Journal of Development Economics 140 (2019) 269–278

Contents lists available at ScienceDirect

Journal of Development Economics

journal homepage: www.elsevier.com/locate/devec

Liquidity constraints, informal institutions, and the adoption of weather insurance: A randomized controlled Trial in Ethiopia

Temesgen Belissa [a,b], Erwin Bulte [a,c], Francesco Cecchi [a,d,*], Shubhashis Gangopadhyay [d,e,f,g], Robert Lensink [a,d]

[a] Development Economics Group, Wageningen University, the Netherlands
[b] Haramaya University, Ethiopia
[c] Utrecht University, the Netherlands
[d] Faculty of Economics and Business, University of Groningen, the Netherlands
[e] India Development Foundation, India
[f] University of Gothenburg, Sweden
[g] Indian School of Public Policy, India

A B S T R A C T

We report the results of a drought insurance experiment in Ethiopia, and examine whether uptake of index-based insurance is enhanced if we allow farmers to pay *after* harvest (addressing a liquidity constraint). We also test to what extent uptake can be enhanced by promoting insurance via informal risk-sharing institutions (*Iddirs*), to reduce trust and information problems. The delayed payment insurance product increases uptake substantially when compared to standard insurance, from 8% to 24%, and leveraging informal institutions results in even greater uptake (43%). We also find suggestive evidence that the delayed premium product is indeed better at targeting the liquidity constrained. However, default rates associated with delayed payments are relatively high and concentrated in a small number of *Iddirs* – potentially compromising the economic viability of the novel product. We discuss how default rates can be reduced.

1. Introduction

The majority of the world's poor reside in rural areas and their economic fate depends crucially on the performance of the agricultural sector (e.g., World Bank, 2007; Haggblade et al., 2007; Christiaensen et al., 2010). Despite global efforts to promote the intensification of rain-fed agriculture, the diffusion of modern agricultural technologies – such as improved crop varieties and fertilizer – remains low. Evidence is growing that downside (production) risk is an important factor impeding the uptake of these technologies (e.g. Emerick et al., 2016).[1] Purchasing external inputs in a context where harvests may fail is risky – exposing farmers to the risk of unsustainable debts and the loss of valuable assets (Boucher et al., 2008). The pursuit of “low-risk-low-expected return” activities may be perfectly rational in such a context (Walker and Ryan, 1990). Increasing the uptake of insurance against weather shocks in rain-fed production systems may therefore be an important component of strategies to modernize agriculture and lift large swaths of people out of poverty (e.g., Cai, 2016; Elabed and Carter, 2014; Hill et al., 2019; Karlan et al., 2014; Mobarak and Rosenzweig, 2013).

In recent years, experiments with index-insurance products have sought to overcome well-known problems associated with indemnity-based insurance: (i) prohibitive transaction costs, (ii) asymmetric information and moral hazard, and (iii) co-variate shocks that are hard to re-insure. Index-insurance delinks payouts from farm-level losses, and allows farmers to purchase coverage based on an index correlated with these losses. This may be a measure of average biomass productivity or a measure of local rainfall during a certain time period – variables that are objectively quantifiable and verifiable. Payouts are triggered when the index falls short of a pre-determined threshold.

While index insurance may promote agricultural intensification, challenges for development remain because adoption of index insurance is *also* far from complete – adoption rates typically hover below 10% (Cole et al., 2013). The literature identifies several reasons for low uptake of index insurance. Not surprisingly, demand is sensitive to prices. However, Cole et al. (2013) argue that uptake would remain far from complete even if rainfall insurance would be priced at payout ratios similar to those found in US retail insurance contracts. This suggests non-price frictions are important as well. For example, index insurance

* Corresponding author. Development Economics Group, Wageningen University, the Netherlands.
E-mail address: francesco.cecchi@wur.nl (F. Cecchi).

[1] Of course many other factors also play a role in explaining slow diffusion of new technologies. These include heterogeneity in (net) benefits and profitability (Suri, 2011), under-performing extension systems, and lack of liquidity (including lack of access to credit). For a recent overview, refer to Foster and Rosenzweig (2010).

https://doi.org/10.1016/j.jdeveco.2019.06.006
Received 27 September 2018; Received in revised form 28 May 2019; Accepted 12 June 2019
Available online 29 June 2019

provides only imperfect coverage for household shocks if individual damages are not perfectly correlated with the index – as is typically the case. If the index is not identical to on-farm losses, residual risk (or basis risk) remains.[2] Other reasons for imperfect uptake exist (see Cole and Xiong, 2017 for an overview). For example, lack of experience with shocks may also matter as does precise knowledge about the probability of disaster (Cai and Song, 2017).

In this paper we report on the outcomes of an RCT in rural Ethiopia that focused on two major reasons for low adoption of insurance as identified by Cole et al. (2013): (i) lack of liquidity to pay for the insurance premium, and (ii) lack of information about, or trust in, the insurance product. Consider the former first. To study the role of liquidity constraints during the planting season we allow (randomly selected) farmers to pay the premium *after* harvest. Many smallholders are unable to mobilize the resources needed to pay for payment of the premium upfront.[3] The standard insurance product is based on farmers paying the premium when disposable income is at its lowest and the marginal utility of cash is at its highest – just before the "hunger season." In return, they might receive compensation after harvest when, no matter how meagre, disposable income is often higher than in the planting season. We allow smallholders to postpone premium payment until *after* the harvest, and henceforth call this insurance product *IOU*. The properties of the *IOU*, except for the delayed payment, are identical to those of a standard product, but the delayed premium is slightly higher to account for the opportunity cost of time (making the two premiums inter-temporally equivalent). A crucial issue for the viability of delayed payment schemes is default after production uncertainty has been resolved in case there was no payout. We probe this issue by exploring contracts and leveraging group dynamics to raise the cost of default.

Second, we randomly vary the marketing channel, and leverage support of leaders of *Iddirs* for the product in some experimental arms.[4] Insurance products are "complex" and low levels of financial literacy among target populations imply not all potential beneficiaries understand its logic (e.g. Cole et al., 2013; Cai et al., 2015a,b). Smallholders may also be unsure about the intentions of the insurance company. The idea is that through training and mobilizing customary leaders, we can effectively share knowledge and leverage trust. *Iddirs* are informal social institutions in Ethiopia, originally created to help their members organize burial ceremonies, but currently engaged in a broader spectrum of activities and mutual assistance. We informed *Iddir* leaders about how the index insurance works, informed them about the trustworthiness of the insurance company, and encouraged them to share their new knowledge with members of their *Iddir* and endorse the insurance product. This approach to building trust is akin to an intervention studied by Cole et al. (2013), who involved trusted local agents to recommend insurance educators. In their RCT in India, endorsements increased demand by 36 percent.

Our intervention does not enable us to cleanly distinguish between trust and information effects as mediating mechanisms. The idea is that customary leaders can effectively transmit information to members and that endorsements by such leaders, who are trusted individuals, build confidence. Most of our analysis picks up an aggregate effect – improved knowledge about both the product (information) as well as the company (trust). It may also pick up an effect of group members mimicking the behavior of their leader.

In addition to Cole et al. (2013), who study various barriers to the uptake of insurance, our experiment is closely related to the following papers. First and foremost, it extends the important findings of Casaburi and Willis (2018) outside the contract farming setting. They study delayed payments of the premium to induce insurance uptake when insurance is interlinked with a contract farming scheme. This prevents defaults on the premium payment commitments as premiums are deducted from the revenues paid after harvest (but contract enforcement issues remain because of the risk of side-selling). Uptake increases to 72%, compared to 5% for the standard contract. But it remains an open question whether this result extends to other contracting arrangements, because most smallholders are not engaged in contract farming. Perhaps default in contexts that do not involve contract farming is so extensive that it undermines the scope for upscaling delayed payment solutions?[5]

Second, Dercon et al. (2014) study marketing index insurance through local informal groups because there might be important coordination benefits from group-wise purchasing of index insurance – in the presence of basis risk, formal and informal insurance may be complements (see also De Janvry et al., 2014).[6] Dercon et al. (2014) evaluate the impact of an intervention that trains *Iddir* members to benefit from post-payout redistribution, and find that such a training increases the uptake of insurance. Importantly, our approach does not seek to reduce basis risk by promoting informal sharing. Members purchase their own insurance at the co-op, but are informed about the benefits through a traditional leader rather than a company representative, extension agent, or co-op employee. In other words, insurance was sold to individual members using the standard practices of the insurer, and we did *not* sell insurance to *Iddirs*. Our design further extends the findings of Dercon et al. (2014) because it combines marketing through informal groups with delayed premium—with possible synergies both in terms of uptake and defaults.

We use a factorial design involving 144 *Iddirs* and 8579 individual subjects to test whether delayed premium payments and the promotion of insurance via *Iddirs* affect adoption of index insurance. We also analyse several approaches to mitigate default. We test for "level effects" and complementarities. Our main results are that the *IOU* has a large accentuating effect on uptake when introduced in isolation, from 8% to 24%. This result is in line with the findings of Casaburi and Willis (2018) in the context of contract farming. However, in terms of effect size the

[2] Individual losses may be high while the index does not reach the threshold, implying insured farmers are worse off than in the absence of insurance because they paid the premium (Clarke, 2016). "False negatives" undermine the expected utility of adoption, especially for highly risk averse farmers. The combination of uncertain rainfall and uncertain payouts implies the farmer faces a compound lottery, inviting ambiguity aversion (Elabed and Carter, 2014). Interventions that aimed to reduce basis risk indeed manage to increase uptake (Elabed et al., 2013), but adoption of index insurance continues to fall short of expectations.

[3] Such outcomes may be due to several factors, including poverty gap dynamics and present bias (hyperbolic discounting leading to procrastination – see Duflo et al., 2011).

[4] In Ethiopia, *Iddirs* are indigenous voluntary mutual help associations made up by a group of persons united by ties of family and friendship, by living in the same *Kebele*, by jobs, or by belonging to the same ethnic group. The number of members, the composition, the functions, and the organization can differ from one *Iddir* to another. All *Iddirs* are based on voluntary mutual agreements and request intense participation from their members.

[5] Cole et al. (2013) study the importance of relaxing liquidity constraints by randomly providing subjects with endowments that would enable them to buy one policy. They find a large effect, but also acknowledge it is difficult to distinguish between the liquidity effect of endowments and a potential reciprocity effect caused by receiving an endowment.

[6] This enables group members to redistribute payouts among each other. Since members have superior knowledge about true damages, this may reduce basis risk. Other potential advantages of selling to groups are reduced transaction (marketing) costs, and relaxation of the liquidity constraint (if groups are involved in joint purchasing of inputs or joint selling of outputs). Observe that traditional indemnity-based insurance typically serves as a substitute mechanism for informal sharing arrangements, rather than a complement (e.g., Arnott and Stiglitz 1991).

effect they observe is much larger (from 5% to 72%).[7] We find some evidence that the demand-increasing effect of the *IOU* may be larger for people with low savings or income, supporting the idea that liquidity constraints impede uptake of insurance. Promoting standard insurance via *Iddirs* instead does not significantly increase adoption, but the combination of *IOU* and *Iddir* outperforms all other modalities.

As expected, and extending the analysis of Casaburi and Willis (2018), we find that a significant share of *IOU* insurance purchases results in default. For the basic *IOU* treatment we find a default rate of more than 15%, which might jeopardize the viability of the scheme outside of contract farming settings. Nonetheless we show that defaults can be contained by auxiliary measures, and conclude that a bundle of measures – combining the delayed payment option and measures to curb default – holds promise for future upscaling.

The remainder of this paper is organized as follows. Section 2 sketches the context, explains the intervention and hypotheses. Section 3 explains the randomization strategy, and introduces our data. We demonstrate random assignment "worked" in that we created well-balanced experimental arms. Section 4 presents the results with respect to uptake, heterogeneity and default rates. A discussion of findings ensues in Section 5.

2. Intervention

We worked together with Oromia Insurance Company (OIC) in Ethiopia. This organization, in collaboration with the Japan International Cooperation Agency (JICA), developed drought index insurance for crops in the Rift Valley zone of Ethiopia. The product was originally implemented in five districts: Boset, Bora, Ilfata, Adamitullu-Jido-Kombolcha (AJK), and Arsi Negele. It is marketed and sold twice per year, in months preceding the two rainy seasons (April and September). Insurance provides coverage against losses during the seedling and flowering stages of crop growth. It is marketed and sold via local cooperatives. A household that buys insurance pays a premium of ETB 100 per policy (ETB 20 = USD 1). The payout depends on the level of rainfall measured at the nearest meteorological station. For rainfall levels below a threshold but above the so-called exit level, a partial payout of ETB 250 is made. If rainfall is below the exit level, OIC pays out ETB 500 per policy.

As was the case in comparable undertakings, take-up of the standard index insurance product proved very low—approximately 7–8% of the targeted population. OIC suspected two constraints to be mainly responsible for low uptake: lack of liquidity and trust (or information). To test this, and explore potential solutions, we designed an RCT with multiple treatment arms. Specifically, to relax a binding liquidity constraint we introduce an *IOU* and allow farmers to pay the premium after harvest. To compensate for the delay in payment, the premium of the *IOU* was set at 106, with the 6% surcharge based on the interbank rate in Ethiopia. To eliminate the default risk that emerged for the insurance company after allowing delayed payment we promised to pay the premium for any defaulting clients.

To generate trust and promote the diffusion of relevant knowledge we trained randomly selected *Iddir* leaders. During the training sessions, important aspects of agricultural insurance and the details of the insurance modality that was offered to them (*IOU* or standard insurance) were explained, and we emphasized the trustworthiness of the insurance company. *Iddir* leaders were not (financially) incentivized to recruit members to sign up for insurance, but we asked them to share information about the insurance product and company with their group members. *Iddir* leaders belonging to groups not assigned to *Iddir* promotions received an unrelated placebo information session. They were informed about the insurance product in the standard way – through co-op agents and development agents. We test the following hypotheses:

Hypothesis 1. Delayed payments of insurance premiums relaxes a liquidity constraint and will increase the uptake of the index rainfall insurance product.

Hypothesis 2. Leveraging the social capital of Iddir leaders by asking them to inform their group members and endorse the insurance product will enhance the knowledge and trust of group members, and will increase the uptake of the index rainfall insurance product.

Delayed payment introduces the risk of (strategic) default, compromising the returns to the insurance company and possibly threatening the viability of the IOU scheme. Selling policies through *Iddirs* promotions may suffer from lower default if there are social sanctions associated with not repaying debts. However, bandwagon effects and coordination may imply that groups decide to default collectively – in which case default rates in treatment arms leveraging *Iddir* leadership may increase. As is well-known from the microfinance group lending literature (see e.g. Ahlin and Townsend, 2007), repayment rates may rise with social sanctions, but too much social capital may also induce collusion against the bank, which undermines the bank's possibility to leverage the social capital of Iddir leaders Another approach to discouraging default is to write harsh contracts emphasizing potential legal consequences of breaching the agreement. The idea is that this would raise the cost of (strategic) default, reducing default rates. By discouraging strategic default, contracts should also lower uptake rates as strategic defaulters now find the product less attractive. Observe that contracts may also discourage uptake of people who do not intend to default *ex ante*, but who are uncertain about their ability to pay the premium *ex post* and fear potential negative consequences.

Hypothesis 3. The effect of leveraging Iddir leadership on default rates is ambiguous and context-specific. The effect of contracts that increase the expected cost of default is to lower default and uptake rates.

The study took place in three districts in the Rift Valley zone that regularly suffer from drought shocks: Bora, Adami Tullu and Arsi Negele. From each district we randomly selected four *Kebele*, and 12 *Iddirs* per *Kebele*, or a total of 144 *Iddirs.* We obtained lists of all *Iddir* members in our sample. On our pre-sales registration list, all households were registered as a member of only one *Iddir*.[8] Fig. 1 presents a timeline of activities, with those performed by the research team in orange, and those performed by IOC in blue. We started with a baseline survey of slightly above 8500 smallholders in the Spring of 2016 (April and May). This was done to verify that the randomization process had produced balanced and comparable groups across treatments. We collected data on household demographic characteristics including age, sex, marital status, education and family size; household income, households' level of exposure to drought and experience in buying crop insurance before the experiment. Further, we collected data on household production and saving variables. The survey questionnaires were relatively short and took the enumerators about 30–45 min per interview.[9]

During the same period we also organized information sessions for

[7] This difference in magnitude may be driven by the specific setting in which Casaburi and Willis (2018) operate, i.e. contract farming. It may also be due to the fact that our insurance product is purely index-based, whereas their product has an indemnity-based component. Finally, it might also be explained by different exposure to the insurance product prior to the experiment.

[8] A few households were found to be members of 2 *Iddirs*, and to be considered in the experiment these subjects we asked them to choose membership of only one *Iddir*—the one with which their household identified more strongly. Excluding these observations from the sample does not materially affect our results.

[9] In total we recruited 13 enumerators and 3 supervisors. All activities including training the *Iddir* leaders, data collection and processing were overseen by a field coordinator. All questionnaires approved by supervisors were sent to statisticians to digitalize. The coordinator received the soft copies of completed questionnaires, and verified whether they were completed appropriately—including a double-blind re-entering of data for a random subsample.

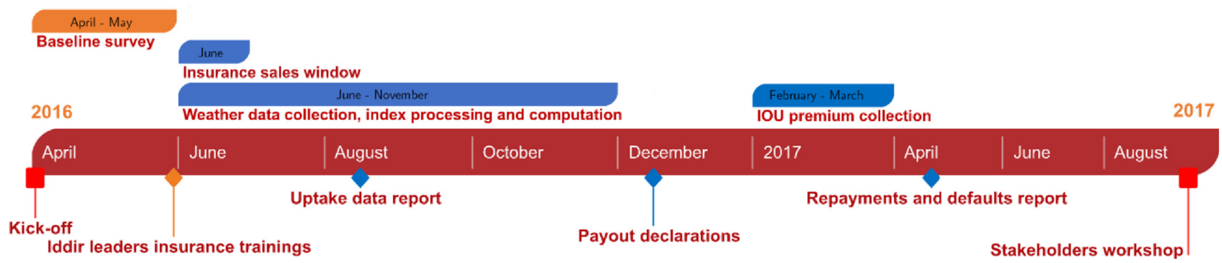

Fig. 1. Timeline of activities.

Iddir leaders in order to prepare them to promote the specific insurance product assigned to their group. Standard insurance and *IOU* were sold from the end of May and throughout June of 2016.[10] After that IOC collected and processed weather data for the entire growing season, produced an uptake report for the study area (August 2016), organized meetings to inform insured farmers of the insurance payouts (December 2016). Importantly, in the season in which the experiment took place no payouts were disbursed by OIC in the study area. OIC then collected the *IOU* premiums in February and March 2017 and produced an *IOU* payment and default report. The premium of defaulting farmers was later compensated to IOC by the research team.[11] Finally, in September a closing workshop was organized in Addis Ababa involving representatives from all stakeholders and partners.

3. Randomization

We use multi-level randomization at the *Iddir* level to assign the 144 *Iddirs* to six experimental arms (number of *Iddirs* and observations in brackets)[12]

1) Standard Index Insurance [IBI: 16 *Iddirs*, N = 853];
2) Standard Index Insurance via *Iddir* promotions [IBI_Iddir: 48 *Iddirs*, N = 3056];
3) *IOU* insurance [IOU: 16 *Iddirs*, N = 685];
4) *IOU* insurance with Contract [IOU_C: 16 *Iddirs*, N = 633];
5) *IOU* insurance via *Iddir* promotions [IOU_Iddir: 24 *Iddirs*, N = 1887]; and
6) *IOU* insurance via *Iddir* promotions with Contract [IOU_Iddir_C: 24 *Iddirs*, N = 1465]

Group 1 is the control group (Standard index-based insurance). *Iddir* members in group 2 are offered the standard product, but are informed about that product via their leader to enhance trust and information. Group 3 is offered the simple *IOU* with deferred payment of the premium. Group 4 is offered the *IOU* but should sign a contract intended to increase the (perceived) costs of default. This contract explicitly stated that members were legally liable for the full premium.[13] Group 5 were offered the *IOU* and promotion by the *Iddir* leader and, finally, *Iddir* members in Group 6 were offered the most elaborate package including *IOU*, *Iddir* leader promotion, as well as the binding contract.

To verify whether randomization resulted in balanced groups we regress household observables on treatment group dummies and a constant (see Tables 1a and 1b below). The constant reflects the comparison group. The coefficients indicate whether other groups are significantly different from the comparison group, and we test for differences between other groups by Wald tests. Table 1 contains the following demographic variables: *Age* (in years); *Sex* (male = 1; female = 0); *Marital status* (married = 1; not-married = 0); *Education* (years of schooling); *Family size*; *Total income in the last month* (in Birr); *Drought* (a dummy taking value of 1 if the household experienced a drought in the last three years); and *Insurance* (a dummy taking the value of 1 if the household had purchased index insurance during the past three years). Table 2 presents similar tests for a vector of farming variables, capturing quantities of crops produced in the last cropping season (*maize, haricot, teff, sorghum, wheat, and barely*); a measure of total land under cultivation, and a dummy taking the value 1 if the household had any formal savings.

Tables 1 and 2 suggest the randomization worked well, especially regarding crop production at baseline—different treatment groups produce on average the same products. Compared to control group, the average age in treatment groups *IOU* and *IOU with Contract* is slightly lower; households in the *IOU* group experienced a bit more drought in previous years; and households in *IOU* and *IOU with Contract* were slightly less likely be insured before. There are also some imbalances regarding family size, and regarding drought experiences. However, differences are small, and we will control for these observables in some regression models below. In the follow-up data collection we were able to retrieve all baseline respondents so our analysis is not compromised by (non-random) attrition.

[10] While we did allow people to purchase multiple insurance policies, our data shows that at most one policy unit was purchased (so we do not analyse the effect of our interventions on the intensive margin). This is in line with behavior observed by the insurance company outside our experiment. It is also consistent with evidence reported by Cole et al. (2013), who interpret this as (non-experimental) evidence of the existence of liquidity constraints. However, since our design with delayed payments addresses this concern, other (non-price) frictions likely remain important in addition to liquidity constraints in limiting demand.

[11] The research team also conducted Focus Group Discussions (FGDs) and in-depth stakeholder interviews to better understand the reasons for uptake, and to triangulate quantitative results. We organized the FGDs at all 12 Farmer Training Centres (FTCs). The number of households involved per discussion was around 15. All our enumerators, supervisors and the coordinator of the field work were involved in the FGDs. On average, each conducted about 7 FGDs, lasting about one and half an hour per session. We also organized FGDs with the total 98 Iddir leaders at two centres in Arsi Negele and Meki Batu towns. Finally, we conducted in-depth interviews with the chief executive officer and the manager of the Microinsurance Department of OIC.

[12] Observe that the number of households varies across treatment arms. This is a consequence of purposeful over-sampling of members in groups 2, 5 and 6 so that these groups can be further sub-divided in follow-up work focusing on the *Iddir* channel. However, the number of subjects in the other treatment arms is sufficiently large for meaningful econometric analysis – exceeding 600 farmers per arm.

[13] This contract suggested that legal action could follow in case of contract breach, including seizure of assets. The contract was designed to be similar to a contract signed when taking out a microfinance loan in the area, but the explicit mentioning of 'legal action' and 'asset seizures' imply the contract could appear stricter than some of MFI contracts used in the region. In fact, since the transaction costs associated with pursuing legal sanctions against defaulting clients would (far) outweigh the immediate benefits (clients purchased at most one policy worth a few USD), the contract represents to some extent 'cheap talk', unlikely to be enforced by the insurance company. Nevertheless, it is possible that the prospect of legal consequences not only disciplines some clients and encourages repayment, it may also 'scare off' other clients—limiting uptake.

Table 1
Balance tests on socio-economic variables.

	Age (years)	Sex (1 = male)	Marital status	Education (years)	Family size	Monthly income	Drought dummy	Insured Before
Index Insurance via Iddir	−0.84	0.11	−0.01	0.05	0.14	−198.24	0.01	−0.05
	(1.138)	(0.089)	(0.029)	(0.426)	(0.325)	(186.348)	(0.049)	(0.045)
IOU Insurance	−2.34**	0.01	−0.03	0.40	−0.19	−58.50	0.07*	−0.09*
	(0.854)	(0.072)	(0.032)	(0.396)	(0.286)	(400.776)	(0.033)	(0.036)
IOU Insurance with Contract	−1.80*	0.02	0.00	0.11	−0.38	−160.66	0.05	−0.08**
	(0.781)	(0.063)	(0.022)	(0.355)	(0.244)	(245.663)	(0.028)	(0.030)
IOU Insurance via Iddir	−0.48	0.12	−0.02	0.34	0.32	303.50	−0.05	0.08
	(1.356)	(0.109)	(0.036)	(0.559)	(0.362)	(558.396)	(0.057)	(0.064)
IOU via Iddir with Contract	−1.10	0.16	−0.02	0.05	0.43	62.84	−0.06	−0.03
	(1.361)	(0.096)	(0.031)	(0.473)	(0.429)	(248.140)	(0.059)	(0.051)
Constant (*Index Insurance*)	39.40**	0.47**	0.90**	1.91**	5.67**	854.30**	0.87**	0.12**
Observations	8579	8579	8579	8579	8579	8579	8579	8579
Wald Tests								
IBI_Iddir = IOU	0.11	0.23	0.59	0.44	0.17	0.71	0.07	0.08
IBI_Iddir = IOU_C	0.41	0.23	0.65	0.89	0.03	0.86	0.41	0.24
IBI_Iddir = IOU_Iddir	0.76	0.94	0.76	0.55	0.46	0.36	0.18	0.01
IBI_Iddir = IOU_Iddir_C	0.84	0.58	0.85	0.99	0.38	0.22	0.15	0.58
IOU = IOU_C	0.44	0.82	0.28	0.35	0.26	0.61	0.12	0.58
IOU = IOU_Iddir	0.11	0.29	0.84	0.92	0.08	0.58	0.005	0.001
IOU = IOU_Iddir_C	0.30	0.11	0.71	0.49	0.10	0.78	0.005	0.08
IOU_C = IOU_Iddir	0.33	0.32	0.50	0.67	0.01	0.42	0.05	0.002
IOU_C = IOU_Iddir_C	0.61	0.11	0.56	0.91	0.03	0.41	0.04	0.16
IOU_Iddir = IOU_Iddir_C	0.66	0.71	0.88	0.59	0.76	0.67	0.87	0.05

Notes: Robust standard errors in parentheses, clustered for 144 *Iddirs*; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Wald tests show p-values of equality. The constant reflects the average in the control group: Standard Index Insurance.

Table 2
Balance tests for production variables and savings.

	Maize	Haricot	Teff	Sorghum	Wheat	Barley	Land	Savings
Index Insurance via Iddir	2.30	0.19	−0.10	0.07	2.73	−0.13	−0.40	0.06
	(1.201)	(0.158)	(0.380)	(0.144)	(4.212)	(0.132)	(0.867)	(0.068)
IOU Insurance	0.37	−0.04	−0.05	−0.10	−1.18	−0.14	0.31	0.00
	(0.751)	(0.067)	(0.406)	(0.074)	(1.277)	(0.152)	(0.617)	(0.042)
IOU Insurance with Contract	0.40	0.03	0.10	−0.08	−0.85	−0.06	−0.05	−0.03
	(0.730)	(0.069)	(0.295)	(0.059)	(0.991)	(0.128)	(0.415)	(0.035)
IOU Insurance via Iddir	0.54	−0.01	−0.05	−0.01	0.74	−0.20	−1.24	0.02
	(1.167)	(0.073)	(0.452)	(0.100)	(2.112)	(0.126)	(0.850)	(0.061)
IOU via Iddir with Contract	2.23	0.17	−0.34	0.01	−1.03	−0.14	0.82	0.01
	(1.513)	(0.148)	(0.375)	(0.103)	(1.767)	(0.134)	(1.178)	(0.068)
Constant (*Index Insurance*)	6.54**	0.21**	1.35**	0.19*	5.09**	0.29*	8.06**	0.21**
Observations	8579	8579	8579	8579	8579	8579	8579	8579
Wald tests								
IBI_Iddir = IOU	0.14	0.13	0.93	0.19	0.34	0.86	0.49	0.38
IBI_Iddir = IOU_C	0.12	0.30	0.66	0.27	0.39	0.58	0.70	0.16
IBI_Iddir = IOU_Iddir	0.12	0.18	0.92	0.59	0.65	0.27	0.18	0.49
IBI_Iddir = IOU_Iddir_C	0.96	0.89	0.52	0.69	0.37	0.82	0.24	0.47
IOU = IOU_C	0.94	0.18	0.60	0.53	0.50	0.53	0.34	0.35
IOU = IOU_Iddir	0.88	0.61	1.00	0.19	0.31	0.57	0.14	0.78
IOU = IOU_Iddir_C	0.24	0.15	0.54	0.14	0.90	1.00	0.70	0.88
IOU_C = IOU_Iddir	0.90	0.60	0.77	0.35	0.41	0.20	0.19	0.41
IOU_C = IOU_Iddir_C	0.24	0.35	0.31	0.27	0.51	0.48	0.48	0.52
IOU_Iddir = IOU_Iddir_C	0.25	0.22	0.52	0.84	0.40	0.47	0.04	0.92

Notes: Robust standard errors in parentheses, clustered for 144 *Iddirs*; ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Wald tests show p-values of equality. The constant reflects the average in the control group: Standard Index Insurance.

4. Results

4.1. Uptake

Fig. 2 presents insurance uptake across treatment arms.[14] The delayed payment of insurance offered by the *IOU* product increases uptake substantially when compared to standard insurance, from 8% to 24%. By far, the combination of *IOU* and promotion through *Iddir* outperforms all other treatments: uptake rates increase to around 43%.

Table 3 presents a regression analysis of the same results. Column 1 shows the same parsimonious model of Fig. 2. The uptake change induced by *Iddir* promotions in isolation is statistically insignificant, as is *IOU* with binding contract. Column 2 further adds *Kebele* fixed effects and all baseline socio-economic characteristics. The coefficients and significance levels remain largely the same. We discuss Column 3 below. The main results are as follows:

Result 1. *Delaying weather insurance payment (IOU) increases uptake almost threefold.*

Result 2. *Promoting weather insurance via Iddir leaders increases uptake of IOU, not the standard product. There is a synergetic effect of delayed payment*

[14] The error bars here and below refer to 95% confidence intervals with clustered standard errors.

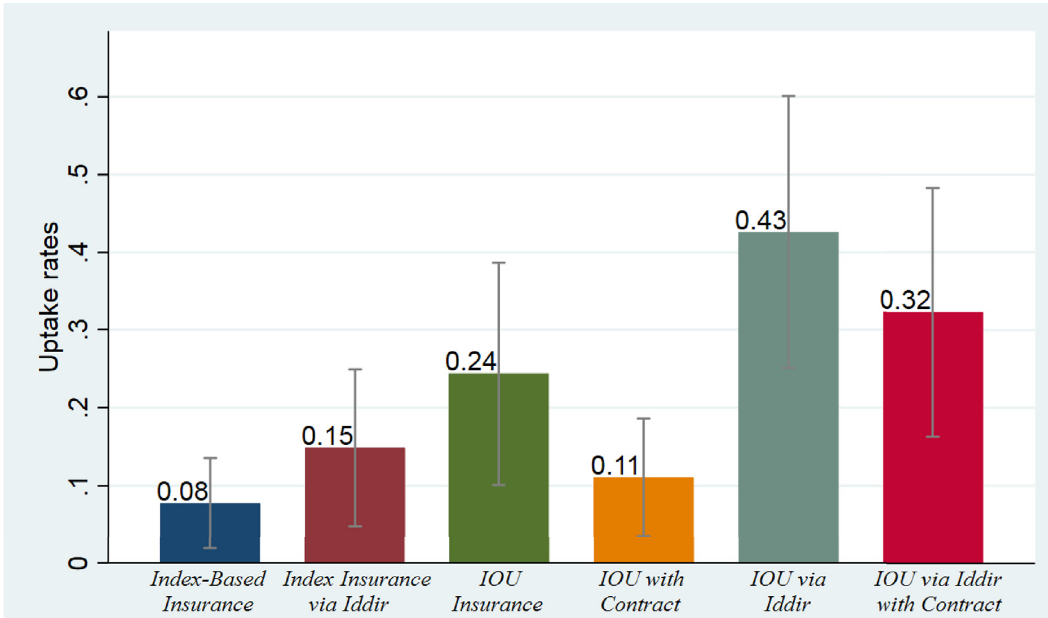

Fig. 2. Uptake rates across IOU treatments, 95% CI clustered at Iddir level.

Table 3
Insurance uptake rates increase under IOU.

	(1) Parsimonious model	(2) Additional controls	(3) Excluding Dalota Mati
Index Insurance via Iddir	0.07	0.00	0.00
	(0.059)	(0.047)	(0.049)
IOU Insurance	0.17	0.14	0.11
	(0.065)**	(0.060)**	(0.056)*
IOU Insurance with Contract	0.03	0.02	0.00
	(0.041)	(0.044)	(0.045)
IOU Insurance via Iddir	0.35	0.34	0.34
	(0.094)***	(0.072)***	(0.076)***
IOU via Iddir with Contract	0.25	0.17	0.16
	(0.086)***	(0.050)***	(0.052)***
Constant	0.08	0.04	0.05
	(0.029)***	(0.108)	(0.109)
Additional controls	No	Yes	Yes
Kebele fixed effects	No	Yes	Yes
Iddir clustered s.e.	144	144	132
Observations	8579	8579	7969
Adjusted R-squared	0.086	0.314	0.328
Wald tests			
IBI_Iddir = IOU	0.28	0.07	0.15
IBI_Iddir = IOU_C	0.55	0.76	0.96
IBI_Iddir = IOU_Iddir	0.01	0.00	0.00
IBI_Iddir = IOU_Iddir_C	0.07	0.00	0.01
IOU = IOU_C	0.01	0.01	0.02
IOU = IOU_Iddir	0.11	0.03	0.01
IOU = IOU_Iddir_C	0.47	0.69	0.44
IOU_C = IOU_Iddir	0.00	0.00	0.00
IOU_C = IOU_Iddir_C	0.02	0.01	0.01
IOU_Iddir = IOU_Iddir_C	0.39	0.03	0.03

Robust standard errors in parentheses adjusted for 144 clusters at the Iddir level. Kebele fixed effects capture 12 Kebele (municipalities) across 3 Districts. Additional controls include *Age, Male, Married, Education level, Family size, Income last month, Drought dummy, Insured before dummy, Maize production, Haricot production, Teff production, Sorghum production, Wheat production, Barley production, Land size, and Savings*. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Wald tests show p-values of equality.

and leveraging informal institutions.

Additional important lessons can be gleaned from Table 3. Introducing a binding contract to the *IOU* has a chastening effect on uptake rates with and without *Iddir* promotions. The contract was in fact designed to disincentivize opportunistic behavior and strategic defaults, in a similar fashion to contracts offered by other local financial institutions. It's effect on uptake rates suggests much of the additional adoption induced by delayed payment is either motivated by the prospect of strategic default, or the result of farmers who are unsure about their ability to pay the future premium – and thus scared away once a binding contract is introduced – also in the absence of opportunistic intentions. In both cases, hardly a promising outcome for the insurance company! This said, the uptake rate of *IOU via Iddir with Contract* is still much greater than that of standard insurance, significant at the 1% level. People need a high degree of trust to sign a binding contract—especially when the consequences of signing are possibly not fully understood. We speculate that the *Iddir* could assuage such concerns by acting as a trusted third party, resulting in increased uptake rates also in the presence of a contract. This holds promise of a scenario where uptake can be increased whilst (strategic) defaults kept under control.

Result 3. *Uptake of individual IOU contracts is not significantly greater than standard insurance in the presence of a binding contract. However, if customary leadership are leveraged to promote adoption, uptake of the IOU with a contract remains significantly higher than that of standard insurance (but significantly lower than IOU mediated by Iddir leaders without a contract).*

4.2. Heterogeneity

Can we attribute the increase in uptake under *IOU* insurance to the relaxation of the liquidity constraint, as shown by Cole et al. (2013) and Casaburi and Willis (2018)? We test this by performing a heterogeneity analysis. Using our baseline data we purposely divide the sample at some threshold to identify if there is any evidence that uptake rates increased further among the liquidity-constrained. To proxy for liquidity, we distinguish between households with above and below-median income, and between households with and without savings (self-reported).

Table 4 shows that, for both proxies, the coefficients of the simple *IOU* product are higher for the liquidity-constrained (Columns 1-2 for income and 4-5 for savings). However, while the *IOU* coefficient of the (more) constrained subsample is consistently different from zero, and the coefficient for the complementary sample is not, the relevant coefficients are

Table 4
Does IOU appeal to the liquidity constrained?.

VARIABLES	Median Income (IHS)			Savings		
	(1)	(2)	(3)	(4)	(5)	(6)
	Below	Above	Pooled	No	Yes	Pooled
Interaction variable			−0.06 (0.056)			−0.02 (0.066)
Index Insurance via Iddir	−0.01 (0.053)	0.01 (0.064)	−0.01 (0.054)	−0.01 (0.045)	0.07 (0.100)	−0.01 (0.043)
× *Interaction variable*			0.03 (0.077)			0.08 (0.105)
IOU Insurance	0.15 (0.068) **	0.12 (0.083)	0.15 (0.068) **	0.15 (0.063) **	0.09 (0.097)	0.15 (0.064) **
× *Interaction variable*			−0.02 (0.098)			−0.04 (0.101)
IOU Insurance with Contract	0.04 (0.049)	0.00 (0.053)	0.04 (0.048)	0.05 (0.049)	−0.14 (0.055) **	0.05 (0.048)
× *Interaction variable*			−0.03 (0.058)			−0.18 (0.065) ***
IOU Insurance via Iddir	0.30 (0.080) ***	0.34 (0.078) ***	0.32 (0.082) ***	0.31 (0.078) ***	0.43 (0.085) ***	0.32 (0.077) ***
× *Interaction variable*			0.04 (0.075)			0.13 (0.096)
IOU via Iddir with Contract	0.13 (0.062) **	0.19 (0.064) ***	0.11 (0.058) *	0.10 (0.043) **	0.35 (0.089) ***	0.12 (0.045) ***
× *Interaction variable*			0.10 (0.076)			0.28 (0.078) ***
Constant	0.06 (0.108)	0.20 (0.119) *	0.04 (0.107)	−0.03 (0.102)	0.32 (0.172) *	0.16 (0.102)
Additional controls	Yes	Yes	Yes	Yes	Yes	Yes
Kebele fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Iddir clustered s.e.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4383	4196	8579	6534	2045	8579
Adjusted R-squared	0.253	0.372	0.315	0.267	0.450	0.315

Robust standard errors in parentheses adjusted for 116 clusters at the Iddir level. Kebele fixed effects capture 12 Kebele (municipalities) across 3 Districts. Additional controls include *Age, Male, Married, Education level, Family size, Drought dummy, Insured before dummy, Maize production, Haricot production, Teff production, Sorghum production, Wheat production, Barley production, Land size.* ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

not statistically different from each other (according to a Wald test).[15] This can also be seen by the insignificance of the interaction term (Columns 3 and 6). We interpret this as weak and preliminary evidence that lack of liquidity at the time of insurance purchase may be a potential reason to shy away from standard IBI insurance products, and that delayed premium payments help to relax this constraint.

Result 4. *The liquidity-constrained are more likely to take up insurance with delayed payment. However, the uptake rate between constrained and unconstrained is not statistically different.*

Observe that this effect disappears when the *IOU* is combined with a contract or promoted in the *Iddir*. When the IOU is promoted by the *Iddir* leader, "richer" households are more responsive and increase uptake.[16] This might reflect differential exposure to the message if the leader targets wealthier group members for specific messages. It is interesting to observe that the contract especially discourages uptake of the wealthier sub-group when the *IOU* is promoted by conventional channels, but has a much lower attenuating effect when endorsed by *Iddir* leaders.

4.3. Defaults

Next we look at defaults in more detail. Fig. 3 shows default rates for the 1514 participants that purchased *IOU* insurance under the various treatments (obviously default is not a concern for the standard insurance product, with up-front payment). As expected, the default rate is highest for the basic *IOU* product, i.e. the product with the lowest default cost. This rate is nearly 17%, which may compromise the financial viability of the product. Assuming an actuarially fair insurance product, the *IOU* premium would have to go up to accommodate default: for a default rate of 17%, the premium has to increase by more than 20%. It remains an open question whether such pricing will curtail demand for the insurance product, or even induce additional defaults.

Default rates appear lower when the *IOU* is combined with *Iddir* promotion and a contract, which holds promise for further research. However, these differences are statistically insignificant when clustering standard errors at the *Iddir* level. What explains this finding? Closer inspection of our data reveals extreme clustering of defaults in a small number of *Iddirs* – reducing the statistical power of our analysis. More specifically, all 134 defaults in our dataset come from only four *Iddirs* out of the subsample of 90 *Iddirs* that were offered IOUs (all belonging to the same *Kebele*: Dalota Mati). In each of these four *Iddirs*, every member who had purchased an *IOU* policy defaulted. Default rates in the various treatment arms therefore primarily depend on whether the arm contains one of the bad *Iddirs* (and the number and size of other *Iddirs* without any defaulting members).

What explains the extreme clustering of default in 4 *Iddirs*, all in the same *Kebele*? We conducted 12 focus group discussions at the cooperative level. During these FGDs it was argued that members of defaulting *Iddirs* in our sample suffered from low rainfall but did not qualify for pay-out as threshold values for rainfall were (just) reached. Insured farmers "complained that they have faced drought, to a certain extent" (FDG report). The FGD discussions thus point to the well-known problem of basis risk.[17] To assess whether defaults in our case where indeed caused by basis risk we analysed rainfall in the *Kebele* in our sample. We compared their rainfall patterns over the period covered by the insurance, using a different dataset from that used by the insurer, and conducting an independent analysis.[18] Fig. 4 shows that Dalota Mati does not present a significantly worse rainfall pattern than the other areas in our study, in terms of absolute rainfall levels (left) and rainfall with respect to the previous 3-year average (right).[19] A regression analysis for 2016, controlling for the small number of clusters (12) using the Cameron et al.

[15] This may be a consequence of lack of power or of imperfect correlation between our three proxies and liquidity.

[16] Except for *IOU via Iddir with Contract* × Savings (column 6), the interaction is positive but insignificant.

[17] There were no payouts from the insurer the year we implemented our experiment no insured farmer in the study area received compensation. It must be noted though that the absence of payouts is not per se a sign of the unfairness of the insurance product or basis risk: the insurance is designed to trigger only in a fraction of the years it is purchased. There were payouts in the years immediately before and after our experiment took place.

[18] The weather data used for this purpose is the Africa Rainfall Climatology Version 2 (ARC2) data set, produced by the Famine Early Warning System (FEWS) of the National Oceanic and Atmospheric Administration (NOAA). The data is gridded modelled weather data which is produced from two input sources. It relies on 3-hourly geostationary infrared (IR) data centred over Africa from the European Organization for the Exploitation of Meteorological Satellites (EUMETSAT) and quality-controlled Global Telecommunication System (GTS) gauge observations reporting 24 h rainfall accumulations over Africa (Novella and Thiaw, 2013).

[19] We cannot rule out that *Iddir* members collectively defaulted because they suffered from negative basis risk in previous years, before the RCT started.

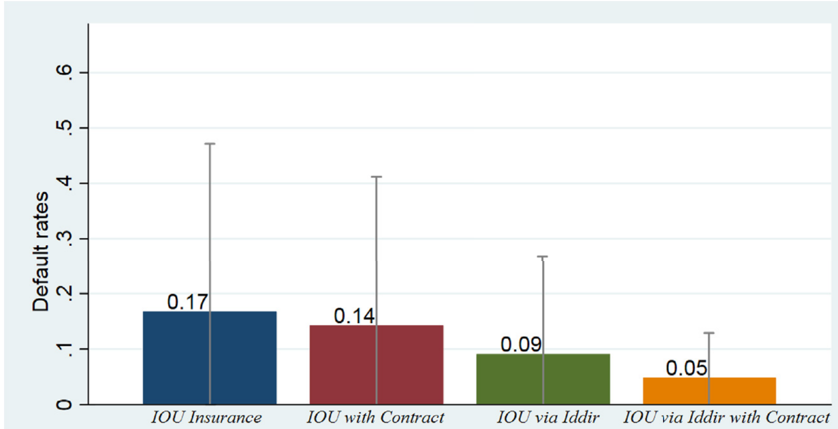

Fig. 3. Default rates across IOU treatments, 95% CI clustered at Iddir level.

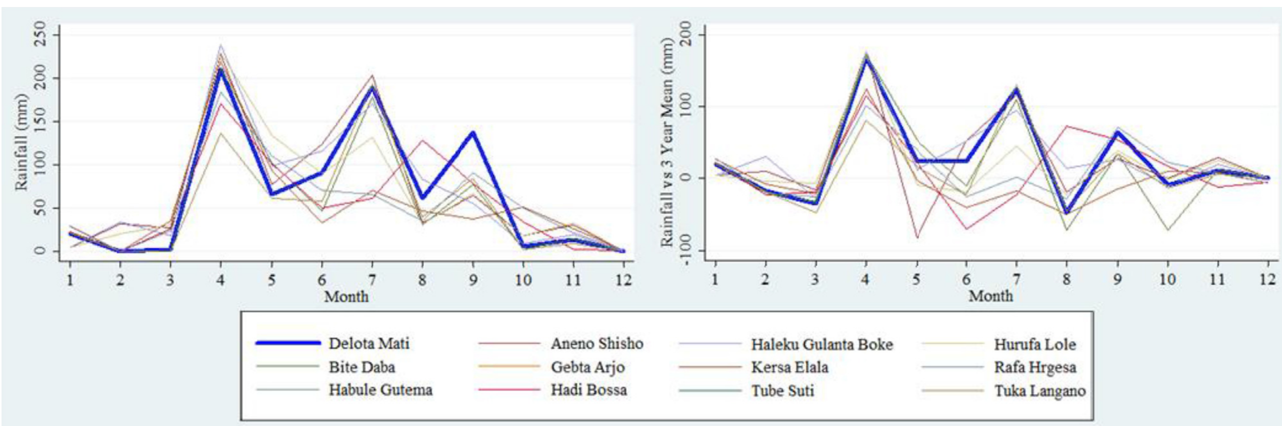

Fig. 4. Dalota Mati does not appear to have suffered from worse rainfall patterns (in absolute terms, left, and compared to 3-year average, right).

(2011) correction, reveals that the total rain that fell in Dalota Mati is not significantly different from other *Kebele* (p-value = 0.334). If anything, in the months of July and September, both within the insurance window, rainfall was significantly higher than average.[20]

There is no empirical basis for the claim that farmers in the defaulting *Iddirs* of Dalota Mati suffered from less rainfall than farmers in the remaining *Kebeles*. Instead, *Iddir* members appear to have signalled their discontent with the product, perhaps because it did not allow for excessive rain, or rain intensity, or variability within the insured window. It is possible that people collectively decided to default strategically, and that such coordination took place at the *Kebele* rather than *Iddir* level—since nobody in Dalota Mati paid for the delayed premium. We did not anticipate such coordinated responses, and believe this finding points to an important potential risk for parties offering services with delayed payment. They may imply that communities did not sanction defaulters, and possibly even threatened to sanction non-defaulters. Coordinated responses of smallholders might complicate re-insurance on international markets, threaten the liquidity of insurance companies and the viability of *IOU* products. There may be interesting parallels between the collective default situation in our experiment and the massive default crisis that earlier struck India (e.g. Polgreen and Bajaj, 2010). Breza (2012) studies loan repayment in Andra Pradesh, and finds that non-repayers negatively affect repayment of their peers, even in the absence of formal joint liability. It also is possible that default responses were exacerbated by the 3-month time lag between the insured window and premium collection. This would be in line with Field et al. (2013) who find that microfinance clients with a 2-month grace period after loan disbursement exhibit six to nine percentage point higher default rates than without grace period.

Result 5. *Defaults are strongly clustered at the Iddir level, and no significant difference in default rates can be observed across IOU treatments. Defaults appear to be the outcome of a social negotiation process rather than the outcome of an adverse weather shock.*

Finally, we explore the robustness of the earlier results to the exclusion of the defaulting *Iddirs*. In column 3 of Table 3 we report the regression results of the earlier model, but here we drop from the analysis all *Iddirs* from Dalota Mati. If increases in uptake under the different *IOU* treatments are solely due to opportunistic behavior, excluding areas in which we observed potentially strategic defaults should downsize our estimated changes in uptake. We find instead that our results are robust to excluding Dalota Mati participants. Once again the largest increases in uptake are achieved by combining the *IOU* product with *Iddir* promotions.

5. Discussion

The uptake of agricultural insurance by African smallholders remains very low. This not only impairs the ability of smallholders to smooth consumption levels over time, it also mitigates incentives for intensification and modernization. Finding (scalable) approaches to boost uptake has appeared as an important topic on the international research agenda.

[20] Regression results not shown but available on request.

The main finding of our experiment is that uptake can be promoted by novel insurance products featuring delayed payment of premiums – shifting expenditures from periods when capital is very scarce (and the marginal utility of money is very high) to periods with relatively abundant access to money. While delayed payment should not matter in a world with perfect markets inhabited solely by *Homo economicus* (who would save surpluses from capital-abundant periods to finance worthwhile investments in capital-scarce periods), it is well-known that behavioral factors and market imperfections may restrict the pursuit of such strategies in practice (e.g. Baland et al., 2011). The potential of delayed payments was recently illustrated in the context of contract farming by Casaburi and Willis (2018). It is an open but important question whether addressing liquidity constraints through delayed payments are also effective in promoting demand in more standard settings. It is also an open question whether the potential success of such an approach would be undermined by massive defaults.

While low trust in standard insurance products (and companies) might matter for adoption, marketing via *Iddirs* and leveraging support of customary leaders is not sufficient to have a significant impact. The same holds for an *IOU* with a legal contract aimed at ruling out defaults. However, the combination of marketing via *Iddirs* and *IOUs* has a large impact on adoption. Our study suggests that the combination of an *IOU* with a marketing treatment that involves a socially trusted customary channel may be successful in enhancing uptake of index insurance. The effects sizes we find are smaller than those of Casaburi and Willis (2018) – who find an uptake rate peaking at 72%– but our most successful treatment increases uptake more than fivefold—from 8% to 43%.

However, to make this a cost-effective scalable intervention, it is important to ensure that default rates are low. Our pilot suggests that default rates of a simple *IOU* product are high, perhaps curbing the enthusiasm of insurance companies to further pilot products involving delayed payment. Our point estimates of default rates in experimental arms that involve "binding contracts" or local leadership (or both) appear lower than default rates of a simple *IOU* product. But we also find that defaults are concentrated in a very small number of *Iddirs*, suggesting co-ordination on default.

Co-ordination on non-payment threatens the viability of the *IOU* product. From the group-lending literature it is well-known that a bank's possibility to harness 'social capital' may, under certain conditions, be undermined by borrowers who collectively collude against the bank (Besley and Coate, 1995). Our *IOU* intervention seems to some extent be affected by a similar problem: if farmers realize there are no social costs associated with default (or if they believe they will not have access to future *IOUs* because of defaulting *Iddir* members), strategic default becomes more attractive. This was not the case in Casaburi and Willis (2018) as their intervention was embedded in the interlinked markets setting through a contract-farming scheme.

Future research could examine whether combining the *IOU* intervention with a formal joint liability clause within an *Iddir* setting would be a viable solution in a non-contract-farming context. It remains an open question whether introducing joint liability in combination with dynamic incentives would reduce strategic defaults. While peer-monitoring and social sanctioning may contribute to enforce repayments, the potential for bandwagon defaults such as those we observed would not be ruled out. From this perspective it seems particularly important to complement our "static demand analysis" with dynamic analyses following potential adopters and their uptake and default decisions over time. A dynamic analysis also seems germane in light of the apparent importance of trust (in the insurance product and company) in smallholders' uptake decisions. Trust is likely to evolve rapidly over time.

Future research could also focus on identifying other innovative approaches to address the liquidity problem that appears to cripple the insurance market in rural developing country contexts, without exposing organizations involved in selling insurance to undue risks. One example is combining insurance and credit (but see Gine and Yang, 2009). Another example is a logical extension of our approach. Vouchers for *next-year's* insurance can be sold during *this year's* harvest season, enabling farmers to pre-finance the purchase of policies when liquidity constraints do not bind. See Duflo et al. (2011) for an example in the context of pre-financing next season's fertilizer. However, in a context of constant prices this amounts to saving at zero rate of interest.

Acknowledgements

We would like to thank ESRC/DFID (ES/N013344/1 "Delivering Inclusive Financial Development and Growth")**,** 3ie (TW13.1014) and CIMMYT (CGIAR Research Program on Maize) for financial support. We thanks two anonymous referees for helpful comments and suggestions. The contents and opinions expressed herein are those of the authors and do not necessarily reflect the views of the associated and/or supporting institutions.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jdeveco.2019.06.006.

References

Ahlin, C., Townsend, R.M., 2007. Selection into and across credit contracts: theory and field research. J. Econom. 136, 665–698.
Arnott, R., Stiglitz, J.E., 1991. Moral hazard and nonmarket institutions: dysfunctional crowding out of peer monitoring? Am. Econ. Rev. 179–190.
Baland, J.-M., Guirkinger, C., Mali, C., 2011. Pretending to be poor: borrowing to escape forced solidarity in Cameroon. Econ. Dev. Cult. Change 60, 1–16.
Besley, T., Coate, S., 1995. Group lending, repayment incentives and social collateral. J. Dev. Econ. 46, 1–18.
Boucher, S., Carter, M., Guirkinger, C., 2008. Risk rationing and wealth effects in credit markets: theory and implications for agricultural development. Am. J. Agric. Econ. 90, 409–423.
Breza, E., 2012. Peer Effects and Loan Repayment: Evidence from the Krishna Default Crisis. Harvard University. Working Paper.
Cai, H., Chen, Y., Fang, H., Zhou, L.-A., 2015a. The effect of microinsurance on economic activities: evidence from a randomized field experiment. Rev. Econ. Stat. 97, 287–300.
Cai, J., Song, C., 2017. Do disaster experience and knowledge affect insurance take-up decisions? J. Dev. Econ. 124, 83–94.
Cai, J., de Janvry, A., Sadoulet, E., 2015b. Social networks and the decision to insure. Am. Econ. J. Appl. Econ. 7, 81–108.
Cai, J., 2016. The impact of insurance provision on household production and financial decisions. Am. Econ. J. Econ. Policy 8, 44–82.
Cameron, A., Gelbach, C.J.B., Miller, D.L., 2011. Robust inference with multiway clustering. J. Bus. Econ. Stat. 29 (2), 238–249.
Casaburi, L., Willis, J., 2018. Time versus state in insurance: experimental evidence from contract farming in Kenya. Am. Econ. Rev. 108 (12), 3778–3813.
Christiaensen, L., Demery, L., Kuhl, J., 2010. The (Evolving) Role of Agriculture in Poverty Reduction: an Empirical Perspective. UNU-WIDER Working Paper #2010/36.
Clarke, D., 2016. A theory of rational demand for index insurance. Am. Econ. J. Microecon. 8, 283–306.
Cole, S., Gine, X., Tobacman, J., Topalova, P., Townsend, R., Vickerey, J., 2013. Barriers to household risk management: evidence from India. Am. Econ. J. Appl. Econ. 5, 104–135.
Cole, S., Xiong, W., 2017. Agricultural insurance and economic development. Annual Review of Economics 9, 235–262.
De Janvry, A., Dequiedt, V., Sadoulet, E., 2014. The demand for insurance against common shocks. J. Dev. Econ. 106, 227–238.
Dercon, S., Vargass Hill, R., Clarke, D., Outes-Leon, I., Taffesse, A., 2014. Offering rainfall insurance to informal groups: evidence from a field experiment in Ethiopia. J. Dev. Econ. 106, 132–143.
Duflo, E., Kremer, M., Robinson, J., 2011. Nudging farmers to use fertilizer: theory and experimental evidence from Kenya. Am. Econ. Rev. 101 (6), 2350–2390.
Elabed, G., Carter, M., 2014. Ex-ante impacts of agricultural insurance: Evidence from a field experiment in Mali. University of California at Davis. Working Paper.
Elabed, G., Bellemare, M., Carter, M., Guirkinger, C., 2013. Managing basis risk with multiscale index insurance. Agric. Econ. 44, 419–431.
Emerick, K., de Janvry, A., Sadoulet, E., Dar, M., 2016. Technological innovations, downside risk, and the modernization of agriculture. Am. Econ. Rev. 106, 1537–1561.
Field, E., Pande, R., Papp, J., Rigol, N., 2013. Does the classic microfinance model discourage entrepreneurship among the poor? Experimental evidence from India. Am. Econ. Rev. 103 (6), 2196–2226.
Foster, A.D., Rosenzweig, M., 2010. Microeconomics of technology adoption. Annual Review of Economics 2, 395–424.

Gine, X., Yang, D., 2009. Insurance, credit, and technology adoption: field experimental evidence from Malawi. J. Dev. Econ. 89, 1–11.

Haggblade, S., Hazell, P., Dorosh, P., 2007. Sectoral growth linkages between agriculture and the rural nonfarm economy. In: Haggblade, S., Hazell, P., Reardon, T. (Eds.), Transforming the Rural Nonfarm Economy: Opportunities and Threats in the Developing World. The Johns Hopkins University Press, Baltimore.

Hill, R.V., Kumar, N., Magnan, N., Makhija, S., de Nicola, F., Spielman, D.J., Ward, P.S., 2019. Ex ante and ex post effects of hybrid index insurance in Bangladesh. J. Dev. Econ. 136, 1–17.

Karlan, D., Osei, R., Osei-Akoto, I., Udry, C., 2014. Agricultural decisions after relaxing risk and credit constraints. Q. J. Econ. 129, 597–652.

Mobarak, A.M., Rosenzweig, M., 2013. Informal risk sharing, index insurance and risk taking in developing countries. Am. Econ. Rev. 103, 375–380.

Novella, N., Thiaw, W., 2013. African rainfall Climatology version 2 for famine early warning systems. Journal of Applied Meteorology and Climatology 52, 588–606.

Polgreen, L., Bajaj, V., 2010. Microcredit is imperiled in India by defaults. N. Y. Times A5. November 18, 2010.

Suri, T., 2011. Selection and comparative advantage in technology adoption. Econometrica 79 (1), 159–209.

Walker, T., Ryan, J., 1990. Village and Household Economies in India's Semiarid Tropics. Johns Hopkins University Press, Baltimore.

World Bank, 2007. World Bank Report 2008: Agriculture for Development. The World Bank, Washington DC.