Uptake of interlinked index-based insurance with credit and agricultural inputs: Experimental evidence from Ethiopia

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Abstract

Provision of integrated credit, insurance and agricultural technologies can enormously help to promote agricultural intensification and tackle food insecurity and poverty in developing countries. Recent field experiments have shown that index-based insurance (IBI) have the potential to overcome the well-known moral hazard and adverse selection problems that often plague the development of rural financial markets. However, adoptions of IBI have unexpectedly met low uptake and up-scaling challenges. Evidence on the extent to which interlinking IBI with credit and agricultural input increases the uptake of IBI is scant. We conducted a randomized controlled trail (RCT) with 1661 smallholders in Ethiopia, randomly offering them with a standalone IBI, IBI interlinked with credit and IBI interlinked with both credit and agricultural inputs. Our results show that the uptake of the standalone IBI is low amounting to only 8.8 per cent the total demand. However, interlinking IBI with credit increases uptake by 24.5 percent while further interlinking IBI with both credit and agricultural input increases the uptake by 32.2 percent. Our findings imply that increased interlinkage enhances uptake that can help to upscale agricultural risk management options for smallholder farmers.

Keywords: index-based insurance, insurance-linked credit, agricultural inputs, randomized controlled trail

JEL Classification Codes: O44, Q41, D92, G22

1. Introduction

Agricultural risk and limited access to credit are key impediments to agricultural productivity and constitute a major source of poverty among smallholder farmers in developing countries. While insurance provides a market mechanism to shield the welfare of smallholders from the adverse effects of weather and seasonality based variations, agricultural loans serve farmers to acquire and adopt high-risk high-return agricultural inputs such as improved seed varieties, fertilizer, pesticide and herbicide. Interlinking insurance with credit and agricultural technology is thus important for the mutual benefit of smallholder borrowers and lenders (Karlan et al. 2014). The benefit to the smallholder is both access to loan in order to acquire inputs that enhance productivity, and access to insurance to hedge down-side production risk. Similarly, lenders can also benefit from the interlinked insurance-credit since insured farmers possess a higher potential to repay loans because default risk from lending for insured borrower farmers is lower than the risk to lend for uninsured ones (McIntosh, Sarris and Papadopoulos 2013, Farrin and Miranda 2015). This incentive thus can motivate lenders to enter markets with minimized default risk that would otherwise cannot be anticipated when the production risk that leads to default risk is not insured. In this way, insurance can help to crowd-in credit supply. And as farmers need such arrangement, it can also crowds-in credit demand. Previous studies reveal that financial market imperfections prevail among smallholders farmers in developing countries, in the form of credit and insurance rationing that impede the economic potential of the poor to surmount the critical threshold, leading to poverty traps (Boucher et al 2008; Barnett, Barrett and Skees 2008, Carter, Cheng and Sarris 2016). As an integrative solution for this, the interlinked insurance-credit-input system is a win-win strategy that forms a financial environment where insurance and credit complementarily reinforce (crowd-in) each other, and where both the borrower and the lender remain better off.

Interlinked insurance-credit-input intervention is based on the premise that lack of credit among smallholder farmers can limit their access to insurance and their potential to adopt high-risk high-return agricultural inputs. In this study, we design an innovative interlinked insurance-credit-input intervention that forms a platform that provides farmers with a

sandwich of three important rural technologies: index-based insurance (IBI), IBI linked credit (ILC) and agricultural input (AI). Index-based insurance is a climate risk management strategy that can provide welfare benefits for the poor (Carter et al. 2016, Barrett 2011). It is an innovative hedging instrument that mitigates drought shocks and seasonality based weather risks induced by climate change (Barnett et al. 2008, Chantarat et al. 2013, Skees 2008, Barrett 2011). In IBI innovation, payout is triggered when the index of a selective weather variable falls below a given threshold, signalling risk. Usually, intensity of rainfall or vegetative cover on the earth surface measured by satellite remote sensing constitutes the current generation of such an index (Skees 2008, Takahashi et al. 2016). A reliable index closely correlates with the insured asset, objectively quantifiable and publicly verifiable in order not to be manipulated by both the insurer and the insured (Skees 2008, Jensen, Mude and Barrett 2018, Barnett et al. 2008). IBI innovations are thus useful to overcome challenges that often plague the development of rural financial markets like the functioning of indemnity insurances for long. First, IBI delinks loss assessment from individual behaviour to overcome moral hazard problems. Second, IBI design is based on publicly verifiable data (e.g., rainfall data based on satellite measures), so it partially tackles the problem of adverse selection. Third, the use of a single index to estimate losses of a group of farms minimizes transaction costs. Hence, IBIs uniquely overcome classic incentive problems like information asymmetry and transaction costs associated with claim verification and contract enforcement in rural financial markets (Barnett et al. 2008).

The second ingredient of this innovative interlinked insurance-credit-input intervention is what we call an IBI linked credit (ILC). ILC is a bundling of index insurance and credit which works as a market-based solution to minimize downside risks and unlock credit to smallholder farmers (Gine and Yang 2009; Shee and Turvey 2012; Shee, Turvey and Woodward 2015). This mechanism provides smallholder farmers with a linked financial product that embeds within its structure an insurance protection which, when triggers, offsets loan payments due to the lender providing a risk-efficient balance between business and financial risks (Shee and Turvey 2012; Farrin and Miranda 2015, Shee and Turvey 2012). The innovation does not require farmers to pay premiums upfront and out-of-pocket, hence it removes liquidity constraints of farmers to acquire high-risk high-return inputs (Udry 1990, Clarke and Mahul 2011, Karlan et al.

2014). To target some amount of the loan to acquire these inputs, our intervention embeds agricultural input coupons (AIC) that smallholder's use to take improved seed variety, fertilizer, pesticide and/or herbicide from input suppliers in Ethiopia. AIC thus constitutes the third component of the intervention. In this way, the interlinked insurance-credit-input intervention together could combine the advantages of all the three and hence can achieve better targeting of poorer farmers. Further, through training farmers' representatives the innovation also encourages risk-rationed farmers to take up insurance, loan, financial education and extension.

This study examines the extent to which an innovative interlinked insurance-credit-input intervention enhances uptake of integrated rural technologies including insurance, credit and agricultural input among smallholders. The study is undertaken in the Rift Valley zone of Ethiopia where rainfall shocks such as drought adversely affect household welfare and where the prevalence of credit and insurance rationing was evidenced (Ali and Deininger 2014; Belissa et al. 2018).[1] In the study area, given the need for an effective risk transfer mechanism, high and sustained rural technology uptake by farmers, and the need for increased investment in high-risk high-return agricultural inputs to increase productivity, it is important to assess whether the innovative interlinked insurance-credit-input intervention mechanism increases uptake. The rest of the paper is organized as follows. Section 2 lays out a model of insurance-linked credit and agricultural use. Section 3 describes our intervention and randomization strategy. Section 4 presents the balancing tests of whether the randomization has worked. Section 5 explains our estimation strategy. Section 6 presents the main results. Section 7 concludes the paper.

2. Intervention and randomization strategy

2.1. Components of the intervention

Insurance: Through a local insurance company, Oromia Insurance Company (OIC) in Ethiopia, an IBI product known as a vegetation index crop insurance (VICI)[2] was sold to the smallholders in

[1] Employing a direct elicitation method (DEM) to determine credit rationing status, it is determined that 38% of the sample households in Ethiopian Rift Valley zone are credit constrained.

[2] VICI is an improved IBI product of OIC compared to the weather index crop insurance (WICI).

the study area. The product is designed based on the intensity of vegetation cover or greenery on the earth's surface. Greenery level is measured by a satellite indicator known as normalized difference vegetation index (NDVI)[3]. In VICI design, NDVI is extracted at a geospatial resolution of 1 km × 1 km. The current VICI product used by OIC is based on average NDVI of 16 years. NDVI reflects the already accumulated result of rain on crop growth. It is a primary measurement with no assumptions or calibrations. It is the proven standard index, in use by all early warning units globally. Actual decal NDVI data for a given period is calculated for a set of households grouped in a one crop production system (CPS) zone. The NDVI compiled for grids of 1 km × 1 km will then be arranged in percentile ranges from 1 to 20, 25 and 50. Based on these percentiles, benchmark values for trigger and exit index points which will be compared to the actual risk level are determined[4]. In the design of VICI, it is assumed that since uptake gradually increases, it is possible to pool more risks across areas with greater geo-spatial variations that can help to reduce transaction costs. Hence, OIC expects nearly about one out of six households who purchased IBI may face losses. Hence, the sum to be insured per policy is given as follows:

$$S_{vici} = \frac{P}{0.15}$$

[3] NDVI is measured through images obtained from a geo-satellite weather infrastructure known as GeoNetCast System. The system reads to see if the observed area contains live green vegetation or not. The data from these images are converted into digital numbers (DN-values), i.e. Integers from 0 to 255 creating the NDVI.

[4] The mechanics of the VICI product design has the following characteristics. The index is based on greenness level. The source of the satellite data is a weather infrastructure known as GeoNetCast. The system converts satellite images into digital numbers ranging from 0 to 255. It uses NDVI data for the last 16 years and reads deviation from this long-term average. In order to deal with transaction costs, it divides the geographical coverage into CPS zones. NDVI is computed for each zone at grids of 1 km × 1 km. NDVI data are usually arranged in percentiles, and payout is calculated for a decal or every 10 days period. Hence, trigger and exit thresholds are computed for CPS zones and 10-day period specific. The insurance coverage period is crop growth season specific. Payout is not crop-specific, but 1km × 1 km grid (location) specific.

For each household who decides to take IBI, a premium of ETB[5] 100 per policy was paid to OIC. Payout which is a maximum of sum insured is determined according to the level of the NDVI. To explain how this works at OIC, let T, E and A represent trigger, exit and actual parametric values of the NDVI index. Then, the amount of payout in each insurance period is calculated for individual VICI buyer households as follows:

$$I_{vici} = \left(\frac{T-A}{T-E}\right)\left(\frac{P}{0.15}\right)$$

In determining payouts for VICI purchasers, OIC uses a linearly proportional indemnification (LPI) approach. For instance, for a single insurance with premium of ETB 100, the payout for a complete loss is 100/0.15 which is about ETB 667. Using LPI, for instance, in areas where the index indicates a 50% loss, a partial payout of about ETB 333.5 is paid to the farmers.

Credit: Smallholders were also offered with a risk contingent credit product of ETB 200 in which they are not required to repay their loan if an indexed risk event occurs. The amount and repayment of this loan is contingent on the level of the risk that the households experience. Our project purchases index insurance coverage equal to the value of the loan plus interest from OIC and passes the premium costs to the borrower in the form of a higher interest rate. Households can acquire IBI from OIC and take credit from financial institutions by their own effort.

Agricultural input: Households were also offered with an agricultural input coupon (AIC) that worth ETB 300. We told them to redeem this coupon at the local input supplier offices−cooperative unions through the arrangement we made by the project. Farmers can take the proportional amounts of chemical fertilizer, improved seeds and/or herbicides or pesticides using the coupon. Similar to the IBI, the repayment of the AI loan is postponed towards shortly after harvest. All loans also bear a 1% monthly risk-free interest rate until repaid.

Repayment structure: The repayment structure and the farmers' burden of debt depend on the level of the risk and the amount of loss realizations that farmers face. The total maturity value

[5] ETB (Ethiopian Birr), 1 USD = 27 ETB

of the interlinked IBI-RCC and input is ETB 600 with a maturity value of ETB 636 over six months period. Farmers were required to repay back a maximum of ETB 636 under a full rainfall with no trigger of insurance. On the other hand farmers can earn a maximum of ETB 698 (i.e., ETB 1334−636 = ÈTB 698) under a 100 percent trigger that implies a complete loss of their harvest. All intermittent payout values are determined as per the linearly proportional indemnification (LPI) formula.

2.2. *Sample size and power of the experimental design*

The sample size in this study is mainly determined by the available budget. Yet, we have some freedom in the choice of the sampling strategy. As we randomized at the level of community known as 'garee' in our study area, we have a choice between putting many garees in our sample and then survey a small amount of households per many garees, or to sample many households per few garees and then reduce the size of garees. In terms of power, given the total sample size, an increase in the size of garees (and hence involving less households per garee) is preferable, if intra-class correlations (ICC) are positive. However, if we increase the number of garees, the survey costs will increase due to larger distances. Moreover, the more garees we use in the study, it would be more "restricted". Since the product may not be actively marketed, we need a 'control' group. Taking all these into account, we decided to sample on average about 35 households from each of the 47 garees. We show below that this sample size enables us to detect relatively small effect sizes. Following Djimeu and Houndolo (2016) we calculate the minimum detectable effect (MDE) of the cluster randomized controlled trials with individual-level outcomes with covariates using the formula below:

$$MDE(\delta) = \frac{t_1 + t_2}{\sqrt{p(1-p)}}\sigma_y\sqrt{\left[\rho + \frac{1-\rho}{n}\right](1-R^2)}$$

where MDE represents the minimum detectable effect size; t_1 is the t-value corresponding to the desired significance level of the test; t_2 is the t-value corresponding to the desired power of the experimental design; p is the proportion of individuals assigned to the treatment group; σ_y is the standard deviation of the outcome variable; ρ is the intra-class correlation (ICC)

coefficient; n is the number of individuals per cluster and R^2 is outcome variance. Table 1 presents the description and values of these parameters used in determining sample size and power of the experimental design.

Table 1: Parameters used in determining sample size and power of the experimental design

Parameters	Description of parameters	Value
α	Significance level	0.05
β	Power of the test	0.80
$Tail$	One-tail or two-tail test	2
t_1	T-value corresponding to the desired significance level of the test	1.96
t_2	T-value corresponding to the desired power of the experimental design	0.84
σ_y	Standard deviation of the outcome variable	0.43
J	Number of clusters of the treatment and control group	47
ρ	Intra-class correlation (ICC) coefficient	0.047
p	Proportion of individuals assigned to the treatment groups	0.25
n	Average sample size per cluster	35
R^2	Proportion of outcome variance explained by the covariates	0.079
δ	Minimum detectable effect	0.107

Note: The parameters used in determining sample size and powers of the experimental design in Table 1 are based on the assumptions of cluster randomized controlled trials with individual-level outcomes with covariates (Djimeu and Houndolo 2016). Since we are initially uncertain about the direction of the effect of the treatments on uptake, we used a two-tail test. We set the significance level at 0.05 and the desired power of the test at 0.8. The values of t_1 and t_2 (i.e., t_α and $t_{1-\beta}$) used are 1.96 and 0.84, respectively. Due to budget constraints, we decided to involve about 1660 participants constituting 47 clusters with sample size of 35 individuals per cluster. In total, we included 1661 households divided into the control group and three treatment arms: IBI, IBI interlinked with credit and IBI interlinked with credit and agricultural inputs. The standard deviation of the outcome variable uptake is considered as $\sigma_y = 0.43$ based on the variance $\sigma_y^2 = p(1-p)$ where p, the proportion of individuals assigned to each of the treatment group is 0.25 in our data. Similarly, we considered an ICC coefficient of 0.047 and an $R^2 = 0.079$, both based on the actual data of the experiment. Based on these parameters, the estimated MDE in this study is 0.107. Several parameters are relatively standard, such as power (which we set at 80%), and significance level (which we set at 5%). Our power analysis is based on 3ie Sample size and minimum detectable effect calculator© developed in-house and available online as *3ie Sample size and minimum detectable effect calculator©*, so that readers can run their own power analyses.

2.3. RCT experiment

We conducted a randomized controlled trial (RCT) with a randomly selected 1661 households from two kebeles in the Rift Valley zone of Ethiopia. From each kebele, we randomly selected worker groups knows as '*garees*'. We invited 50 garees (35 from Desta Abjata and 15 garees from Qamo Garbi kebele) to come with lists of their members. Through kebele leaders, we arranged training at the Farmers' Training Center (FTC). From these, 47 garees have shown up on the training. We collected lists of members from all garee leaders. All households in the two kebeles were members of a *garee*, and there is no a household who has a multiple membership in different garees. We used group level randomization to randomly assign the 47 garees into one of the following four groups: Control group (T_1), standalone insurance group (T_2), interlinked insurance with credit group (T_3), and interlinked insurance with credit and agricultural input group (T_4). We preferred randomizing treatments and control at the group level rather than at the individual level to mitigate concerns about fairness. In our case if farmers in the same neighborhood area were assigned to different treatments there could have been resentment from farmers. The randomization was specifically undertaken as follows. First, based on random lottery basis, we kept one-fourth of the garee leaders as controls. We label the control group as group T_1. This group has got no insurance, credit or input from the intervention. But they can buy the standard insurance from OIC by their own. Second, we assigned the next one-fourth of the households into IBI group (T_2). Garees assigned to T_2 were those who draw the card labelled with 'IBI'. We informed group T_2 garees that their members will get ETB 100 insurance policy from OIC. In addition, like any households, members can buy insurance from OIC by their own. Thirdly, we assigned the next one-fourth of the garees into interlinked IBI with credit. Garees assigned to T_3 were those who draw the card which was labelled with 'IBI+ILC'. We informed group T_3 that their members will get ETB 100 insurance policy and ETB 200 credit through the intervention. In addition, members can also buy any amount of insurance or acquire any amount of credit from financial institutions by their own effort. Fourthly, we assigned the final one-fourth of the garees into the interlinked insurance with credit and agricultural input group. These garees were those who draw the card labelled 'IBI+ILC +AIC'. We informed group T_4 households that their members were allowed to get ETB

100 insurance policy, ETB 200 risk-contingent credit and an agricultural input coupon worth of ETB 300 that can be redeemed at input suppliers' office (cooperative unions). Members of this group took fertilizer and improved wheat seed varieties from the suppliers showing their coupon.

3. Balancing tests

In measuring and interpreting the effects of treatments, various studies show that randomization ensures unbiased allocation of treatments to the study participants. However, randomization alone cannot provide the guarantee for a particular trial that the study participants in each treatment group will have similar characteristics (Schulz, Altman and Moher 2010). This is very important in light of potential non-random non-compliance. Hence, it is important to verify whether randomization resulted in similar groups in terms of observables. Such test, at best, secures unbiased treatment allocation, but not necessary balance (Tu, Shalay and Pater 2000). Since in practice following randomization, some important covariates may not be balanced between treatment groups especially when the sample size is small; it is therefore a usual practice in randomized controlled trial experiments to present baseline information on prognostic factors (Altman 1985). This practice allows for quick judgment of the success or otherwise of the randomization procedure, and as a result, provides basic information on which confidence on subsequent treatment comparison hinges. In this study, we have undertaken, balancing tests by estimating OLS models, regressing household observables on treatment group dummies and a constant (see Tables 2a and 2b below).

Table 2a: Balance tests on socio-economic variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatments	Age	Gender	Education	Family size	Marital status	2015 drought	2016 drought
T_2	−0.175	0.000	0.820***	0.913***	0.024**	−0.192***	0.192***
	(0.603)	(0.023)	(0.233)	(0.207)	(0.011)	(0.021)	(0.021)
T_3	−0.059	0.010	0.222	−0.002	−0.000	−0.056***	0.049**
	(0.605)	(0.023)	(0.234)	(0.208)	(0.011)	(0.021)	(0.021)
T_4	1.189*	0.022	0.680***	0.445**	0.012	-0.031	0.031

	(0.608)	(0.023)	(0.235)	(0.209)	(0.011)	(0.021)	(0.021)
Constant (T_1)	35.764***	0.862***	3.850***	5.833***	1.000***	0.957***	0.040***
	(0.427)	(0.016)	(0.165)	(0.147)	(0.008)	(0.015)	(0.015)
$T_2 = T_3$	0.848	0.676	0.011	0.000	0.029	0.000	0.000
$T_2 = T_4$	0.025	0.348	0.550	0.026	0.294	0.000	0.000
$T_3 = T_4$	0.041	0.602	0.053	0.033	0.261	0.243	0.397
Observations	1,661	1,661	1,661	1,659	1,661	1,661	1,661
R-squared	0.004	0.001	0.010	0.016	0.004	0.054	0.057

Notes: Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Test gives p-values of Wald tests referring to groups specified after the test.

The constant term reflects the comparison group, and the estimated coefficients indicate whether the other groups significantly differ from the comparison group. We also examine whether there are differences between these other groups by performing Wald tests. In this regard, careful selection of covariates and baseline tests of significance to determine which covariate to include in the model are important. In Table 2a, we present regression results for some demographic variables including age (in years), gender (1 male; 0 female), marital status (married = 1; not-married=0), education (years of schooling), family size and drought dummies (= 1 for experiencing drought in 2015 and 2016). Table 2b (not shown here; available on request) presents similar tests for household amount of saving, amount of outstanding loan, size of land size owned by the household, a series of farming variables capturing quantities of certain 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 value 1 if the household had any formal savings. In addition, we included the variable credit rationing whether the household is credit rationed (1=for credit rationed)[6] in the analysis. Randomization seems to have worked

[6] We used a direct elicitation method (DEM) (Boucher et al., 2009) to identify the credit rationing status of each household. With this method, we can identify credit constrained households according to their decision to borrow and the lender's decision to supply credit. The credit rationing module starts by asking whether the respondent has applied for a formal loan in the past five years. If so, it asks whether the application has been accepted. Households that have not applied for a formal loan indicate their reasons for not applying. According to their responses, all households can be categorized into one of four mutually exclusive groups: credit unconstrained, quantity (or supply-side) rationed, risk rationed, and transaction cost rationed. Households that apply for formal loans and receive them are categorized as unconstrained. However, if households applied for (more) credit at the

reasonably well. In terms of balance vis-a-vis the comparison group we find that the average family size is somewhat larger in T_2 and T_4 groups.

This group has also achieved a relatively higher education. Households in group T_2 and T_3 were also experienced a bit more drought. We also find some other slight imbalances upon comparing the coefficients of the various treatment arms to each other. Tables 2a and 2b suggest that the randomization has worked reasonably well, especially regarding crop production (Table 2b)—farmers of the different treatment groups produce on average the same products. There are also some imbalances. Yet these small imbalances are not a reason of concern, and do not disqualify the randomization.

In analyzing the effects of treatments in experiments, those with statistically significant difference between groups are automatically accounted for in the analysis, and those that are not significant are ignored (Meinert 2012). However, the basic argument against the afore-mentioned approach is that, since study participants are randomly allocated to treatment groups in the first instance, then, any observed difference must have been due to chance. It then appears absurd to again test whether the observed difference is purely by chance or not, which is what the test of significance does. Ignoring baseline covariate tests that have prognostic influence but not significantly different between groups remains at odds with the correctness of the use of hypothesis testing approach for covariate selection. In fact, a significant imbalance will not matter if a factor does not predict outcome; whereas, a non-significant imbalance can benefit from covariate adjustment.

4. Empirical strategy

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prevailing interest rate and their application was rejected, they are classified as quantity rationed. If households have not applied for a formal loan in the past five years, because the bank branch is too far from their homes or the application procedure involves too much paperwork and waiting time, we categorize them as transaction cost rationed. If instead households do not apply for loans because they do not want to offer their land, house, or other assets as collateral that might be taken by the bank, we consider them risk rationed. Some households that are able to borrow do not apply because they do not need credit; they are also credit unconstrained. Finally, households that would have applied for loan, had they known the bank would lend to them, are another group of supply-side rationed households. We sum together the risk- and transaction cost rationed households into a group of demand constrained households; then we sum the demand constrained households and supply constrained households into a larger group of credit constrained households.

We estimate the effects of the standalone and the interlinked treatments on IBI adoption decision of the households as follows:

$$Y_{IBI} = \gamma_1 + \gamma_2 T_2 + \gamma_3 T_3 + \gamma_4 T_4 + \gamma_i X_i + \varepsilon_i$$

whereas Y_{IBI} represents the uptake of IBI, γ_1 represents the constant indicating IBI uptake of the control group; the coefficients γ_2, γ_3 and γ_4 measure the increase in uptake due to IBI, first level interlinkage and second level interlinkage, respectively. Further, T_2 is the treatment variable for IBI taking the value 1 for households provided with IBI and 0 for the others; T_3 is the treatment variable for IBI interlinked with credit taking the value 1 for households offered with IBI+ILC and 0 for the others; T_4 is the treatment variable for IBI interlinked with credit and agricultural inputs taking the value 1 for households offered with IBI+ILC +AIC and 0 for the others. Similarly, X_i is a vector of covariates that affect uptake of IBI including household demographic characteristics such as age, gender, level of education and family size; drought experiences of the household, land size, saving, indebtedness and credit rationing status of the household; and ε_i is the stochastic term capturing all unobservable factors in the data. Hence, the parameter γ_i measures the effect of the different covariates on the uptake of IBI.

5. Results

Table 3 below shows the results of the randomization. A total of 1661 households who were interviewed in our baseline survey were randomly assigned into four groups: Control groups who can buy IBI from OIC by their own, IBI groups households for whom the project buys IBI, IBI+ILC – households for whom the project buys IBI and offered an insurance-linked credit (first level interlinkage) and households for whom the project buys IBI, offered a ILC and agricultural input coupon (second level interlinkage).

Table 3: Descriptive statistics results of the randomization

Group	Random sample	Percent	Uptake	Percent
Control (T_1)	420	0.253	37	0.088
IBI (T_2)	421	0.253	115	0.273
IBI+ILC (T_3)	414	0.249	139	0.336

IBI+ILC +AIC (T_4)	406	0.244	168	0.414
Total	1661	1.000		

Table 3 indicates that from 420 households (25.3%) who were kept as controls, only 37 households (8.8%) of them have bought insurance from OIC by their own paying the premium up-front. Hence, the uptake of IBI for the control group is 8.8%. Second, from 421 households (25.3%) form who incentives of buying IBI is facilitated by the project, 27.3% of them accepted the offer. Here, the premium payment is made by the project, but the agreement is if the weather condition is good households will pay back the premium to the project. But if the weather condition is worse, OIC will payback part of the payout as premium back payment to the project and part of the payout as compensation of losses to the farmers.

Table 3 also shows that as a result of the first level interlinkage (i.e. adding ILC on IBI); the uptake has increased to 33.6%. So, intuitively, this indicates that net increase in uptake due to the ILC component is 6.3%. Further, the result of the second level interlinkage in Table 3 indicates that due to the additional AIC component on IBI+ILC, uptake was increased to 41.4%. This indicates that adding AIC has further increased uptake by 7.8%. In general, the randomization results indicate that each level of incentivized offer or interlinkage has positively contributed to the increase in uptake. However, these are simple measures of descriptive statistics. As such these results are not adequate to causally infer the impact of each component on uptake. Hence, more rigorous estimates that take the role of other covariates into account were provided and discussed in the subsequent sections.

Table 4 provides the econometric estimation results of the impact of insurance-credit-input interlinkage on IBI uptake. The constant term results stands for the uptake of the control group. Thus in Table 3, the result $\gamma_0 = 0.088$ is highly significant at 1% level. This is in line with the adoption statistics of OIC which are between 7%−10%. Table 3 also shows that controlling for all other covariates the uptake of the control group is as large as 24.6%, and this is significant at 5% level. Table 3 also shows that controlling for all other factors that can influence adoption, the offer of IBI increases uptake 17.6%. This means a household who wins the IBI offer through

the incentives arranged in this study has a 17.7% increased uptake as compared with a household who did not get this incentive, given that the two households have relatively similar economic characteristics.

And the impact of IBI in increasing uptake is highly significant at 1% level. Further, our results also indicate that an average household who offered IBI and ILC has an increased uptake by 24.5% controlling for all covariates. This result reveals that interlinking credit with insurances increase uptake by 24.5 percentage points and this result is highly significant at 1% level. In addition, the net increase in uptake due to the credit is 6.9% computed as $\gamma_2 - \gamma_1 = 24.5 - 17.6 = 6.9\%$. Finally, Table 3 shows that the second level of interlinkage that is adding the AIC increases the uptake of insurance by 32.2% controlling for all the possible confounding factors that can affect the uptake of insurance. From this result, we compute that the net increase in uptake is 7.7%, computed as $\gamma_3 - \gamma_2 = 32.2 - 24.5 = 7.7\%$. The result is highly significant at 1% level.

Table 4: the impact of insurance-credit-input interlinkage on IBI uptake

Variables	(1)	(2)
Constant (T_1)	0.088***	0.246**
	(0.021)	(0.121)
IBI (T_2)	0.185***	0.176***
	(0.030)	(0.031)
IBI+ILC (T_3)	0.248***	0.245***
	(0.030)	(0.030)
IBI+ILC+AIC (T_4)	0.326***	0.322***
	(0.030)	(0.031)
Age		0.001
		(0.001)
Gender		−0.095**
		(0.038)
Education		−0.000
		(0.004)
Family size		0.001
		(0.004)

2015 drought		−0.103
		(0.106)
2016 drought		−0.087
		(0.108)
Land size		0.000
		(0.002)
Saving		0.024
		(0.028)
Outstanding loan		−0.038
		(0.024)
Credit rationed		−0.023
		(0.030)
Observations	1,661	1,659
R-squared	0.072	0.079

Notes: Robust standard errors given in parentheses; *** p<0.01, ** p<0.05, * p<0.1. Results reported in Table 4 are estimated based on OLS regressions. Column (1) reports the effects of the treatments on IBI uptake without including full set of covariates. Estimations in column (2) used the same procedure as estimations in column (1) but in this case we included full sets of covariates.

Hence, the regression results clearly indicate that interlinking IBI with credit significantly increases uptake. In addition, considering increased two levels of interlinking, interlinking IBI+ILC+AIC much more increase uptake than one-level of interlinking, that is interlinking IBI only with ILC. This informs us that there is a tendency for monotonous increase in uptake as the intensity of interlinkage increases.

6. Conclusion

Index-based insurance is increasingly recognized as a pro-poor climate risk management strategy over the recent years. Overcoming the classic information asymmetry problems that often plague the functioning of rural financial markets, IBIs were proved to have significant potential to improve welfare. Uptake of IBI at micro-level, however, remains quite low. Interlinking IBI with credit and agricultural inputs might enhance uptake and strengthen the mutual functioning of rural financial systems and the adoption of agricultural technologies. However, due to basis risk, IBI might fail to trigger payout after the insured incurs significant

loss. Hence, understanding whether interlinking IBI with credit and input complement each other is highly important yet uninvestigated issue, particularly to inform policy aimed at improving rural financial markets and adoption of productivity enhancing inputs. In this study, we estimated the effects of interlinking IBI with a risk contingent credit and agricultural inputs using data based on an RCT experiment in the Rift Valley zone of Ethiopia. Estimated results indicate that the uptake of IBI alone is very low. However, interlinking IBI with a insurance-linked credit significantly increases uptake. Further interlinking IBI with both credit and agricultural input even further increases the uptake of IBI. Adopters of IBI can expect insurance payout and increased earnings from productivity enhancing inputs to be profitable after repaying loans. As a result, their demand for insurance, credit and agricultural inputs can increase simultaneously. Hence, insurance, credit and agricultural inputs can complement each other, and IBI-credit-input can enlarge welfare improvement space of smallholders in developing countries.

To successfully meet the risk management needs of smallholder farmers who are usually credit constrained it is important to innovate and develop financial services that enhance uptake. Insurance, credit, and agricultural inputs are often offered independently of each other but so far there has been limited uptake of them by farmer. Our research however, shows that interlinking them together could combine the advantages of all three and hence can enhance the uptake significantly. In terms of policy making, this research shows that integrating insurance, credit and agricultural inputs can help to upscale agricultural risk management options for smallholder farmers.

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References

Ali, D.A., and K. Deininger., 2014. Causes and implications of credit rationing in rural Ethiopia: The importance of zonal variation. *Journal of African Economies.*

Altman, D. G. (1985) Comparability of randomised groups. *The Statistician*, 125-136.

Barnett, B. J., C. B. Barrett & J. R. Skees (2008) Poverty traps and index-based risk transfer products. *World Development,* 36, 1766-1785.

Barrett, C. B. (2011) Covariate catastrophic risk management in the developing world: Discussion. *American Journal of Agricultural Economics,* 93, 512-513.

Belissa T.K., Lensink, B.W & Anne Winkel (2018) Effects of weather index insurance on demand and supply of credit Evidence from Ethiopia. *American Journal of Agricultural Economics*, revised and submitted.

Boucher, S.R., Carter, M.R. and Guirkinger, C. (2008). Risk rationing and wealth effects in credit markets: theory and implications for agricultural development. *American Journal of Agricultural Economics*, 90(2), 409-423.

Carter, M. R., L. Cheng & A. Sarris (2016) Where and how index insurance can boost the adoption of improved agricultural technologies. *Journal of Development Economics,* 118, 59-71.

Chantarat, S., A. G. Mude, C. B. Barrett & M. R. Carter (2013) Designing index-based livestock insurance for managing asset risk in northern Kenya. *Journal of Risk and Insurance,* 80, 205-237.

Clarke, D. & O. Mahul (2011) Disaster risk financing and contingent credit: a dynamic analysis.

Djimeu, EW and Houndolo, D-G (2016). Power calculation for causal inference in social science: Sample size and minimum detectable effect determination, 3ie impact evaluation manual, 3ie Working Paper 26. New Delhi: International Initiative for Impact Evaluation (3ie).

Farrin, K. & M. J. Miranda (2015) A heterogeneous agent model of credit-linked index insurance and farm technology adoption. *Journal of Development Economics,* 116, 199-211.

Giné, X. and D. Yang (2009). Insurance, Credit, and Technology Adoption: Field Experimental Evidence from Malawi, Journal of Development Economics 89 (2009) 1-11.

Jensen, N. D., A. G. Mude & C. B. Barrett (2018) How basis risk and spatiotemporal adverse selection influence demand for index insurance: Evidence from northern Kenya. *Food Policy,* 74**,** 172-198.

Karlan, D., R. Osei, I. Osei-Akoto & C. Udry (2014) Agricultural Decisions after Relaxing Credit and Risk Constraints. *The Quarterly Journal of Economics,* 129**,** 597-652.

McIntosh, C., A. Sarris & F. Papadopoulos (2013) Productivity, credit, risk, and the demand for weather index insurance in smallholder agriculture in Ethiopia. *Agricultural Economics,* 44**,** 399-417.

Meinert, C. L. (2012) Clinical Trials Design, Conduct. *MONOGRAPHS IN EPIDEMIOLOGY AND BIOSTATISTICS,* 39**,** ALL-ALL.

Schulz, K. F., D. G. Altman & D. Moher (2010) CONSORT 2010 statement: updated guidelines for reporting parallel group randomised trials. *BMC medicine,* 8**,** 18.

Shee, A. & C. G. Turvey (2012) Collateral-free lending with risk-contingent credit for agricultural development: Indemnifying loans against pulse crop price risk in India. *Agricultural Economics,* 43**,** 561-574.

Shee, A., Turvey, C.G. and Woodard, J.D. (2015). A field study for assessing risk-contingent credit for Kenyan pastoralists and dairy farmers Agricultural Finance Review, 75(3): 330-348.

Skees, J. R. (2008) Innovations in index insurance for the poor in lower income countries. *Agricultural and Resource Economics Review,* 37**,** 1-15.

Takahashi, K., M. Ikegami, M. Sheahan & C. B. Barrett (2016) Experimental evidence on the drivers of index-based livestock insurance demand in Southern Ethiopia. *World Development,* 78**,** 324-340.

Tu, D., K. Shalay & J. Pater (2000) Adjustment of treatment effect for covariates in clinical trials: statistical and regulatory issues. *Drug Information Journal,* 34**,** 511-523.

Udry, C. (1990) Credit markets in Northern Nigeria: Credit as insurance in a rural economy. *The World Bank Economic Review,* 4**,** 251-269.