Assessing digital opportunities for the distribution and product design of agricultural microinsurance in Mali – a discrete choice experiment

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Abstract

Agricultural index-based microinsurance is perceived as a promising risk management tool for smallholders. Recently, several mobile-delivered insurance schemes entered the market, but farmers' preferences for these products remain largely unknown so far. We address this knowledge gap by means of a discrete choice experiment conducted among 721 maize farmers in Mali. The experiment presents an easy-to-understand multi-peril crop insurance linked to a greenness index. It focuses on attributes related to the distribution channel and product design. Using mixed logit models, we find that it is not the mobile-delivery itself, but rather the opportunities coming with mobile-delivered insurance that are attractive to farmers. Product bundles that include mobile-delivered weather information and agricultural advice in addition to the insurance policy and recommendations for the insurance by fellow farmers increase the likelihood to take out an insurance. These results are highly relevant for future product improvements and ultimately to improve adoption rates.

Keywords Microinsurance, mobile services, product design, smallholders, microfinance

JEL code G52, Q14

1. Introduction

The agricultural sector is of great importance for many developing countries in terms of economic contribution, employment generation, and source of livelihoods. It has always been exposed to a variety of production risks such as weather risks or pest and diseases. Due to climate change, extreme weather events occur more often and globally rising average temperatures allow new pests and diseases to spread in regions where they have been unobserved before. Current debates focus on how to improve resilience, particularly towards extreme weather events, and the IPCC identified index insurance as one major enabler of societal resilience (IPCC, 2022).

Agricultural index insurance gained popularity over the last decades as they enabled cost-efficient provision of microinsurance to smallholders in remote areas. In index-based insurance schemes, farmers receive an indemnity based on a pre-defined triggering level of a certain index. In weather index-based insurance, the indices are commonly based on weather station or satellite data. Thereby, on farm loss assessment becomes obsolete and problems of conventional insurance schemes such as moral hazard and adverse selection are reduced (Barnett and Mahul, 2007).

Recently, several microinsurance providers entered the market with mobile-delivered insurance products (Raithatha and Priebe, 2020). Depending on the degree of digitization, interested farmers can get informed, subscribe to the insurance, pay premiums, and receive indemnities via their cell phone. Offering a mobile-delivered insurance does not only lower operational costs for the insurance provider, but it is also sought to substantially reduce transaction costs for customers. Mobile-delivered insurance eliminates the need to go to an agency office, decreases waiting times for payouts, and enables the provision of new product bundles.

Seizing the potential of digital services is likely to become an important aspect for agricultural risk management – especially in the face of climate change. Mobile phone subscriptions in least developed countries increased by nearly 30 % during that last 10 years reaching 79 subscriptions per 100 inhabitants in 2022 (ITU, 2022). With the rise of mobile money, the necessary infrastructure for mobile-delivered services is largely available by now. Yet, farmers' preferences regarding mobile-delivered insurance services remain unknown so far.

We aim at identifying the importance and opportunities of mobile-delivered agricultural microinsurance by answering the following three research questions: Do smallholders prefer insurance products that can be taken out via mobile phones? What are appropriate product bundles for mobile-delivered agricultural insurance schemes? Can referral schemes help to bridge a potentially emerging trust gap in mobile-delivered insurance schemes? Insights into farmers' preferences are critical to align insurance products with customer needs. Well-adapted insurance policies, in turn, are beneficial to achieve high adoption rates and to realize the loss-hedging potential of microinsurance. Knowledge on farmers' preferences further provides guidance for policymakers when considering governmental support for certain insurance products.

We address our research questions by means of a discrete choice experiment (DCE) conducted among 721 smallholder maize producers in southern Mali. We repeatedly presented two easy-to-understand fictional multi-peril crop insurance schemes to them with differing product attributes and used mixed and conditional logit models to elicit farmers' preferences. Our results show a strong preference for the multi-peril crop insurance product as opposed to not being insured. Similarly, we found a strong preference for product bundles enabled through the distribution via mobile phones such as weather information or digital farming advice. Lastly, recommendations for the insurance scheme by fellow farmers increased the likelihood to adopt the multi-peril crop insurance, hinting at a trust building effect of referral schemes.

Our research adds to the existing body of literature in several ways. Firstly, we are, to the best of our knowledge, the first to assess preferences regarding a mobile-delivered insurance scheme. Discrete choice experiments have previously been used to elicit preferences and willingness-to-pay of product attributes of index insurance (e.g. Ward and Makhija, 2018; Doherty *et al.*, 2021; Linhoff, Musshoff and Parlasca, 2022; Ghosh *et al.*, 2021). The rational for these studies is based on surprisingly low levels of adoption of index-insurance and the idea that well-suited insurance schemes may overcome certain adoption barriers. To date, it remains unclear if and how the opportunities of digital services may change the adoption rates.

Secondly, we assess novel and promising product bundles. Bundling insurance with other products has, in general, been discussed as a means to increase attractiveness of insurance schemes (Platteau, Bock and Gelade, 2017). Ward and Makhija (2018) found, for instance, that the willingness-to-pay for a product bundle of insurance and drought tolerant seeds is higher than the actuarially fair price of both products combined. With mobile-delivered insurance on the rise, new product bundles with mobile services become technically feasible. We analyse the potential of a product bundle with weather information and farming advice as both were found to have positive impacts on agricultural outcomes (Rajkhowa and Qaim, 2021; Mudombi and Nhamo, 2014).

Lastly, we contribute by providing evidence on preferences for multi-peril crop insurance. Previous studies have analysed preferences for weather index-based insurance that are mainly based on precipitation or temperature indices (Abdi *et al.*, 2022). In this study, we assess a multi-peril crop insurance based on a fictional "greenness" index inspired by normalized difference vegetation index (NDVI). While Turvey and Mclaurin (2012) advised against purely NDVI based crop insurance products due to high basis risk, Kölle, Buchholz and Musshoff (2022) find that complementing weather indices with NDVI data is a viable option to reduce basis risk. This study provides first evidence on how an insurance scheme based on satellite pictures would be perceived in Mali.

The remainder of the paper is organized as follows. In Section 2 we present the experimental set up and the implementation. Section 3 provides the methodological foundation of the paper. Section 4 presents and discusses the findings before conclusions are presented in Section 5.

2. Experimental design and implementation

To assess smallholder preferences, we conducted a DCE. DCEs capture stated preferences and allow to identify formerly unrevealed preferences. Study participants are repeatedly confronted with a hypothetical purchase situation in which they are presented with at least two potential products. The presented products differ with regards to certain product attributes. By systematically varying the combination of attributes the importance of the different attributes for the purchase of a product can be quantified. As the presented products and the product attributes can be entirely fictional, DCEs are well-suited for preference assessments for novel products for which real-world data are scarce. This applies to the present context since mobile-delivered insurance products are a new development in the microinsurance sector and some of the features of interest for our study would be technically feasible, but are not yet implemented.

2.1 Experimental set-up

In the DCE, the respondents were offered fictional multi-peril crop insurance contracts tailored to maize production. On each choice card there were two insurance contract options and an opt-out option. Both insurance alternatives shared several characteristics. The insurance policy was designed such that it triggers a one-time payment of 40,000 CFA[1] given a negative deviation of 25 % from the yearly average of a greenness index at the respondent's location prior to the average harvest time. The height of the indemnity corresponds to a quarter of the average

[1] CFA refers to the CFA-France BCEAO. The currency is tied to the Euro with a fixed exchange rate of 655.96 CFA = 1 Euro.

revenue per ha maize as indicated by local insurance partners. The insurance policy covers one crop growing cycle and can be taken out right after the harvest of the previous season.

Besides these shared characteristics, the presented insurance products differed in six attributes whereof the first is the distribution channel. As the present study aims at identifying the importance and opportunities of the mobile distribution of insurance products, some attribute levels were conditional on the distribution channel. An overview of the attributes and their levels is provided in Table 1.

Table 1. Selected attributes and levels.

Attribute	Level	Effect-coded (E)/ Continuous (C)
Distribution channel	Distributed via an agency (A), distributed via mobile phones (M)	E
Premium per hectare	5,000 CFA, 7,000 CFA, 9,000 CFA, 11,000 CFA per hectare (apply to A and M)	C
Travel time for interaction with the insurance service provider	If (A): 0 min, 30 min, 60 min, 90 min If (M): 0 min	C
Credit access through the insurance	0 CFA, 150,000 CFA, 300,000 CFA	C
Additional information services provided via mobile phones	If (A): no additional services If (M): no additional service, weather forecasts per SMS, Whatsapp group including farming advice, mobile application with farming advice and weather forecasts	E
Recommendation by peers	0, 1, 3, 5 fellow farmers recommended the insurance	C

The attribute “distribution channel” specified whether the offered insurance would be distributed via an agency office or via the mobile network. In the former case, the farmers have to get in touch with an insurance agent to take out the contract, pay the premium, make a claim, and receive a potential payout. Payments have to be made in cash. All steps along the customer journey imply either the need to travel to an agency office or to wait until the insurance field agent returns to the area. While for the insurance contract distributed via an agency no other company is involved in the business, the telecom provider plays an active role in the mobile-delivered insurance product. Subscription to the insurance can be done via a USSD[2] menu and premium payments have to be made via mobile money. In case the farmer is eligible for a payout, the indemnity payment is triggered automatically and transferred via mobile money.

The second attribute was premium per hectare. Previous studies identified the premium as a main driver for demand (Cole *et al.*, 2013; Hill, Robles and Ceballos, 2016; Matsuda and Kurosaki, 2019), thereby making it an important attribute for the experiment. Regardless of the distribution channel, the insurance contracts are offered at either 5,000 CFA, 7,000 CFA, 9,000 CFA, or 11,000 CFA. We assume that a negative 25 % deviation of the yearly average occurs every 10 years and consequently, the actuarially fair price of the insurance would be at 4,000 CFA. Considering high set-up costs of index insurance as well as the provision of extra services, the included price levels exceed the actuarially fair price. This allows to identify whether there is a market potential or rather a need for subsidization for the products.

Depending on the distribution channel, the required travel time to interact with an agent differed. In the mobile-delivered insurance policy, the farmer is not required to travel. For the ordinary insurance contract, there is one case in which the agent comes to the farmer, implying no travel time. The travel time to the agency office is otherwise specified in minutes ranging from 30 to 90 minutes. By specifying travel time and not travel distance we allowed the respondents to consider their individual perception of mobility depending on the means of transport available to them.

Access to credit through the subscription to one of the offered insurance policies was the fourth attribute. The levels included either no credit access, access to a credit of 150,000 CFA at most, or access to a credit of 300,000 CFA at most. The loan duration was in both cases set at 6 months. The fictional loan requires a fee of 10 % per year of the loan amount which is said to cover the interest as well as administrative costs. Depending on the distribution channel, the loan is either offered in form of mobile money or conventional credit from a bank. Evidence on bundling insurance with credit has been mixed so far (Galarza and Carter, 2011; Giné and Yang, 2009). By including this attribute, we are able to add new evidence to the discussion.

The fifth attribute was purposefully tailored towards the possibilities of mobile-delivered insurance schemes and addresses potential extra services. In case the insurance contract was distributed via an agency office, there were no extra services included. For a mobile-delivered

[2] USSD (Unstructured Supplementary Service Data) menus can be accessed by dialing codes using the available keys on a cell phone. The system operates similarly to SMS and allows to transfer a predefined set of information according to the selected USSD code.

insurance there were four levels where no extra services served as base level. The first extra service consists of weekly weather information send out as voice message per SMS. The second extra service is a Whatsapp group with exclusive access for insurance subscribers in which texts and voice messages on crop protection are shared and the third level is a mobile application that comprises weather forecasts and farming advice in form of text, voice recordings, and videos.

Finally, we also included hypothetical recommendations of friends. The respondents were asked to assume that either no, one, three, or five fellow farmers recommended the respective insurance product to them. For this attribute there was no difference depending on the distribution mechanism. The reasoning for including this attribute is that trust matters in the adoption of insurance schemes (Platteau, Bock and Gelade, 2017; Cole *et al.*, 2013; Linhoff, Musshoff and Parlasca, 2022). We argue that also recommendations may build up trust. Thereby, they could help alleviate a potentially emerging trust gap when farmers are no longer in touch with an agent to subscribe to the insurance.

Following Scarpa and Rose (2008), we used a D-efficient design to limit the number of choice cards per respondent. We used Ngene to calculate the best D-efficient design for 12 choice cards blocked into two groups. The design was constrained by four conditions such that in case of a mobile-delivered insurance, the travel time would always be zero and that in case of a conventional distribution, the attribute for extra service would be set to zero. Given these constraints, it was not possible to obtain full attribute level balance. A pre-test among 150 farmers yielded a first indication of the impact of each attribute. The results of a mixed logit model were used to refine the priors for the final experimental design. The final design had a D-error of 0.09.

2.2 Study context

Data were collected in southern Mali in collaboration with the insurance provider OKO Mali SaRL (OKO). Mali is a land-locked country in West Africa that is among the least developed countries in the world. It heavily depends on agriculture. In 2021, 36 % of its GDP came from agricultural production (World Bank, 2022a) and more than 60 % of the workforce is employed in the agricultural sector (World Bank, 2022b). Moreover, the majority of farmers engage in subsistence farming (FAO, 2017). Climate risks increasingly jeopardize agricultural success and thus also livelihoods. Climate adaptation and risk mitigation methods are therefore of primary interest in the region.

In this context, OKO started to offer a mobile-delivered index-based insurance for maize producers in 2020. OKO's insurance policy pays out in case of drought or inundation. Triggering and exit levels are largely localized based on a variety of different factors including satellite derived precipitation data for the respective location of the farmer. The insurance policies have to be taken out via the mobile phone and premiums need to be paid via mobile money. Still, OKO agents travel to the villages to facilitate the first subscription to the insurance scheme. Furthermore, OKO operates a call center to provide consultations and support for their clients.

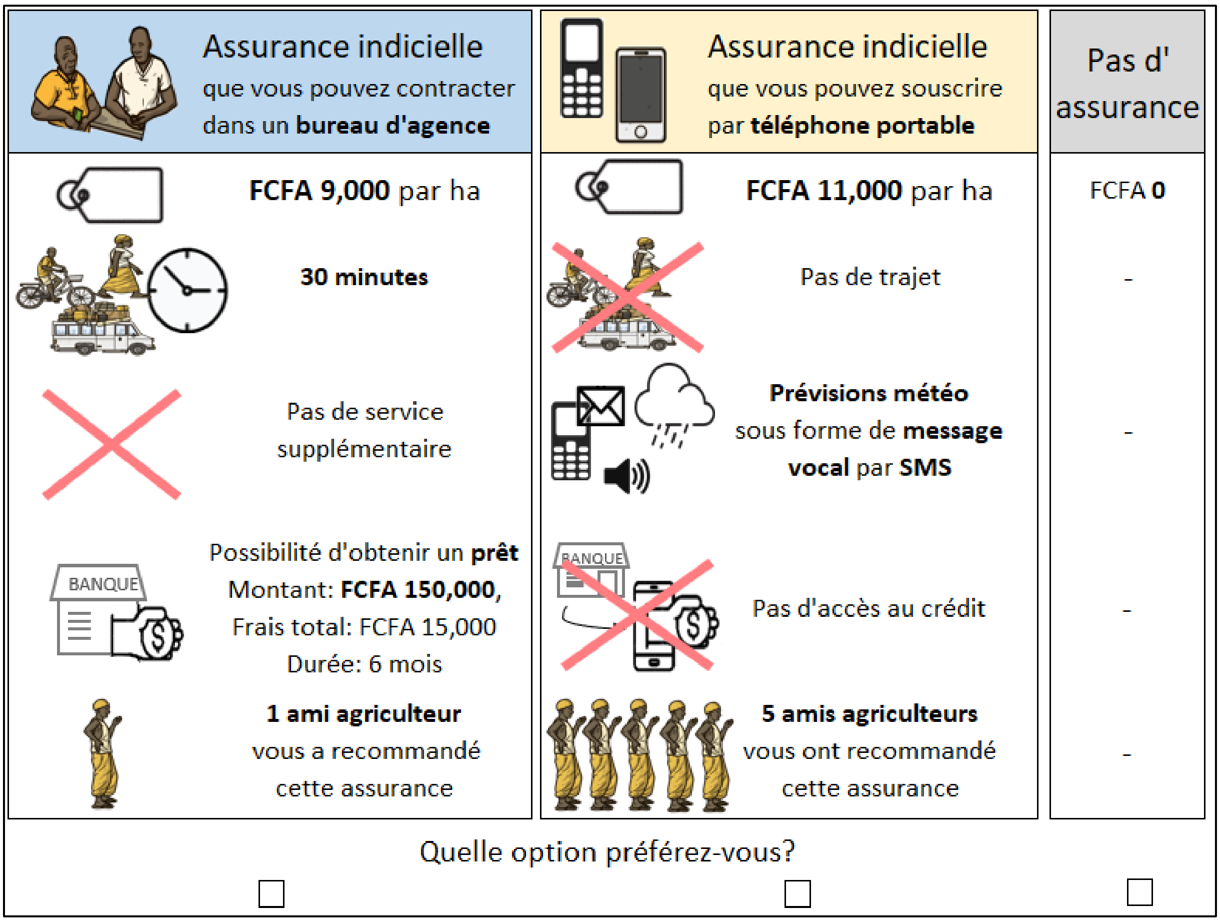
The insurance scheme in the DCE purposefully differs from the insurance provided by OKO. In the DCE we presented a fictional multi-peril crop insurance which is based solely on a greenness index. In contrast to OKO who insure drought and inundation, the presented scheme covers all hazards that affect not only the vegetation on the insured farmland, but also on surrounding land. Presenting the easy-to-understand index allowed to keep the same product across all respondents regardless of their location. By collaborating with OKO we ensured to have a mixed sample of farmers who are currently using index insurance as well as farmers who are not insured but who have been exposed to insurance before.

2.3 Implementation

The DCE was conducted in in-person interviews in the regions Kayes, Koulikoro, Bamako, Ségou, and Sikasso in October and November 2021. A total of 721 respondents participated in the survey including the DCE. Thereof, 350 farmers have been insured with OKO in the season prior to the survey. The remaining share of farmers has either never been insured with OKO (n=157), but requested information about OKO's insurance scheme, or has been insured once in the previous year (n=214). Sampling was done randomly based on a client list provided by OKO.

In the beginning of the interview, respondents were asked for their consent to participate in a fully anonymized survey and the interview continued only in case of agreement. Depending on the respondent's preference, the interviews were either held in French or Bambara, the local language. The text on the choice cards was in French. Due to low levels of literacy (World Bank, 2022), the choice cards were illustrated to facilitate the understanding. An exemplary choice card is provided in Figure 1.

Figure 1: Exemplary choice card.



To ensure high data quality for the analysis, we opted for strict quality controls. We asked for the consent of the respondent as to record the experiment. For those who agreed (89 %), the voice recording was started before the first explanation was given and ended as soon as the last choice of the respondent was made. Thereby, we could check if all relevant information was provided, if the enumerator influenced the choice, and how long it took to complete the DCE. We checked 10 % of the interviews and concluded that there were no general problems in conducting the DCE. On average the DCE took 9:21 min. We dropped the longest and shortest 5 % of the observations (n=65) arguing that neither rushing through the experiment nor being distracted so that it takes substantially longer reflects conscious decision-making behavior.

Furthermore, all respondents were asked to answer a seventh choice card with a dominant alternative. In case the dominant alternative was not chosen, the observation was dropped (n=143). Lastly, we also dropped observations in which the respondent always chose the first or always the second option (n=14), a behavior also known as straight-lining. The final sample for which we can assume the highest data quality possible consist of 499 respondents.

3. Methodology

3.1 Methodological framework

McFadden's (1973) random utility model serves as basis for the econometric analysis of DCEs. It assumes utility-maximizing behavior of the decision maker. In a DCE, decision makers have to choose an option *j* out of a finite set of alternatives *J*. The utility *U* that a decision maker *n* obtains from choosing alternative *j* is the sum of an observable utility component V_{nj} and an unobserved random component ε_{nj} such that

$$U_{\mathrm{nj}} = V_{\mathrm{nj}} + \varepsilon_{\mathrm{nj}}\ , \ \ j = 1, \dots, J \tag{1}$$

The observable component V_{nj} is a function of the vector of attributes of the alternative, denoted x_j, and observable characteristics of the decision maker, labeled s_n, so that

$$V_{nj} = V\left(x_j, s_n\right) \forall\, j \tag{2}$$

As $\varepsilon_{\mathrm{nj}} \ \forall\, j$ remains unknown, it is treated as random. Following Train (2009), the joint density function of the random vector $\varepsilon'_n = \left(\varepsilon_{n1,} \dots, \varepsilon_{nJ}\right)$ is denoted with $f(\varepsilon_n)$. With these assumptions, the following probability of choosing alternative *i* can be derived

$$Prob_{ni} \ = Prob\left[\left(U_{ni} \geq U_{nj}\right) \ \forall \ \ i \neq j\right] \tag{3}$$

$$= Prob\left[\left(V_{ni} + \varepsilon_{ni}\right) \geq \left(V_{nj} + \varepsilon_{nj}\right) \forall \ \ i \neq j\right] \tag{4}$$

$$= Prob \ \left[\left(\varepsilon_{nj} - \varepsilon_{ni}\right) \leq \left(V_{ni} - \ V_{nj}\right) \forall\, i \neq j\right] \tag{5}$$

The probability in Eq. (5) illustrates the cumulative distribution that the difference in the amount of unobserved utility from option *i* and option *j*, is smaller than the difference in observed utility from both options. Having specified the joint density function of ε_n the choice probability can be rewritten to

$$Prob_{ni} = \int I \ \left(\left(\varepsilon_{nj} - \varepsilon_{ni}\right) < \left(V_{ni} - V_{nj}\right) \forall\, i \neq j\right) \ f(\varepsilon_n)\, d\varepsilon_n, \tag{6}$$

where $I(\cdot)$ becomes 1 if the expression in parentheses is true, and 0 otherwise. In order to analyze the choice based on this framework, several different evaluation techniques can be applied. The approaches utilized in this study are described in the next Section.

3.2 Estimation strategy

Based on the random utility model (see Section 2.1), we estimated a mixed logit model and used a multinomial logit (MNL) model for robustness checks. While the MNL model is simple to estimate and interpret, the mixed logit model is more flexible and overcomes several limitations of the MNL model. Hence, the MNL model is only used for robustness checks.

We specified the base model as follows

$$U_j = \beta_1 ASC + \beta_2 M + \beta_3 P + \beta_4 TT + \beta_5 CA + \beta_6 SMS + \beta_7 WG + \beta_8 APP + \beta_9 R + \varepsilon_j \qquad (7)$$

where U_j is the utility of choosing alternative j. The higher the utility of alternative j, the higher is the probability of choosing it. β' is the vector of utility coefficients indicating the weight of a certain attribute on the utility level. *ASC* is an alternative specific constant (ASC) which takes 0 for the opt-out option and 1 for the insurance options. In DCEs, a bias towards status quo was observed (Auspurg and Liebe, 2011). Given that we analyze a product that none of the farmers has access to, it is possible that there is a bias towards the opt-out alternative which we account for by including the ASC. *M* is a binary variable that takes 1 if the alternative offers a mobile-delivered insurance, treating conventional insurance distribution as the base level. *P* is the premium rate which is treated as a continuous variable. *TT* denotes travel time and is treated as a continuous variable as well as *CA*, which refers to credit access. *SMS*, *WG* and *APP* are dummy variables for the attribute "extra services" indicating text message, Whatsapp group and application (see Table 1), that each take 1 if the insurance product comes with an extra service and 0 otherwise. No extra service is treated as base level for this attribute. *R* denotes recommendations by peers. Assuming that preferences for the premium rates are homogenous, the coefficient for the premium is fixed. For the remaining attributes we assume that heterogeneity in taste may exist. Hence, they are treated as random and assumed to be normally distributed.

To explore sources of preference heterogeneity for the insurance, we also estimated a mixed logit model including interaction terms between socioeconomic variables and the ASC and between socioeconomic variables and the distribution channel.

4. Results and Discussion

4.1 Descriptive results

Descriptive statistics of the sample are presented in Table 2. The sample purposefully consists mainly of male farmers since the insurance product is tailored to maize which is primarily cultivated by men. Furthermore, great gender power imbalance persists in Mali. By law, the household head has to be a male person (Whitehouse, 2022). Hence, men are likely to be the decisionmaker in the near future as well.

Table 2. Descriptive statistics.

	Unit	Mean	Std. Dev.
Age	years	46.18	12.35
Cultivated area	ha	15.02	13.33
Frequency of experienced harvest losses [a)]	number	2.47	1.25
Gender of the respondent	0/1 (1=male)	0.92	-
Household size	persons	22.32	15.47
Insured with OKO in the season prior to the survey	0/1 (1=insured)	0.52	-
Jigisemejiri participant	0/1 (1=yes)	0.14	-
Mobile money use: Never	0/1 (1=never)	0.11	-
Mobile money use: Weekly or more often	0/1 (1=weekly)	0.26	-
No education received	0/1 (1=true)	0.28	-
Owns mobile phone	0/1 (1=true)	0.98	-
Remittances received within the last year	0/1 (1=true)	0.31	-
Understands written French	0/1 (1=true)	0.25	-

Notes: Mean values for dummy variables (0/1) indicate ratios. n=499.
a) A harvest loss refers to a loss of at least 25% of the harvest in a typical year. The frequency refers to a 10-year time period.

To relate our sample to a greater context we compared the sample statistics to findings from the Malian Agricultural Survey in 2017 (CPS, 2018). The characteristics of the sampled households closely resemble those of typical agricultural households in Mali in terms of the type of housing (walls, roof, and sanitation) and the characteristics of the household head (gender, age, and education). However, the households in our study tend to be larger and cultivate more land per household than the typical farming households in southern Mali. Farmers in the sample all cultivated maize, but their level of risk experience differed. On average farmers experienced 2.5 heavy harvest losses during the last ten years. 14 % of the sampled farmers stated to be beneficiaries of the national social protection program Jigisemejiri und nearly a third has received remittances from abroad. Main remittance destinations were the neighboring countries.

Nearly the entire sample was familiar with mobile phones and mobile money use. 98 % of the respondents own a mobile phone and only 11 % don't use mobile money. Roughly a quarter uses mobile money on a weekly basis or even more often. In 2021, the mobile phone subscription ratio in Mali was at 100 subscriptions per 100 inhabitants and network coverage reached 100% (ITU 2022). Hence, we assume that the mobile phone ownership is representative for the target population and that mobile-delivered services are technically feasible.

4.2 Results of the discrete choice experiment

The results of the mixed logit regression can be found in Table 3. The ASC is neither statistically significant nor are the effect sizes robust to changes in the model. The preference heterogeneity regarding the general interest in the offered multi-peril crop insurance is very high. Yet, looking at absolute numbers, only 20 respondents constantly chose the opt-out option, thereby indicating that there was an overall interest in the offered product. The high level of statistical significance of the attributes indicates that the chosen attributes are of relevance to the respondents. Effect sizes for the attribute levels are robust against different model specifications. The results of the MNL model can be found in Annex 1.

Looking at the attributes, the following picture emerges. The premium rate has a statistically significant negative effect on the likelihood to choose an insurance. The effect size, however, is small particularly when considering that the unit of the premium rate is set at 1,000 CFA. This suggests that respondents are relatively insensitive towards price changes as long as other highly valued product attributes are present.

Regarding the distribution channel, the results draw a more complex picture. The mobile-delivered option does not have a statistically significantly positive effect on the adoption of the insurance product compared to the alternative distributed via an agency office. On the contrary, the effect size is even negative in the base model as well as in the model including interaction terms. We argue that no direct value was attached to the distribution via cell phones. Instead, the influence of the mobile distribution is likely to be captured in the other attributes. Travel time had a substantial negative effect on the adoption decision of the product. This hints at an indirect preference for the mobile-delivered product since the latter does not involve any travel time. Similarly, offering additional information services had a statistically significantly positive effect on the adoption of an alternative. We hypothesize that even though the respondents did not directly prefer the distribution via mobile phone they indirectly valued the possibilities enabled by the technology. Still, the standard deviations indicate large variations in taste regarding the delivery mode.

The interest in additional information services was generally high. All suggested additional information services increased the likelihood to adopt the offered insurance scheme. The most preferred option among farmers was the mobile application with weather information and farming advice presented in form of text, vocal messages and videos. Given that this was the most comprehensive level of the attribute, this was to be expected. For none of the three services, preference heterogeneity was observed. This underlines a generally high acceptance of and interest in these services. Since personalized farming advice (Rajkhowa and Qaim, 2021) as well as weather information services (e.g. Mudombi and Nhamo, 2014; Roudier *et al.*, 2016) were found to positively influence a farmer's production decisions and welfare, our finding should be an additional motivation for insurance providers to consider product bundles with information services.

Table 3. Mixed logit results.

	(1)	(2)
Alternative specific constant (ASC)	0.67 [0.47]	-0.00 [0.65]
Mobile-delivered (dummy)	-0.19 [0.16]	-0.25 [0.41]
Premium rate (in 1,000 CFA)	-0.07*** [0.01]	-0.08*** [0.01]
Travel time (in min)	-0.02*** [0.00]	-0.02*** [0.00]
Credit (in 100,000 CFA)	0.31*** [0.03]	0.32*** [0.04]
SMS weather forecast (dummy)	0.44** [0.19]	0.44** [0.19]
WhatsApp group (dummy)	0.55*** [0.20]	0.54*** [0.20]
Mobile application (dummy)	0.76*** [0.17]	0.76*** [0.17]
Recommendations	0.06*** [0.02]	0.06*** [0.02]
Interactions		
Distribution channel * Insured in last season		0.46** [0.18]
Distribution channel * Age		-0.01 [0.01]
Distribution channel * Frequency of mobile money use		0.00 [0.06]
ASC * Insured in last season		0.59** [0.25]
ASC * Remittances received during last year		-0.45* [0.27]
ASC * Frequency of experienced harvest losses		0.20** [0.08]
SD		
Alternative specific constant (ASC)	1.74*** [0.22]	1.21*** [0.45]
Mobile-delivered (dummy)	1.02*** [0.10]	1.03*** [0.10]
Travel time (in min)	0.02*** [0.00]	0.02*** [0.00]
Credit (in 100,000 CFA)	0.39*** [0.05]	0.43*** [0.06]
SMS weather forecast (dummy)	0.15 [0.24]	0.41** [0.18]
WhatsApp group (dummy)	-0.07 [0.23]	0.44** [0.22]
Mobile application (dummy)	-0.08 [0.21]	0.35 [0.25]
Recommendations	0.15*** [0.03]	0.16*** [0.04]
Chi2	558.22	510.01
AIC	5214.81	5209.40
BIC	5335.56	5372.77

Notes: Standard errors in brackets, * p<.1, ** p<.05, *** p<.01, n=499.

Besides, credit access was perceived as a positive product attribute. This is in line with findings by Galarza and Carter (2011), but goes against results by Giné and Yang (2009). In our experiment credit access in the mobile-delivered alternative was granted in form of mobile money loans. Hence, we contribute to this discourse by providing first evidence on the relation to mobile money loans. When comparing the effect sizes of credit access and additional information services, credit access seems to be the preferred service as it is scaled in 100,000

CFA while the service attributes are dummy coded. However, the heterogeneity in preferences for credits is very high whereas respondents were similarly interested in the additional services.

Similar to the product bundles, recommendations by fellow farmers increased the likelihood to choose an insurance offer. The positive effect size was considerably smaller than for the other attributes, but one recommendation would offset a increase in the premium rate by 1,000 CFA thereby underlining a tremendous effect of recommendations. Establishing incentivized referral schemes could therefore support general customer acquisition efforts.

When controlling for socioeconomic aspects via interaction terms, the results remained stable. We tested whether being insured in the season prior to the survey, receiving remittances, or the frequency of experienced harvest losses has an influence on the preference for the insurance itself. Farmers who have been insured were more likely to choose an insurance product and the higher the frequency of experienced harvest losses the stronger also the preference for the multi-peril crop insurance. In contrast, farmers who received remittances throughout the last year, tend not to attach value to the insurance option.

Interaction terms with the distribution channel showed that the interest in mobile-delivered insurance options is rather universal. Neither the age nor the level of experience with mobile money had a statistically significant effect on the likelihood to adopt a mobile-delivered insurance option. Being insured with OKO in the last season increased the likelihood to adopt a mobile-delivered option statistically significantly. This was to be expected since OKO provides a mobile-delivered product which implies that these customers already gained experience with mobile-delivered insurance schemes.

5. Conclusion

Extreme weather events and other natural hazards increasingly put agricultural yields at risk. Well-designed index insurance schemes are perceived as a promising means for smallholders to manage these risks. With digital technologies on the rise, we aimed at identifying the potential and attractiveness of mobile technologies in the index insurance sector.

By means of a DCE, we elicit farmers preferences regarding the design of a multi-peril crop insurance and still hypothetical but technically feasible product attributes. Our findings indicate that farmers show a moderate interest in the presented multi-peril crop insurance scheme based on an easy-to-understand “greenness”-index. The decision to choose a certain insurance offer seems to be strongly driven by product features enabled by the distribution via a cell phone. The fact that mobile-delivered insurance do not entail travelling is highly valued as well as the offered product bundles. We find that farmers value the opportunities of additional mobile-delivered services coupled to the insurance regardless of whether they are provided via text messages, a messenger group or an app. Our results further show that referral schemes may be helpful to increase the adoption and we hypothesize that this is due to an increased level of trust.

The following recommendations emerge: considering the interest in coupled products, insurance adoption rates are likely to increase when the product is coupled to information services, particularly to easy-to-implement services such as weekly weather alerts. Insurance providers, regardless of whether their product is distributed via mobile phones or not, could consider referral schemes to increase adoption rates. For policy makers these insights provide guidance on what to look out for when deciding on the design of subsidized insurance schemes.

References

Abdi, M. J., Raffar, N., Zulkafli, Z., Nurulhuda, K., Rehan, B. M., Muharam, F. M., Khosim, N. A. and Tangang, F. (2022). Index-based insurance and hydroclimatic risk management in agriculture: A systematic review of index selection and yield-index modelling methods. *International Journal of Disaster Risk Reduction* 67: 102653.

Auspurg, K. and Liebe, U. (2011). Choice-Experimente und die Messung von Handlungsentscheidungen in der Soziologie. *KZfSS Kölner Zeitschrift für Soziologie und Sozialpsychologie* 63(2): 301–314.

Barnett, B. J. and Mahul, O. (2007). Weather Index Insurance for Agriculture and Rural Areas in Lower-Income Countries. *American Journal of Agricultural Economics* 89(5): 1241–1247.

Cole, S., Giné, X., Tobacman, J., Townsend, R., Topalova, P. and Vickery, J. (2013). Barriers to Household Risk Management: Evidence from India. *American Economic Journal: Applied Economics* 5(1): 104–135.

CPS (2018). Enquête Agricole de Conjoncture Intégrée aux Conditions de Vie des Ménages (ECA-I) 2017. Ref. MLI_2017_EAC-I_v02_M.

Doherty, E., Mellett, S., Norton, D., McDermott, T. K. J., Hora, D. O. and Ryan, M. (2021). A discrete choice experiment exploring farmer preferences for insurance against extreme weather events. *Journal of environmental management* 290: 112607.

FAO (2017). Mali Country factsheet on food and agriculture policy trends. https://www.fao.org/3/i7617e/i7617e.pdf, Accessed January 27, 2023.

Galarza, F. and Carter, M. R. (2011). Risk Preferences and Demand for Insurance in Peru: A Field Experiment. *Discussion paper DD/11/08*.

Ghosh, R. K., Gupta, S., Singh, V. and Ward, P. S. (2021). Demand for Crop Insurance in Developing Countries: New Evidence from India. *Journal of agricultural economics* 72(1): 293–320.

Giné, X. and Yang, D. (2009). Insurance, credit, and technology adoption: Field experimental evidencefrom Malawi. *Journal of Development Economics* 89(1): 1–11.

Hill, R. V., Robles, M. and Ceballos, F. (2016). Demand for a Simple Weather Insurance Product in India: Theory and Evidence. *American Journal of Agricultural Economics* 98(4): 1250–1270.

IPCC (2022). Climate Change 2022: Impacts, Adaptation and Vulnerability: Contribution of Working Group II to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, UK, New York, NY USA.

ITU (2022). Key indicators for the world and special regions (totals and penetration rates).

Kölle, W., Buchholz, M. and Musshoff, O. (2022). Do high-resolution satellite indices at field level reduce basis risk of satellite-based weather index insurance? *Agricultural Finance Review* 82(4): 616–640.

Linhoff, M., Musshoff, O. and Parlasca, M. (2022). Insuring against droughts: addressing issues of trust, transparency and liquidity in the demand for livestock index insurance. *Climate and Development*.

Matsuda, A. and Kurosaki, T. (2019). Demand for temperature and rainfall index insurance in India. *Agricultural Economics* 50(3): 353–366.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (ed.), *Frontiers in Econometrics*. New York: Academic Press, 105–142.

Mudombi, S. and Nhamo, G. (2014). Access to Weather Forecasting and Early Warning Information by Communal Farmers in Seke and Murewa Districts, Zimbabwe. *Journal of Human Ecology* 48(3): 357–366.

Platteau, J.-P., Bock, O. de and Gelade, W. (2017). The Demand for Microinsurance: A Literature Review. *World Development* 94: 139–156.

Raithatha, R. and Priebe, j. (2020). Agricultural insurance for smallholder farmers - Digital innovations for scale.

Rajkhowa, P. and Qaim, M. (2021). Personalized digital extension services and agricultural performance: Evidence from smallholder farmers in India. *PloS one* 16(10): e0259319.

Roudier, P., Alhassane, A., Baron, C., Louvet, S. and Sultan, B. (2016). Assessing the benefits of weather and seasonal forecasts to millet growers in Niger. *Agricultural and Forest Meteorology* 223: 168–180.

Scarpa, R. and Rose, J. M. (2008). Design efficiency for non-market valuation with choice modelling: how to measure it, what to report and why*. *Australian Journal of Agricultural and Resource Economics* 52(3): 253–282.

Turvey, C. G. and Mclaurin, M. K. (2012). Applicability of the Normalized Difference Vegetation Index (NDVI) in Index-Based Crop Insurance Design. *Weather, Climate, and Society* 4(4): 271–284.

Ward, P. S. and Makhija, S. (2018). New modalities for managing drought risk in rainfed agriculture: Evidence from a discrete choice experiment in Odisha, India. *World Development* 107: 163–175.

Whitehouse, B. (2022). Left in the Cold. *Journal of Legal Anthropology* 6(1): 73–94.

World Bank (2022a). Agriculture, forestry, and fishing, value added (% of GDP). https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS?locations=ML, Accessed January 27, 2023.

World Bank (2022b). Employment in agriculture (% of total employment) (modeled ILO estimate). https://data.worldbank.org/indicator/SL.AGR.EMPL.ZS?locations=ML, Accessed January 27, 2023.

Annex

Annex 1 – Conditional logit results

	(1)	(2)
Alternative specific constant (ASC)	-0.02 [0.33]	-0.53 [0.41]
Mobile-delivered (dummy)	-0.03 [0.11]	0.07 [0.24]
Premium rate (in 1,000 CFA)	-0.05*** [0.01]	-0.05*** [0.01]
Travel time (in min)	-0.01*** [0.00]	-0.01*** [0.00]
Credit (in 100,000 CFA)	0.23*** [0.02]	0.23*** [0.02]
SMS weather forecast (dummy)	0.26** [0.13]	0.26** [0.13]
WhatsApp group (dummy)	0.30** [0.14]	0.31** [0.14]
Mobile application (dummy)	0.47*** [0.12]	0.48*** [0.12]
Recommendations	0.05*** [0.01]	0.05*** [0.01]
Interactions		
Distribution channel * Insured in last season		0.25** [0.11]
Distribution channel * Age		-0.00 [0.00]
Distribution channel * Frequency of mobile money use		-0.02 [0.04]
ASC * Insured in last season		0.43*** [0.12]
ASC * Remittances received during last year		-0.35*** [0.11]
ASC * Frequency of experienced harvest losses		0.15*** [0.04]
N (respondents*6*3)	8982	8982
Pseudo R^2	0.128	0.138
Chi2	839.45	905.07
AIC	5757.04	5703.42
BIC	5820.96	5809.96

Notes: Standard errors in brackets, * p<.1, ** p<.05, *** p<.01, n=499.