

Württemberg, Daniel

Working Paper

Index Based Insurance in Developing Countries: Rational Neglect?

Suggested Citation: Würtenberger, Daniel (2019) : Index Based Insurance in Developing Countries: Rational Neglect?, ZBW – Leibniz Information Centre for Economics, Kiel, Hamburg

This Version is available at:

<https://hdl.handle.net/10419/206408>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Index-Based Insurance in Developing Countries: Rational Neglect?

Abstract

Microinsurance adoption in developing countries is low, despite its potential to foster economic growth. Recent research is not able to explain the low demand within the neoclassical framework. I contribute to this stream of research by proposing rational as well as boundedly rational explanations for the low attractiveness of microinsurance within a stochastic framework. More precisely, I analyze weather index insurance. My model makes separate predictions for *close farmers*, whose location is near a weather station, and *distant farmers*. Results show that the latter ask for less than 50% insurance coverage even under perfect rationality. I extend the model by integrating incorrect beliefs. I can show that a lack of trust reduces insurance demand most for close farmers, while a lack of knowledge about the insurance negatively affects the demand of distant farmers. Moreover, subsidies are more effective for close than for distant farmers.

Keywords: index insurance; basis risk; microinsurance; developing countries; understanding of insurance products; trust in insurer

JEL-codes: G22, D91, Q12, O13, O16

Date: October 22, 2019

1 Introduction

Almost 75% of the world population that lives by less than 1\$ per day are tied to the farming sector. Hence, the economies of most developing countries highly depend on agriculture and thus, the farming sector is crucial for fostering economic growth (World Bank, 2017). Life for the poor employed in this sector is very risky due to the randomness of rainfall.¹ In India, 90% of variation in the crop production level is rooted in the variation of rainfall (Parchure, 2002). Carter et al. (2014) find that droughts affect the largest group of farmers and cause the highest damage costs. Further, due to climate change, exposition of farmers to droughts is expected to deteriorate over time (Henderson et al., 2017). As a result, a large part of the GDP in developing countries is generated through highly volatile agricultural income, which, in turn, impedes a society's capacity to innovate and develop (Fafchamps, 2003). To overcome the income variation, farmers need instruments like microinsurance schemes to smooth income and rely on consumption plans.

Formal insurers, meanwhile, face one main problem: the total value insured in developing countries is of small scale. At the same time, administrative costs are similarly large as in developed countries, since in both cases it is time consuming and expensive to verify insurance claims.² Consequently, an insurance company that is striving for profit would have to charge premiums that are most likely prohibitively expensive for a majority of farmers (Patt et al., 2009).

Starting in 2003, an attempt to overcome this imbalance of total value insured and administrative costs has been piloted: index insurance. In place of offering personalized contracts and therefore linking the payout to individual losses, index insurance conditions the indemnity payment on an observable index. Frequently, indices capture climatic data such as rainfall or temperature, which are measured at a regional meteorological station and not at the insured farmer's exact position (Radhakrishna et al., 2006). Hence, on the one hand, moral hazard and adverse selection are eliminated (Carter et al.,

¹Besides farmers, every person who is tied to the agricultural marketing chain via contractual relationships, such as agricultural banks or suppliers, is exposed to the risk the farming sector bears (Miranda and Gonzalez-Vega, 2011).

²Cull et al. (2009) document that annual operating costs for non-bank microfinance loans in India range from 17% to 26% of loan value, far higher than the corresponding costs in developed countries.

2014; Giné et al., 2008). On the other hand, however, there may exist a discrepancy between the index value measured at the regional station and the farmer's position. This characteristic of index insurance, called *basis risk*, certainly influences the quality of the insurance contract.³

The introduction of index insurance products has been regarded as a promising approach to foster economic growth (Patt et al., 2009; Hellmuth et al., 2009). With index insurance the situation of farmers is expected to become better not only due to the ability of income smoothing but also due to considerable welfare gains (Cole et al., 2017) and adoption of new technologies (Carter et al., 2016). Carter et al. (2014) predict farmers to demand the index insurance if it is offered at an actuarially fair price, using a neoclassical model. However, the insurance market is characterized by low demand (Karlan et al., 2014; Gaurav et al., 2011), even if the product is highly subsidized (Mobarak and Rosenzweig, 2012), although farmers are familiar with the risk of being employed in the farming sector (Cole et al., 2013a).

In their meta study, Eling et al. (2014) list several reasons for the low demand of index insurance in developing countries. These are for example liquidity constraints, lack of trust in the insurer and a lack of financial literacy. Nevertheless, according to Giné et al. (2008), farmers mention basis risk as one of the most important reasons to decide against index insurance products. Further, Cole et al. (2013b) show that farmer's willingness to pay for the insurance contract significantly decreases if the nearest weather station is replaced by a more distant one. According to these findings, Clarke (2016) set up a model where he puts forth basis risk as an explanation for the low demand of index insurance recorded in several RCTs. He argues while explanations such as lack of trust and understanding about the product may be relevant, basis risk alone can explain why risk averse individuals demand little coverage.⁴ However, Clarke (2016) does not attempt to quantify how

³Following Miranda and Farrin (2012) basis risk does not completely vanish by setting the weather station directly at the farmer's field. It still exists a natural limit which includes factors at the farm level, i.e., sub-optimal exposure to sunlight, wind damage, fire and disease. However, in this work, I neglect these factors and concentrate on the impact of distance between the weather station and the farmer's field.

⁴From a neoclassical point of view, risk averse agents ask for full insurance coverage if the insurance premium is actuarially fair (Sarris, 2002). In developed countries such a behavior is also empirically observable. Since in developing countries existences depend on agricultural income, demand for insurance should be even higher as in developed ones.

much of the gap between current demand levels and full insurance is due to different explanations.

In this work, I fill in this research gap by better understanding the relevant mechanisms driving the low demand of farmers, in particular, depending on the distance to their nearest weather station, i.e., basis risk. This issue addresses a relevant problem since different mechanisms will require different policy actions.⁵

I suggest rational explanations of farmers' low demand of index-based weather insurance by setting up a stochastic model of index insurance demand within an expected utility framework. Similar to Clarke (2016), this approach stands in contrast to previous research that is mainly concerned about convincing farmers of the insurance product without taking into account the (objective) failure of the contract for many farmers. With index insurance, farmers located closer to a weather station face smaller basis risk than farmers located further away. Hence, the distance to the nearest weather station certainly affects the decision to insure (Mobarak and Rosenzweig, 2012). An important assumption of my model is that the variance of basis risk increases in the distance between farmer and weather station. To the best of my knowledge, no other model exists that in particular captures the stochastic distribution of basis risk and analyzes optimal insurance behavior depending on the farmers' distance to the nearest weather station. The contingency on distance allows distinguishing the results for different groups of farmers, *close farmers* with a distance below 10km to the nearest weather station and all others, the *distant farmers*. My main finding is that from a rational point of view, close farmers should ask for more than 50% insurance coverage, distant farmers for less than 50%.

Additionally, incorrect beliefs of farmers may negatively affect insurance demand. Therefore, in an extension of my model, I investigate the consequences of farmers' incorrect beliefs about the indemnity payment by the insurer. I distinguish between a *trust bias*, i.e., overestimating the downside risk, and a *savvy bias*, i.e., underestimating the possibility of income smoothing with the help of insurance products.⁶ I find that the behavior of

⁵For example, if basis risk is the issue, then increasing the density of weather stations may be important, but if lack of trust or understanding about the product is the source, the product itself may be designed differently.

⁶Downside risk is defined as an (unexpected) loss, i.e., the realized random variable is smaller than its expected value. Upside risk is in turn defined as an (unexpected) gain, i.e., the realized random variable is bigger than its expected value.

close farmers is consistent with a trust bias. For distant farmers, the savvy bias dominates.

In sum, from the perspective of farmers with incorrect beliefs the insurance contract performs poorly. To overcome incorrect beliefs about the performance of the contract, experience with the insurance product might help farmers to make consistent estimates of basis risk over time. For nudging the learning process, subsidies are likely to be an effective instrument for microinsurance adoption in the short-run, but only for close and not for distant farmers. Particularly, prior to convincing distant farmers to demand index insurance, the quality of the insurance contract should be improved. This requires increasing the density of weather stations or using more than one close weather station in the farmer's neighborhood to calculate indemnity payments. Therefore, the Inverse Distance Weighting approach should guarantee a more reliable estimator of farmers' actual losses. Further, instead of single farmers, farmer groups or financial institutions could demand index insurance. This way decision-makers would be less likely subject to the biases described before.

The paper is structured as follows. In the next section, I introduce the theoretical set up of the model. Section 3 presents the results that are the basis for the policy implications in section 4. In the last section, I discuss my findings and conclude.

2 Theoretical Setup

In the following, I set up the framework of the model about weather index insurance for farmers who are subject to drought risks. In particular, I investigate how the income depends on the realized rainfall, how farmers are exposed to weather risk, and to what extent they are able to insure against it. Above all, I focus on the composition of the basis risk and how it depends on realized rainfall at the farmer's field and at the nearest weather station.

Income is stochastic $X_t^f \sim F_X$ depending on rainfall at a farmer's field $R_t^f \sim F_R$ (arbitrary distribution with positive support, i.e., $R_t^f \geq 0$) at time t located at L^f . If rainfall R_t^f is above a certain threshold \underline{r} , the farmer breaks even and his income is positive. Below the threshold, a farmer suffers a loss

due to expenditures for seed and work. I further define \bar{x} as the maximum gain and \underline{x} as the maximum loss.

Assumption 2.1 (Dependence of Income and Rainfall). *I define income X_t^f as a concave function of rainfall R_t^f which satisfies:⁷*

$$X_t^f(R_t^f) = -\underline{x} + (\bar{x} + \underline{x}) \cdot (1 - e^{-\lambda R_t^f}), \lambda > 0.$$

For arbitrary rainfall $R_t^f \sim F_R$ with positive support, it follows that $X_t^f \in [\underline{x}, \bar{x}]$. Further, I define $\mathbb{E}[X_t^f] = \mu_X$ and $\mathbb{V}[X_t^f] = \sigma_X^2$.

The relationship of rainfall and income postulated in Assumption 2.1 is illustrated in Figure 1.

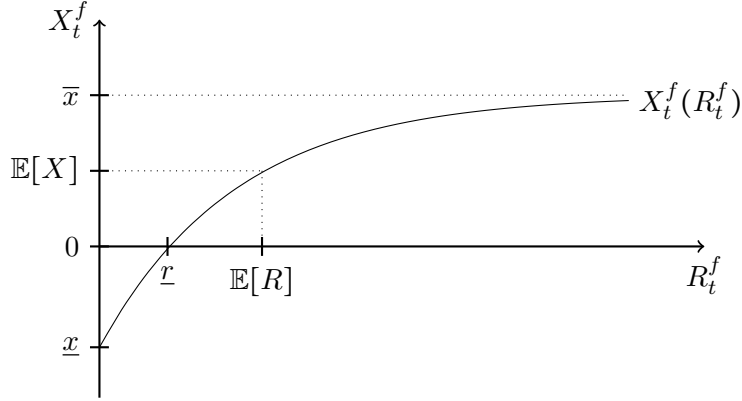


Figure 1: Relationship between rainfall and income

I assume that the insurer offers unit size insurance policies with fixed premium and an indemnity payment contingent on the realized rainfall at the nearest weather station of the demanding farmer.⁸ Based on these conditions (premium, distance to the nearest weather station, indemnity payment), the farmer then decides about the number n of policies to demand. For full insurance coverage, the farmer would demand the number of policies that is necessary to cover the expected income when no crop failure occurs which I

⁷For simplicity, risks as floods resulting from high rainfall are neglected since they are beyond the scope of this work which primarily regards the hedging of drought risks.

⁸I further assume that the offered policies are of sufficiently small unit size in order to make the product also accessible to poor households. Hence, also partial coverage (depending on land holdings, seed varieties etc.) is possible. The index insurance design relates, for instance, to the one used in Cole et al. (2013a).

denote with $\tilde{x} = \mathbb{E}[X|X > 0]$.⁹ I define an insurance contract consisting of n unit size insurance policies as a couple $(p_t, \tilde{x} - X_t^i)$ with premium payment p_t and indemnity payment $\tilde{x} - X_t^i$. $X_t^i(R_t^i)$ is the estimated income of a farmer as calculated by the insurer. It is based on the realized rainfall R_t^i at the nearest weather station located at $L^i \in \mathcal{L}^i$, where \mathcal{L}^i is the set of weather station located in the farmer's neighborhood. The insurer assumes that a farmer's income is generated in the following way:

$$X_t^i(R_t^i) = -\underline{x} + (\bar{x} + \underline{x}) \cdot (1 - e^{-\lambda R_t^i}) \quad , \lambda > 0.$$

Let R_t^f and R_t^i and hence, X_t^f and X_t^i follow the same distribution, i.e., $X_t^f, X_t^i \sim F_X$. Consequently, $\mathbb{E}[X_t^f] = \mathbb{E}[X_t^i]$ holds. The relationship between rainfall and income as calculated by the insurer is illustrated in Figure 2.

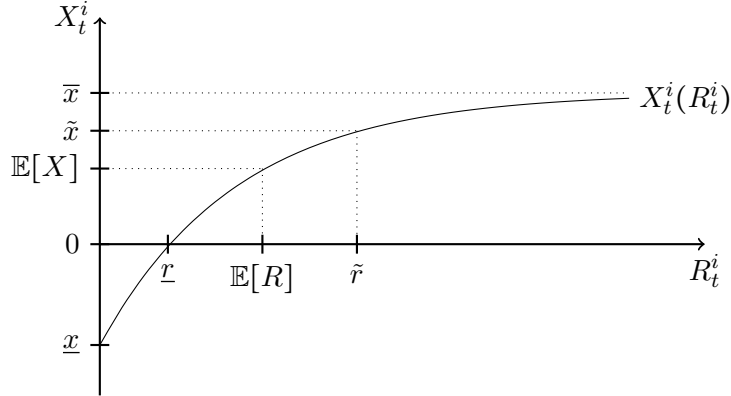


Figure 2: Relationship between rainfall and estimated income

Each period, a farmer can decide, which share of income he is willing to insure, denoted by $k_t \in [0, 1]$.¹⁰ Further, I assume that premiums are actuarially fair with zero loading factor and, thus, with a riskless market

⁹Hence, the definition of full insurance coverage is a decision of the farmers which in turn determines the number of policies to demand. For instance, this could be influenced by the land holdings and kind of seeds.

¹⁰The variable $k_t \in [0, 1]$ refers to the normalization of number of policies demanded by a farmer, where $k_t = 1$ depicts the scenario where the farmer demands the number of policies such that total insurance coverage is reached (i.e., \tilde{x} , depending on land holdings, seed varieties etc.). The insurance design even allows to overinsure, i.e., $k_t > 1$. In the following we concentrate on maximum full insurance coverage.

interest rate $r_m > 0$, I obtain

$$p_t = \frac{k_t(\tilde{x} - \mathbb{E}[X_{t+1}^i])}{1 + r_m}. \quad (1)$$

Assumption 2.2 (Stagnation of Parameters). *The market interest rate r_m , the thresholds $\underline{r}, \underline{x}, \bar{x}$ and the distribution of rainfall F_R and, hence, income F_X remain constant over time.*¹¹

Applying Assumption 2.2 to equation (1) the premium becomes

$$p_t = \frac{k_t(\tilde{x} - \mathbb{E}[X])}{1 + r_m}.$$

In the model, I investigate basis risk, which results from the differences between the actual loss, and the indemnity payment by the insurer. More precisely, I analyze the divergence of the income as calculated by the insurer and by the farmer, depending on the distance to the nearest weather station. Certainly, the nearer the weather station is located to the farmer's field, the better the insurer's estimation of the farmer's income. I assume that beyond a certain distance \bar{d} , the incomes X^f, X^i are independently distributed. In-putting the point estimates of Mobarak and Rosenzweig (2012), it holds that $\bar{d} \approx 14km$.

Assumption 2.3 (Relation Between Farmers' Income and Income Estimated by Insurer). *Let the correlation between a farmer's income X^f and the estimated income X^i depend on the distance to the nearest weather station:*

$$d := \min_{L^i \in \mathcal{L}^i} \{ \|L^i - L^f\| \}.$$

To depict the influence of distance on basis risk I define

$$\Delta = \frac{d}{\bar{d}} \text{ and } X^f, X \sim F_X, X^f \perp\!\!\!\perp X.$$

¹¹Since the time interval between underwriting the insurance and receiving the indemnity payment is very short, this assumption is reasonable.

The estimated income X^i depends on the normalized distance Δ and on farmer's actual income X^f :

$$X^i = \begin{cases} (1 - \Delta)X^f + \Delta X & , \text{ if } \Delta < 1 \\ X & , \text{ if } \Delta \geq 1. \end{cases}$$

The distance to the nearest weather station is normalized, hence, $\Delta = 0$ ($d = 0$) implies identity and $\Delta = 1$ ($d = \bar{d}$) independence of the weather events. Based on the expressions in Assumption 2.3, the distribution f_ε of basis risk $X^i - X^f =: \varepsilon$ can be determined.

Theorem 2.1 (Basis Risk). *Let X^f, X^i be distributed according to Assumption 2.3. For the basis risk $\varepsilon = X^i - X^f$ it holds that*

$$\varepsilon \sim F_\varepsilon, \quad \text{s.t. } \mathbb{E}[\varepsilon] = 0, \quad \mathbb{V}[\varepsilon] = 2(\Delta\sigma_X)^2, \quad \Delta \in [0, 1].$$

Proof: Appendix A.1.

Theorem 2.1 is consistent with intuitive reasoning that a larger distance to the nearest weather station implies a higher variance of basis risk. Further, this variance is even quadratically increasing in distance, however, it is limited with $\max_\Delta \mathbb{V}[\varepsilon] = 2\sigma_X^2$. The (in-)dependence of random variables in Assumption 2.3 as well as the variance $\mathbb{V}[\varepsilon]$ characterizing basis risk described in Theorem 2.1 are illustrated in Figure 3.

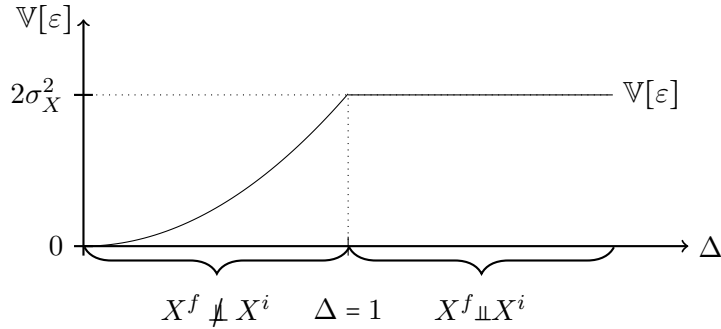


Figure 3: Relationship between normalized distance and basis risk

According to Cole et al. (2013a), 89% of farmers in their sample cite drought as the most important risk they face. Hence, an appropriate utility function should incorporate utility decreasing in variance of income.

Assumption 2.4 (μ - σ^2 -Preferences). *The preferences of farmers are represented by an utility function $u(\cdot)$ depending on income X which satisfies:*

$$u(X) = \mu_X - \rho\sigma_X^2,$$

where $\rho > 0$ depicts the degree of risk aversion, $\mathbb{E}[X] = \mu_X$ and $\mathbb{V}[X] = \sigma_X^2$.

Since according to Assumption 2.4 farmers are risk averse (i.e., positive risk premium), rational farmers are willing to pay a (positive) premium to receive the expected income $\mathbb{E}[X]$ with certainty. Hence, a rational farmer will ask for insurance, if the premium is sufficiently low and if no basis risk exists (i.e., $X^f = X^i$). The higher the degree of risk aversion and the higher the variance of income, the higher the premium a rational farmer is willing to pay.

3 Results

In the following, I want to derive the optimal insurance coverage of a rational farmer, depending on the normalized distance Δ to the nearest weather station, using the theoretical set up from section 2. After solving the optimization problem for rational farmers in subsection 3.1, I address incorrect beliefs of farmers about the indemnity payment in subsection 3.2. In section 3.3, I suggest how to efficiently implement subsidies.

3.1 Rational Insurance Coverage

I assume that farmers maximize their expected utility over income X_{t+1}^k contingent on the fraction insured in period $t + 1$ by choosing the optimal (partial) insurance coverage k , i.e., in period t the farmer solves the optimization problem

$$\max_{k_t \in [0,1]} \mathbb{E}[u(X_{t+1}^k)] \quad s.t. \quad X_{t+1}^k = X_{t+1}^f + k_t(\tilde{x} - X_{t+1}^i) - (1 + r_m)p_t. \quad (2)$$

The first part of the constraint in equation (2) corresponds to the actual income of the farmer, the second part to the partial indemnity payment and the third part to the compounded premium. Instead of $\tilde{x} - X_{t+1}^i$, farmers consider the individually accurate indemnity payment $\tilde{x} - X_{t+1}^f$ resulting in

basis risk ε_{t+1} . Hence:

$$X_{t+1}^k = (1 - k_t)X_{t+1}^f + k_t(\tilde{x} + \underbrace{X_{t+1}^f - X_{t+1}^i}_{=\varepsilon_{t+1}}) - (1 + r_m)p_t \quad (3)$$

$$= X_{t+1}^f + k_t(\tilde{x} - X_{t+1}^f) + k_t\varepsilon_{t+1} - (1 + r_m)p_t. \quad (4)$$

In equations (3) and (4), I disentangle basis risk from the remaining random variables in order to address optimal insurance coverage under correct as well as incorrect beliefs about basis risk. Rational risk averse farmers are willing to pay a (risk) premium in order to get the expected value of income with certainty.¹² However, the presence of basis risk complicates the decision since the index insurance contract does not guarantee a fixed amount of income. The following Theorem 3.1 solves the optimization problem of equation (2).

Theorem 3.1 (Rational Insurance Coverage).

With $\varepsilon \sim F_\varepsilon$, the income $X^k = X^f + k_t(\tilde{x} - X^f) + k_t\varepsilon_{t+1} - (1 + r_m)p_t = k_t\tilde{x} + (1 - k_t)X^f + k_t\varepsilon_{t+1} - (1 + r_m)p_t$, that depends on the share k_t insured, is distributed according to:

$$X_{t+1}^k \sim F_X^k, \quad s.t. \quad \mathbb{E}[X^k] = \mu_X, \\ \mathbb{V}[X^k] = (1 - k_t)^2\sigma_X^2 + 2(k_t\Delta\sigma_X)^2 - 2(1 - k_t)k_t\Delta\sigma_X^2.$$

Risk averse farmers with μ - σ^2 -preferences, who maximize expected utility $\mathbb{E}[u(X_{t+1}^k)]$, choose an optimal insurance coverage of

$$k_t(\Delta) = \begin{cases} \frac{1+\Delta}{1+2\Delta^2+2\Delta} & , \quad \text{if } \Delta \in [0, 1) \\ 0.4 & , \quad \text{if } \Delta \geq 1, \end{cases}$$

$$\frac{\partial k_t}{\partial \Delta} < 0, \quad \Delta \in [0, 1).$$

Proof: Appendix A.2.

Figure 4 plots the share k_t of income that rational farmers choose to insure depending on the normalized distance Δ . For $\Delta = 0$, which means

¹²Since $RP > 0$ the farmer is willing to pay a positive amount for getting the expected value $\mathbb{E}X$ of income with certainty. With $\tilde{x} > \mathbb{E}X$ the farmer is even willing to pay an amount larger than RP for getting \tilde{x} with certainty.

that the location of weather station equals the location of farmer's field (i.e., $L^i = L^f$), I obtain $k_t = 1$. Hence, in the absence of basis risk, rational farmers choose full insurance coverage. Since $\frac{\partial k_t}{\partial \Delta} < 0$, $\Delta \in [0, 1)$, rational farmers ask for less insurance coverage the larger the normalized distance Δ to the nearest weather station is. The value $\Delta \geq 1$, i.e., the rainfall at a farmer's field and at the nearest weather station are identically and independently distributed, implies $k_t = 0.4$. For $\Delta = 1/\sqrt{2}$ it holds that $k_t = 1/2$ and consequently, $\Delta = 1/\sqrt{2} \Leftrightarrow d \approx 10\text{km}$ can be considered as crucial distance for the decision to insure.¹³ Thus, I hereafter distinguish between farmers located less than 10km from the nearest weather station, denoted as *close farmers* and the remaining ones, denoted as *distant farmers*.

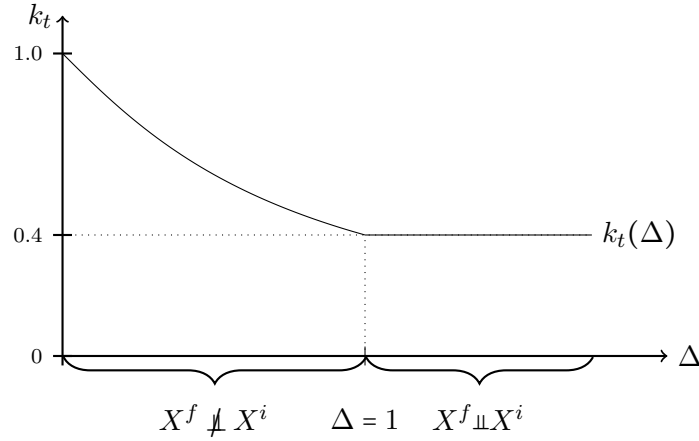


Figure 4: Partial insurance demand $k_t(\Delta)$

Proposition 3.1 (Rational Insurance Coverage). *For rational risk averse farmers, the optimal insurance coverage only depends on the normalized distance Δ to the nearest weather station, i.e., it is independent from the variance σ_X^2 of income and the degree ρ of risk aversion. Rational farmers even ask for partial insurance coverage when income distributions X^i, X^f*

¹³In section 2, I introduced the point estimate of $\bar{d} = 14\text{km}$ above which distance two weather events are independently distributed (Mobarak and Rosenzweig, 2012). Hence, it holds $d = \bar{d} \cdot \Delta = 14\text{km} \cdot 1/\sqrt{2} \approx 10\text{km}$. The presented framework allows farmers to demand a number of (small) insurance policies (irrespective of actual landholdings) which enables partial insurance coverage. However, if the premium is sufficiently large, farmers face the decision whether to insure or not. Therefore, $k_t = 0.5$ is an important threshold to consider.

are independent. Nevertheless, rational distant farmers ask for less than 50%, rational close farmers for more than 50% insurance coverage.

First, Proposition 3.1 contradicts findings of Clarke (2016) who predicts insurance demand to be decreasing in risk aversion when including basis risk. Second, it demonstrates that even in the presence of basis risk, the farmer optimally chooses at least partial insurance coverage. In particular, $k_t \geq 0.4$ if the farmer is fully rational. Even when weather stations are located far away, farmers can smooth income if the rainfall at the weather station and at the farmer's field are identically distributed. On the one hand, this result contradicts previous theoretical research that argues that rational farmers should choose full insurance coverage (e.g., Carter et al., 2014), i.e., $k_t = 1$ independent of the normalized distance Δ . On the other hand, it is also inconsistent with empirical observations since (actuarially fair) insurance markets in developing countries are characterized by a very low demand (Gaurav et al., 2011; Karlan et al., 2014), i.e., $k_t \ll 0.4$.

3.2 Boundedly Rational Insurance Coverage

Empirically, insurance demand falls short of the predictions of my rational insurance model. One reason why many more farmers than expected decide to forego insurance coverage (even if X^i, X^f are dependent) may be that farmers hold incorrect beliefs about the basis risk ε . Generally, I expand my model by allowing farmers to hold incorrect beliefs θ_{t+1} about basis risk ε_{t+1} , so that ε_{t+1} first order stochastically dominates θ_{t+1} , i.e., $\mathbb{P}[\varepsilon_{t+1} \leq x] < \mathbb{P}[\theta_{t+1} \leq x]$. This implies that if a farmer sufficiently overestimates the basis risk, his decision will be to forego insurance demand. In my model, the overestimation of basis risk could be rooted in two causes: either in a lack of trust or in a lack of understanding of the product.¹⁴ In the following, I propose several hypotheses on farmer's incorrect belief θ about basis risk ε .

¹⁴In the field experiment of Cole et al. (2013a), farmers were 36% (or 10.1 percentage points) more likely to demand the insurance product if a locally trusted agent recommends it, compared to farmers who were offered the product without locally trusted recommendation corroborating the *lack of trust* in the insurance provider. In Giné et al. (2008) farmers mention a *lack of understanding* of the product as the most important driver for neglecting index insurance. Further, Cole et al. (2017) show that among farmers who ask for insurance, literate farmers were 15% more likely to shift to cash crops with higher risk but higher expected return. This indicates an understanding of the ability to smooth income with the insurance contract.

First, although upside and downside basis risk are equally likely, i.e., $\mathbb{P}[\varepsilon_{t+1} < 0] = \mathbb{P}[\varepsilon_{t+1} > 0] = 1/2$, through a lack of trust, farmers might perceive a higher downside basis risk than upside basis risk. Trust in the insurer can be defined as

'the probability that the insurer will pay the claim if the low income [farmer] experiences the insured loss is high enough for the low income [farmer] to engage in the insurance contract and pay the insurance premium.'

(Morsink and Geurts, 2011, p. 10)

Hence, if downside basis risk is overestimated and thus, the probability that the insurer will pay an indemnity payment in favor of the farmer is underestimated, the farmer might neglect insurance due to a lack of trust.

Hypothesis 3.1 (Trust Bias).

$$\mathbb{P}[\theta_{t+1} < 0] > \mathbb{P}[\theta_{t+1} > 0] \Rightarrow \theta(\tau) \sim F_{\theta(\tau)}, \text{ s.t. } \mathbb{E}[\theta(\tau)] = -\tau, \\ \mathbb{V}[\theta(\tau)] = 2(\Delta\sigma_X)^2, \quad \tau > 0.$$

The parameter τ introduced in Hypothesis 3.1 is a reasonable proxy for the lack of trust in the following way: if τ is high and the incorrect probability of receiving an indemnity payment in favor of the farmer low, the farmer might forego insurance.

Second, I consider the farmers' possible lack of understanding of the insurance product. Certainly, one of the main purposes of weather insurance is to smooth income. If farmers do not understand how the insurance product works, they are not able to perceive this opportunity. In particular, even if a farmer is able to distinguish between downside and upside basis risk, he might overestimate the variance of the basis risk and thus, underestimate the accuracy of the income calculation by the insurer. This underestimation results in an underestimation of income smoothing through weather insurance.

Hypothesis 3.2 (Savvy Bias).

$$\sigma_\varepsilon^2 < \sigma_\theta^2 \Rightarrow \theta(\zeta) \sim F_{\theta(\zeta)}, \text{ s.t. } \mathbb{E}[\theta(\zeta)] = 0, \\ \mathbb{V}[\theta(\zeta)] = 2\zeta(\Delta\sigma_X)^2, \quad \zeta > 1.$$

The parameter ζ introduced in Hypothesis 3.2 is a reasonable proxy for the lack of understanding of the insurance product since the overestimated variance captures the underestimation of income smoothing.

Finally, I consider the case in which a farmer overestimates both, the downside basis risk and variance.

Hypothesis 3.3 (Combined Bias).

$$\begin{aligned}\theta(\tau, \zeta) &\sim F_{\theta(\tau, \zeta)}, \quad s.t. \quad \mathbb{E}[\theta(\tau, \zeta)] = -\tau, \\ \mathbb{V}[\theta(\tau, \zeta)] &= 2\zeta(\Delta\sigma_X)^2, \quad \tau > 0, \zeta > 1.\end{aligned}$$

In this case, both types of incorrect beliefs are present and the optimization problem becomes

$$\max_{k_t \in [0, 1]} \mathbb{E}[u(X_{t+1}^k)] \quad s.t. \quad X_{t+1}^k = X_{t+1}^f + k_t(\tilde{x} - X_{t+1}^f) + k_t\theta_{t+1}(\tau, \zeta) - (1 + r_m)p_t.$$

Solving the optimization problem results in the Theorem 3.2 about the optimal insurance coverage k_t .

Theorem 3.2 (Boundedly Rational Insurance Coverage).

With $\theta(\tau, \zeta) \sim F_{\theta(\tau, \zeta)}$, the income $X^k = X^f + k_t(\tilde{x} - X^f) + k_t\theta_{t+1}(\tau, \zeta) - (1 + r_m)p_t = k_t\tilde{x} + (1 - k_t)X^f + k_t\theta_{t+1}(\tau, \zeta) - (1 + r_m)p_t$, that depends on the share k_t insured, is distributed according to:

$$\begin{aligned}X_{t+1}^k &\sim F_X^k, \quad s.t. \quad \mathbb{E}[X^k] = \mu_X - \tau k_t, \\ \mathbb{V}[X^k] &= (1 - k_t)^2\sigma_X^2 + 2\zeta(k_t\Delta\sigma_X)^2 - 2(1 - k_t)k_t\Delta\sigma_X^2.\end{aligned}$$

Risk averse farmers with μ - σ^2 -preferences, who maximize expected utility $\mathbb{E}[u(X_{t+1}^k)]$, choose an optimal insurance coverage of

$$k_t(\Delta, \tau, \zeta) = \frac{1 + \Delta - \frac{\tau}{\rho\sigma_X^2}}{1 + 2\zeta\Delta^2 + 2\Delta} \cdot \mathbb{1}_{\{\Delta \in [0, 1)\}} + \frac{2 - \frac{\tau}{\rho\sigma_X^2}}{3 + 2\zeta} \cdot \mathbb{1}_{\{\Delta \geq 1\}},$$

$$\frac{\partial k_t}{\partial \zeta}, \frac{\partial k_t}{\partial \tau}, \frac{\partial k_t}{\partial \Delta} < 0, \quad \frac{\partial k_t}{\partial \rho} \frac{\partial k_t}{\partial \sigma_X^2} > 0, \quad (\zeta, \tau, \rho) \in [0, \infty]^3, \quad \Delta \in [0, 1).$$

Proof: Appendix A.3.

Figure 5 plots the share k_t of income, that farmers want to insure depending on their incorrect belief $\theta(\tau, \zeta)$ (of either Hypotheses 3.1 to 3.3) and normalized distance Δ .

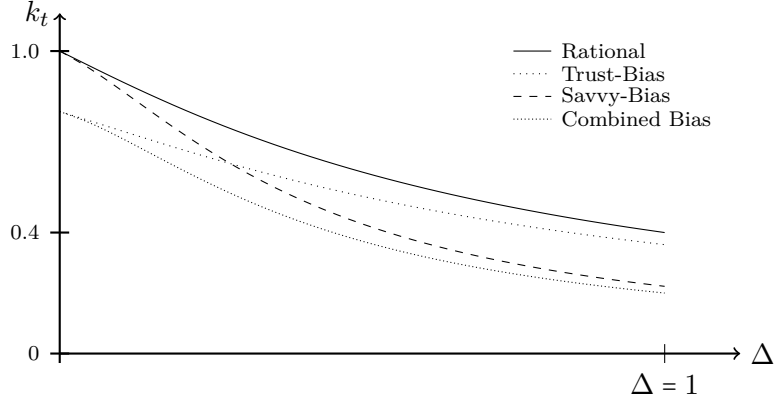


Figure 5: Partial insurance demand $k_t(\Delta)$ and incorrect beliefs

Proposition 3.2 (Boundedly Rational Insurance Coverage).

- (i) A lack of trust in the insurer ($\tau > 0$) has a negative effect on insurance demand. More precisely, the influence decreases in the normalized distance Δ to the nearest weather station, i.e., the effect is substantial for close farmers, but less so for distant farmers:

$$\frac{\partial}{\partial \Delta} \left(k_t^\varepsilon - k_t^{\theta(\tau)} \right) < 0, \quad \Delta \in [0, 1).$$

- (ii) A lack of understanding of the insurance product ($\zeta > 1$) has a negative effect on insurance demand. More precisely, the effect increases in the normalized distance Δ to the nearest weather station, i.e., influence is substantial for distant farmers, but less so for close farmers:

$$\frac{\partial}{\partial \Delta} \left(k_t^\varepsilon - k_t^{\theta(\zeta)} \right) > 0, \quad \Delta \in [0, 1).$$

- (iii) A combined lack of trust and understanding has a lower (absolute) negative impact on insurance demand than the sum of each separate bias:

$$k_t^\varepsilon - k_t^{\theta(\tau, \zeta)} < \left| k_t^\varepsilon - k_t^{\theta(\tau)} \right| + \left| k_t^\varepsilon - k_t^{\theta(\zeta)} \right|.$$

Proof: Appendix A.4.

It is plausible to expect that the trust and savvy bias for each normalized distance Δ will vanish over time, if farmers get experienced with the insurance product, i.e., $\tau \rightarrow 0, \zeta \rightarrow 1$. Hence, with an arbitrary number t of points in time with income X_1^i, \dots, X_t^i , the belief $\theta(\tau, \zeta)$ is a consistent estimator of the basis risk ε for increasing t , i.e.,

$$\theta(X_1^i, \dots, X_t^i)(\tau, \zeta) \xrightarrow{a.s.} \varepsilon, \quad t \rightarrow \infty,$$

which suggests that own experience may raise insurance demand over time.¹⁵

3.3 Boundedly Rational Subsidized Insurance Coverage

In order to gain experience and overcome their incorrect beliefs, farmers have to adopt insurance at some point. Adoption is likely to increase by subsidizing the product in the short-run.¹⁶ In the following, I analyze the influence of subsidies $s \in (0, 1]$ on the behavior of farmers who hold both types of incorrect beliefs (combined bias). In this case, the optimization problem becomes

$$\begin{aligned} \max_{k_t \in [0, 1]} \mathbb{E}[u(X_{t+1}^k)] \quad s.t. \quad X_{t+1}^k = X_{t+1}^f + k_t(\tilde{x} - X_{t+1}^f) \\ + k_t \theta_{t+1}(\tau, \zeta) - (1 + r_m)p_t(1 - s). \end{aligned}$$

Solving the optimization problem results in the Theorem 3.3 about the optimal insurance coverage k_t .

Theorem 3.3 (Boundedly Rational Subsidized Insurance Coverage).

With $\theta(\tau, \zeta) \sim F_{\theta(\tau, \zeta)}$ and subsidy $s \in (0, 1]$, the income $X^k = X^f + k_t(\tilde{x} - X^f) + k_t \theta_{t+1}(\tau, \zeta) - (1 + r_m)p_t(1 - s) = k_t \tilde{x} + (1 - k_t)X^f + k_t \theta_{t+1}(\tau, \zeta) - (1 +$

¹⁵There is a big literature on challenges to learning (Foster and Rosenzweig, 2010). So it is not obvious beliefs would always converge to the true parameters once usage increases. It could, for instance, depend on peer adoption (Cai et al., 2015). However, Cole et al. (2013a) find a significant increase in take-up probability of index insurance, if the household demanded insurance in the previous period (Cole et al. (2013a) also control for average indemnity payments). As they only consider farmers located close to weather stations, this might be an indicator that in case of a more reliable estimation of the farmer's loss (which is at least partially fulfilled for close farmers), experience with the product would indeed improve the subjective valuation of the index insurance over time.

¹⁶Cole et al. (2013a) find that a 10% price reduction, relative to the actuarially fair insurance premium, increases the demand by 10.4% to 11.6%. This equals a strong elasticity between 1.04 and 1.16. Other studies that use larger price variations, obtain an elasticity of 0.46 (Karlan et al., 2014) and 0.44 (Mobarak and Rosenzweig, 2012) around the actuarially fair premium.

$r_m)p_t(1-s)$, that depends on the share k_t insured, is distributed according to:

$$\begin{aligned} X_{t+1}^k &\sim F_X^k, \quad \text{s.t.} \quad \mathbb{E}[X^k] = \mu_X + sk_t(\tilde{x} - \mu_X) - \tau k_t, \\ \mathbb{V}[X^k] &= (1 - k_t)^2 \sigma_X^2 + 2\zeta(k_t \Delta \sigma_X)^2 - 2(1 - k_t)k_t \Delta \sigma_X^2. \end{aligned}$$

Risk averse farmers with μ - σ^2 -preferences, who maximize expected utility $\mathbb{E}[u(X_{t+1}^k)]$, choose an optimal insurance coverage of

$$k_t(\Delta, \tau, \zeta, s) = \frac{1 + \Delta + \frac{s(\tilde{x} - \mu_X) - \tau}{\rho \sigma_X^2}}{1 + 2\zeta \Delta^2 + 2\Delta} \cdot \mathbb{1}_{\{\Delta \in [0,1)\}} + \frac{2 + \frac{s(\tilde{x} - \mu_X) - \tau}{\rho \sigma_X^2}}{3 + 2\zeta} \cdot \mathbb{1}_{\{\Delta \geq 1\}},$$

$$\frac{\partial k_t}{\partial \zeta}, \frac{\partial k_t}{\partial \tau}, \frac{\partial k_t}{\partial \Delta}, \frac{\partial \mu_X}{\partial \Delta} < 0, \quad \frac{\partial k_t}{\partial \rho}, \frac{\partial k_t}{\partial s}, \frac{\partial k_t}{\partial \sigma_X^2} > 0, \quad (\zeta, \tau, \rho) \in [0, \infty]^3, \quad (\Delta, s) \in [0, 1]^2.$$

Proof: Appendix A.5.

Figure 6 plots the share k_t of income that farmers with incorrect beliefs want to insure when subsidies are provided, depending on normalized distance Δ .¹⁷

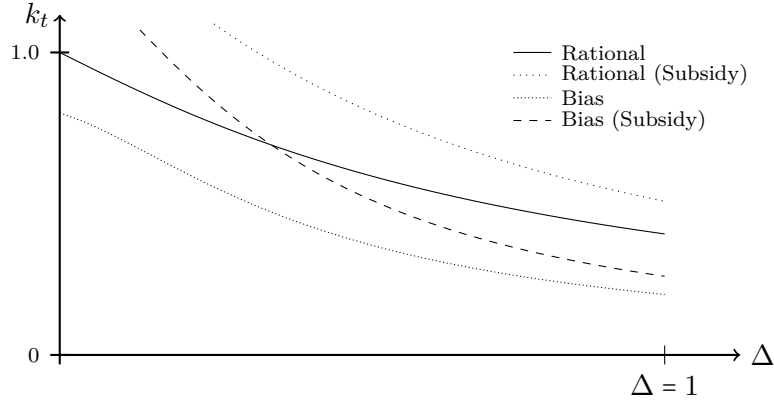


Figure 6: Partial insurance demand $k_t(\Delta)$ with subsidy and incorrect beliefs

¹⁷If farmers are located sufficiently close to the nearest weather station, they optimally would even overinsure (i.e., $k_t > 1$). This results from the subsidy on an actuarially fair index insurance.

Proposition 3.3 (Effectiveness of Subsidies). *For close farmers subsidies are very effective, for distant farmers less effective, i.e.,*

$$\frac{\partial}{\partial \Delta}(k_t(s) - k_t(0)) < 0, \quad \Delta \in [0, 1).$$

Proof: Appendix A.6.

According to Theorem 3.1 and Proposition 3.3, index insurance is actually an effective product for close farmers to whom subsidies can be provided to increase insurance demand in the short-run. As a result, a farmer's belief about basis risk may become more accurate in the long-run. For distant farmers, index insurance is neither an effective instrument for income smoothing nor is it beneficial to subsidize it. For this reason, first and foremost, it is the quality of the insurance contract that should be improved so that index insurance is also beneficial for distant farmers.

4 Discussion and Policy Implications

Although index insurance has been regarded as a promising instrument to foster economic development (Outreville, 2013), actual demand is low (Karlan et al., 2014; Gaurav et al., 2011). In my stochastic model, I analyze possible rational and boundedly rational explanations. Based on my model, this section discusses policy implications to improve index insurance demand. The suggestions can be divided into two categories: first, improving farmers' subjective perception and second, the objective quality of the insurance.

I have shown that effects of incorrect beliefs in the form of a lack of trust in the insurer or a poor understanding of the product attenuate the demand for insurance and are heterogeneous in distance between farmer and nearest weather station. In my model the lack of trust is a particularly important driver of low insurance demand, which relates to Patt et al. (2009) and also Cole et al. (2013a), who suggest that cooperating with locally trusted agents who recommend the insurance product may overcome the lack of trust. Additional to previous research, I find that trust has a higher impact on insurance demand for close than for distant farmers. Hence, my findings support the conclusion of Cole et al. (2013a) to use locally trusted agents, in particular for close farmers.

Certainly, the understanding of the product is important for the demand decision. Relating to Giné et al. (2008), I have shown that a lower understanding of income smoothing dramatically decreases insurance demand. This result also supports the work of Gaurav et al. (2011) who point out that understanding the insurance product is an important factor for insurance demand.¹⁸ A new insight of my model is that the understanding of income smoothing with insurance products influences close farmers less than distant farmers. Education trainings might thus be an effective way to increase insurance demand, especially for distant farmers.

Finally, instead of insuring a single farmer, a group of farmers or financial institutions could demand index insurance. This way decision-makers would be less likely subject to the before mentioned biases.

It is plausible, that over time farmers' estimator $\theta(\tau, \zeta)$ of the basis risk becomes more consistent. Nevertheless, insurers have to convince farmers of the product for them to experience it. Therefore, for the first adoption of insurance, subsidies might help in the short-run. I find that subsidies are less effective for distant than for close farmers. Further, rational distant farmers ask for less than 50% insurance coverage. For this reason and in contrast to previous research, subsidies should focus on close farmers only. To calculate the size of the subsidy that is necessary to shift k_t above certain thresholds, a deeper understanding of the incorrect beliefs farmers hold is required. Field experiments might shed further light on this issue.

Aside from the farmer's incorrect beliefs about the product, the objective insurance quality is another important reason for the low demand. In particular, rational insurance demand is decreasing in distance and equals only 40% coverage if the distance to the nearest weather station is sufficiently large. Evidence that inaccurate indemnity payments deteriorate the (low) take-up behavior over time is provided by Karlan et al. (2014): a farmer who demanded the product in the previous period, but did not receive any indemnity payment, is 17% less likely to demand the insurance in the following period, compared to a farmer who did not demand the insurance product. However, farmers who received an indemnity payment in the previous period are only around 5% more likely to demand the insurance

¹⁸Gaurav et al. (2011) implement a two day lasting educational program that includes games and information sessions. Participation in this program increases the take-up rate by 5.3 percentage points, compared to farmers who did not participate in the educational program.

compared to farmers without any insurance experience. Hence, the effect of negative experience is more than three times larger than the effect of positive experience. Providing distant farmers with index insurance might be counterproductive since for this group inaccurate indemnity payments are more likely to occur and, hence, the assumption of consistent updating of beliefs might not hold. According to Cole et al. (2013a), the distance between the farmer's position and the nearest weather station can be large (e.g. 30km). Hence, weather events at a farmer's field and the weather station might be independently distributed.¹⁹ In an interview with the World Bank (2016), Clarke compares the inaccurate indemnity payments by the insurers to the flip of a coin: the probability that a regional weather station correctly estimates the rainfall at the farmer's location and thus, the possible loss, is very small.²⁰ His statement refers to the results reported in Clarke et al. (2012), which are presented in Figure 7.²¹ The correlation between the losses and the actual payouts under the index insurance is weak. Using the estimated regression line, it can be observed that even if the yield is almost zero, the index insurance only pays out an indemnity equal to 12% of the insured sum. If the yield equals its long-run average, i.e., 100%, the insurance payout still equals 8% of the insured sum. Approximately one half of the index insurance payouts are overestimations of losses and one half underestimations of gains.

This relates to my model since beyond a certain distance, weather events are considered to be independently distributed. Consequently, beyond a certain distance ($\approx 10km$) even rational farmers should ask for less than 50% insurance coverage. Hence, one possible solution might be restricting the access to the insurance market to close farmers.

Another possible solution is increasing the density of weather stations, which, however, results in higher costs. Further, for new weather stations no

¹⁹According to point estimates of Mobarak and Rosenzweig (2012), across a distance of more than 14km, weather events are independently distributed. Farmers and weather stations may be (approximately) uniformly distributed across the landscape using 30km as maximum distance. Hence, for $1 - \frac{\pi 14^2}{\pi 30^2} \approx 78\%$ of farmers weather event at the farmer's field and the weather station are independently distributed.

²⁰More literally, in the interview with the World Bank Clarke said: *'If a car insurance policy let the insurer flip a coin to decide whether or not to reimburse you for your totaled car, most people wouldn't buy it'* (World Bank, 2016).

²¹The lines show the point estimate and 95% confidence intervals for an Epanechnikov kernel with a bandwidth of 0.8.

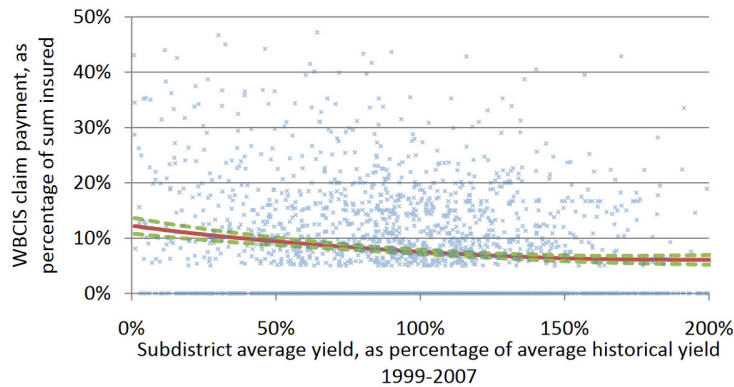


Figure 7: Scatter plot and kernel regression: claim payments against yields, for all weather index products sold in one state in one year (Clarke et al., 2012, p. 10)

past rainfall data exists, implying ambiguities for calculating the actuarially fair insurance premium (Miranda and Farrin, 2012).

Currently, the payout of the insurance is only linked to the nearest weather station. Thus, the rainfall at a farmer's location is interpolated using the Nearest Neighbor Method.²² Applying this method is straightforward, but it certainly entails risks. A possible improvement might be including more stations in the calculation and assign the rainfall at the farmer's location a weighted mean value. Those weights should be inversely proportional to the distance: a larger distance results in a smaller influence on the estimated mean. This interpolation approach, called Inverse Distance Weighting (IWS), can be extended to an arbitrary number of weather stations.

I expect a substantial reduction of the basis risk if IWS was used. Furthermore, since the calculation would be based on already existing weather stations, it does not entail significant additional costs. However, the use of IWS certainly increases the complexity of the product. Since the level of education in rural areas is very low (Cole et al., 2013a) a trade-off in the design of the product exists, between the quality and the ease of understanding. Hence, one challenge in designing index insurance contracts is

²²With the Nearest Neighbor method, an unknown point takes the value of its nearest neighbor. No other points are taken into account.

'minimiz[ing] the basis risk while attempting to maintain contract transparency.'

(Miranda and Farrin, 2012, p. 394)

No matter by how much the quality of the index insurance can be improved, a non-personalized contract will never cover every yield loss.

In sum, two main approaches to increase the demand for index insurance products can be derived.

First, farmer's subjective assessment of the product should be improved by targeting four factors. These include education programs about income smoothing possibilities (especially targeted at distant farmers) and cooperation with locally trusted agents (especially targeted at close farmers). Further, the purchaser of insurance should not be the individual farmer but rather producer groups or financial institutions. Finally, subsidies for close farmers should be implemented to foster first adoption of insurance in the short-run.

Second, the objective quality of the product should be improved by reducing the basis risk. This can be implemented by either increasing the density of weather stations or using IWS.

In this respect, it should also be stressed that the policy implications presented above result in additional costs and therefore a possible increase in premium. Since the product is price-elastic, in the short-run, well allocated subsidies might be beneficial to alleviate the price increase. In particular, after improving the attractiveness of index insurance in the short-run, subsidies might also be an effective instrument for distant farmer's first insurance adoption. In the long-run, these measures may lead to a higher reputation of index insurance so that the population coverage may increase and administrative costs are distributed across a larger group.

5 Conclusion

So far, low demand in insurance markets of developing countries has been solely investigated in rather general theoretical frameworks. Most, models predict high demand of weather index insurance among risk averse farmers if they behave in a rational manner (Carter et al., 2014). Empirical research thus judges low demand in developing countries as irrational behavior without calling into question the benefit of the insurance contract for all farmers

with accessibility to the insurance market. Since it is consistent with the neoclassical point of view that index insurance, due to the basis risk, might be a risky investment, this paper investigates whether farmers behave in rational way, when neglecting index insurance.²³

The findings of my model that follows an expected utility approach, show that even rational farmers do not ask for full insurance if the weather station is not directly located at their field. Overall, insurance demand decreases in increasing distance.²⁴ Hence, rational farmers ask for less than half coverage, already in case that the weather station is located further away than about 10km.²⁵

Since in developing countries modest insurance demand is observed even for farmers in close proximity to weather stations, I investigate whether this is consistent with farmers who hold incorrect beliefs about the indemnity payment and hence, about the basis risk. I find that, on the one hand, incorrect belief of basis risk that reflects a lack of trust, i.e., in particular overestimation of downside basis risk, leads to substantially lower insurance demand of farmers close to the weather station. However, the impact of the lack of trust decreases for farmers located further away. On the other hand, a incorrect evaluation of the opportunity to smooth income with the insurance product that reflects poor understanding, reduces the demand much more for farmers located way off the weather station than for farmers located nearby. In order to mitigate the negative impact of the before mentioned biases, a group of farmers or financial institutions instead of a single farmer could demand index insurance.

Experience with the insurance product could help to overcome both incorrect beliefs, since trust and understanding might grow over time. To foster first adoption of the product in the short-run, subsidies might be an appropriate instrument. Based on my model, I find that subsidies are an effective instrument for index insurance adoption if the weather station is located in the neighborhood of the farmer (<10km), but are less effective

²³Insurance might be considered as a risky investment since the premium is a certain loss while the indemnity payment remains uncertain. Clarke (2016) shows that in the presence of basis risk insurance demand is decreasing in risk aversion.

²⁴In this first step, I relax assumptions as liquidity constraints and only concentrate on basis risk. Consequently, my results may even underestimate the extent of rational behavior in the field and hence, may be seen as upper limit for rational insurance demand.

²⁵This holds with the point estimator of Mobarak and Rosenzweig (2012), that weather events in locations beyond a distance of more than 14km are independently distributed.

if the weather station is located further away. This relates to studies of Karlan et al. (2014) and Mobarak and Rosenzweig (2012) who empirically observe modest insurance demand even when insurance products are highly subsidized.

Hence, possible policy instruments include employing locally trusted agents who recommend the product (Cole et al., 2013a) in order to build trust, in particular, addressing farmers who are in close proximity (<10km) to the weather station. For the remaining farmers, education on the purpose of the insurance contract, especially income smoothing (Gaurav et al., 2011) might help. The finding that for the latter index insurance is an ineffective means to smooth income calls for improving the quality of the insurance product. For attenuation of basis risk one could either increase the density of weather stations or include more weather stations around the farmer's field in the calculation of the indemnity payment.

Of course, all these suggestions come at the cost of a more complex product and possibly a poor understanding of the insurance by farmers. Possible extensions of the model may consider an arbitrary number n of weather stations, which decreases variance of basis risk, but also complicates understanding of the insurance product. Further research is needed to find the optimal number of weather stations that should be taken into account. Moreover, it would be desirable to have better knowledge about actual belief formation for calculating the amount of subsidy that is necessary to shift the optimal insurance coverage above specific thresholds. Both research questions can be addressed in appropriate field experiments.

References

- Cai, J., De Janvry, A. and Sadoulet, E. (2015). Social networks and the decision to insure, *American Economic Journal: Applied Economics* **7**(2): 81–108.
- Carter, M., de Janvry, A., Sadoulet, E., Sarris, A. et al. (2014). Index-based weather insurance for developing countries: A review of evidence and a set of propositions for up-scaling, *Development Policies Working Paper* **111**.
- Carter, M. R., Cheng, L. and Sarris, A. (2016). Where and how index insurance can boost the adoption of improved agricultural technologies, *Journal of Development Economics* **118**: 59–71.
- Clarke, D. J. (2016). A theory of rational demand for index insurance, *American Economic Journal: Microeconomics* **8**(1): 283–306.
- Clarke, D. J., Clarke, D., Mahul, O., Rao, K. N. and Verma, N. (2012). Weather based crop insurance in India. Working Paper, The World Bank.
- Cole, S., Giné, X., Tobacman, J., Topalova, P., Townsend, R. and Vickery, J. (2013a). Barriers to household risk management: Evidence from India, *American Economic Journal: Applied Economics* **5**(1): 104–135.
- Cole, S., Giné, X. and Vickery, J. (2013b). How does risk management influence production decisions? Evidence from a field experiment.
- Cole, S., Giné, X. and Vickery, J. (2017). How does risk management influence production decisions? Evidence from a field experiment, *The Review of Financial Studies* **30**(6): 1935–1970.
- Cull, R., Demirgüç-Kunt, A. and Morduch, J. (2009). Microfinance meets the market, *Journal of Economic Perspectives* **23**(1): 167–192.
- Eling, M., Pradhan, S. and Schmit, J. T. (2014). The determinants of microinsurance demand, *The Geneva Papers on Risk and Insurance – Issues and Practice* **39**(2): 224–263.
- Fafchamps, M. (2003). *Rural poverty, risk and development*, Edward Elgar Publishing.

- Foster, A. D. and Rosenzweig, M. R. (2010). Microeconomics of technology adoption, *Annu. Rev. Econ.* **2**(1): 395–424.
- Gaurav, S., Cole, S. and Tobacman, J. (2011). Marketing complex financial products in emerging markets: Evidence from rainfall insurance in India, *Journal of Marketing Research* **48**(SPL): S150–S162.
- Giné, X., Townsend, R. and Vickery, J. (2008). Patterns of rainfall insurance participation in rural India, *The World Bank Economic Review* **22**(3): 539–566.
- Hellmuth, M. E., Osgood, D. E., Hess, U., Moorhead, A. and Bhojwani, H. (2009). Index insurance and climate risk: Prospects for development and disaster management. Climate and Society No. 2. International Research Institute for Climate and Society (IRI), Columbia University, New York, USA.
- Henderson, J. V., Storeygard, A. and Deichmann, U. (2017). Has climate change driven urbanization in Africa?, *Journal of Development Economics* **124**: 60–82.
- Karlan, D., Osei, R., Osei-Akoto, I. and Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints, *The Quarterly Journal of Economics* **129**(2): 597–652.
- Miranda, M. J. and Farrin, K. (2012). Index insurance for developing countries., *Applied Economic Perspectives & Policy* **34**(3): 391–427.
- Miranda, M. J. and Gonzalez-Vega, C. (2011). Systemic risk, index insurance, and optimal management of agricultural loan portfolios in developing countries, *American Journal of Agricultural Economics* **93**(2): 399–406.
- Mobarak, A. M. and Rosenzweig, M. (2012). Selling formal insurance to the informally insured. Working Paper, Yale Economics Department.
- Morsink, K. and Geurts, P. (2011). Informal trust building factors and the demand for microinsurance., *7th annual international microinsurance conference, Rio de Janeiro*.

- Outreville, J. F. (2013). The relationship between insurance and economic development: 85 empirical papers for a review of the literature, *Risk Management and Insurance Review* **16**(1): 71–122.
- Parchure, R. (2002). Varsha bonds and options: Capital market solutions for crop insurance problems. Working Paper, UTI Institute of Capital Markets, Mumbai.
- Patt, A., Peterson, N., Carter, M., Velez, M., Hess, U. and Suarez, P. (2009). Making index insurance attractive to farmers, *Mitigation and Adaptation Strategies for Global Change* **14**(8): 737–753.
- Radhakrishna, R., Rao, S., Dev, S. M. and Subbarao, K. (2006). India in a globalising world – some aspects of macro economy, agriculture and poverty, *Academic Foundation, New Delhi*.
- Sarris, A. (2002). The demand for commodity insurance by developing country agricultural producers: Theory and an application to Cocoa in Ghana. Working Paper, The World Bank, Policy Research.
- World Bank (2016). What can index insurance offer to development?, <http://www.worldbank.org/en/news/feature/2016/11/10/what-can-index-insurance-offer-to-development> (28th of June 2017).
- World Bank (2017). Understanding poverty: Agriculture and food, <http://www.worldbank.org/en/topic/agriculture/overview> (14th of December 2017).

A Appendix

A.1 Proof of Theorem 2.1

For the proof of Theorem 2.1 I first have to proof the following Lemma A.1

Lemma A.1. *For differences $D = X - Y$, $X \sim F_X$, $Y \sim F_Y$ we know that*

$$f_Z(z) = \int_{\mathbb{R}} f_X(z+y)f_Y(y)dy.$$

Proof: Let $X, Y \sim F$ i.i.d. and $Z = X - Y$, we obtain

$$\begin{aligned} F_Z(z) &= \mathbb{P}[Z \leq z] = \mathbb{P}[X - Y \leq z] = \int_{(x,y) \in \mathbb{R}^2: x-y \leq z} f_{(X,Y)}(x,y) dx dy \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{t+y} f_{(X,Y)}(x,y) dx dy \stackrel{\text{Subst.}}{=} \int_{-\infty}^{\infty} \int_{-\infty}^t f_{(X,Y)}(z+y,y) dz dy \\ &\stackrel{\text{Fubini}}{=} \int_{-\infty}^t \underbrace{\int_{-\infty}^{\infty} f_{X,Y}(z+y,y) dy}_{=f_Z(z)} dz \stackrel{X,Y \text{ iid}}{=} \int_{-\infty}^t \underbrace{\int_{-\infty}^{\infty} f_X(z+y)f_Y(y) dy}_{=f_Z(z)} dz. \end{aligned}$$

□

It holds

$$\varepsilon = X^i - X^f = (1 - \Delta)X^f + \Delta X - X^f = \Delta(X - X^f).$$

We know that any linear transformation of normally distributed random variables is again normally distributed. For differences $D = X - Y$, $X \sim F_X$, $Y \sim F_Y$ from Lemma A.1 we know that

$$f_Z(z) = \int_{\mathbb{R}} f_X(z+y)f_Y(y)dy.$$

Further, we know

$$\begin{aligned} \mathbb{E}[S] &= \mathbb{E}[X] - \mathbb{E}[Y] \\ \text{Var}(S) &= \text{Var}(X) + \text{Var}(Y) - \text{Cov}(X, Y) \\ \text{Var}(\alpha S) &= \alpha^2 \text{Var}(S) \quad , \quad \alpha \in \mathbb{R}. \end{aligned}$$

In the model I assume that X, X^f iid. Further, let $X, X^f \sim F_X$ with $\mathbb{E}[X] = \mu_X$ and $\mathbb{V}[X] = \sigma_X^2$. Since for iid. r.v. it holds $Cov(X, X^f) = 0$, I obtain $X - X^f \sim F_{X-X^f}$ with $\mathbb{E}[X - X^f] = 0$ and $\mathbb{V}[X - X^f] = 2\sigma_X^2$, it follows:

$$\Delta(X - X^f) = \varepsilon \sim F_\varepsilon \text{ with } \mathbb{E}[\varepsilon] = 0 \text{ and } \mathbb{V}[\varepsilon] = 2(\Delta\sigma_X)^2.$$

□

A.2 Proof of Theorem 3.1

We calculate the Covariance:

$$\begin{aligned} Cov((1 - k_t)X^f, k_t\varepsilon) &= Cov((1 - k_t)X^f, k_t\Delta(X^f - X)) \\ &= (1 - k_t)k_t\Delta Cov(X^f, X - X^f) \\ &= (1 - k_t)k_t\Delta \underbrace{Cov(X^f, X)}_{=0} - \underbrace{Cov(X^f, X^f)}_{=\sigma_X^2} \\ &= -(1 - k_t)k_t\Delta\sigma_X^2. \end{aligned}$$

For income we obtain

$$\begin{aligned} \mathbb{E}[X^k] &= k_t\tilde{x} + (1 - k_t)\mu_X + k_t \cdot 0 - (1 + r_m)p_t = k_t\tilde{x} + \mu_X - k_t\mu_X - (\tilde{x} - \mu_X)k_t = \mu_X \\ \mathbb{V}[X^k] &= (1 - k_t)^2\sigma_X^2 + k_t^2\sigma_\varepsilon^2 + 2k_t(1 - k_t)\sigma_{X,\varepsilon} \\ &= (1 - k_t)^2\sigma_X^2 + 2(k_t\Delta\sigma_X)^2 - 2 \cdot (1 - k_t)k_t\Delta\sigma_X^2. \end{aligned}$$

If we maximize expected utility over k_t

$$\max_{k_t} \mathbb{E}[u(x)] \Leftrightarrow \max_{k_t} \underbrace{\{\mathbb{E}[X^k] - \rho\mathbb{V}[X^k]\}}_{:=\otimes(k_t)},$$

we obtain

$$\begin{aligned} \frac{\partial \otimes(k_t)}{\partial k_t} = 0 &\Leftrightarrow k_t = k_t(\Delta) = \frac{1 + \Delta}{1 + 2\Delta^2 + 2\Delta}, \quad \Delta \in [0, 1] \\ k_t(1) &= 0.4. \end{aligned}$$

□

A.3 Proof of Theorem 3.2

We calculate the Covariance:²⁶

$$\begin{aligned}
Cov((1 - k_t)X^f, k_t\theta(\tau, \zeta)) &= Cov((1 - k_t)X^f, k_t\Delta(X^f - X)) \\
&= (1 - k_t)k_t\Delta Cov(X^f, X - X^f) \\
&= (1 - k_t)k_t\Delta \underbrace{Cov(X^f, X)}_{=0} - \underbrace{Cov(X^f, X^f)}_{=\sigma_X^2} \\
&= -(1 - k_t)k_t\Delta\sigma_X^2.
\end{aligned}$$

For income we obtain

$$\begin{aligned}
\mathbb{E}[X^k] &= k_t\tilde{x} + (1 - k_t)\mu_X + k_t \cdot (-\tau) - (1 + r_m)p_t \\
&= k_t\tilde{x} + (1 - k_t)\mu_X - k_t\tau - (\tilde{x} - \mu_X)k_t = \mu_X - k_t\tau \\
\mathbb{V}[X^k] &= (1 - k_t)^2\sigma_X^2 + k_t^2\sigma_{\theta(\tau, \zeta)}^2 + 2k_t(1 - k_t)\sigma_{X, \theta(\tau, \zeta)} \\
&= (1 - k_t)^2\sigma_X^2 + 2\zeta(k_t\Delta\sigma_X)^2 - 2 \cdot (1 - k_t)k_t\Delta\sigma_X^2.
\end{aligned}$$

If we maximize expected utility over k_t

$$\max_{k_t} \mathbb{E}[u(x)] \Leftrightarrow \max_{k_t} \underbrace{\{\mathbb{E}[X^k] - \rho\mathbb{V}[X^k]\}}_{:=\otimes(k_t)},$$

we obtain

$$\begin{aligned}
\frac{\partial \otimes(k_t)}{\partial k_t} = 0 &\Leftrightarrow k_t = k_t(\Delta, \tau, \zeta) = \frac{1 + \Delta - \frac{\tau}{2\rho\sigma_X^2}}{1 + 2\zeta\Delta^2 + 2\Delta}, \quad \Delta \in [0, 1] \\
k_t(1) &= \frac{2 - \frac{\tau}{2\rho\sigma_X^2}}{3 + 2\zeta}.
\end{aligned}$$

□

²⁶I assume that farmers underestimate covariance between income and basis risk, hence, they overestimate variance of income using insurance coverage.

A.4 Proof of Proposition 3.2

(i) I have to show that

$$\frac{\partial}{\partial \Delta} \left(k_t^\varepsilon - k_t^{\theta(\tau)} \right) < 0.$$

Hence, I obtain

$$\begin{aligned} \frac{\partial}{\partial \Delta} \left(k_t^\varepsilon - k_t^{\theta(\tau)} \right) &= \frac{\partial}{\partial \Delta} \left(\frac{1 + \Delta}{1 + 2\Delta^2 + 2\Delta} - \frac{1 + \Delta - \frac{\tau}{2\rho\sigma_X^2}}{1 + 2\Delta^2 + 2\Delta} \right) \\ &= \frac{\tau}{2\rho\sigma_X^2} \cdot \frac{\partial}{\partial \Delta} (1 + 2\Delta^2 + 2\Delta)^{-1} \\ &= \underbrace{-\frac{\tau}{2\rho\sigma_X^2}}_{<0} \cdot \underbrace{(1 + 2\Delta^2 + 2\Delta)^{-2}}_{>0} \cdot \underbrace{(4\Delta + 2)}_{>0} < 0. \end{aligned}$$

□

(ii) I have to show that

$$\frac{\partial}{\partial \Delta} \left(k_t^\varepsilon - k_t^{\theta(\zeta)} \right) > 0.$$

Hence, I obtain

$$\frac{\partial}{\partial \Delta} \left(k_t^\varepsilon - k_t^{\theta(\zeta)} \right) = \frac{\partial}{\partial \Delta} \left(\frac{1 + \Delta}{1 + 2\Delta^2 + 2\Delta} - \frac{1 + \Delta}{1 + 2\zeta\Delta^2 + 2\Delta} \right).$$

Since numerators are equal, I can also show that the deviation between denominators is increasing, that means

$$\begin{aligned} \frac{\partial}{\partial \Delta} (1 + 2\zeta\Delta^2 + 2\Delta - (1 + 2\Delta^2 + 2\Delta)) &= \frac{\partial}{\partial \Delta} (2\zeta\Delta^2 - 2\Delta^2) \\ &= (\zeta - 1) \cdot \frac{\partial}{\partial \Delta} (2\Delta^2) \\ &= \underbrace{(\zeta - 1)}_{>0} \cdot \underbrace{4\Delta}_{>0} > 0. \end{aligned}$$

It follows, that

$$\frac{\partial}{\partial \Delta} \left(k_t^\varepsilon - k_t^{\theta(\zeta)} \right) > 0.$$

□

(iii) I have to show that for all $\Delta > 0$ it holds

$$k_t^\varepsilon - k_t^{\theta(\tau, \zeta)} < |k_t^\varepsilon - k_t^{\theta(\tau)}| + |k_t^\varepsilon - k_t^{\theta(\zeta)}|.$$

I start with $\Delta \in [0, 1]$:

$$\begin{aligned} k_t^\varepsilon - k_t^{\theta(\tau, \zeta)} &< k_t^\varepsilon - k_t^{\theta(\tau)} + k_t^\varepsilon - k_t^{\theta(\zeta)} \\ \Leftrightarrow k_t^{\theta(\zeta)} - k_t^{\theta(\tau, \zeta)} &< k_t^\varepsilon - k_t^{\theta(\tau)}. \end{aligned}$$

If I insert values for k_t I obtain

$$\begin{aligned} \frac{1 + \Delta}{1 + 2\zeta\Delta^2 + 2\Delta} - \frac{1 + \Delta - \frac{\tau}{2\rho\sigma_X^2}}{1 + 2\zeta\Delta^2 + 2\Delta} &< \frac{1 + \Delta}{1 + 2\Delta^2 + 2\Delta} - \frac{1 + \Delta - \frac{\tau}{2\rho\sigma_X^2}}{1 + 2\Delta^2 + 2\Delta} \\ \Leftrightarrow \frac{\frac{\tau}{2\rho\sigma_X^2}}{1 + 2\zeta\Delta^2 + 2\Delta} &< \frac{\frac{\tau}{2\rho\sigma_X^2}}{1 + 2\Delta^2 + 2\Delta} \\ \Leftrightarrow 1 + 2\zeta\Delta^2 + 2\Delta &> 1 + 2\Delta^2 + 2\Delta \\ \Leftrightarrow \zeta &> 1. \end{aligned}$$

I proceed with $\Delta > 1$:

$$\begin{aligned} k_t^\varepsilon - k_t^{\theta(\tau, \zeta)} &< k_t^\varepsilon - k_t^{\theta(\tau)} + k_t^\varepsilon - k_t^{\theta(\zeta)} \\ \Leftrightarrow k_t^{\theta(\zeta)} - k_t^{\theta(\tau, \zeta)} &< k_t^\varepsilon - k_t^{\theta(\tau)}. \end{aligned}$$

If I insert values for k_t I obtain

$$\begin{aligned} \frac{2}{3 + 2\zeta} - \frac{2 - \frac{\tau}{2\rho\sigma_X^2}}{3 + 2\zeta} &< 0.4 - \frac{2 - \frac{\tau}{2\rho\sigma_X^2}}{3 + 2} \\ \Leftrightarrow \frac{\frac{\tau}{2\rho\sigma_X^2}}{3 + 2\zeta} &< \frac{\frac{\tau}{2\rho\sigma_X^2}}{5} \\ \Leftrightarrow 3 + 2\zeta &> 5 \\ \Leftrightarrow \zeta &> 1. \end{aligned}$$

□

A.5 Proof of Theorem 3.3

We calculate the Covariance:²⁷

$$\begin{aligned}
Cov((1 - k_t)X^f, k_t\theta(\tau, \zeta)) &= Cov((1 - k_t)X^f, k_t\Delta(X^f - X)) \\
&= (1 - k_t)k_t\Delta Cov(X^f, X - X^f) \\
&= (1 - k_t)k_t\Delta \underbrace{Cov(X^f, X)}_{=0} - \underbrace{Cov(X^f, X^f)}_{=\sigma_X^2} \\
&= -(1 - k_t)k_t\Delta\sigma_X^2.
\end{aligned}$$

For income we obtain

$$\begin{aligned}
\mathbb{E}[X^k] &= k_t\tilde{x} + (1 - k_t)\mu_X + k_t \cdot (-\tau) - (1 + r_m)p_t(1 - s) \\
&= k_t\tilde{x} + (1 - k_t)\mu_X - k_t\tau - (\tilde{x} - \mu_X)k_t(1 - s) = \mu_X - k_t\tau + sk_t(\tilde{x} - \mu_X) \\
\mathbb{V}[X^k] &= (1 - k_t)^2\sigma_X^2 + k_t^2\sigma_{\theta(\tau, \zeta)}^2 + 2k_t(1 - k_t)\sigma_{X, \theta(\tau, \zeta)} \\
&= (1 - k_t)^2\sigma_X^2 + 2\zeta(k_t\Delta\sigma_X)^2 - 2 \cdot (1 - k_t)k_t\Delta\sigma_X^2.
\end{aligned}$$

If we maximize expected utility over k_t

$$\max_{k_t} \mathbb{E}[u(x)] \Leftrightarrow \max_{k_t} \underbrace{\{\mathbb{E}[X^k] - \rho\mathbb{V}[X^k]\}}_{:=\otimes(k_t)},$$

we obtain

$$\begin{aligned}
\frac{\partial \otimes(k_t)}{\partial k_t} = 0 &\Leftrightarrow k_t = k_t(\Delta, \tau, \zeta) = \frac{1 + \Delta + \frac{s(\tilde{x} - \mu_X) - \tau}{2\rho\sigma_X^2}}{1 + 2\zeta\Delta^2 + 2\Delta}, \quad \Delta \in [0, 1] \\
k_t(1) &= \frac{2 + \frac{s(\tilde{x} - \mu_X) - \tau}{2\rho\sigma_X^2}}{3 + 2\zeta}.
\end{aligned}$$

□

²⁷I assume that farmers underestimate covariance between income and basis risk, hence, they overestimate variance of income using insurance coverage.

A.6 Proof of Proposition 3.3

I have to show that

$$\frac{\partial}{\partial \Delta}(k_t(s) - k_t(0)) < 0.$$

Hence, I obtain

$$\begin{aligned} \frac{\partial}{\partial \Delta}(k_t(s) - k_t(0)) &= \frac{\partial}{\partial \Delta} \left(\frac{1 + \Delta + \frac{s(\tilde{x} - \mu_X) - \tau}{2\rho\sigma_X^2}}{1 + 2\zeta\Delta^2 + 2\Delta} - \frac{1 + \Delta - \frac{\tau}{2\rho\sigma_X^2}}{1 + 2\zeta\Delta^2 + 2\Delta} \right) \\ &= \frac{\partial}{\partial \Delta} \left(\frac{\frac{s(\tilde{x} - \mu_X)}{2\rho\sigma_X^2}}{1 + 2\zeta\Delta^2 + 2\Delta} \right) \\ &= \frac{s(\tilde{x} - \mu_X)}{2\rho\sigma_X^2} \cdot \frac{\partial}{\partial \Delta} (1 + 2\zeta\Delta^2 + 2\Delta)^{-1} \\ &= \underbrace{-\frac{s(\tilde{x} - \mu_X)}{2\rho\sigma_X^2}}_{<0} \cdot \underbrace{(1 + 2\zeta\Delta^2 + 2\Delta)^{-2}}_{>0} \cdot \underbrace{(4\zeta\Delta + 2)}_{>0} < 0. \end{aligned}$$

□