires that a sufficiently large number of farmers is unaware of the loss-hedging benefit before the RCT takes place.

not impact the relationship between loss aversion and insurance demand other than by affecting farmers' awareness of the loss-hedging benefit that insurance provides (A2).

An ideal experiment would require that every farmer is initially unaware of the loss-hedging benefit of insurance and every farmer in the treatment group becomes (due to the education module) aware of the loss-hedging benefit. Each requirement by itself and, particularly, the overlap of both is unlikely to be met in the field. Nevertheless, assumption A1 ensures that the share of farmers that are aware of the loss-hedging benefit is larger in the treatment than in the control group.[16] Accordingly, any differences in outcome variables between the two groups can possibly be attributed to differences in the awareness of the loss-hedging benefit that insurance provides. The same holds for differences in the effect of covariates on outcome variables. However, the insurance education treatment might also impact factors other than awareness of the loss-hedging benefit. The concern is whether we are measuring the true effect of awareness or whether the findings could be driven by other factors, such as the education module causing an increase in the perceived riskiness of farming. To exclusively attribute systematic differences in the effect of loss aversion on insurance demand to differences in awareness of the loss-hedging benefit, assumption A2 must be met. Finally, it is unlikely that every single farmer in the control group is unaware and every single farmer in the treatment group becomes (due to the education module) aware of the loss-hedging benefit of insurance. Thus, an identification based on the random assignment of an insurance education treatment works against us, making us less likely to find statistically significant effects. Accordingly, our analysis most likely provides an underestimate of the true effect of insurance understanding on the relationship between loss aversion and index insurance demand. In the following section, we briefly introduce the RCT of Cole et al. (2013) and discuss the assumptions A1 and A2 for this specific set up.

3.2 Design

In 2006, Cole et al. (2013) conducted different experiments in two rural regions of India, Andhra Pradesh and Gujarat. The setting related to our

[16]This implication requires that the initial share is similar in the control and treatment group. An assumption that is met due to random treatment assignment.

hypothesis is the one in Andhra Pradesh. Out of an entire sample population of 1,053 farmers in this region, Cole et al. (2013) randomly selected 700. These farmers were visited by trained research institute employees and received a small monetary compensation for welcoming the employee; they were further able to buy the insurance policy on the spot. For information regarding contract details we refer to Cole et al. (2013). The authors randomized the content of the visits independently along three dimensions. First, locally trusted people endorsed the employee prior to visits. Second, some farmers received an additional high reward at the time of the visit. Third, and most interesting for us, some farmers received further education about the product.[17] From now on, we refer to these three treatments as Endorsement, High Reward, and Insurance Education. Table 18 in the Appendix provides an overview of group sizes in the different treatments. Additionally, Cole et al. (2013) used surveys to record basic demographic characteristics, risk attitudes and, farmers' decisions on whether to demand insurance. Table 19 in the Appendix provides summary statistics.

Utilizing the Insurance Education treatment for a test of our core hypothesis requires that assumptions A1 and A2 are met. Cole et al. (2013) show that a significant portion of these farmers cannot answer simple financial questions. They further show that the understanding of the core component of the index insurance is low. The insurance pays out an indemnity if the rainfall measured at the closest weather station falls below a certain threshold. The possible payout is set in millimeters of rainfall. However, less than one-quarter of the sample population is familiar with this unit of measurement.[18] Accordingly, the majority of farmers cannot relate insurance payouts to harvest losses. Thus, farmers have only limited understanding of the loss-hedging benefit of the insurance.[19] The Insurance Education treatment was designed in cooperation with the local agricultural university to specifically address this issue. Thus, in-line with Cole et al.'s (2013) interpretation of the treatment, we conclude that it positively

[17] Cole et al. (2013) use the treatments to investigate the effect of first, trust, second, liquidity constraints and third, insurance understanding on insurance demand. Our work replicates the third investigation, but with PT preferences, i.e., by introducing the behavioral bias loss aversion.

[18] According to Cole et al. (2013), the most common measure used in farming in this specific region is depth of soil moisture in the ground. Only 22% of the sample population understand how millimeters of rain translate into depth of soil moisture.

[19] The authors conclude that their set up 'provides prima facie evidence that households have only limited understanding of the product' (Cole et al., 2013, p. 16).

affected the overall understanding of the insurance and, particularly, the awareness of the loss-hedging benefit that insurance provides. Accordingly, assumption A1 is met.

A first concern regarding assumption A2 is that the insurance education module could increase the perceived riskiness of farming. However, the literature agrees that the local population is, independent of any treatments, aware of the riskiness of farming (Giné et al., 2008; Hazell and Hess, 2010; Fisher and Snapp, 2014). Furthermore, it is unlikely that an insurance education module in which farmers learn how millimeters of rainfall translate into depth of soil moisture in the ground is related to the perceived riskiness of farming. A second concern is that the insurance education module could increase trust in the provider. In this case, farmers assigned to the Insurance Education treatment might perceive any product offered during the visit as less risky. It is unlikely that the content of the education module affects trust in the provider. Thus, the only way the Insurance Education treatment could increase trust in the provider would be through personal interaction during the treatment. However, every visited farmer (700 of 1,053) interacted with a research institute employee. To assuage the concern that our results are driven by trust in the provider rather than by awareness of the loss-hedging benefit that insurance provides, we conduct a separate analysis that only includes visited farmers. This approach can be found as a robustness check in a later section of the paper. Furthermore, Cole et al. (2013) conducted the first treatment (Endorsement) to explicitly investigate the impact of trust in the provider. Thus, if trust in the provider would be of importance for the relationship between loss aversion and insurance demand, we should observe systematic differences in the effect of loss aversion for those who did receive the Endorsement treatment and those who did not. As we show in the empirical analysis, this is not the case.

3.3 Specification

Cole et al. (2013) did not elicit loss and risk aversion parameters simultaneously.[20] Instead, within their experiments, each farmer only had to choose one of the six Binswanger (1981) lotteries listed in the first three columns

[20]Simultaneous elicitation of loss and risk aversion parameters is proposed by Tanaka et al. (2010) and, for example, used by Liu (2013) in a different agricultural context.

of Table 6. The payoff of any of these lotteries was determined by the toss of a fair coin.

Table 6: Binswanger lotteries

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Lottery	Heads	Tails	$\mathbb{E}$[Payoff]	Share	Loss (Heads)	Gain (Tails)	$\frac{G_i-G_{i+1}}{L_i-L_{i+1}} \leq \lambda \leq \frac{G_i-G_{i-1}}{L_i-L_{i-1}}$	λ_{main}
(1)	25	25	25	10.3%	0	0	$7 \leq \lambda$	8.5
(2)	20	60	40	25.6%	5	35	$4 \leq \lambda \leq 7$	5.5
(3)	15	80	47.5	18.0%	10	55	$3 \leq \lambda \leq 4$	3.5
(4)	10	95	52.5	25.3%	15	70	$2 \leq \lambda \leq 3$	2.5
(5)	5	105	55	11.0%	20	80	$1 \leq \lambda \leq 2$	1.5
(6)	0	110	55	9.9%	25	85	$\lambda \leq 1$	1

Following Binswanger (1981), Cole et al. (2013) interpret farmers' choices as indicators of risk aversion. The payoffs of the choice task range between Rs. $0-110$ whereas farmers' mean yearly income is Rs. $57,991$ and farmers' median yearly income is Rs. $34,116$.[21] Thus, the payouts of the experimental choice task are small relative to farmers' real world income.[22] Accordingly, lottery choices only reflect risk aversion if farmers are assumed to evaluate the possible experimental income in isolation from their lifetime income (Rabin, 2000). This assumption is not necessarily met (for a discussion we refer to Harrison et al., 2007; Heinemann, 2008). Following other experimental studies (Fehr and Goette, 2007; Gächter et al., 2007; Karle et al., 2015; Beshears et al., 2017), we assume that farmers integrate the potential income from the choice task with their lifetime income. According to Rabin's (2000) calibration theorem, this essentially implies that farmers must be risk neutral for low-stake gambles. The intuition for this is, as Fehr and Goette (2007) explain, that risk averse behavior for low-stake gambles would imply absurd degrees of risk aversion in medium- and high-stake gambles.

Under Expected Utility, risk neutrality implies that farmers should choose the lotteries with the largest expected payoffs (Lottery (5) or Lottery (6); see Column (4) of Table 6). If we observe lottery choices that are not consis-

[21]The differences between mean and median are driven by significant income differences between agricultural laborers and skilled, respectively landed farmers (Cole et al., 2013). Given these values, the maximum income from the choice task amounts to 2.3% ($= 12 \cdot 110/57{,}991$) of the average monthly income. Hence, stakes are much smaller than in the high-stake decision task of Binswanger (1981) with stakes amounting to a month's average income.

[22]We thank an anonymous referee for suggesting a comparison between the experimental income and farmers' real worlds income.

tent with this predictions, then this might indicate loss aversion (Fehr and Goette, 2007; Gächter et al., 2007). Only 20.9% (= 11.0% + 9.9%) of the sample population choose the lotteries with the largest expected payoff (see Column (5) of Table 6). 10.3% even choose Lottery (1), the lottery with the lowest expected payoff.

In the Binswanger (1981) choice set, Lottery (1) is risk-free. Harrison and Rutström (2008) argue that this certain amount may provide a natural reference point for subjects to identify gains and losses, which, in turn, might frame choices in a manner that is sign dependent.[23] We follow this argument and contemplate the possibility that farmers' choices indicate loss aversion. Accordingly, we encode all possible lottery outcomes as either gains or losses with respect to the reference point of the certain amount of 25. For instance, an outcome of 20 in Lottery (2) is encoded to a loss of 5 (= 20 − 25). Losses and gains are displayed in Column (6) and (7) of Table 6.

Similar to the procedure of Gächter et al. (2007) and Fehr and Goette (2007), we can then determine loss aversion in the risky choice task by applying PT. Neglecting probability weighting and assuming risk neutrality, the PT Value of Lottery (i) is given by $V_i = 0.5 \cdot G_i - \lambda \cdot 0.5 \cdot L_i$, where G_i and L_i denote the gain and the loss associated with Lottery (i); and λ denotes the parameter of loss aversion.[24] A farmer chooses Lottery (i) if its PT Value V_i is at least as large as the PT Value of the five other lotteries. Thus, $V_i \geq V_j \ \forall j \neq i$ has to hold. Inserting the PT Value and rearranging leads to $0.5 \cdot (G_i - G_j) \geq \lambda \cdot 0.5 \cdot (L_i - L_j) \ \forall j \neq i$. In Part B.2 of the Appendix, we show that these conditions impose a lower and upper bound for the loss aversion parameter. The bounds depend on the possible gains and losses associated with Lottery (i) and its two neighboring Lotteries ($i - 1$) and ($i + 1$). Farmers' choices of Lottery (i) require a loss aversion parameter λ such that $\frac{G_i - G_{i+1}}{L_i - L_{i+1}} \leq \lambda \leq \frac{G_i - G_{i-1}}{L_i - L_{i-1}}$ holds. The first and last lottery only have one neighboring lottery. Thus, we can only derive

[23] This argument is supported by empirical findings showing that subjects faced with a choice task do not use the status quo as the reference point, but, instead use the risk-free option and evaluate the outcomes of the other options relative to this reference point (Hershey and Schoemaker, 1985; Robinson et al., 2001; Bleichrodt et al., 2001).

[24] We neglect probability weighting to ensure that the assumptions imposed to derive the loss aversion measure coincide with the assumptions of the model section. As we show in Part B.2 of the Appendix, the assumption can be relaxed and it is sufficient to assume that subjects weight a 0.5-chance for gaining or losing equally ($\pi^{+}(0.5) = \pi^{-}(0.5)$). This assumption is, for instance, fulfilled by the probability weighting function proposed by Prelec et al. (1998).

one interval bound. Column (8) of Table 6 displays the parameter intervals associated with farmers' choices in the Binswanger (1981) choice task.[25]

As the loss aversion parameter cannot be uniquely inferred, we impose the following values for the main regression analysis (see Column (9) of Table 6). For Lottery (2) to Lottery (5), we use intervals' midpoints. For Lottery (6), we impose the value $\lambda = 1$ to ensure that subjects are not assumed to be loss-seeking.[26] Regarding Lottery (1), we note that the distances between our imposed values and the lower interval bounds are 1.5 (= 5.5 – 4) for Lottery (2), and 0.5 for Lotteries (3), (4) and (5). The distance can not be calculated for Lottery (6). However, arguing that farmers are unlikely to be loss seeking, the lower bound would be 1 which would imply that the distance is 0. The sequence of distances is weakly decreasing. To ensure that Lottery (1) fits into this sequence, we impose the value $\lambda = 8.5$ (= 7 (lower bound) + 1.5 (maximum distance)). Using these values, the mean loss aversion parameter is $\lambda = 3.8$ and the median is $\lambda = 3.5$. In line with PT preferences estimated in other developing countries (Liu, 2013; Holden and Quiggin, 2017), this value is larger than the one estimated by Kahneman and Tversky (1979) in student experiments. As we discuss in the robustness section, the regression results are not driven by these specific parameter choices but are robust to several redefinitions.[27]

Our main analysis closely follows the empirical strategy of Cole et al. (2013). Each household is one observation. Cole et al. (2013) only report choices within the Binswanger (1981) lotteries for 941 out of 1,053 farmers. Thus, the sample size reduces from 1,053 to 941. Because the assignment of the three treatments is random, the empirical specification is straight-

[25]Deriving the measure of loss aversion, we assume that farmers are risk neutral for low-stake gambles. In contrast to the income from the experimental gamble, the income from farming as well as the size of possible losses due to droughts is large (Cole et al., 2017; Jayachandran, 2006). Thus, the decision to insure can be regarded as a high-stake decision. Accordingly, assuming that farmers are risk neutral for low-stake gambles does not necessarily imply that farmers are risk neutral when making the insurance purchase decision. Our predictions addressing the impact of loss aversion on index insurance demand hold under risk neutrality, i.e., $\alpha = 1$, as well as under risk aversion, i.e., $\alpha \leq 1$. Thus, even if one would argue that our assumption should imply risk-neutrality for the insurance demand decision our model predictions would remain unchanged.

[26]According to our loss aversion measure, a small share of the sample is not loss averse (Lottery (6); 9.9%). This observation is in line with other studies eliciting PT preferences (Gächter et al., 2007; Liu, 2013).

[27]In one of the robustness checks, for example, we follow the procedure of Gächter et al. (2007) and impose upper interval bounds. However, lottery choices do not imply an upper bound for Lottery (1). Thus, we still need to impose one additional value.

forward.[28] For the entire sample we estimate a linear probability model of household insurance demand as a function of the treatment variables and household level controls. In contrast to Cole et al. (2013), our main interest is the link between loss aversion and insurance demand across groups with varying levels of insurance understanding. Accordingly, we add an interaction term of loss aversion with the binary indicator for participation in the randomized Insurance Education treatment. Finally, we include interaction terms of loss aversion with dummy variables for the other two treatments and village fixed effects to control for multiple treatment effects and unobserved village specific characteristics. Hence, our model to be estimated equals:

$$\begin{aligned} Y_{i,v} = \alpha \cdot \lambda_i + \beta_1 \cdot V_i + \beta_2 \cdot T_{1,i} + \beta_3 \cdot T_{2,i} + \beta_4 \cdot T_{3,i} + \beta_5 \cdot \lambda_i \times T_{1,i} \\ + \beta_6 \cdot \lambda_i \times T_{2,i} + \gamma \cdot \lambda_i \times T_{3,i} + \beta_X \cdot X_i + f_v + \varepsilon_i. \end{aligned} \tag{4}$$

As in Cole et al. (2013), our dependent variable Y is a dummy that is one, if farmer i in village v demands at least one insurance contract. Loss aversion is depicted by λ. V is a dummy variable indicating whether visits took place. T_1, T_2 and T_3 are dummy variables for the Endorsement, High Reward and Insurance Education treatments. X equals a vector of the same household level controls as used by Cole et al. (2013).[29] Finally, f_v denotes village fixed effects. A negative estimate of α and a positive estimate of γ with a magnitude larger than α would provide empirical support for our core Hypothesis 2.1.

[28] To test the successful randomization of the Insurance Education treatment, Table 19 in the Appendix presents summary statistics for the whole sample and two subsamples created based on the dummy variable for the Insurance Education treatment. T-tests of covariate means do not invalidate the assumption of random treatment allocation.

[29] These are: percentage of cultivated land that is irrigated; above average expected monsoon rain (normalized); whether the household demanded weather insurance in 2004; insurance skills (normalized); whether the household has other insurance; whether the household does not know the provider BASIX; whether the household belongs to a water user group (either a borowell users association or water user group); the number of community groups that the household belongs to and indicator variables for whether the household belongs to a scheduled caste/tribe; whether the household is muslim; gender, log household age and log household size; dummy for secondary education status; interaction whether endorsements occurred in the village and whether the individual household was visited, to identify local spillovers from endorsement.

3.4 Results

Table 7 presents take-up rates of different loss aversion cohorts in the subsamples of farmers who did not (No Education) and who did receive the Insurance Education treatment (Education).

Table 7: Take-up rates of different loss aversion cohorts

	Loss aversion	≤ 1	1-2	2-3	3-4	4-7	≥ 7
No Education	Take-up rate	43.1%	33.8%	22.87%	20%	18.18%	17.39%
	Observations	58	71	153	110	165	69
Education	Take-up rate	40%	43.75%	47.06%	42.37%	44.73%	32.14%
	Observations	35	32	85	59	76	28

Among the farmers who did not receive the Insurance Education treatment, loss aversion seems to be negatively related to the take-up rate. Among the farmers who did receive the Insurance Education treatment, the negative relationship vanishes.

Table 8 presents our regression results.[30] Within the different specifications, we sequentially add further variables. In Specification (1), we regress insurance demand only on a dummy variable for visits, the three treatment dummies and the loss aversion parameter. Specification (2) adds village fixed effects. In Specification (3), we include the interaction term of loss aversion with the Insurance Education treatment dummy. Specification (4) further adds household level controls. Finally, by additionally including interaction terms between loss aversion and the other two treatment dummies, Specification (5) represents our main model equation (4).

Across all five specifications, the coefficients of the Visit dummy and the dummies for the treatments High Reward and Endorsement are qualitatively and quantitatively similar to the results of Cole et al. (2013).[31] Furthermore, the coefficient of loss aversion is negative and significant in Specification (1). The effect vanishes after adding village fixed effects in Specification

[30] Table 8 simplifies the regression concentrating on treatments, loss aversion and interaction terms. The complete regression output is presented in Table 20 of the Appendix. In the estimated OLS regressions, we use the loss aversion parameters displayed in Column (9) of Table 6.

[31] Being assigned to a household visit alone increases insurance demand by 14.6 percentage points in specification (5) to 19.3 percentage points in Specification (1). A high reward increases insurance demand by 26.9 percentage points in Specification (5) to 38.1 percentage points in Specification (3). The effect of the Endorsement treatment varies between 6.0 percentage points in Specification (1) and 11.3 percentage points in Specification (5).

Table 8: Determinants of insurance demand

	Dependent variable:				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.012**	−0.007	−0.016**	−0.012*	−0.016**
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)
Loss Aversion × Insurance Education (1 =Yes)			0.029**	0.029**	0.026**
			(0.012)	(0.012)	(0.012)
Visit (1 =Yes)	0.193***	0.192***	0.190***	0.146***	0.146***
	(0.036)	(0.035)	(0.035)	(0.050)	(0.050)
Endorsement (1 =Yes)	0.060*	0.080**	0.078**	0.060	0.113*
	(0.033)	(0.035)	(0.035)	(0.036)	(0.063)
High Reward (1 =Yes)	0.381***	0.376***	0.381***	0.375***	0.269***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.056)
Insurance Education (1 =Yes)	−0.006	−0.011	−0.117**	−0.113**	−0.099*
	(0.031)	(0.030)	(0.054)	(0.054)	(0.055)
Loss Aversion × Endorsement (1 =Yes)					−0.013
					(0.014)
Loss Aversion × High Reward (1 =Yes)					0.029**
					(0.013)
Constant	0.090***				
	(0.032)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Household Controls	No	No	No	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R^2	0.280	0.356	0.360	0.387	0.391
Adjusted R^2	0.276	0.327	0.330	0.347	0.350
Residual Std. Error	0.391	0.377	0.376	0.371	0.370

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

(2). When interacting the loss aversion parameter with the dummy for the Insurance Education treatment in Specifications (3) and (4), where the latter controls for farmer characteristics, we estimate a significant negative effect of loss aversion and a significant positive effect of its interaction with the Insurance Education treatment dummy. More precisely, given an increase in loss aversion by one standard deviation (sd = 2.195, see Table 19) the likelihood to demand at least one insurance contract decreases by 2.6 (= 2.195×-0.012) percentage points in Specification (4) to 3.5 (= 2.195×-0.016) percentage points in Specification (3). However, for farmers assigned to the Insurance Education treatment, the same change results in an increase by 2.9 (= $2.195 \times (-0.016+0.029)$) percentage points in Specification (3) to 3.7 (= $2.195 \times (-0.012+0.029)$) percentage points in Specification (4). The effects remain stable if we add interaction terms of the other two treatment dummies with loss aversion in Specification (5). According to the summary statistics in Table 19 of the Appendix, the mean take-up rate is 30.2% within the entire sample, 43.2% within the subsample of farmers who received the Education treatment and 23.6% within the subsample of farmers who did not receive the Education treatment. Thus, the effects have a meaningful magnitude. Hence, the empirical findings support our core Hypothesis 2.1.

The empirical analysis further points out two aspects beyond the core hypothesis. First, the findings of Specification (5) suggest that the effect of the High Reward treatment on insurance demand is increasing with loss aversion. Following Cole et al. (2013), the high reward could be regarded as a tool to overcome liquidity constraints. In this sense, the reward is a high subsidy. Accordingly, farmers with a larger aversion towards losses react more sensitively to a high subsidy than the other farmers. This finding provides suggestive evidence for our Proposition 2.2 which predicts minimum subsidy requirements for farmers who are unaware of the loss-hedging benefit of insurance to increase with loss aversion.[32]

Second, the empirical findings of Specification (3), (4) and (5) suggest that the effect of the Insurance Education treatment is also heterogeneous

[32] The interaction term Loss Aversion × High Reward (1=Yes) is estimated within the entire sample. Thus, for this explanation to hold, the overall awareness of the loss-hedging benefit that insurance provides has to be low. As discussed earlier, this is, indeed, the case. Splitting the sample in farmers who received and who did not receive the Insurance Education treatment, we show that the heterogeneous effect is actually driven by the ones who are, on average, less likely to be aware of the loss-hedging benefit that insurance provides (see Table 21 and Table 22 in the Appendix).

in loss aversion. In particular, the Insurance Education treatment only positively impacts the insurance demand of farmers with an above median aversion towards losses.[33] There are two potential resolutions for this puzzling finding.[34] The first resolution relates to the preferred personal equilibrium approach (Kőszegi and Rabin, 2006, 2007) that endogenizes expectations as the reference point. Consistent with this approach, it could be the case that out of the farmers who received insurance education only the ones with a high aversion towards losses plan to buy it. Thus, these farmers would use the reference point wealth with insurance coverage, whereas the others (farmers with a smaller aversion towards losses) would use the reference point wealth without insurance coverage. The shift in the reference point may, as also suggested in the conclusion of Gottlieb and Mitchell (2015) for a general insurance context, explain the divergence in preferences.[35] The second resolution suggests that the empirical finding might reflect a strategic consideration of those receiving insurance education. Farmers learn that they should only buy insurance if their aversion towards losses exceeds a threshold. Accordingly, only the farmers with a high aversion towards losses decide to buy the insurance.[36]

3.5 Robustness

Besley and Case (1993) argue that with cross-sectional data any ex post measures of covariates could be affected by previous adoption decisions and are, therefore, endogenous. Although farmers in our sample make their insurance demand decision at the same time the survey is conducted, previous insurance demand might be regarded as a possible source of endogeneity. We replicate our regressions on a subsample of farmers that did not demand any

[33] The impact of the Insurance Education treatment is negative for $-0.117 + \lambda \cdot 0.029 < 0$. This is equivalent to $\lambda < 4.0$. In Specification (4) and (5) the impact is negative for loss aversion parameters below 3.9 (0.113/0.029) and 3.8 (0.099/0.026) respectively. The median loss aversion in the sample is 3.5. The observation that the Education treatment does not have an overall positive effect on insurance demand is in-line with the findings of Cole et al. (2013).

[34] We thank an anonymous referee for suggesting these two resolutions.

[35] Gottlieb and Mitchell (2015) suggest that the same subject might have different reference points in different insurance markets. Consistent with the models of (Kőszegi and Rabin, 2006, 2007), they suggest that the shift in reference point could be induced through the effect of framing.

[36] For this resolution to hold we need to assume that farmers who do not receive insurance education are confused about the product and, therefore, do not follow a systematic buying strategy.

insurance in the previous period. As presented in Table 23 of the Appendix, the same qualitative results as in Table 8 are observable.

Our sample includes visited as well as non-visited farmers. We replicate our main analysis on the sample of visited farmers for two different reasons. First, as discussed earlier, one could argue that the personal interaction included in the Insurance Education treatment increases trust in the provider, which, in turn, could impact the relationship between loss aversion and insurance demand.[37] Replicating the main analysis on the sample of visited farmers ensures that every farmer interacted with a research institute employee. Accordingly, the level of trust induced through personal interaction should not vary within the sample. Second, one could argue that although the visited farmers were chosen randomly, this group is not comparable to the group of non-visited farmers. Visited farmers were able to demand the insurance policy on the spot, higher effort was required by the non-visited ones. These farmers could only buy the insurance at local branches. Furthermore, the three treatments were independently randomized among the visited. Thus, multiple treatments were possible. Accordingly, a farmer assigned to the Insurance Education treatment is, by construction of the experiment, more likely to receive a second treatment than a farmer that is not visited. Table 24 in the Appendix displays the results of our main empirical analysis on the sample of visited farmers. The estimates and their significance levels remain stable.

According to our main specification, the impact of the Insurance Education treatment as well as the High Reward treatment is increasing with loss aversion. Furthermore, as already discussed, the analyzed setting features multiple treatments. To verify that the estimated joint impact of loss aversion and the Insurance Education treatment is not driven by a spillover effect of the High Reward treatment, we replicate our analysis on the subsample of farmers that did not receive the High Reward treatment. The estimates presented in Table 25 of the Appendix are quantitatively similar to the ones of our main regression Table 8.

[37]In Specification (5) of our main analysis, we do not observe systematic differences in the relationship between loss aversion and insurance demand among farmers who were assigned to Endorsement treatment and farmers who were not. This already suggests that trust is not of major importance for the relationship between loss aversion and insurance demand.

Our measure of loss aversion suggests that farmers' choices in the Binswanger (1981) choice task impose a lower and upper bound for the loss aversion parameter. However, we need to impose fixed values for the regression analysis. The values used for the main analysis are displayed in Column (9) of Table 6. Our choice for Lottery (1) might seem particularly arbitrary.[38] To overcome the concern that our results are driven by this specific choice, we repeat our main analysis with varying value choices for Lottery (1). We use $\lambda = 7.5$ (= 7 (lower bound) + 0.5 (minimum distance between lower bounds and imposed values)) and $\lambda = 7.75$ (= 7 (lower bound) + 0.75 (mean distance between lower bounds and imposed values)). As displayed in Tables 26 and 27 of the Appendix, our estimates and their significance levels remain stable.

We additionally follow the approach of Gächter et al. (2007) and impose upper interval bounds. However, the lottery choices do not imply an upper bound for Lottery (1). We, thus, conduct different analysis with varying value choices for Lottery (1). We use $\lambda = 8$ (= 7 (lower bound) + 1 (minimum distance between lower and upper bound)), $\lambda = 8.5$ (= 7 (lower bound) + 1.5 (mean distance between lower and upper bound)) and $\lambda = 10$ (= 7 (lower bound) + 3 (maximum distance between lower and upper bound)). The estimates presented in Table 28, 29 and 30 of the Appendix are quantitatively similar to the ones of our main regression Table 8. We further run one set of regressions in which we use ordinal indicators. We assign the indicators in increasing order meaning that we assign the Lottery (6) whose choice requires the smallest aversion towards losses the indicator 1. The advantage of this method is that we do not need to impose any specific values. As displayed in Table 31 of the Appendix, the loss aversion coefficient remains negative and statistically significant and the interaction term positive and statistically significant.

We also replicate Specification (3) to (5) of Table 8 without village fixed effects. Again, as presented in Table 32 in the Appendix, our findings remain robust.

Finally, regarding the econometric part, estimating a discrete choice model using OLS comes at some costs. We replicate our main analysis using probit regressions. As presented in Table 33 of the Appendix, the sign

[38] We used interval midpoints for Lottery (2) to Lottery (5). For Lottery (6) we used the value $\lambda = 1$ to ensure that farmers are not assumed to be loss seeking.

of the estimates are the same as the ones of our main regression and also the significance levels remain stable.

4 Discussion

We have made a number of specific modeling choices for the sake of clarity, many of which could be revisited or relaxed. The model is built on the simplifying assumption that farmers gain utility over final wealth. In Part A of the Online Appendix, we extend the model by integrating the same two reference points in the intertemporal index insurance demand model of Carter et al. (2014). The extension does not change the model predictions.

Our core model assumption is that the level of insurance understanding is the only determinant of the reference point. We, therefore, neglect any other aspects that might impact the reference point formation, such as the importance of salient memories (Schwartzstein, 2014).[39] Furthermore, against traditional definition but in line with recent developments (Kőszegi and Rabin, 2006; Schmidt et al., 2008; De Giorgi and Post, 2011; Gottlieb and Mitchell, 2015), farmers' reference points are assumed to be endogenous and state dependent. We suggest that insurance-literate farmers are aware of the loss-hedging benefit of insurance and, therefore, only expect an indemnity payment if a loss occurs. Accordingly, we assume that these farmers use the reference point wealth with coverage of an insurance that pays out and indemnity whenever a loss occurs ('Perfect Insurance Coverage'). With similar reasoning, one could argue that insurance-literate farmers may use the reference point wealth with index insurance coverage. These farmers are also aware of the loss-hedging benefit of insurance. Thus, they do not regard the insurance as an investment. Given the overall benefits of the index insurance, these farmers even accept the rare occurrences in which a harvest loss does not trigger an indemnity payment. Thus, in contrast to the reference point 'Perfect Insurance Coverage', these farmers do not evaluate the downside basis risk scenario as a subjective loss. We analyze the choice of the reference point wealth under index insurance coverage in Part C of

[39] Salient memories are of particular interest in the index insurance context because it is very likely to believe that the attitudes towards the insurance of farmers who bought an insurance but suffered from basis risk change dramatically. For a further discussion of reference point formation within financial decision making we refer Baucells et al. (2011).

the Appendix. In-line with the predictions for the reference point 'Perfect Insurance Coverage' demand increases with loss aversion.

Our behavioral model analyzes the demand for an insurance that might not pay out in the case of loss but might also pay out in the case of no loss. This is a particular feature of an index insurance. In a broader insurance context, it could be interesting to analyze the impact of loss aversion on the demand for an insurance that might not pay out in the case of loss but never pays out in case of no loss. This is often referred to as contract non-performance (Biener et al., 2017). Using the same reference points as in our main model, Part D in the Appendix shows that in such a scenario the predictions regarding the impact of loss aversion on insurance demand remain unchanged.

We use the dataset of the field experiments conducted by Cole et al. (2013) to test our core hypothesis. The drawback of this approach is that Cole et al. (2013) did not elicit parameters for loss aversion. As discussed in detail in Section 3.3, we have to impose strict assumptions to interpret choices in the Binswanger (1981) choice task as indicators of loss aversion. Most importantly, we have to assume that farmers integrate the potential experimental income with their lifetime income. Combining this assumption with the observation that the experimental income is relatively small compared to real world income implies that farmers would have to be risk neutral when choosing a lottery (Rabin, 2000). Although the assumption that subjects integrate experimental income with lifetime income is not uncommon (see for example Fehr and Goette, 2007; Gächter et al., 2007; Dupas and Robinson, 2013; Karle et al., 2015; Beshears et al., 2017), the implication of risk-neutrality runs counter to the classical interpretation of the Binswanger (1981) choice task. If we give up the assumption that farmers integrate the experimental income with lifetime income and interpret lottery choices as indicators of risk aversion, our empirical findings suggest that insurance understanding mitigates the negative effect of risk aversion on index insurance demand.[40] The analysis in Part E of the Appendix shows that index insurance demand is decreasing with risk aversion for the reference point 'No Insurance Coverage' and increasing with risk aversion for the reference point 'Perfect Insurance Coverage'. Accordingly, the empirical findings are

[40] Cole et al. (2013) map lottery choices into an index between 0 and 1, where large values indicate higher degrees of risk aversion. We have replicated our regressions analysis with these risk aversion parameters. Results are displayed in Table 34 of the Appendix.

also consistent with the predicted relationship between risk aversion and index insurance demand.

We can even derive the same predictions in a model without any reference point. One possibility to set up such a model would be to assume that insurance understanding affects farmers' perception of the correlation between insurances' net transfer and farmers' net loss. Farmers without further understanding of the insurance regard the insurance as a gamble and, therefore, perceive the correlation to be weak, or, in the extreme case, equal to zero (no correlation). According to the model of Clarke (2016), insurance demand would decrease with risk aversion. In contrast, farmers who are aware of the risk-hedging benefit of an insurance perceive the correlation to be strong or, in the extreme case, equal to one (perfect correlation). Given a sufficiently large perceived correlation, insurance demand increases with risk aversion (Clarke, 2016).[41]

In line with our model, we suggest that both, aversion towards risks as well as aversion towards losses, combined with the low level of insurance understanding offer reasonable explanations for the low take-up rates of index insurance products. The empirical set up of Cole et al. (2013) does not allow us to disentangle loss from risk aversion. Accordingly, we can not separate the effect of loss aversion from that of risk aversion. However, we believe that our findings are a relevant and important first support for our core hypothesis.[42]

5 Conclusion and policy implications

This paper studies the impact of loss aversion on index insurance demand. We extend existing Prospect Theory insurance demand models (Gottlieb and Mitchell, 2015; Hwang, 2016; Schmidt, 2016) by including basis risk. Choosing two different reference points, we attempt to capture different levels of insurance understanding and, therefore, different levels of awareness of the loss-hedging benefit that insurance provides. According to our model, the impact of loss aversion on index insurance demand is heterogeneous

[41] For the case of perfect correlation, classical insurance demand models (Carter et al., 2014; Sarris, 2002) also predict a positive relationship between insurance demand and risk aversion.

[42] Even if one argues that the lotteries can only be used to proxy risk attitudes, the results of Goldstein et al. (2008) who estimate a positive correlation between risk and loss aversion equal to 0.64 support a strong connection between risk and loss attitudes.

in insurance understanding. The index insurance demand of farmers who are unaware of the loss-hedging benefit of index insurance is predicted to decrease with loss aversion, whereas the effect is the opposite for farmers who are aware of the loss-hedging benefit. Furthermore, our model predicts that farmers who are unaware of the loss-hedging benefit of insurance and have median PT parameters reject an even highly subsidized index insurance offer.

We employ the dataset of Cole et al. (2013) who conducted field experiments in rural regions of India in 2006. In one of three treatments, Cole et al. (2013) randomly assigned insurance education modules to 350 out of 1053 farmers. We use this treatment as an exogenous variation in farmers' level of insurance understanding and, therefore, awareness of the loss-hedging benefit that insurance provides. The experimental setting ensures that both groups were exposed to similar institutions and economic conditions. Furthermore, identical index insurance contracts were offered to all farmers. Our findings support our model conjecture that insurance understanding mitigates the negative effect of loss aversion on index insurance demand. The findings are robust to several model specifications that include varying sets of household-level and village-level controls as well as varying methodological approaches. The drawback of this set-up is that Cole et al. (2013) did not elicit loss aversion. We need to impose strict assumptions to interpret lottery choices in the Binswanger (1981) choice task - a task that is usually applied to elicit risk aversion - as indicators of loss aversion. Having said this, our findings could also be read as insurance understanding mitigating the negative effect of risk aversion on index insurance demand. The empirical set up of Cole et al. (2013) does not allow us to separate the effect of loss aversion from that of risk aversion. Accordingly, further experiments need to be conducted to find out if the low index insurance take-up rates are related to a lack of insurance understanding combined with risk aversion, loss aversion or, what we believe is most likely, a combination of risk and loss aversion.

Our analysis provides a case-study for how differences in technology understanding can systematically impact the effect of loss aversion on technology adoption. The results support previous findings on the individual effect of loss aversion (Liu, 2013) and product understanding (Emerick et al., 2016) on technology adoption and extend this literature by analyzing the joint impact of these two factors in a specific scenario.

As droughts are one of the main risks faced by the poor in developing countries, the low adoption rates of formal agricultural insurance have received considerable attention among policy makers in recent years. The theoretical and empirical findings of our study are especially relevant for addressing two puzzles in this context. First, we offer an explanation for the low take-up rates of even highly subsidized insurance: lack of product understanding. According to our model, farmers who are unaware of the loss-hedging benefit of insurance do not even buy a highly subsidized insurance offered at a price equal to 50% of its actuarially fair value. Therefore, as long as farmers do not understand the product, moderately subsidizing the insurance should not be regarded as an effective tool to significantly increase the insurance demand.

Still, investments in insurance education have been made by the public and private sector with many organizations implementing insurance education initiatives on a region-wide scale. Thus, and second, the findings of our study may help to resolve the puzzle why many of these programs were either only partially successful or not successful at all. Our results suggest that policy makers should, in the ideal case, carefully assess individual preferences among their target population before they administer insurance education initiatives. In our context, for example, educators should be aware that the impact of their modules varies significantly with differences in individuals' loss aversion. Furthermore, the basis risk negatively impacts the insurance demand of farmers who understand the insurance. In this case, the deviation of the indemnity payment from the actual loss needs to be reduced, i.e., the quality of the index insurance needs to be improved. Finally, due to hedonic editing as proposed by PT, the index insurance indemnity payments should become more frequent to increase its attractiveness.

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A Online Appendix: Intertemporal models

This section models farmers decision on adopting a new technology: index insurance. The time horizon is two periods, $t = 1, 2$. Each period's consumption $c(\cdot)$ is a function of the exogenous but stochastic income Y_t and possible insurance indemnity payments. Let $\bar{c}$ stand for the permanent consumption that is assumed to be the same in both periods.[43] Furthermore, $\gamma \in [0, 1]$ is the smoothing parameter that depends on several farmers' characteristics. Finally, according to Deaton (1992), the consumption of a farmer who is limited in his ability to smooth consumption can be approximated by:[44]

$$c(Y_t) = \bar{c} + \gamma(Y_t - \mathbb{E}[Y_t]).$$

In the first period the farmer can demand the index insurance for a premium Π. In the second period, the insured farmer receives an indemnity payment Z if the index conditions are fulfilled. Furthermore, outcomes of the second period are discounted. According to recent experimental findings, the discount factor applied by farmers is low. Therefore, we distinguish between the farmer's discount factor δ_f and the market discount factor δ_m and impose the condition $\delta_f < \delta_m$.

In contrast to Carter et al. (2014), we assume that farmers do not obey asset integration. Instead, they evaluate monetary outcomes in terms of gains and losses with respect to some reference point. According to PT, a farmer's value function equals

$$v_t(x) = \begin{cases} (x - r_t)^{\alpha} & , \text{if} \quad x \geq r_t \\ -\lambda(r_t - x)^{\beta} & , \text{if} \quad x < r_t. \end{cases} \tag{5}$$

r_t is the reference point at time t, α the coefficient of diminishing marginal sensitivity for gains, β the coefficient of diminishing marginal sensitivity for losses and λ the coefficient of loss aversion. Given these model assumptions,

[43]This assumption is reasonable because the time horizon between purchasing the index insurance and possibly receiving a payout is short. As a result, basic consumption needs should not change dramatically.

[44]For a farmer with perfect smoothing ability, the consumption in period t is expected to be independent of current resources. This is the case for $\gamma = 0$. If the smoothing parameter takes its maximum value, i.e., $\gamma = 1$, no smoothing is possible and current consumption moves exactly as current income.

a farmer is indifferent between demanding and rejecting the insurance, iff

$$v_1[c(Y_1 - \Pi)] + \delta_f \mathbb{E}[v_2[c(Y_2 + Z)]] = v_1[c(Y_1)] + \delta_f \mathbb{E}[v_2[c(Y_2)]]. \quad (6)$$

The premium Π that solves this implicit equation equals the farmer's (maximum) willingness to pay (WTP). We use equation (6) to predict how PT preferences impact farmers' WTP within the choice of different reference points. In particular, we distinguish between two groups: farmers with and without a deeper understanding of the insurance. We refer to these as *educated farmers* and *naive farmers*. We assume that naive farmers are not aware of insurance's loss-hedging benefit. Instead, they regard the index insurance as an uncertain investment. A natural reference point to compare the payoffs of an investment to, is the case of not investing at all. Thus, we chose the case of not investing as an naive farmer's reference point and refer to it as *No Insurance Coverage*. Consequently, compared to this reference point, any insurance indemnity payment equals a subjective gain. Furthermore, within this scenario farmers neglect basis risk.[45]

In contrast, educated farmers are aware of insurance's loss-hedging benefit. In particular, they expect a full indemnity payment in case of crop failure. Thus, they regard any indemnity payment below the actual value of crop failure as a loss. A natural reference point to model this situation is a *Perfect Insurance*.[46] Due to the possible deviation of the index insurance from a perfect insurance, this scenario includes basis risk.

A.1 Reference point: No insurance coverage

A naive farmer's reference point in each period is the income without insurance coverage. Hence, the reference points for $t = 1$ and $t = 2$ are:

$$r_1 = c(Y_1) = \bar{c} + \gamma(Y_1 - \mathbb{E}[Y_1]) = \bar{c} + \gamma \triangle Y_1,$$
$$r_2 = c(Y_2) = \bar{c} + \gamma(Y_2 - \mathbb{E}[Y_2]) = \bar{c} + \gamma \triangle Y_2.$$

[45]Farmer without insurance coverage do not receive any indemnity payment in case of crop failure. Thus, a possible non-performance of the index insurance in case of crop failure is not evaluated as a loss.

[46]By perfect insurance we refer to an insurance whose indemnity payment always equals the actual value of crop failure.

According to PT, the possible outcomes of equation (6) have to be encoded with respect to these reference points.

Table 9: Coding of outcomes relative to no insurance coverage

		$t=1$				$t=2$		
insurance	$c(Y_1-\Pi)$	$-r_1$	$=$	$-\gamma\Pi<0$	$c(Y_2+Z)$	$-r_2$	$=$	γZ
no insurance	$c(Y_1)$	$-r_1$	$=$	0	$c(Y_2)$	$-r_2$	$=$	0

As Table 9 shows, if an naive farmer rejects insurance, the outcomes correspond to the reference points. As a result, the farmer neither experiences a gain nor a loss. If he, instead, demands the insurance, the premium is considered a loss and the possible payout of the insurance a gain. Due to the nature of the consumption function, these outcomes are multiplied by the smoothing factor γ. Using the value function (5) and the coded outcomes, the equation (6) for the WTP becomes

$$-\lambda(\gamma\Pi)^{\beta}+\delta_f\gamma^{\alpha}\mathbb{E}[Z^{\alpha}]=0.$$

Therefore, a farmer will demand the insurance, if

$$\Pi\leq\left(\frac{\delta_f}{\lambda}\cdot\gamma^{\alpha-\beta}\mathbb{E}[Z^{\alpha}]\right)^{1/\beta}. \tag{7}$$

Based on equation (7), the following proposition summarizes the predictions for naive farmers.

Proposition A.1 (WTP of naive farmers under Prospect Theory)**.** *Given the reference point 'No insurance coverage', naive farmers' WTP is:*

1. *increasing with the discount factor.*
2. *increasing with the expected subjective valuation of indemnity payments.*
3. *independent of the basis risk.*
4. *decreasing in loss aversion.*

Proof: *Appendix A.5.1.*

In order to derive further insights of naive farmers' index insurance demand, we now focus on one specific scenario. We assume that the farmers and the insurance provider operate on a market in which assumption A.1 holds.

Assumption A.1 (Actuarially fair premium)**.** *A privately owned insurer that operates on the free market will never charge a premium lower than the actuarially fair value* $\delta_m \mathbb{E}(Z)$*.*[47] *Typically, a safety loading factor* $l > 0$ *is added to the premium. Thus, the premium equals* $(1 + l) \cdot \delta_m \mathbb{E}(Z)$*.*

We first analyze whether a farmer will demand an actuarially fair priced insurance (i.e., $l = 0$). Otherwise, it is straightforward that a privately owned insurer aiming for profit (i.e., $l > 0$), will not generate any demand for its product. For the sake of simplicity, let the diminishing marginal sensitivity for gains and losses be equal, i.e., $\alpha \approx \beta$.[48] A farmer demands a fairly priced insurance product, i.e., $l = 0$, iff

$$\delta_m \mathbb{E}[Z] \leq \left(\frac{\delta_f}{\lambda} \mathbb{E}[Z^\alpha] \right)^{\frac{1}{\alpha}} . \tag{8}$$

Inequality (8) can only hold if $\lambda \leq 1$.[49] This condition implies that losses do not loom larger than gains and therefore contradicts one of the main and heaviest tested assumptions of PT. Resulting, we state that this condition is never fulfilled.[50] Therefore, cases in which naive farmers are offered an insurance at a price higher than the actuarially fair value need not to be analyzed as these offers are rejected anyway. Thus, we state the following proposition.

Proposition A.2 (Neglect of insurance among naive farmers)**.** *naive farmers whose reference point is 'No insurance coverage' will not demand insurance offered at or above its actuarially fair value.*

[47]If an insurer charges a lower premium, then, due to the law of large numbers, it will run out of money eventually.

[48]This assumption is supported by Tversky and Kahneman (1992) who find a median value of $\alpha_m = \beta_m = 0.88$.

[49]Proof: Appendix A.5.2.

[50]This implication is straightforward since the naive farmer regards the insurance as an investment and the decision to demand the insurance as being independent of crop risk. Hence, he will not demand a negative return, positive risk insurance contract.

We further analyze the insurance demand if the premium is lower than its actuarially fair value.[51] We therefore assume that Assumption A.2 holds.

Assumption A.2 (Subsidy)**.** *With a subsidy factor* $s \in (0,1)$*, the insurance premium becomes* $\Pi = (1-s)\cdot\delta_m\mathbb{E}(Z)$.

A naive farmer will demand the index insurance, iff

$$(1-s)\cdot\delta_m\mathbb{E}[Z] \leq \left(\frac{\delta_f}{\lambda}\mathbb{E}[Z^\alpha]\right)^{\frac{1}{\alpha}}. \tag{9}$$

On the basis of Assumption A.2, Proposition A.3 states minimum restrictions for the subsidy s such that an naive farmer demands insurance coverage.

Proposition A.3 (Requirements for the subsidy)**.** *The subsidized insurance is not attractive for an naive farmer if one or both of the inequalities*

$$s \geq 1 - \lambda^{-1/\alpha} \tag{10}$$

$$s \geq 1 - \frac{\delta_f}{\delta_m} \tag{11}$$

are not fulfilled. The minimum subsidy requirements are increasing with loss aversion and decreasing with farmer's discount factor.[52]

<u>Proof</u>*: Appendix A.5.3.*

Using the median PT parameters condition (10) shows that the insurance is not attractive if $s < 0.6$.[53] As a result, an naive farmer will not demand the insurance even if the charged premium amounts to only half of its actuarially fair price, i.e., $s = 0.5$. The second condition (11) creates a lower bound with respect to the ratio of the farmer's and market discount factor. Using the median farmer discount factor, $s \geq 0.2$ has to hold.[54]

[51] A possibility for a premium lower than its actuarially fair value to occur are development subsidies.

[52] It is important to mention that these conditions are necessary but not sufficient for inequality (9) to hold.

[53] The median values $\alpha_m = 0.88, \lambda_m = 2.25$ of Kahneman and Tversky (1979) were estimated in experiments with a small number of students. These populations are among the least representative on a lot of dimensions (Henrich et al., 2010). However, using PT parameters estimated by Liu (2013) and Holden and Quiggin (2017) in a closer context lead to similar minimum subsidy requirements.

[54] The market discount factor can, for example, be estimated by using long-term government bond yields. But certainly $\delta_m < 1$ holds. Hence, condition (11) can be modified

A.2 Reference Point: Perfect insurance (discrete)

An educated farmer's reference point is a perfect insurance. Thus, due to a possible deviation of the index insurance from the perfect insurance, basis risk enters our model. We define the basis downside risk parameter q and the upside risk parameter q' as the probability that the index insurance underestimates or, respectively, overestimates the actual loss. We further assume that both probabilities are the same, i.e., $q = q'$.[55] Therefore, with probability $1-2q$ the indemnity payment is correct. Furthermore, as Clarke (2016), we assume that the amount by which the insurance underestimates the crop failure is the same as the amount by which the insurance overestimates it. Table 10 summarizes the relationship between the perfect insurance Z_2 and the index insurance Z_1:

Table 10: Comparison of perfect and index insurance
Source: Clarke (2016)

Scenario	Probability	Deviation $(Z_1 - Z_2)$
Underestimation of crop failure	q	$-\triangle L$
Accurate estimation	$1-2q$	0
Overestimation of crop failure	q	$\triangle L$

We further assume that from a farmer's point of view, the premium of a perfect insurance equals the premium of an index insurance.[56] Accordingly, the reference points for $t = 1$ and $t = 2$ are:

$$r_1 = c(Y_1 - \Pi) = \bar{c} + \gamma(Y_1 - \Pi - \mathbb{E}[Y_1]),$$
$$r_2 = c(Y_2 + Z_2) = \bar{c} + \gamma(Y_2 + Z_2 - \mathbb{E}[Y_2]).$$

Recalling, the inequality for the WTP is

$$v_1[c(Y_1 - \Pi)] + \delta_f \mathbb{E}[v_2[c(Y_2 + Z_1)]] \geq v_1[c(Y_1)] + \delta_f \mathbb{E}[v_2[c(Y_2)]]. \quad (12)$$

Table 11 displays the coding of the outcomes in the two periods:

to $m \leq \delta_f$. According to Giné et al. (2008), the median monthly discount factor applied by farmers is approximately 0.8.

[55]This assumption corresponds to the findings of Clarke et al. (2012).

[56]PT aims to reflect a farmer's points of view. Farmers in rural regions of developing countries are not expected to understand that index insurances should entail lower administrative costs. Thus, we deem this assumption reasonable.

Table 11: Coding of outcomes relative to perfect insurance

	$t=1$				$t=2$			
insurance	$c(Y_1-\Pi)$	$-r_1$	=	0	$c(Y_2+Z_1)$	$-r_2$	=	$\gamma(Z_1-Z_2)$
no insurance	$c(Y_1)$	$-r_1$	=	$\gamma\Pi>0$	$c(Y_2)$	$-r_2$	=	$-\gamma Z_2$

If a farmer decides to demand the index insurance, the premium in the first period is equal to the premium of the perfect insurance, and thus, the outcome turns zero. In contrast, if a farmer does not demand the insurance, the farmer saves, relative to the reference point, the premium. Applying the PT value function (5) to the first-period outcomes leads to

$$v_1[c(y_1-\Pi)]=0,$$
$$v_1[c(y_1)]=(\gamma\Pi)^\alpha.$$

If a farmer rejects the insurance, he does not receive the possible payout of the perfect insurance in the second period. This leads to

$$\mathbb{E}[v_2[c(Y_2)]]=-\gamma^\beta\lambda\mathbb{E}[Z_2^\beta].$$

In contrast, if he demands the index insurance, the second-period outcome, relative to the reference point, is the deviation of the index insurance payout from the perfect insurance payout. Referring to Table 10 and using the probability weighting function π, the valuation becomes

$$\mathbb{E}[v_2[c(Y_2+Z_1)]]=\pi(q)[\gamma^\alpha(\triangle L)^\alpha-\gamma^\beta\lambda(\triangle L)^\beta].$$

Plugging these values into inequality (12), the index insurance demand condition is given by

$$0+\delta_f\pi(q)\underbrace{[\gamma^\alpha(\triangle L)^\alpha-\gamma^\beta\lambda(\triangle L)^\beta]}_{:=\otimes}\geq(\gamma\Pi)^\alpha-\delta_f\gamma^\beta\lambda\mathbb{E}[Z_2^\beta].$$

Solving for the premium Π leads to

$$\Pi\leq\frac{\left(\delta_f\pi(q)\otimes+\delta_f\gamma^\beta\lambda\mathbb{E}[Z_2^\beta]\right)^{1/\alpha}}{\gamma}. \tag{13}$$

Based on equation (13), the following proposition summarizes the predictions for educated farmers.

Proposition A.4 (WTP of educated farmers under Prospect Theory). *Given the reference point 'Perfect insurance', educated farmers' WTP is:*

1. *increasing with the discount factor.*
2. *increasing with the expected subjective valuation of indemnity payments.*
3. *increasing with the basis risk.*
4. *increasing with loss aversion.*

Proof: Appendix A.5.4.

While the propositions regarding the discount factor and the expected subjective valuation of the indemnity payment coincide with the propositions for the WTP of an educated farmer, the other two show discrepancies.

A.3 Reference Point: Perfect insurance (continuous)

We apply the baseline assumption that $Z_1 - Z_2 \sim \mathbb{N}(0, \sigma^2)$. In this case, $\mathbb{E}[Z_1 - Z_2] = 0$. Furthermore, the normal distribution is symmetric, hence, the probability for overestimation is the same as the probability for underestimation and it can represent infinitely many scenarios. Finally, the variance σ^2 represents the basis risk. A higher variance, and therefore higher basis risk leads to higher possible estimation errors. If the basis risk is small, i.e., $\sigma^2 \approx 0$, with high probability only small estimation errors occur.

If an educated farmer demands the insurance, his valuation of the second-period outcome is equal to the expected difference between the index insurance and the perfect insurance. This difference is normally distributed around the mean zero. Therefore, with probability $1/2$ it is positive or negative. As a result, the expected second-period valuation of an educated farmer who purchases the insurance product is equal to:

$$\begin{aligned}\mathbb{E}[v_2[c(Y_2 + Z_2)]] &= \frac{1}{2} \cdot \delta_f \gamma^\alpha \cdot (\sigma^2)^{\alpha/100} f(\alpha) - \frac{1}{2} \cdot \lambda \delta_f \gamma^\alpha \cdot (\sigma^2)^{\alpha/100} f(\alpha) \\ &= \frac{1}{2} \cdot \delta_f \gamma^\alpha \cdot (1 - \lambda) \cdot (\sigma^2)^{\alpha/100} f(\alpha),\end{aligned}$$

where $f(\alpha)$ denotes a strictly positive function depending on the parameter α.[57] Using these values, an educated farmer will purchase the insurance product, if

$$0 + \frac{1}{2}\delta_f \gamma^\alpha (1-\lambda)\cdot(\sigma^2)^{\alpha/100} f(\alpha) \geq (\gamma\Pi)^\alpha - \delta_f \gamma^\alpha \lambda \mathbb{E}[Z_2^\alpha].$$

Consequently, the insurance purchase condition with respect to the premium Π becomes

$$\Pi \leq \left(\frac{1}{2}\delta_f (1-\lambda)\cdot(\sigma^2)^{\alpha/100} f(\alpha) + \delta_f \lambda \mathbb{E}[Z_2^\alpha]\right)^{1/\alpha}.$$

The inequality above leads to the following Proposition A.5.

Proposition A.5 (WTP of educated farmers under Prospect Theory II)**.** *Given the reference point 'Perfect insurance (continous)', the WTP of educated farmers is characterized in the following way:*

1. *A higher discount factor leads to a higher WTP.*
2. *A higher expected subjective valuation of the future indemnity payment leads to a higher WTP.*
3. *An increase in the basis risk influences the WTP negatively.*
4. *An increase in loss aversion results into a higher WTP.*

Proof: Appendix A.6.2

All propositions correspond to the results in the discrete case. The main difference is that the basis risk parameter and the amount by which an insurance underestimates/overestimates the value of crop failure are captured by one variable: the variance of the normal distribution.

Hence, transforming the discrete scenario from the previous section to a more realistic, continuous representation leaves all important implications unchanged.

A.4 Model predictions

This section summarizes the model predictions and compares them to the base model of Carter et al. (2014) and empirical findings. Column (1) of

[57] Proof: Appendix A.6.1.

Table 12 summarizes the predictions of the expected utility model of Carter et al. (2014). Columns (2) and (3) compare these to the predictions of our behavioral model. In line with the base model of Carter et al. (2014), the behavioral model predicts the WTP of both farmer types to be increasing with the discount factor as well as in the expected subjective valuation of the indemnity payment. In contrast to Carter et al. (2014), the behavioral model predicts heterogeneous effects of basis risk and loss aversion among farmer with different levels of insurance understanding. In particular, basis risk negatively impacts the WTP of an educated farmer whereas it is not related to the WTP of an naive farmer. Furthermore, an increase in loss aversion increases the WTP of an educated farmer and decreases the WTP of an naive farmer.

Table 12: Comparison of rational and behavioral insurance demand model

	Expected Utility	Prospect Theory		Empirical Findings	
	Carter et al. (2014)	Naive	Educated	Naive	Educated
	(1)	(2)	(3)	(4)	(5)
Discount rate	+	+	+	∘	∘
Expected payout	+	+	+	+	+
Basis risk	−	∘	−	∘	−
Loss aversion	n.a.	−	+	n.a.	n.a.

As displayed by column (4) and (5) of Table 12, a large part of our propositions has already been tested by the empirical literature.[58] First, in contrast to our Propositions A.1.1 and A.4.1, Cole et al. (2013) and Giné et al. (2008) find index insurance demand to be independent of the discount rate. Second, under the assumption that past average payout in a farmer's village can be used as an approximation of the expected subjective valuation of the indemnity payment, Propositions A.1.2 and A.4.2 find support by Cole et al. (2013). Third, recent findings of Jensen et al. (2018) suggest that deeper understanding of the product increases sensitivity to basis risk considerably. In particular, Jensen et al. (2018) find only very little relation-

[58]Instead of measuring farmer's WTP, empirical research mainly focus on observed insurance demand. But, because the market demand curve originates from the premium individuals are willing to pay, the demand is an appropriate measure for the WTP.

ship between basis risk and demand among farmers that were not further educated about the index insurance.

The only part of our propositions that has not been tested by the empirical literature are Proposition A.1.4 and A.4.4. We therefore combine these to our core Hypothesis A.1:

Hypothesis A.1. *The impact of loss aversion on the WTP varies with the level of insurance understanding. While the WTP is increasing with loss aversion among educated farmers it is decreasing with loss aversion among Naive farmers.*

A.5 Proofs of the intertemporal model (discrete)

A.5.1 Proof of Proposition A.1

The equation for the WTP equals

$$\Pi = \left(\frac{\delta_f}{\lambda} \cdot \gamma^{\alpha-\beta}\mathbb{E}[Z^\alpha]\right)^{1/\beta}.$$

Calculating the partial derivatives leads to the proofs of the corresponding propositions:

$$1.\ \frac{\partial\Pi}{\partial\delta_f} = \underbrace{\frac{1}{\beta}\left(\frac{\delta_f}{\lambda} \cdot \gamma^{\alpha-\beta}\mathbb{E}[Z^\alpha]\right)^{1/\beta-1}}_{>0} \cdot \underbrace{\frac{1}{\lambda}\gamma^{\alpha-\beta}\mathbb{E}\left[Z^\alpha\right]}_{>0} > 0 \ \Rightarrow \ \text{Prop. A.1.1,}$$

$$2.\ \frac{\partial\Pi}{\partial\mathbb{E}(\mathbb{Z}^\alpha)} = \underbrace{\frac{1}{\beta}\left(\frac{\delta_f}{\lambda} \cdot \gamma^{\alpha-\beta}\mathbb{E}[Z^\alpha]\right)^{1/\beta-1}}_{>0} \cdot \underbrace{\frac{\delta_f}{\lambda}\gamma^{\alpha-\beta}}_{>0} > 0 \ \Rightarrow \ \text{Prop. A.1.2,}$$

$$4.\ \frac{\partial\Pi}{\partial\lambda} = \underbrace{\frac{1}{\beta}\left(\frac{\delta_f}{\lambda} \cdot \gamma^{\alpha-\beta}\mathbb{E}[Z^\alpha]\right)^{1/\beta-1}}_{>0} \cdot \underbrace{-\frac{\delta_f}{\lambda^2}\gamma^{\alpha-\beta}\mathbb{E}\left[Z^\alpha\right]}_{<0} < 0 \ \Rightarrow \ \text{Prop. A.1.4.}$$

Farmers without insurance coverage do not receive any indemnity payment in case of crop failure. Thus, a possible non-performance of the index insurance in case of crop failure is not evaluated as a loss ⇒ Proposition A.1.3.
□

A.5.2 Proof of Equation (8)

The discussed inequality equals

$$\delta_m \mathbb{E}(Z) \leq \left[\frac{\delta_f}{\lambda}\mathbb{E}(Z^\alpha)\right]^{1/\alpha}.$$

A few mathematical tools have to be considered: First, PT assumes diminishing marginal sensitivity for losses and gains(i.e., $\alpha < 1$ and $\beta < 1$). Accordingly, Z^α is a concave function and Jensen's inequality is applicable. Second, because of $\delta_f < 1 < \frac{1}{\alpha}$, certainly $\left(\delta_f\right)^{1/\alpha} < \delta_f$ has to hold. Finally, the discount rate δ_f applied by the farmers is low. Therefore, $\delta_f < \delta_m$ is assumed. To summarize, the following three inequalities hold:

(i) $\mathbb{E}(Z^\alpha) \leq [\mathbb{E}(Z)]^\alpha$

(ii) $\left(\delta_f\right)^{1/\alpha} \leq \delta_f$

(iii) $\delta_f \leq \delta_m$

We show that $\lambda \leq 1$ holds:

$$\begin{aligned}
\delta_m \mathbb{E}(Z) &\leq \left[\frac{\delta_f}{\lambda}\mathbb{E}(Z^\alpha)\right]^{1/\alpha} = \left(\frac{\delta_f}{\lambda}\right)^{1/\alpha} (\mathbb{E}(Z^\alpha))^{1/\alpha} \\
&\overset{(i)}{\leq} \left[\frac{\delta_f}{\lambda}\right]^{1/\alpha} \cdot \mathbb{E}(Z) = \left(\frac{1}{\lambda}\right)^{1/\alpha} \cdot \left(\delta_f\right)^{1/\alpha} \cdot \mathbb{E}(Z) \\
&\overset{(ii)}{\leq} \left[\frac{1}{\lambda}\right]^{1/\alpha} \delta_f \cdot \mathbb{E}(Z) \overset{(iii)}{\leq} \left[\frac{1}{\lambda}\right]^{1/\alpha} \delta_m \mathbb{E}(Z).
\end{aligned}$$

Hence,

$$\delta_m \mathbb{E}[Z] \leq \left(\frac{1}{\lambda}\right)^{1/\alpha} \delta_m \mathbb{E}[Z]$$

has to be statisfied. This is equivalent to

$$1 \leq \left(\frac{1}{\lambda}\right)^{1/\alpha} \quad \Leftrightarrow \quad \lambda \leq 1.$$

□

A.5.3 Proof of Proposition A.3

The inequality discussed is given by

$$(1-s)\cdot\delta_m\mathbb{E}(Z)\leq\left[\frac{\delta_f}{\lambda}\mathbb{E}(Z^\alpha)\right]^{1/\alpha}.$$

With similar argumentations as in the previous proof of Equation (8), the following inequalities certainly hold:

(i) $\mathbb{E}(Z^\alpha)\leq[\mathbb{E}(Z)]^\alpha$

(ii) $\left(\delta_f\right)^{1/\alpha}\leq\delta_f$

(iii) $\delta_f\leq\delta_m$

(iv) $\left(\frac{1}{\lambda}\right)^{1/\alpha}\leq 1$

First, $s\geq 1-\lambda^{-1/\alpha}$ is shown:

$$\begin{aligned}
&(1-s)\cdot\delta_m\mathbb{E}(Z)\leq\left[\frac{\delta_f}{\lambda}\mathbb{E}(Z^\alpha)\right]^{1/\alpha}\\
\Leftrightarrow&(1-s)\cdot\delta_m\mathbb{E}(Z)\leq\left(\frac{1}{\lambda}\right)^{1/\alpha}\left[\delta_f\mathbb{E}(Z^\alpha)\right]^{1/\alpha}\overset{(i),(ii),(iii)}{\leq}\left(\frac{1}{\lambda}\right)^{1/\alpha}\delta_m\mathbb{E}(Z)\\
\Leftrightarrow&(1-s)\leq\left(\frac{1}{\lambda}\right)^{1/\alpha}\\
\Leftrightarrow&s\geq 1-\lambda^{-1/\alpha}.
\end{aligned}$$

Second, $s\geq 1-\frac{\delta_f}{\delta_m}$ is shown:

$$\begin{aligned}
&(1-s)\cdot\delta_m\mathbb{E}(Z)\leq\left[\frac{\delta_f}{\lambda}\mathbb{E}(Z^\alpha)\right]^{1/\alpha}\\
\Leftrightarrow&(1-s)\cdot\delta_m\mathbb{E}(Z)\leq\left(\frac{1}{\lambda}\right)^{1/\alpha}\left[\delta_f\mathbb{E}(Z^\alpha)\right]^{1/\alpha}\overset{(i),(ii),(iv)}{\leq}1\cdot\delta_f\mathbb{E}(Z)\\
\Leftrightarrow&(1-s)\leq\frac{\delta_f}{\delta_m}\\
\Leftrightarrow&s\geq 1-\frac{\delta_f}{\delta_m}.
\end{aligned}$$

□

A.5.4 Proof of Proposition A.4

Solving for the premium Π leads to

$$\Pi \leq \frac{1}{\gamma} \cdot \left(\underbrace{\delta_f \pi(q) \otimes + \delta_f \gamma^\beta \lambda \mathbb{E}[Z_2^\beta]}_{:=(\star)} \right)^{1/\alpha}. \tag{14}$$

For the effect of the subjective valuation, we calculate the derivative of the upper boarder for the premium:

$$\frac{\partial \Pi}{\partial Z_1} = \frac{1}{\alpha\gamma} \underbrace{(\star)^{1/\alpha - 1}}_{>0} \cdot \delta_f \cdot \pi(q) \cdot \underbrace{\left[\alpha \underbrace{[\gamma(\Delta L)]^{\alpha-1}}_{>0} \cdot \gamma - \lambda\beta \underbrace{[\gamma(\Delta L)]^{\beta-1}}_{>0} \cdot (-\gamma) \right]}_{>0} > 0.$$

Since we consider the case of positive insurance demand ($\Pi > 0$), $(\star) > 0$ has to hold. ⇒ Prop. A.4.2

Since it holds $\otimes < 0$, an increase in the basis risk parameter q leads to a smaller WTP.[59] If we again assume $\beta \approx \alpha$,

$$\otimes = \gamma^\alpha (\triangle L)^\alpha [1 - \lambda]$$

holds. As the loss aversion parameter is always larger than one ($\lambda > 1$), an increasing error in estimating $\triangle L$ leads to a more negative value of $\otimes$ and therefore to a decreasing WTP. ⇒ Prop. A.4.3

Condition (14) becomes

$$\Pi \leq \left(\delta_f \pi(q) (\triangle L)^\alpha [1 - \lambda] + \delta_f \lambda \mathbb{E}[Z_2^\alpha] \right)^{1/\alpha}.$$

[59] According to PT, *'the aggravation one experiences in losing a sum of money appears to be greater than the pleasure associated with gaining the same amount'*(Kahneman and Tversky, 1979, p. 279), e.g., $v(x) < -v(-x)$. Now, even when arguing that the insurance's actuaries are approximating the value of crop failure well and therefore conclude that the basis risk parameter is small, the influence of the basis risk should still not be neglected, because, according to PT, small probabilities are often overestimated, i.e., $\pi(q) > q$. Thus, farmers will overestimate small basis risk parameters.

To analyze the remaining partial derivatives, the following inequalities are needed:

(i) $\pi(q)(\triangle L)^\alpha > 0$

(ii) $\pi(q)(\triangle L)^\alpha = \mathbb{E}\left[(Z_2 - Z_1)^\alpha \mathbb{1}_{\{Z_2 > Z_1\}}\right] \overset{Z_1>0}{<} \mathbb{E}(Z_2^\alpha)$.

Calculation of the partial derivatives leads to:

$$\begin{aligned}
\frac{\partial \Pi}{\partial \delta_f} &= \frac{1}{\alpha} \cdot \delta_f^{1/\alpha - 1} \cdot [\pi(q)(\triangle L)^\alpha + \lambda(\mathbb{E}[Z_2^\alpha] - \pi(q)(\triangle L)^\alpha)] \\
&\overset{(i),(ii)}{>} 0 \Rightarrow \text{Prop. A.4.1}, \\
\frac{\partial \Pi}{\partial \lambda} &= \frac{1}{\alpha}\left(\delta_f \pi(q)(\triangle L)^\alpha [1-\lambda] + \delta_f \lambda \mathbb{E}[Z_2^\alpha]\right)^{1/\alpha - 1} \cdot \delta_f (\mathbb{E}(Z_2^\alpha) - \pi(q)(\triangle L)^\alpha) \\
&\overset{(ii)}{>} 0 \Rightarrow \text{Prop., A.4.4}.
\end{aligned}$$

□

A.6 Proofs of the intertemporal model (continous)

A.6.1 Deviation of $f(\alpha)$

For a random Variable X with density function f_x

$$\mathbb{E}\left[X^\alpha\right] = \int_{-\infty}^{\infty} x^\alpha f_x(x) dx.$$

Furthermore, because of $(Z_1 - Z_2) \sim \mathbb{N}(0, \sigma^2)$, the regarded density is given by

$$f_{Z_1 - Z_2} = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-x^2}{2\sigma^2}\right).$$

Due to the symmetry of the normal distribution, with probability $\frac{1}{2}$ the difference is negative or positive. For the negative values, following prospect theory, $v(-x) = -\lambda v(x)$ holds. Hence, it holds

$$\begin{aligned}
\mathbb{E}[(Z_1 - Z_2)^\alpha] &= \frac{1}{2} \cdot (1-\lambda) \cdot \int_0^\infty x^\alpha \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-x^2}{2\sigma^2}\right) dx \\
&= \frac{1}{2} \cdot (1-\lambda) \cdot \frac{(\sigma^2)^{\alpha/100} \cdot \Gamma\left(\frac{1+\alpha}{2}\right)}{2^{1-\alpha/200}\sqrt{\pi}},
\end{aligned}$$

where Γ denotes the Gamma-function with

$$\Gamma(z) = \int_0^\infty t^{z-1}\exp(-t)dt.$$

To conclude:

$$\mathbb{E}[(Z_1 - Z_2)^\alpha] = \frac{1}{2}\cdot(1-\lambda)(\sigma^2)^{\alpha/100}\cdot f(\alpha),$$

with

$$f(\alpha) = \Gamma\left(\frac{1+\alpha}{2}\right)\frac{1}{2^{1-\alpha/200}\sqrt{\pi}} > 0 \ \forall \ \alpha > 0.$$

□

A.6.2 Proof of Proposition A.5

The WTP equals

$$\Pi = \left(\frac{1}{2}\delta_f(1-\lambda)\cdot(\sigma^2)^{\alpha/100}f(\alpha) + \delta_f\lambda\mathbb{E}[Z_2^\alpha]\right)^{1/\alpha}.$$

The following inequalities hold:

i) $\frac{1}{2}\cdot(\sigma^2)^{\alpha/100}\cdot f(\alpha) > 0$

ii) $\frac{1}{2}\cdot(\sigma^2)^{\alpha/100}\cdot f(\alpha) = \mathbb{E}\left[(Z_2 - Z_1)^\alpha \mathbb{1}_{\{Z_2 > Z_1\}}\right] \overset{Z_1>0}{<} \mathbb{E}[Z_2^\alpha].$

Calculation of the partial derivatives leads to:

$$\begin{aligned}
\frac{\partial\Pi}{\partial\delta_f} &= \frac{1}{\alpha}\cdot\delta_f^{(1/\alpha)-1}\cdot\left[\frac{1}{2}(\sigma^2)^{\alpha/100}f(\alpha) + \lambda\left(\mathbb{E}[Z_2^\alpha] - \frac{1}{2}\cdot(\sigma^2)^{\alpha/100}f(\alpha)\right)\right] \overset{(i),(ii)}{>} 0,\\
\frac{\partial\Pi}{\partial\lambda} &= \frac{1}{\alpha}\cdot\left(\frac{1}{2}\delta_f(1-\lambda)\cdot(\sigma^2)^{\alpha/100}f(\alpha) + \delta_f\lambda\mathbb{E}[Z_2^\alpha]\right)^{1/\alpha-1}\\
&\quad\cdot\delta_f\left(\mathbb{E}[Z_2^\alpha] - \frac{1}{2}\cdot(\sigma^2)^{\alpha/100}f(\alpha)\right) \overset{(ii)}{>} 0,\\
\frac{\partial\Pi}{\partial\sigma^2} &= \frac{1}{\alpha}\cdot\left(\frac{1}{2}\delta_f(1-\lambda)\cdot(\sigma^2)^{\alpha/100}f(\alpha) + \delta_f\lambda\mathbb{E}[Z_2^\alpha]\right)^{1/\alpha-1}\\
&\quad\cdot\frac{\alpha}{100}\cdot\frac{1}{2}\delta_f(1-\lambda)\cdot(\sigma^2)^{\alpha/100-1}f(\alpha) < 0.
\end{aligned}$$

□

B Appendix 1: Proofs

B.1 Proof of Proposition 2.2

Given a subsidized insurance premium, the condition such that a farmer buys the insurance becomes

$$-\lambda(1-p)((1-s)pI)^{\alpha}+p((1-p(1-s))I)^{\alpha}\geq 0.$$

This condition can be simplified to

$$\begin{aligned}
&p((1-p(1-s)))^{\alpha}\geq\lambda(1-p)((1-s)p)^{\alpha}.\\
\Leftrightarrow&\frac{p}{1-p}\frac{((1-p(1-s)))^{\alpha}}{((1-s)p)^{\alpha}}\geq\lambda\\
\Leftrightarrow&\frac{p}{1-p}\left(\frac{1}{(1-s)p}-1\right)^{\alpha}\geq\lambda\\
\Leftrightarrow&\frac{1}{(1-s)p}-1\geq\left(\lambda\frac{1-p}{p}\right)^{1/\alpha}\\
\Leftrightarrow&\frac{1}{(1-s)p}\geq\left(\lambda\frac{1-p}{p}\right)^{1/\alpha}+1\\
\Leftrightarrow&\frac{1}{1-s}\geq p\left(\left(\lambda\frac{1-p}{p}\right)^{1/\alpha}+1\right)\\
\Leftrightarrow&1-s\leq\frac{1}{p\left(\left(\lambda\frac{1-p}{p}\right)^{1/\alpha}+1\right)}\\
\Leftrightarrow&s\geq 1-\frac{1}{p\left(\left(\lambda\frac{1-p}{p}\right)^{1/\alpha}+1\right)}\qquad\square
\end{aligned}$$

B.2 Measure of loss aversion: upper and lower bound

Table 13: Binswanger lotteries

(1)	(2)	(3)	(4)	(5)	(6)
Lottery	Loss	Gain	Low. Bound ($\lambda \geq \frac{G_i - G_{i+1}}{L_i - L_{i+1}}$)	Up. Bound ($\lambda \leq \frac{G_i - G_{i-1}}{L_i - L_{i-1}}$)	Low. Bound - Up. Bound
(1)	0	0	$V_1 \geq V_2 \Leftrightarrow \lambda \geq 7$	-	≥ 7
(2)	5	35	$V_2 \geq V_3 \Leftrightarrow \lambda \geq 4$	$V_2 \geq V_1 \Leftrightarrow \lambda \leq 7$	4-7
(3)	10	55	$V_3 \geq V_4 \Leftrightarrow \lambda \geq 3$	$V_3 \geq V_2 \Leftrightarrow \lambda \leq 4$	3-4
(4)	15	70	$V_4 \geq V_5 \Leftrightarrow \lambda \geq 2$	$V_4 \geq V_3 \Leftrightarrow \lambda \leq 3$	2-3
(5)	20	80	$V_5 \geq V_6 \Leftrightarrow \lambda \geq 1$	$V_5 \geq V_4 \Leftrightarrow \lambda \leq 2$	1-2
(6)	25	85	-	$V_6 \geq V_5 \Leftrightarrow \lambda \leq 1$	≤ 1

Neglecting probability weighting and assuming that farmers are risk neutral and use the risk-free Lottery (1) as the reference point, the PT Value of Lottery (i) is $V_i = 0.5 \cdot G_i - \lambda \cdot 0.5 \cdot L_i$, where G_i and L_i denote the loss and the gain associated with Lottery (i); and λ denotes the parameter of loss aversion. The losses and gains associated with each lottery are displayed in Column (2) and (3) of Table 13. The aim of this Proof is to show that farmers' choices for Lottery (i) require that $\frac{G_i - G_{i+1}}{L_i - L_{i+1}} \leq \lambda \leq \frac{G_i - G_{i-1}}{L_i - L_{i-1}}$ holds.
We start with deriving the lower bound $\frac{G_i - G_{i+1}}{L_i - L_{i+1}} \leq \lambda$.
A farmer prefers Lottery (i) over Lottery $(i+1)$ if $V_i \geq V_{i+1}$ holds. Using the PT Value, the inequality becomes

$$
\begin{aligned}
&0.5 \cdot G_i - \lambda \cdot 0.5 \cdot L_i \geq 0.5 \cdot G_{i+1} - \lambda \cdot 0.5 \cdot L_{i+1} \\
\Leftrightarrow &0.5 \cdot (G_i - G_{i+1}) \geq \lambda \cdot 0.5 \cdot (L_i - L_{i+1}) \\
\Leftrightarrow &(G_i - G_{i+1}) \geq \lambda \cdot (L_i - L_{i+1}).
\end{aligned}
$$

Because $L_i - L_{i+1} < 0$ holds for all i, the inequality above can be rearranged to $\lambda \geq G_i - G_{i+1} / L_i - L_{i+1}$.[60] Column (4) of Table 13 displays the loss aversion parameters required such that $V_i \geq V_{i+1}$ holds. The sequence of the parameters is strictly decreasing. Thus, it follows that $V_i \geq V_{i+1}$ implies $V_i \geq V_{i+k}$ $\forall k > 1$.[61] Accordingly, it is sufficient to consider the condition $V_i \geq V_{i+1}$ to estimate the lower loss aversion bound associated with farmers' choices for

[60] Note that the sign of the inequality flipped from $\geq$ into $\leq$ because we divided both sides by the negative term $L_i - L_{i-1}$.

[61] A numerical example: $V_1 \geq V_2$ requires $\lambda \geq 7$. $V_2 \geq V_3$ requires $\lambda \geq 4$. Thus, if $V_1 \geq V_2$ is fulfilled, $V_2 \geq V_3$ is also fulfilled. Thus, it follows that $V_1 (\geq V_2) \geq V_3$.

Lottery (i).

The argumentation for the upper bound ($\lambda \leq \frac{G_i - G_{i-1}}{L_i - L_{i-1}}$) is the same.
A farmer prefers Lottery (i) over Lottery ($i-1$) if $V_i \geq V_{i-1}$ holds. Using the PT Value, the inequality becomes

$$\begin{aligned}
&0.5 \cdot G_i - \lambda \cdot 0.5 \cdot L_i \geq 0.5 \cdot G_{i-1} - \lambda \cdot 0.5 \cdot L_{i-1} \\
\Leftrightarrow &0.5 \cdot (G_i - G_{i-1}) \geq \lambda \cdot 0.5 \cdot (L_i - L_{i-1}) \\
\Leftrightarrow &(G_i - G_{i-1}) \geq \lambda \cdot (L_i - L_{i-1}).
\end{aligned}$$

Because $L_i - L_{i-1} > 0$ holds for all i, the inequality above can be rearranged to $\lambda \leq {G_i - G_{i-1}}/{L_i - L_{i-1}}$. Column (5) displays the loss aversion parameter required such that $V_i \geq V_{i-1}$ holds. Note that the sequence of parameters is again strictly decreasing. [62] Thus, this time it follows that $V_i \geq V_{i-1}$ implies $V_i \geq V_{i-j}\ \forall j > 1$.[63] Accordingly, it is sufficient to consider the condition $V_i \geq V_{i-1}$ to estimate the upper bound associated with farmers' choices of Lottery (i).
To conclude, the lower bound ensures that $V_i \geq V_{i+k}$ holds $\forall k > 0$ and the upper bound ensures that $V_i \geq V_{i-j}$ holds $\forall j > 0$. Thus, the interval between these two bounds ensures that the PT Value of Lottery (i) (weakly) dominates all other lotteries meaning that $V_i \geq V_u$ holds $\forall\ u \neq i$. The parameter intervals associated with each lottery are displayed in Column (6) of Table 13 .
Finally, it is not necessary to neglect probability weighting. We can derive the same intervals if we impose the weaker assumption that farmer weight a 0.5-chance for gaining or losing equally ($\pi^+(0.5) = \pi^-(0.5) = \pi(0.5)$). This assumption is, for instance, fulfilled by the probability weighting function proposed by Prelec et al. (1998). Imposing this assumption, $V_i \geq V_{i+1}$ implies $\pi(0.5) \cdot G_i - \lambda \cdot \pi(0.5) \cdot L_i \geq \pi(0.5) \cdot G_{i+1} - \lambda \cdot \pi(0.5) \cdot L_{i+1}$. This can be simplified to $(G_i - G_{i+1}) \geq \lambda \cdot (L_i - L_{i+1})$. Thus, we obtain the same condition as we did when we neglected probability weighting. The same holds for $V_i \geq V_{i-1}$.

[62] The inequality sign turned from $\geq$ into $\leq$.

[63] A numerical example: $V_3 \geq V_2$ requires $\lambda \leq 4$. $V_2 \geq V_1$ requires $\lambda \leq 7$. Thus, if $V_3 \geq V_2$ is fulfilled, $V_2 \geq V_1$ is also fulfilled. Thus, it follows that $V_3 (\geq V_2) \geq V_1$.

C Appendix 2: Reference point index insurance

Table 14: Index insurance as reference point

State	Loss		No Loss	
	Indemnity	No Indemnity	Indemnity	No Indemnity
	(1)	(2)	(3)	(4)
Probability	$p(1-q_1)$	r	r	$(1-p)(1-q_2)$
Gains/Losses, No Insurance	$(p-1)I<0$	pI	$(p-1)I$	pI
Gains/Losses, Index Insurance	0	0	0	0

We use $p(1-q_1)+r=p$ and $r+(1-p)(1-q_2)=1-p$. Farmers demand index insurance if

$$\underbrace{-\lambda p[(1-p)\cdot I]^\alpha + (1-p)(pI)^\alpha}_{value\ no\ insurance} \leq \underbrace{0}_{value\ index\ insurance}$$
$$\Leftrightarrow \frac{(1-p)(pI)^\alpha}{p(1-p)^\alpha \cdot I^\alpha} \leq \lambda$$
$$\left(\frac{1-p}{p}\right)^{1-\alpha} \leq \lambda.$$

We can see that an increase in λ makes the condition more likely to be fullfilled.

D Appendix 3: Behavioral model (only downside basis risk)

We consider an insurance that only possibly underestimates the actual loss. In order to keep the analysis simple, we focus on a model with only three states of the world. A loss L will occur with probability p, no loss with probability $1-p$. Furthermore, to include the downside basis risk, we assume that given a loss, there is a probability $q_1 > 0$ that the insurance does not pay out the indemnity payment I. We label farmer's initial wealth level with W and, finally, assume that the $\Pi = pI$. Thus, the negative basis risk is not priced in the insurance. Table 15 summarizes the outcomes for a farmer who demands the insurance and a farmer who does not demand the insurance.

Table 15: Four state framework

State	Loss		No Loss
	Indemnity	No Indemnity	No Indemnity
	(1)	(2)	(3)
Probability	$p(1-q_1)$	pq_1	$1-p$
Gains/Losses, Insurance Cover	$W-pI-L+I$	$W-pI-L$	$W-pI$
Gains/Losses, No Insurance Cover	$W-L$	$W-L$	W

D.1 Reference point no insurance coverage

Table 16 summarizes the encoded outcomes relative to the first reference point 'No Insurance Coverage':

Table 16: Reference point no insurance coverage

State	Loss		No Loss
	Indemnity	No Indemnity	No Indemnity
	(1)	(2)	(3)
Probability	$p(1-q_1)$	r	$1-p$
Gains/Losses, Insurance Cover	$-pI+I$	$-pI$	$-pI$
Gains/Losses, No Insurance Cover	0	0	0

Accordingly, a farmer will buy the insurance iff

$$-\lambda(1-p+r)(pI)^{\alpha} + p(1-q_1)((1-p)I)^{\alpha} \geq 0.$$

It is obvious that the insurance demand is decreasing with loss aversion and basis risk probability.

D.2 Reference point perfect insurance

Table 17 summarizes the encoded outcomes if 'Perfect Insurance' is chosen as a reference point

Table 17: Reference point perfect insurance

State	Loss		No Loss
	Indemnity	No Indemnity	No Indemnity
	(1)	(2)	(3)
Probability	$p(1-q_1)$	r	$1-p$
Gains/Losses, Insurance Cover	0	$-I$	0
Gains/Losses, No Insurance Cover	$(p-1)I$	$(p-1)I$	pI

Accordingly, a farmer will buy the insurance, iff

$$-r\lambda I^{\alpha} + > -p\lambda\left((1-p)I\right)^{\alpha} + (1-p)\left(pI\right)^{\alpha}.$$

Rearranging leads to

$$\lambda(p(1-p)^{\alpha} - r) - (1-p)p^{\alpha} > 0.$$

It is obvious that the insurance demand is decreasing with the basis risk probability. Furthermore, as in the main model case, the positive impact of loss aversion depends on the condition $p(1-p)^{\alpha} > r$ which is most likely fulfilled. Rearranging shows that the loss aversion parameter that is required such that farmers buy the insurance is given by

$$\lambda > \frac{(1-p)p^{\alpha}}{(p(1-p)^{\alpha} - r)}. \tag{15}$$

To recall, in our main model 2.2 the condition such that a farmer buys the insurance equals

$$\lambda(p(1-p)^{\alpha} - r) + r - (1-p)p^{\alpha} > 0.$$

Rearranging leads to

$$\lambda > \frac{(1-p)p^{\alpha}}{(p(1-p)^{\alpha}-r)} - r. \tag{16}$$

It is obvious, that condition (16) is weaker than condition (15). Accordingly, under the existence of only downside basis risk, higher loss aversion levels are required to convince a farmer to buy the insurance.

E Appendix 4: Insurance demand and risk aversion

E.1 No insurance coverage

Following inequality (2), we know that farmers demand insurance if

$$-\lambda(1-p)(pI)^{\alpha} + p((1-p)I)^{\alpha} \geq 0.$$

Rearranging for α leads to

$$\begin{aligned} \lambda &\leq \left(\frac{p}{1-p}\right)^{1-\alpha} \\ \Leftrightarrow ln_{\frac{p}{1-p}}\lambda &\leq 1-\alpha \\ \Leftrightarrow \alpha &\leq 1 - ln_{\frac{p}{1-p}}\lambda. \end{aligned}$$

Therefore, insurance demand is most likely decreasing with risk aversion when using no insurance as reference point.

E.2 Perfect insurance

Following inequality (3), we know that farmers demand insurance if

$$r(1-\lambda)I^{\alpha} > -p\lambda\left((1-p)I\right)^{\alpha} + (1-p)\left(pI\right)^{\alpha}.$$

Rearranging leads to

$$\begin{aligned} \lambda(p(1-p)^{\alpha} - r) + r - (1-p)p^{\alpha} &> 0 \\ \Leftrightarrow \lambda p(1-p)^{\alpha} - \lambda r + r - (1-p)p^{\alpha} &> 0 \\ \Leftrightarrow r(1-\lambda) &> (1-p)p^{\alpha} - \lambda p(1-p)^{\alpha} \\ \frac{r(1-\lambda)}{p(1-p)} &> \underbrace{p^{\alpha-1} - \lambda(1-p)^{\alpha-1}}_{=(*)}. \end{aligned}$$

The smaller $(*) = e^{(\alpha-1)ln(p)} - \lambda e^{(\alpha-1)ln(1-p)}$, the more likely the condition is fulfilled:

$$\frac{\partial(*)}{\partial\alpha} = ln(p)e^{(\alpha-1)ln(p)} - \lambda \cdot ln(1-p)e^{(\alpha-1)ln(1-p)} \overset{!}{<} 0$$
$$\Leftrightarrow ln(p)p^{\alpha-1} - \lambda ln(1-p)(1-p)^{\alpha-1} < 0$$
$$\Leftrightarrow ln(p)p^{\alpha-1} < \lambda ln(1-p)(1-p)^{\alpha-1}$$
$$\Leftrightarrow \lambda \underbrace{\left(\frac{ln(p)}{ln(1-p)}\right)}_{>1 \forall p<0.5} > \underbrace{\left(\frac{1-p}{p}\right)^{\alpha-1}}_{<1 \forall p<0.5}$$

which is a most likely fulfilled condition. Therefore, insurance demand is most likely ($p < 0.5$) increasing with risk aversion when using perfect insurance as reference point.

F Appendix 5: Additional tables

Table 18: Treatment overview

	N
Not Visited	347
Visited	700
No Treatment	130
Insurance Education	129
Endorsement	74
High Reward	101
Insurance Education & Endorsement	65
Insurance Education & High Reward	102
Endorsement & High Reward	45
Insurance Education & Endorsement & High Reward	54

Table 19: Summary statistics and t-tests

	Entire Sample Mean (SD)	Insurance Education Mean (SD)	No Insurance Education Mean (SD)	t-test
Take-Up Rate	0.302 (0.459)	0.432 (0.496)	0.236 (0.425)	0.000
Loss Aversion	3.809 (2.195)	3.676 (2.131)	3.875 (2.226)	0.183
Percent of irrigated land	0.417 (0.432)	0.429 (0.437)	0.411 (0.430)	0.544
Above average expected monsoon rain	-0.002 (1.052)	0.046 (1.069)	-0.027 (1.043)	0.319
Insurance demand in 2004 (1=Yes)	0.260 (0.439)	0.248 (0.432)	0.267 (0.443)	0.525
Insurance skills	0.004 (1.000)	0.095 (0.866)	-0.042 (1.058)	0.034
Has other insurance (1=Yes)	0.814 (0.389)	0.819 (0.386)	0.812 (0.391)	0.778
Does not know Basix (1=Yes)	0.294 (0.456)	0.273 (0.446)	0.305 (0.461)	0.303
Belongs to Water User Group (1=Yes)	0.019 (0.137)	0.019 (0.137)	0.019 (0.137)	0.990
No. of community groups	0.740 (0.628)	0.800 (0.639)	0.709 (0.621)	0.039
Belongs to Scheduled Caste/Tribe (1=Yes)	0.112 (0.315)	0.124 (0.330)	0.105 (0.307)	0.410
Muslim (1=Yes)	0.037 (0.189)	0.032 (0.176)	0.040 (0.196)	0.517
Gender (1=Male)	0.946 (0.227)	0.937 (0.244)	0.950 (0.217)	0.406
log household head age	3.855 (0.258)	3.872 (0.250)	3.846 (0.262)	0.136
household size	6.274 (2.826)	6.083 (2.759)	6.371 (2.857)	0.136
High Education (1=Yes)	0.312 (0.464)	0.279 (0.449)	0.329 (0.470)	0.115

Table 20: Determinants of insurance demand (full table)

	Dependent variable:				
	'Insurance Take-Up'				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.012**	−0.007	−0.016**	−0.012*	−0.016**
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)
Visit (1=Yes)	0.193***	0.192***	0.190***	0.146***	0.146***
	(0.036)	(0.035)	(0.035)	(0.050)	(0.050)
Endorsement (1=Yes)	0.060*	0.080**	0.078**	0.060	0.113*
	(0.033)	(0.035)	(0.035)	(0.036)	(0.063)
High Reward (1=Yes)	0.381***	0.376***	0.381***	0.375***	0.269***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.056)
Insurance Education (1=Yes)	−0.006	−0.011	−0.117**	−0.113**	−0.099*
	(0.031)	(0.030)	(0.054)	(0.054)	(0.055)
Loss Aversion × Insurance Education			0.029**	0.029**	0.026**
			(0.012)	(0.012)	(0.012)
Loss Aversion × Endorsement					−0.013
					(0.014)
Loss Aversion × High Reward					0.029**
					(0.013)
Percent of irrigated land				0.008	0.010
				(0.033)	(0.033)
Above average expected monsoon rain				−0.019	−0.021
				(0.013)	(0.013)
Insurance demand in 2004 (1=Yes)				0.077**	0.076**
				(0.034)	(0.034)
Insurance skills				−0.004	−0.004
				(0.016)	(0.016)
Has other insurance (1=Yes)				0.089***	0.089***
				(0.033)	(0.033)
Does not know Basix (1=Yes)				−0.077**	−0.076**
				(0.031)	(0.031)
Belongs to Water User Group (1=Yes)				0.045	0.039
				(0.094)	(0.094)
No. of community-groups				0.019	0.016
				(0.021)	(0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.014	0.022
				(0.042)	(0.042)
Muslim (1=Yes)				−0.023	−0.021
				(0.077)	(0.076)
Gender (1=Male)				0.003	0.011
				(0.057)	(0.057)
Log household head age				0.059	0.053
				(0.052)	(0.052)
Household size				0.003	0.003
				(0.005)	(0.005)
High Education (1=Yes)				0.056*	0.058*
				(0.030)	(0.030)
Village Endorsed (1=Yes)				0.065	0.065
				(0.059)	(0.059)
Constant	0.090***				
	(0.032)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R^2	0.279	0.356	0.361	0.387	0.391
Adjusted R^2	0.275	0.327	0.331	0.348	0.350
Residual Std. Error	0.391	0.377	0.376	0.371	0.370

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 21: Determinants of insurance demand (subsample: Farmer who did not receive insurance education)

	Dependent variable:			
	Insurance Take-Up			
	(1)	(2)	(3)	(4)
Loss Aversion	−0.020***	−0.017***	−0.012*	−0.015*
	(0.006)	(0.006)	(0.007)	(0.008)
Visit (1=Yes)	0.193***	0.191***	0.111**	0.112**
	(0.036)	(0.036)	(0.051)	(0.051)
Endorsement (1=Yes)	0.055	0.068	0.029	0.136*
	(0.042)	(0.044)	(0.047)	(0.077)
High Reward (1=Yes)	0.384***	0.377***	0.368***	0.249***
	(0.040)	(0.040)	(0.040)	(0.068)
Loss Aversion × Endorsement				−0.028*
				(0.016)
Loss Aversion × High Reward				0.031**
				(0.015)
Percent of irrigated land			−0.010	−0.012
			(0.037)	(0.037)
Above average expected monsoon rain			−0.019	−0.021
			(0.014)	(0.014)
Insurance skills			−0.0002	−0.001
			(0.018)	(0.018)
Has other insurance (1=Yes)			0.081**	0.080**
			(0.037)	(0.037)
Does not know Basix (1=Yes)			−0.093***	−0.096***
			(0.034)	(0.034)
Belongs to Water User Group (1=Yes)			−0.085	−0.088
			(0.105)	(0.104)
No. of community-groups			0.049**	0.042*
			(0.024)	(0.024)
Belongs to Scheduled Caste/Tribe (1=Yes)			0.046	0.053
			(0.048)	(0.048)
Muslim (1=Yes)			−0.068	−0.067
			(0.079)	(0.079)
Gender (1=Male)			−0.031	−0.030
			(0.065)	(0.065)
Log household head age			0.035	0.028
			(0.057)	(0.057)
Household size			0.002	0.003
			(0.005)	(0.005)
High Education (1=Yes)			0.102***	0.103***
			(0.032)	(0.032)
Village Endorsed (1=Yes)			0.129**	0.129**
			(0.063)	(0.062)
Constant	0.120***			
	(0.032)			
Village Fixed Effects	No	Yes	Yes	Yes
Observations	626	626	626	626
Mean Dependent Variable	0.236	0.236	0.236	0.236
R^2	0.320	0.396	0.434	0.440
Adjusted R^2	0.316	0.355	0.381	0.385
Residual Std. Error	0.352	0.341	0.335	0.334

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 22: Determinants of insurance demand (subsample: Farmer who received insurance education)

	Dependent variable:			
	Insurance Take-Up			
	(1)	(2)	(3)	(4)
Loss Aversion	0.005	0.014	0.018	0.010
	(0.012)	(0.012)	(0.013)	(0.019)
Endorsement (1=Yes)	0.060	0.100*	0.102*	0.117
	(0.054)	(0.059)	(0.060)	(0.114)
High Reward (1=Yes)	0.386***	0.372***	0.365***	0.285***
	(0.053)	(0.053)	(0.053)	(0.106)
Loss Aversion × Endorsement				−0.004
				(0.026)
Loss Aversion × High Reward				0.023
				(0.026)
Percent of irrigated land			0.120*	0.126*
			(0.071)	(0.072)
Above average expected monsoon rain			−0.011	−0.012
			(0.026)	(0.027)
Insurance skills			0.022	0.024
			(0.035)	(0.036)
Has other insurance (1=Yes)			0.097	0.099
			(0.071)	(0.071)
Does not know Basix (1=Yes)			−0.068	−0.063
			(0.069)	(0.070)
Belongs to Water User Group (1=Yes)			0.304	0.298
			(0.200)	(0.201)
No. of community-groups			−0.013	−0.011
			(0.042)	(0.042)
Belongs to Scheduled Caste/Tribe (1=Yes)			−0.032	−0.020
			(0.088)	(0.090)
Muslim (1=Yes)			0.124	0.124
			(0.202)	(0.202)
Gender (1=Male)			0.096	0.105
			(0.110)	(0.111)
Log household head age			0.027	0.025
			(0.112)	(0.112)
Household size			0.008	0.008
			(0.010)	(0.010)
High Education (1=Yes)			−0.005	−0.002
			(0.064)	(0.064)
Constant	0.211***			
	(0.063)			
Village Fixed Effects	No	Yes	Yes	Yes
Observations	315	315	315	315
Mean Dependent Variable	0.432	0.432	0.432	0.432
R^2	0.154	0.341	0.377	0.379
Adjusted R^2	0.146	0.247	0.253	0.250
Residual Std. Error	0.459	0.431	0.429	0.430

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 23: Determinants of insurance demand (subsample: Farmer who did not demand insurance in 2004)

	Dependent variable:				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.001	0.002	−0.007	−0.008	−0.012
	(0.006)	(0.006)	(0.008)	(0.008)	(0.009)
Visit (1=Yes)	0.186***	0.179***	0.178***	0.162***	0.165***
	(0.039)	(0.039)	(0.039)	(0.056)	(0.056)
Endorsement (1=Yes)	0.011	0.013	0.012	0.004	0.055
	(0.036)	(0.039)	(0.038)	(0.041)	(0.073)
High Reward (1=Yes)	0.447***	0.449***	0.452***	0.449***	0.366***
	(0.034)	(0.034)	(0.034)	(0.035)	(0.064)
Insurance Education (1=Yes)	−0.021	−0.020	−0.125**	−0.123**	−0.121*
	(0.034)	(0.033)	(0.061)	(0.062)	(0.063)
Loss Aversion × Insurance Education			0.027**	0.028**	0.028**
			(0.013)	(0.013)	(0.014)
Loss Aversion × Endorsement					−0.013
					(0.015)
Loss Aversion × High Reward					0.022
					(0.014)
Percent of irrigated land				−0.013	−0.011
				(0.038)	(0.038)
Above average expected monsoon rain				−0.018	−0.019
				(0.014)	(0.014)
Insurance skills				−0.008	−0.009
				(0.017)	(0.017)
Has other insurance (1=Yes)				0.083**	0.083**
				(0.036)	(0.036)
Does not know Basix (1=Yes)				−0.070**	−0.069**
				(0.033)	(0.033)
Belongs to Water User Group (1=Yes)				−0.009	−0.014
				(0.127)	(0.127)
No. of community-groups				0.010	0.007
				(0.024)	(0.024)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.016	0.021
				(0.044)	(0.044)
Muslim (1=Yes)				0.027	0.028
				(0.081)	(0.081)
Gender (1=Male)				−0.020	−0.012
				(0.070)	(0.070)
Log household head age				0.058	0.055
				(0.059)	(0.059)
Household size				0.003	0.004
				(0.005)	(0.005)
High Education (1=Yes)				−0.006	−0.004
				(0.035)	(0.035)
Village Endorsed (1=Yes)				0.019	0.018
				(0.066)	(0.066)
Constant	0.019				
	(0.035)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	696	696	696	696	696
Mean Dependent Variable	0.272	0.272	0.272	0.272	0.272
R^2	0.333	0.393	0.397	0.409	0.412
Adjusted R^2	0.328	0.355	0.358	0.357	0.358
Residual Std. Error	0.365	0.358	0.357	0.357	0.357

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 24: Determinants of insurance demand (subsample: Visited farmers)

	Dependent variable:				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.013	−0.007	−0.023**	−0.017	−0.034**
	(0.008)	(0.008)	(0.011)	(0.011)	(0.014)
Endorsement (1=Yes)	0.060	0.069	0.067	0.061	0.094
	(0.038)	(0.042)	(0.042)	(0.042)	(0.076)
High Reward (1=Yes)	0.381***	0.372***	0.375***	0.365***	0.207***
	(0.037)	(0.036)	(0.036)	(0.036)	(0.069)
Insurance Education (1=Yes)	−0.006	−0.014	−0.150**	−0.138**	−0.137**
	(0.036)	(0.035)	(0.069)	(0.069)	(0.069)
Loss Aversion × Insurance Education			0.036**	0.036**	0.037**
			(0.016)	(0.016)	(0.016)
Loss Aversion × Endorsement					−0.008
					(0.017)
Loss Aversion × High Reward					0.043***
					(0.016)
Percent of irrigated land				−0.002	−0.00002
				(0.048)	(0.048)
Above average expected monsoon rain				−0.022	−0.024
				(0.018)	(0.018)
Insurance demand in 2004 (1=Yes)				0.094**	0.095**
				(0.048)	(0.047)
Insurance skills				0.021	0.023
				(0.025)	(0.025)
Has other insurance (1=Yes)				0.103**	0.103**
				(0.048)	(0.048)
Does not know Basix (1=Yes)				−0.092**	−0.087*
				(0.047)	(0.047)
Belongs to Water User Group (1=Yes)				0.042	0.025
				(0.144)	(0.143)
No. of community-groups				0.010	0.006
				(0.030)	(0.030)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.005	0.023
				(0.060)	(0.060)
Muslim (1=Yes)				−0.031	−0.021
				(0.128)	(0.127)
Gender (1=Male)				0.024	0.045
				(0.082)	(0.082)
Log household head age				0.072	0.063
				(0.077)	(0.076)
Household size				0.005	0.006
				(0.007)	(0.007)
High Education (1=Yes)				0.060	0.063
				(0.043)	(0.043)
Village Endorsed (1=Yes)					
Constant	0.285***				
	(0.047)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	634	634	634	634	634
Mean Dependent Variable	0.427	0.427	0.427	0.427	0.427
R^2	0.158	0.276	0.283	0.316	0.325
Adjusted R^2	0.153	0.227	0.234	0.251	0.258
Residual Std. Error	0.456	0.435	0.433	0.429	0.427

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 25: Determinants of insurance demand (subsample: Farmers who did not receive the high reward)

	Dependent variable:				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.021***	−0.017***	−0.023***	−0.020***	−0.019***
	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Visit (1=Yes)	0.178***	0.158***	0.161***	0.169***	0.169***
	(0.035)	(0.034)	(0.034)	(0.047)	(0.047)
Endorsement (1=Yes)	0.098**	0.141***	0.138***	0.142***	0.178**
	(0.038)	(0.040)	(0.039)	(0.043)	(0.075)
Insurance Education (1=Yes)	0.0004	0.008	−0.089	−0.099	−0.105
	(0.037)	(0.035)	(0.063)	(0.063)	(0.064)
Loss Aversion × Insurance Education			0.024*	0.026**	0.028**
			(0.013)	(0.013)	(0.013)
Loss Aversion × Endorsement					−0.009
					(0.015)
Percent of irrigated land				0.010	0.011
				(0.034)	(0.034)
Above average expected monsoon rain				−0.016	−0.016
				(0.013)	(0.013)
Insurance skills				−0.025	−0.025
				(0.016)	(0.016)
Has other insurance (1=Yes)				0.065*	0.065**
				(0.033)	(0.033)
Does not know Basix (1=Yes)				−0.099***	−0.099***
				(0.031)	(0.031)
Belongs to Water User Group (1=Yes)				0.044	0.046
				(0.097)	(0.097)
No. of community-groups				0.036*	0.035
				(0.021)	(0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.008	0.007
				(0.043)	(0.043)
Muslim (1=Yes)				0.033	0.033
				(0.075)	(0.075)
Gender (1=Male)				−0.011	−0.012
				(0.057)	(0.057)
Log household head age				−0.015	−0.016
				(0.053)	(0.053)
Household size				−0.003	−0.003
				(0.005)	(0.005)
High Education (1=Yes)				0.077**	0.078**
				(0.030)	(0.030)
Village Endorsed (1=Yes)				−0.009	−0.009
				(0.058)	(0.058)
Constant	0.124***				
	(0.031)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	653	653	653	653	653
Mean Dependent Variable	0.153	0.153	0.153	0.153	0.153
R^2	0.108	0.267	0.272	0.312	0.313
Adjusted R^2	0.103	0.219	0.223	0.249	0.248
Residual Std. Error	0.341	0.318	0.318	0.312	0.313

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 26: Determinants of insurance demand ($\lambda = 7 + min(distance) = 7.5$)

	Dependent variable:				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.013**	−0.007	−0.017**	−0.013	−0.018**
	(0.006)	(0.006)	(0.008)	(0.008)	(0.009)
Visit (1=Yes)	0.192***	0.191***	0.189***	0.146***	0.146***
	(0.036)	(0.035)	(0.035)	(0.050)	(0.050)
Endorsement (1=Yes)	0.060*	0.080**	0.078**	0.060	0.121*
	(0.033)	(0.035)	(0.035)	(0.036)	(0.066)
High Reward (1=Yes)	0.381***	0.377***	0.382***	0.375***	0.262***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.059)
Insurance Education (1=Yes)	−0.006	−0.011	−0.130**	−0.125**	−0.110*
	(0.031)	(0.030)	(0.057)	(0.057)	(0.058)
Loss Aversion × Insurance Education			0.033**	0.033**	0.030**
			(0.013)	(0.013)	(0.014)
Loss Aversion × Endorsement					−0.016
					(0.015)
Loss Aversion × High Reward					0.031**
					(0.014)
Percent of irrigated land				0.008	0.010
				(0.033)	(0.033)
Above average expected monsoon rain				−0.019	−0.021
				(0.013)	(0.013)
Insurance demand in 2004 (1=Yes)				0.077**	0.076**
				(0.034)	(0.034)
Insurance skills				−0.004	−0.004
				(0.016)	(0.016)
Has other insurance (1=Yes)				0.090***	0.091***
				(0.033)	(0.033)
Does not know Basix (1=Yes)				−0.076**	−0.075**
				(0.031)	(0.031)
Belongs to Water User Group (1=Yes)				0.045	0.039
				(0.094)	(0.094)
No. of community-groups				0.019	0.016
				(0.021)	(0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.014	0.022
				(0.042)	(0.042)
Muslim (1=Yes)				−0.021	−0.020
				(0.076)	(0.076)
Gender (1=Male)				0.003	0.010
				(0.057)	(0.056)
Log household head age				0.058	0.053
				(0.052)	(0.052)
Household size				0.003	0.003
				(0.005)	(0.005)
High Education (1=Yes)				0.056*	0.058*
				(0.030)	(0.030)
Village Endorsed (1=Yes)				0.064	0.064
				(0.059)	(0.059)
Constant	0.092***				
	(0.033)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R^2	0.279	0.356	0.361	0.387	0.391
Adjusted R^2	0.275	0.327	0.331	0.348	0.350
Residual Std. Error	0.391	0.377	0.376	0.371	0.370

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 27: Determinants of insurance demand
($\lambda = 7 + mean(distance) = 7.75$)

	Dependent variable:				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.013**	−0.007	−0.017**	−0.012	−0.017**
	(0.006)	(0.006)	(0.007)	(0.008)	(0.009)
Visit (1=Yes)	0.193***	0.191***	0.189***	0.146***	0.146***
	(0.036)	(0.035)	(0.035)	(0.050)	(0.050)
Endorsement (1=Yes)	0.060*	0.080**	0.078**	0.060	0.119*
	(0.033)	(0.035)	(0.035)	(0.036)	(0.065)
High Reward (1=Yes)	0.381***	0.376***	0.381***	0.375***	0.264***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.058)
Insurance Education (1=Yes)	−0.006	−0.011	−0.127**	−0.122**	−0.107*
	(0.031)	(0.030)	(0.057)	(0.056)	(0.057)
Loss Aversion × Insurance Education			0.032**	0.032**	0.029**
			(0.013)	(0.013)	(0.013)
Loss Aversion × Endorsement					−0.015
					(0.015)
Loss Aversion × High Reward					0.031**
					(0.014)
Percent of irrigated land				0.008	0.010
				(0.033)	(0.033)
Above average expected monsoon rain				−0.019	−0.021
				(0.013)	(0.013)
Insurance demand in 2004 (1=Yes)				0.077**	0.076**
				(0.034)	(0.034)
Insurance skills				−0.004	−0.004
				(0.016)	(0.016)
Has other insurance (1=Yes)				0.090***	0.090***
				(0.033)	(0.033)
Does not know Basix (1=Yes)				−0.076**	−0.075**
				(0.031)	(0.031)
Belongs to Water User Group (1=Yes)				0.045	0.039
				(0.094)	(0.094)
No. of community-groups				0.019	0.016
				(0.021)	(0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.014	0.022
				(0.042)	(0.042)
Muslim (1=Yes)				−0.022	−0.020
				(0.077)	(0.076)
Gender (1=Male)				0.003	0.010
				(0.057)	(0.056)
Log household head age				0.058	0.053
				(0.052)	(0.052)
Household size				0.003	0.003
				(0.005)	(0.005)
High Education (1=Yes)				0.056*	0.058*
				(0.030)	(0.030)
Village Endorsed (1=Yes)				0.064	0.064
				(0.059)	(0.059)
Constant	0.091***				
	(0.033)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R^2	0.279	0.356	0.361	0.387	0.391
Adjusted R^2	0.275	0.327	0.331	0.348	0.350
Residual Std. Error	0.391	0.377	0.376	0.371	0.370

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 28: Determinants of insurance demand ($\lambda_{upper\ bound} = 8$)

	Dependent variable:				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.010*	−0.005	−0.014**	−0.010	−0.013*
	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)
Visit (1=Yes)	0.191***	0.190***	0.188***	0.146***	0.146***
	(0.036)	(0.035)	(0.035)	(0.050)	(0.050)
Endorsement (1=Yes)	0.060*	0.080**	0.077**	0.059	0.132**
	(0.033)	(0.035)	(0.035)	(0.036)	(0.067)
High Reward (1=Yes)	0.382***	0.377***	0.382***	0.376***	0.268***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.060)
Insurance Education (1=Yes)	−0.005	−0.010	−0.137**	−0.130**	−0.116**
	(0.031)	(0.030)	(0.058)	(0.058)	(0.059)
Loss Aversion × Insurance Education			0.029**	0.029**	0.027**
			(0.011)	(0.011)	(0.012)
Loss Aversion × Endorsement					−0.016
					(0.013)
Loss Aversion × High Reward					0.025**
					(0.012)
Percent of irrigated land				0.009	0.010
				(0.033)	(0.033)
Above average expected monsoon rain				−0.019	−0.020
				(0.013)	(0.013)
Insurance demand in 2004 (1=Yes)				0.077**	0.076**
				(0.034)	(0.034)
Insurance skills				−0.003	−0.003
				(0.016)	(0.016)
Has other insurance (1=Yes)				0.091***	0.093***
				(0.033)	(0.033)
Does not know Basix (1=Yes)				−0.075**	−0.075**
				(0.031)	(0.031)
Belongs to Water User Group (1=Yes)				0.046	0.040
				(0.094)	(0.094)
No. of community-groups				0.019	0.016
				(0.021)	(0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.014	0.022
				(0.042)	(0.042)
Muslim (1=Yes)				−0.019	−0.019
				(0.076)	(0.076)
Gender (1=Male)				0.004	0.008
				(0.056)	(0.056)
Log household head age				0.056	0.052
				(0.052)	(0.052)
Household size				0.003	0.003
				(0.005)	(0.005)
High Education (1=Yes)				0.057*	0.059**
				(0.030)	(0.030)
Village Endorsed (1=Yes)				0.063	0.062
				(0.059)	(0.059)
Constant	0.087**				
	(0.034)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R^2	0.279	0.356	0.360	0.387	0.391
Adjusted R^2	0.275	0.326	0.331	0.348	0.350
Residual Std. Error	0.391 (df = 935)	0.377 (df = 899)	0.376 (df = 898)	0.371 (df = 883)	0.370 (df = 881)

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 29: Determinants of insurance demand ($\lambda_{upper\ bound} = 8.5$)

	Dependent variable:				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.010*	−0.005	−0.014**	−0.010	−0.013*
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
Visit (1=Yes)	0.192***	0.191***	0.188***	0.146***	0.146***
	(0.036)	(0.035)	(0.035)	(0.050)	(0.050)
Endorsement (1=Yes)	0.060*	0.080**	0.077**	0.059	0.129*
	(0.033)	(0.035)	(0.035)	(0.036)	(0.066)
High Reward (1=Yes)	0.381***	0.377***	0.382***	0.376***	0.269***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.059)
Insurance Education (1=Yes)	−0.006	−0.010	−0.132**	−0.126**	−0.113*
	(0.031)	(0.030)	(0.057)	(0.057)	(0.058)
Loss Aversion × Insurance Education			0.028**	0.028**	0.026**
			(0.011)	(0.011)	(0.011)
Loss Aversion × Endorsement					−0.015
					(0.013)
Loss Aversion × High Reward					0.025**
					(0.012)
Percent of irrigated land				0.009	0.010
				(0.033)	(0.033)
Above average expected monsoon rain				−0.019	−0.021
				(0.013)	(0.013)
Insurance demand in 2004 (1=Yes)				0.077**	0.076**
				(0.034)	(0.034)
Insurance skills				−0.003	−0.003
				(0.016)	(0.016)
Has other insurance (1=Yes)				0.090***	0.092***
				(0.033)	(0.033)
Does not know Basix (1=Yes)				−0.076**	−0.075**
				(0.031)	(0.031)
Belongs to Water User Group (1=Yes)				0.046	0.040
				(0.094)	(0.094)
No. of community-groups				0.019	0.016
				(0.021)	(0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.014	0.022
				(0.042)	(0.042)
Muslim (1=Yes)				−0.020	−0.020
				(0.076)	(0.076)
Gender (1=Male)				0.004	0.009
				(0.056)	(0.056)
Log household head age				0.057	0.052
				(0.052)	(0.052)
Household size				0.003	0.003
				(0.005)	(0.005)
High Education (1=Yes)				0.057*	0.059**
				(0.030)	(0.030)
Village Endorsed (1=Yes)				0.064	0.063
				(0.059)	(0.059)
Constant	0.087***				
	(0.033)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R^2	0.279	0.356	0.360	0.387	0.391
Adjusted R^2	0.275	0.327	0.331	0.348	0.350
Residual Std. Error	0.391 (df = 935)	0.377 (df = 899)	0.376 (df = 898)	0.371 (df = 883)	0.370 (df = 881)

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 30: Determinants of insurance demand ($\lambda_{upper\ bound} = 10$)

	Dependent variable:				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.009*	−0.005	−0.013**	−0.009	−0.013*
	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
Visit (1=Yes)	0.193***	0.191***	0.189***	0.146***	0.147***
	(0.036)	(0.035)	(0.035)	(0.050)	(0.050)
Endorsement (1=Yes)	0.060*	0.080**	0.078**	0.059	0.119*
	(0.033)	(0.035)	(0.035)	(0.036)	(0.063)
High Reward (1=Yes)	0.381***	0.377***	0.382***	0.375***	0.275***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.055)
Insurance Education (1=Yes)	−0.006	−0.011	−0.119**	−0.114**	−0.101*
	(0.031)	(0.030)	(0.054)	(0.054)	(0.055)
Loss Aversion × Insurance Education			0.024**	0.024**	0.022**
			(0.010)	(0.010)	(0.010)
Loss Aversion × Endorsement					−0.012
					(0.011)
Loss Aversion × High Reward					0.023**
					(0.010)
Percent of irrigated land				0.009	0.010
				(0.033)	(0.033)
Above average expected monsoon rain				−0.019	−0.021
				(0.013)	(0.013)
Insurance demand in 2004 (1=Yes)				0.077**	0.076**
				(0.034)	(0.034)
Insurance skills				−0.004	−0.004
				(0.016)	(0.016)
Has other insurance (1=Yes)				0.090***	0.090***
				(0.033)	(0.033)
Does not know Basix (1=Yes)				−0.076**	−0.075**
				(0.031)	(0.031)
Belongs to Water User Group (1=Yes)				0.046	0.040
				(0.094)	(0.094)
No. of community-groups				0.019	0.016
				(0.021)	(0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.014	0.022
				(0.042)	(0.042)
Muslim (1=Yes)				−0.022	−0.021
				(0.077)	(0.076)
Gender (1=Male)				0.004	0.010
				(0.057)	(0.056)
Log household head age				0.058	0.052
				(0.052)	(0.052)
Household size				0.003	0.003
				(0.005)	(0.005)
High Education (1=Yes)				0.056*	0.058**
				(0.030)	(0.030)
Village Endorsed (1=Yes)				0.065	0.064
				(0.059)	(0.059)
Constant	0.087***				
	(0.032)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R^2	0.279	0.356	0.360	0.387	0.391
Adjusted R^2	0.275	0.327	0.330	0.347	0.350
Residual Std. Error	0.391 (df = 935)	0.377 (df = 899)	0.376 (df = 898)	0.371 (df = 883)	0.370 (df = 881)

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 31: Determinants of insurance demand ($\lambda \in \{1, \ldots, 6\}$)

	Dependent variable:				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.017**	−0.009	−0.026**	−0.019*	−0.028**
	(0.009)	(0.009)	(0.010)	(0.011)	(0.012)
Visit (1=Yes)	0.192***	0.191***	0.187***	0.146***	0.146***
	(0.036)	(0.035)	(0.035)	(0.050)	(0.050)
Endorsement (1=Yes)	0.060*	0.080**	0.078**	0.059	0.123
	(0.033)	(0.035)	(0.035)	(0.036)	(0.083)
High Reward (1=Yes)	0.380***	0.377***	0.382***	0.376***	0.225***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.074)
Insurance Education (1=Yes)	−0.005	−0.010	−0.200***	−0.193***	−0.168**
	(0.031)	(0.030)	(0.072)	(0.072)	(0.073)
Loss Aversion × Insurance Education			0.052***	0.052***	0.045**
			(0.018)	(0.018)	(0.018)
Loss Aversion × Endorsement					−0.017
					(0.021)
Loss Aversion × High Reward					0.042**
					(0.019)
Percent of irrigated land				0.009	0.010
				(0.033)	(0.033)
Above average expected monsoon rain				−0.019	−0.020
				(0.013)	(0.013)
Insurance demand in 2004 (1=Yes)				0.078**	0.079**
				(0.034)	(0.034)
Insurance skills				−0.004	−0.004
				(0.016)	(0.016)
Has other insurance (1=Yes)				0.090***	0.092***
				(0.033)	(0.033)
Does not know Basix (1=Yes)				−0.074**	−0.073**
				(0.031)	(0.031)
Belongs to Water User Group (1=Yes)				0.044	0.038
				(0.094)	(0.094)
No. of community-groups				0.018	0.016
				(0.021)	(0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.015	0.024
				(0.042)	(0.042)
Muslim (1=Yes)				−0.019	−0.017
				(0.076)	(0.076)
Gender (1=Male)				0.003	0.009
				(0.056)	(0.056)
Log household head age				0.059	0.054
				(0.052)	(0.052)
Household size				0.003	0.003
				(0.005)	(0.005)
High Education (1=Yes)				0.056*	0.057*
				(0.030)	(0.030)
Village Endorsed (1=Yes)				0.063	0.063
				(0.059)	(0.059)
Constant	0.109***				
	(0.040)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R^2	0.279	0.356	0.362	0.389	0.392
Adjusted R^2	0.276	0.327	0.332	0.349	0.351
Residual Std. Error	0.391 (df = 935)	0.377 (df = 899)	0.375 (df = 898)	0.371 (df = 883)	0.370 (df = 881)

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 32: Determinants of insurance demand (regressions without village FE)

	Dependent variable:		
	Insurance Take-Up		
	(1)	(2)	(3)
Loss Aversion	−0.020***	−0.013*	−0.018**
	(0.007)	(0.007)	(0.008)
Visit (1=Yes)	0.192***	0.182***	0.182***
	(0.036)	(0.040)	(0.040)
Endorsement (1=Yes)	0.057*	0.058	0.077
	(0.033)	(0.037)	(0.064)
High Reward (1=Yes)	0.385***	0.382***	0.298***
	(0.031)	(0.031)	(0.056)
Insurance Education (1=Yes)	−0.099*	−0.096*	−0.082
	(0.056)	(0.055)	(0.056)
Loss Aversion × Insurance Education	0.025**	0.024*	0.021*
	(0.013)	(0.012)	(0.013)
Loss Aversion × Endorsement			−0.004
			(0.014)
Loss Aversion × High Reward			0.023*
			(0.013)
Percent of irrigated land		0.023	0.022
		(0.032)	(0.032)
Above average expected monsoon rain		−0.012	−0.013
		(0.012)	(0.012)
Insurance demand in 2004 (1=Yes)		0.061*	0.060*
		(0.031)	(0.031)
Insurance skills		0.025*	0.025*
		(0.014)	(0.014)
Has other insurance (1=Yes)		0.105***	0.104***
		(0.033)	(0.033)
Does not know Basix (1=Yes)		−0.084***	−0.083***
		(0.029)	(0.029)
Belongs to Water User Group (1=Yes)		0.126	0.121
		(0.093)	(0.093)
No. of community-groups		0.028	0.027
		(0.021)	(0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)		0.017	0.024
		(0.041)	(0.041)
Muslim (1=Yes)		0.068	0.071
		(0.067)	(0.067)
Gender (1=Male)		−0.011	−0.004
		(0.057)	(0.057)
Log household head age		0.049	0.045
		(0.052)	(0.052)
Household size		0.005	0.005
		(0.005)	(0.005)
High Education (1=Yes)		0.027	0.029
		(0.029)	(0.029)
Village Endorsed (1=Yes)		−0.002	−0.002
		(0.038)	(0.038)
Constant	0.120***	−0.230	−0.203
	(0.035)	(0.212)	(0.213)
Observations	941	941	941
Mean Dependent Variable	0.302	0.302	0.302
R^2	0.283	0.323	0.326
Adjusted R^2	0.278	0.308	0.309
Residual Std. Error	0.390 (df = 934)	0.382 (df = 919)	0.382 (df = 917)

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 33: Determinants of Insurance Demand (probit regression)

	Dependent variable:				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Loss Aversion	−0.051**	−0.051**	−0.096***	−0.067**	−0.128***
	(0.023)	(0.023)	(0.030)	(0.031)	(0.043)
Visit (1=Yes)	1.014***	1.014***	1.022***	1.066***	1.092***
	(0.162)	(0.162)	(0.163)	(0.187)	(0.190)
Endorsement (1=Yes)	0.177	0.177	0.168	0.193	0.122
	(0.111)	(0.111)	(0.111)	(0.135)	(0.234)
High Reward (1=Yes)	1.008***	1.008***	1.027***	1.097***	0.665***
	(0.106)	(0.106)	(0.107)	(0.112)	(0.210)
Insurance Education (1=Yes)	−0.019	−0.019	−0.421**	−0.433**	−0.407*
	(0.106)	(0.106)	(0.201)	(0.210)	(0.211)
Loss Aversion × Insurance Education			0.110**	0.113**	0.112**
			(0.046)	(0.048)	(0.050)
Loss Aversion × Endorsement					0.025
					(0.053)
Loss Aversion × High Reward					0.121**
					(0.050)
Percent of irrigated land				0.100	0.098
				(0.129)	(0.129)
Above average expected monsoon rain				−0.057	−0.060
				(0.049)	(0.050)
Insurance demand in 2004 (1=Yes)				0.198	0.197
				(0.125)	(0.125)
Insurance skills				0.186***	0.192***
				(0.070)	(0.071)
Has other insurance (1=Yes)				0.473***	0.470***
				(0.148)	(0.149)
Does not know Basix (1=Yes)				−0.425***	−0.415***
				(0.129)	(0.130)
Belongs to Water User Group (1=Yes)				0.477	0.423
				(0.369)	(0.370)
No. of community-groups				0.125	0.126
				(0.084)	(0.084)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.050	0.097
				(0.172)	(0.174)
Muslim (1=Yes)				0.296	0.338
				(0.284)	(0.285)
Gender (1=Male)				0.005	0.067
				(0.235)	(0.240)
Log household head age				0.175	0.148
				(0.217)	(0.218)
Household size				0.019	0.019
				(0.019)	(0.019)
High Education (1=Yes)				0.078	0.078
				(0.117)	(0.117)
Village Endorsed (1=Yes)				0.012	0.003
				(0.138)	(0.138)
Constant	−1.541***	−1.541***	−1.389***	−2.939***	−2.712***
	(0.152)	(0.152)	(0.163)	(0.900)	(0.908)
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
Log Likelihood	−433.694	−433.694	−430.596	−399.257	−396.420
Akaike Inf. Crit.	879.388	879.388	875.192	842.515	840.840

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.

Table 34: Determinants of insurance demand (risk aversion)

	Dependent variable:				
	Insurance Take-Up				
	(1)	(2)	(3)	(4)	(5)
Risk Aversion	−0.099**	−0.051	−0.156***	−0.123**	−0.177**
	(0.050)	(0.049)	(0.060)	(0.060)	(0.070)
Visit (1=Yes)	0.192***	0.191***	0.187***	0.145***	0.145***
	(0.036)	(0.035)	(0.035)	(0.050)	(0.050)
Endorsement (1=Yes)	0.060*	0.080**	0.078**	0.059	0.102
	(0.033)	(0.035)	(0.035)	(0.036)	(0.075)
High Reward (1=Yes)	0.380***	0.376***	0.382***	0.376***	0.255***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.065)
Insurance Education (1=Yes)	−0.006	−0.010	−0.186***	−0.180***	−0.157**
	(0.031)	(0.030)	(0.064)	(0.064)	(0.065)
Risk Aversion × Insurance Education			0.316***	0.314***	0.277***
			(0.102)	(0.101)	(0.104)
Risk Aversion × Endorsement					−0.072
					(0.118)
Risk Aversion × High Reward					0.220**
					(0.105)
Percent of irrigated land				0.009	0.011
				(0.033)	(0.033)
Above average expected monsoon rain				−0.019	−0.020
				(0.013)	(0.013)
Insurance demand in 2004 (1=Yes)				0.079**	0.080**
				(0.034)	(0.034)
Insurance skills				−0.004	−0.004
				(0.016)	(0.016)
Has other insurance (1=Yes)				0.090***	0.091***
				(0.033)	(0.033)
Does not know Basix (1=Yes)				−0.073**	−0.071**
				(0.031)	(0.031)
Belongs to Water User Group (1=Yes)				0.044	0.040
				(0.094)	(0.094)
No. of community-groups				0.019	0.016
				(0.021)	(0.021)
Belongs to Scheduled Caste/Tribe (1=Yes)				0.016	0.024
				(0.042)	(0.042)
Muslim (1=Yes)				−0.021	−0.017
				(0.076)	(0.076)
Gender (1=Male)				0.004	0.009
				(0.056)	(0.056)
Log household head age				0.060	0.057
				(0.052)	(0.052)
Household size				0.003	0.003
				(0.005)	(0.005)
High Education (1=Yes)				0.056*	0.057*
				(0.030)	(0.030)
Village Endorsed (1=Yes)				0.064	0.065
				(0.059)	(0.059)
Constant	0.100***				
	(0.037)				
Village Fixed Effects	No	Yes	Yes	Yes	Yes
Observations	941	941	941	941	941
Mean Dependent Variable	0.302	0.302	0.302	0.302	0.302
R^2	0.279	0.356	0.363	0.390	0.393
Adjusted R^2	0.276	0.327	0.333	0.350	0.352
Residual Std. Error	0.391	0.377	0.375	0.370	0.370

Note: *p<0.1; **p<0.05; ***p<0.01. Robust standard errors in parenthesis.