Effects of Bundled Index-based Insurance with Credit and Agricultural Inputs on Uptake, and Climate-Change Protection Strategies of Common Agricultural Land of Smallholder Farmers.

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Abstract

Provision of integrated insurance, credit and agricultural technologies can significantly help alleviate climate change effects on common agricultural land of smallholder farmers in developing countries. Index-based insurance (IBI) is evidenced to have the potential to protect farmers' common land from climate change shocks such as drought and flood. However, adoption of IBI has met unexpectedly low uptake and up-scaling challenges. Evidence on the extent to which interlinking IBI with credit and agricultural inputs can enhance the uptake and economic impacts of IBI is scant. We conducted a randomized controlled trial with 1661 smallholders in Ethiopia. Results indicate that the uptake of the standalone IBI is low, but interlinking IBI with credit and inputs significantly increases uptake. We estimated the impacts of the interlinked IBI on household consumption and investment in inputs. We find that interlinking IBI with credit and inputs increases household consumption and investment in high-risk high-return inputs. We also estimated the impact of the intervention on climate-change common land protection strategies, finding that the interlinked intervention increases land productivity, improves subjective wellbeing and shock-copying ability of adopters. The findings imply that bundled products enhance the uptake and impact of insurance that can help to protect common land of farmers from climate change shocks.

Keywords: Common land; climate change, IBI, credit-input, RCT

1. Introduction

Agricultural risks are key impediments to agricultural common land 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 smallholder farmers to protect their common land from climate change risks (Karlan et al 2014). 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 et al 2008; Carter et al 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 farmers' common land can be protected from climate change shocks.

In this study, we design an innovative interlinked IBI-credit-input intervention 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; Marr et al 2016). 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 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 et al 2018; 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 et al 2015). This mechanism provides smallholder farmers with a linked financial product that embeds within its structure an insurance protection which, when triggered, 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). 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 includes agricultural input coupons (AIC) that smallholders use to buy 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 combines the advantages of all the three and hence can achieve better outcomes.

Thus, this study examines the extent to which this innovative interlinked insurance-credit-input intervention enhances the uptake and impacts of integrated rural technologies among smallholders. The study is undertaken in the Rift Valley zone of Ethiopia where rainfall shocks and drought adversely affect farmers' common land and where the prevalence of credit and insurance rationing was evidenced (Ali and Deininger 2014; Belissa et al 2018).[1] The rest of the paper is organized as follows. Section 2 lays out our intervention and randomization strategy. Section 3 presents the balancing tests to check whether the randomization has worked. Section 4 explains our estimation strategy. Section 5 analyses the main results. Section 6 concludes the paper.

2. Intervention and randomization strategy

2.1. Components of the intervention

Insurance: Through a local insurance company known as Oromia Insurance Company (OIC) in Ethiopia, an index-based insurance (IBI) product was designed. 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 reduce transaction costs. 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:

$$S_{vici} = \frac{P}{0.15} \tag{1}$$

For each household who decides to take IBI, a premium of ETB[2] 100 per policy was paid to OIC. Payout, which is a maximum of sum insured, is determined according to the index level. To explain how this works at OIC, let T, E and A represent trigger, exit and actual parametric values of the index. Then, the amount of payout in each insurance period is calculated for individual buyer households as follows:

$$I_{vici} = \left(\frac{T-A}{T-E}\right)\left(\frac{P}{0.15}\right) \tag{2}$$

In determining payouts for 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.

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

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 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 in the form of payout (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. 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 showed up for 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. Our RCT design is an encouragement design. 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 encouragement to access 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 from OIC 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 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. Therefore, we produce balance tests in Table 1.

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 1, we present regression results for some demographic variables including age (in years), gender (= 1for male; 0 for female), marital status (= 1 for married; 0 for non-married), education (years of schooling), family size and drought dummies (= 1 for experiencing drought in 2015 and/or 2016).

Table 1: Balance tests on socio-economic variables

Treatments	(1) Age	(2) Gender	(3) Education	(4) Family size	(5) Marital status	(6) 2015 drought	(7) 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.

Randomization seems to have worked reasonably well. In terms of balance, as compared with 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.

4. Empirical strategy

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

$$Z_{ij} = \tau_0 + \tau_1 T_1 + \tau_2 T_2 + \tau_3 T_3 + \tau_i X_{ij} + \varepsilon_{ij} \quad (3)$$

whereas Z_{ij} represents the uptake of IBI, τ_0 represents the constant indicating IBI uptake of the control group (i.e., households who were not encouraged or not participated on promotion); the coefficients τ_1, τ_2 and τ_3 measure the increase in uptake due to IBI, first level interlinkage and second level interlinkage, respectively. Further, T_1 is an indicator variable for assignment to treatment 1 (IBI), taking the value 1 for households assigned to treatment 1 and 0 for the others; T_2 is an indicator variable for assignment to treatment 2 (IBI+ILC) taking the value 1 for households offered with IBI+ILC and 0 for the others; T_3 is an indicator variable for assignment to treatment 3 (IBI+ILC+AIC) taking the value 1 for households offered with IBI+ILC +AIC and 0 for the others. Similarly, X_i is a vector of baseline characteristics or 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 τ_i measures the effect of the different covariates on the uptake of IBI.

4.1. Impact estimation strategy

Our impact analysis focuses on assessing the welfare effects of the innovative interlinked insurance-credit-input intervention on household production and consumption behaviour. The returns to effective implementation of the innovative interlinked insurance-credit-input intervention can be expected to be substantial. By enhancing household investment in high-risk high-return production inputs, such intervention can enhance productivity, smooth consumption and improve the welfare of the smallholders. Thus we evaluate the impact of the innovative interlinked insurance-credit-input intervention on observable outcome variables including enhanced investment in high-risk high-return inputs as well as weekly consumption. We use two approaches, namely, the intent-to-treat (ITT) and the local average treatment (LATE).

4.2. Post-treatment analysis (Intent-to-treat (ITT))

In the ITT analysis, we regress the outcome variables on the randomized groups irrespective of their uptake status. Let T_1 represent the control group (i.e., households who were randomly assigned to the group whose members were not encouraged or not allowed to participate in the interlinked credit-insurance-input intervention). Note that these groups of households in principle can buy the conventional IBI from OIC by their own effort. Similarly, T_2, T_3, and T_4 represent randomization dummies for groups assigned to the promoted IBI, the promoted IBI interlinked with credit and the promoted IBI interlinked with credit and input, respectively. In the first instance, we undertake the ITT analysis. Due to the RCT design, post-treatment outcomes are unbiased. The ITT compares the outcome variables in the treatment groups (i.e., T_2, T_3 and T_4) to the outcome variable(s) of the control group (i.e T_1). For each of the outcome variables, we estimate the ITT effects based on both the post-treatment (single) and difference-in-difference (double) outcomes.

Our ITT model specification based on single post-treatment data can be specified as follows:

$$Y_{ij} = \gamma_0 + \gamma_1 T_1 + \gamma_2 T_2 + \gamma_3 T_3 + \gamma_4 T_4 + \beta X_{ij} + \varepsilon_{ij} \tag{4}$$

where Y_{ij} represent outcome variables including value of investment in high-risk high-return agricultural inputs (i.e., value of investment in improved seed varieties, chemical fertilizer and pesticide/herbicide) as well as value of weekly food consumption, productivity, subjective well-being and shock-copying ability; γ_0 the constant term; T_1, T_2, T_3 and T_4 are randomization dummies as defined above taking values (=1 for households assigned to the specific group and 0 for others); X_{ij} represents household characteristics included to increase the efficiency of the model; and ε_{ij} is stochastic error term. Hence, γ_1, γ_1, γ_3 and γ_4 measure the relative intent-to-treat effect of the conventional IBI, promoted IBI, the promoted IBI interlinked with credit and the promoted IBI interlinked with credit and input, on the outcome variables, respectively. We estimate Eq. (4) using only the single post-treatment data. Given the random assignment to the treatment, $E(\varepsilon_{ij}/T_{ij} = 0)$, so OLS estimates of $\gamma_1, \gamma_2, \gamma_3$ and γ_4 are unbiased, as long as attrition is not differential.

Further, since we have both the baseline and end-line data for some of the outcome variables, we can estimate the impact of the intervention using the difference-in-difference as follows:

$$Y_{ij} = \omega t_2 + \gamma_0 + \gamma_2 T_2 + \gamma_3 T_3 + \gamma_4 T_4 + \gamma_5(t_2 T_2) + \gamma_6(t_2 T_3) + \gamma_7(t_2 T_4) + \beta_i X_{ij} + \varepsilon_{ij} \tag{5}$$

where t_2 or *Post* (as used in the estimation) is the indicator variable for the end-line survey taking the value 1 for end-line survey and 0 for the baseline survey; γ_0, Y_{ij}, T_1; T_2, T_3 and T_4 as well as X_{ij} and ε_{ij} are as defined in eq. (4). Hence, γ_5, γ_6 and γ_7 are our coefficient of interest or DIDs that measure the relative intent-to-treat *overtime* effect of the three components of the intervention on the outcome variables compared to the control group. This means these coefficients measure whether the impact of T_2, T_3 and T_4 is higher than the impact of T_1 on the outcome variables. Here, we undertake Wald tests for comparing T_2 with T_3 and T_4 as well as for comparing T_3 with T_4.

4.3. Local average treatment effect (LATE)

Next, we will undertake a local average treatment effect (LATE) analysis for both the single post-treatment and difference-in-difference effects. LATE depends on the instrumental variable (IV) approach and uses the 2SLS estimator. It uses the actual uptake of a household (rather than mere assignment to treatments) from the group randomly assigned. Let T_2, T_3, and T_4 represent assignment to the treatment dummies for households assigned to the respective groups and Z_{ij} represent actual taken-up of the products: the promoted IBI, the promoted IBI interlinked with credit and the promoted IBI interlinked with credit and input, respectively. We estimate LATE based on the post-treatment data and using a two-stage least square (2SLS) as follows:

$$Z_{ij} = \tau_0 + \tau_1 T_1 + \tau_2 T_2 + \tau_3 T_3 + \tau_4 T_4 + \tau_i X_{ij} + \varepsilon_{ij} \tag{6a}$$

$$Y_{ij} = \gamma_0 + \gamma_1 \hat{Z}_{ij} + \gamma_i X_{ij} + \varepsilon_{ij} \tag{6b}$$

where Z_{ij} represents uptake (= 1 for those households who take-up after the intervention and 0 for others); γ_0, T_1; T_2, T_3 and T_4 as well as X_{ij} and ε_{ij} are as defined above. In eq. (6b), T_2, T_3 and T_4 serve as external instruments for uptake (Z_{ij}).

Similar to the procedures we followed in eq. (5), we can estimate LATE using difference-in-difference for the outcome variables for which we have both the baseline and end-line data as follows:

$$Z_{ij} = \tau_0 + \tau_1 T_1 + \tau_2 T_2 + \tau_3 T_3 + \tau_4 T_4 + \tau_i X_{ij} + \varepsilon_{ij} \tag{7a}$$

$$Y_{ij} = \gamma_0 + \pi t_2 + \gamma \hat{Z}_{ij} + \delta(t_2 \hat{Z}_{ij}) + \beta_1 X_{ij} + \varepsilon_{ij} \tag{7b}$$

where δ measures the DID for LATE. All variables are as defined before. Again T_2, T_3 and T_4 serve as external instruments for uptake (Z_{ij}) in eq. (7b).

5. Results

5.1. Uptake

Table 2 provides the econometric estimation results of the impact of insurance-credit-input interlinkage on IBI uptake, estimated using eq. (3). The constant term result stands for the uptake of the control group. Thus, the result $\gamma_0 = 0.088$ is highly significant at 1% level.

Table 2: the impact of insurance-credit-input interlinkage on IBI uptake

Variables	(1)	(2)
Constant (T_1)	0.088***	0.246**
	(0.021)	(0.121)

	(1)	(2)
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 are clustered at garee level. Results reported 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.
*** p<0.01, ** p<0.05, * p<0.1.

Table 2 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. The offer of IBI also increases uptake by 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. And the impact of IBI in increasing uptake is highly significant at 1% level.

Further, our results also indicate that an average household who was offered IBI and ILC has an increased uptake by 24.5% controlling for all covariates. This result reveals that interlinking credit with insurance 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 2 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.

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 has a much more increase in 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.

5.2. Impact on household investment in high-risk high-return inputs

Table 3 presents the effects of the interlinked intervention on households' total value of investment in high-risk high-return agricultural inputs. Columns 1−4 report the ITT level effect (i.e., the average effect of being assigned to a treatment group) on investment in inputs. Based on the single post-treatment outcome, reported investments in inputs are significantly higher for the insurance interlinked with both credit and inputs. Controlling for all covariates, interlinking IBI with credit as well as interlinking IBI with both credit and agricultural inputs increase total investment in high-risk high-return inputs by ETB 409 and ETB 429, respectively (see Columns 1−2 in Table 3). Further, based on the DID results, the estimated ITT effect shows that interlinking IBI with both credit and input has a significant effect on household investment in high-risk high-return inputs (see Columns 3−4 in Table 3).

Based on the single post-treatment outcome, the DID estimates show that controlling for all potential covariates, interlinking IBI with both credit and agricultural inputs increases the investment in high-risk high-return inputs by ETB 659 (see Column 4 in Table 3).

Table 3 also reports the local average treatment effect (LATE) of the interlinked intervention on household total investment in high-risk high-return inputs. First, results presented under Column 5−6 were estimated for the single post-treatment outcome using 2SLS in which the actual uptake is instrumented by treatment dummies. Due to random treatment and low level of attrition in the data, post-treatment outcomes were unbiased. The estimated results show that, controlling for all covariates, for actual adopters, the intervention has increased total household investment in high-risk high-return inputs by ETB 1490, and this is highly significant at 1 percent level. The differential impact between ITT and LATE estimates is due to the reason that LATE estimates are for real adopters while ITT estimates are only for being assigned to treatments irrespective of the uptake status.

Table 3: Impact on household total investment in high-risk high-return inputs

Variables	ITT				LATE			
	Post treatment (single outcome)		Difference-in-difference		Post treatment (single outcome)		Difference-in-difference	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IBI	-129.700	-255.052	-30.386	-127.601				
	(254.081)	(244.389)	(246.686)	(230.588)				
IBI+ILCC	353.021	409.448*	129.276	187.030				
	(211.216)	(226.417)	(158.737)	(170.940)				
IBI+ILC+AIC	827.681***	428.594*	168.993	-213.372				
	(229.116)	(213.360)	(151.315)	(169.409)				
Post (=1 for end line; =0 for baseline)			338.229***	321.247***			904.424***	478.419***
			(24.673)	(25.314)			(172.166)	(149.881)
Post*IBI			-99.314*	-99.317*				
			(56.390)	(56.510)				
Post*(IBI+ILC)			223.745*	222.120*				
			(124.095)	(124.890)				
Post*(IBI+ILC+AIC)			658.688***	658.685***				
			(106.909)	(107.101)				
Uptake (=1 for uptakers; =0 for non-uptakers)					2,291.742***	1,490.010***	2,087.007***	564.128
					(436.605)	(393.812)	(560.853)	(492.106)
Post*uptake							-1,355.565**	124.514
							(571.276)	(498.038)
Age		17.986**		16.984**		17.431***		16.727***
		(8.565)		(7.184)		(6.112)		(3.909)
Gender		267.759		301.380		387.479**		353.617***
		(331.276)		(263.264)		(171.101)		(109.426)
Married		-390.263**		-414.194***		-368.546		-426.979**
		(185.862)		(103.782)		(296.606)		(189.690)
Education (years)		7.223		15.984		1.933		11.755
		(25.260)		(21.247)		(16.733)		(10.702)
Family size		21.327		16.995		12.480		11.951
		(22.035)		(20.407)		(16.275)		(10.409)
2015 drought		-495.271		-42.459		-318.487		17.754
		(1,309.734)		(846.263)		(462.908)		(296.047)
2016 drought		-331.381		49.972		-316.994		28.092

		(1,170.023)		(784.096)		(468.187)		(299.423)
Land size		153.722***		148.298***		153.414***		146.014***
		(36.038)		(36.697)		(9.773)		(6.250)
Saving		-455.356*		-459.012*		-441.335***		-434.625***
		(228.444)		(261.743)		(124.081)		(79.354)
Outstanding loan		-17.158		67.222		102.395		135.021**
		(165.542)		(152.591)		(102.614)		(65.626)
Credit rationed		-134.908		-64.264		-89.255		-37.743
		(172.000)		(154.895)		(133.189)		(85.179)
Constant	2,248.598***	1,201.740	1,910.369***	443.525	1,872.725***	676.647	1,399.474***	192.462
	(131.875)	(1,162.071)	(112.361)	(720.955)	(131.580)	(626.589)	(162.420)	(423.804)
Observations	1,661	1,659	3,322	3,318	1,661	1,659	3,322	3,318
R-squared	0.033	0.199	0.039	0.219		0.170		0.208

Note: The dependent variable in estimations reported in Table 3 is the total investment in high-risk high-return inputs including chemical fertilizer, improved seed variety and investments in pesticides and/or herbicides. Dependent variable is measured in Ethiopian Birr (ETB). Columns 1-2 report the post-treatment (single) effects of the intervention estimated using eq. (4), with and without controls, respectively. Results reported under columns 1-2 are estimated using OLS. Columns 3-4 report the ITT effects of the intervention with and without controls, estimated using eq. (5), respectively. Results reported under columns 3-4 are estimated using difference-in-difference. Columns 5-6 report the LATE (single post-treatment effects) of the intervention with and without controls, estimated using eq. (6a & 6b), respectively. Uptake is instrumented by randomization dummies. Similarly, columns 7-8 present the IV-based LATE (difference-in-difference effects) of the intervention with and without controls, estimated using eq. (7a & 7b), respectively, where the actual uptake is again instrumented by randomization dummies. Standard errors are clustered at the *garee* level, and reported in parentheses.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

5.3. Impact on consumption

Table 4 presents results of the effect of the interlinked intervention on households' expenditure for weekly consumption. The ITT level effects are reported under Columns 1−4. Based on the post-treatment (single) outcome, the OLS estimates show that interlinking IBI with credit increases expenditure on weekly consumption by ETB 76, while further interlinking IBI provision with credit and agricultural inputs increases household expenditures on weekly consumption by ETB 91. Both results are significant at 1 percent level after controlling for all covariates (see column 2 in Table 8). The double difference ITT estimates are also reported under Column 3−4 in Table 4. Estimated results show that all the three treatments have a statistically significant effect on household consumption (see column 4 in Table 4). Controlling for all covariates, the standalone IBI has increased weekly consumption expenditure by ETB 40. Similarly, interlinking IBI with credit increases household consumption expenditure by ETB 54, while further interlinking IBI with both credit and input increases weekly consumption expenditure by ETB 96.

Finally, the IV-based 2SLS estimations of the impacts of the intervention on consumption are presented under columns 5-8 in Table 4. LATE results reveal that the overall intervention has statistically significant impact in increasing household expenditure on consumptions. The LATE estimates based on the single post-treatment data show that the intervention has increased weekly consumption for actual adopters by ETB 292. This result is statistically significant at 1 percent level. The estimation is also based on the 2SLS that helps to control for the biases arising from time-invariant heterogeneity. Hence, it is evident that the intervention has casually increased households' weekly consumption expenditures.

Table 4: Impact of interlinked insurance-credit-input on household weekly food consumption

Variables	ITT				LATE			
	Post treatment (single outcome)		Difference-in-difference		Post treatment (single outcome)		Difference-in-difference	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IBI	73.699	27.795	33.473	-9.694				
	(47.065)	(36.152)	(44.679)	(34.475)				
IBI+ILC	74.704**	76.160**	19.614	21.498				
	(29.537)	(31.728)	(28.311)	(31.141)				
IBI+ILC+AIC	129.344**	90.710**	32.361	-3.718				
	(48.187)	(38.518)	(39.259)	(33.818)				
Post (=1 for end line; =0 for baseline)			2.453	2.260			90.661***	50.833*
			(2.906)	(3.122)			(28.448)	(26.489)
Post*IBI			40.226***	39.718***				
			(4.434)	(4.249)				
Post*(IBI+ILC)			55.090***	54.416***				
			(3.574)	(3.325)				
Post*(IBI+ILC+AIC)			96.983***	96.475***				
			(11.905)	(11.807)				
Uptake (=1 for uptakers; =0 for non-uptakers)					372.903***	292.225***	306.912***	158.944*
					(68.996)	(65.483)	(92.640)	(86.945)
Post*uptake							-146.554	-4.212
							(94.349)	(87.983)
Age		0.765		0.701		0.526		0.573
		(1.073)		(1.027)		(1.016)		(0.688)
Gender		58.765**		58.204**		85.990***		72.930***
		(26.279)		(24.056)		(28.451)		(19.267)
Married		7.004		10.496		22.659		17.473
		(56.113)		(56.033)		(49.319)		(33.390)
Education (years)		-4.749		-4.069		-4.958*		-4.316**
		(4.037)		(3.873)		(2.782)		(1.884)
Family size		26.492***		25.370***		25.869***		24.957***
		(4.110)		(3.964)		(2.706)		(1.833)
2015 drought		-118.995***		-99.224**		-88.402		-83.683
		(44.024)		(41.742)		(76.972)		(52.112)
2016 drought		-35.314		-20.101		-15.317		-11.196

		(47.361)		(45.765)		(77.850)		(52.706)
Land size		10.127**		9.431***		10.067***		9.263***
		(3.770)		(3.352)		(1.625)		(1.100)
Saving		-32.719		-30.497		-36.933*		-31.622**
		(23.087)		(22.227)		(20.632)		(13.975)
Outstanding loan		-13.929		-11.417		0.695		-2.420
		(23.357)		(21.618)		(17.063)		(11.558)
Credit rationed		-67.314*		-61.020		-59.785***		-56.459***
		(38.016)		(36.477)		(22.147)		(15.000)
Constant	476.750***	332.530***	474.297***	315.469***	442.617***	240.019**	410.691***	244.335***
	(22.336)	(69.471)	(22.193)	(66.673)	(20.793)	(104.189)	(26.850)	(74.676)
Observations	1,661	1,659	3,320	3,316	1,661	1,659	3,320	3,316
R-squared	0.019	0.132	0.018	0.128		0.128		0.123

5.4. Impact on shock-copying ability (ScA)

The results of the effect of the interlinked intervention on households' shock-copying ability are presented in Table 5. The results are estimated using ordered logit regressions and presented in log-odd ratios. Column 1−2 presents the ITT level effects with and without control variables, respectively. Results show that the interlinked insurance improves ScA.

Based on the post-treatment (single) outcome, the ordered logit estimates show that IBI uptake increases the log-odds of reporting higher ScA by 0.989. As we did in Section 6.5, interpretations of the ordered logit results require exponentiation. The above result thus shows that IBI buyers are 2.7 ($\approx e^{0.989}$) times more likely to report higher shock-copying ability than lower SCA. Consistent with our expectations, uptake of IBI has a strong positive effect on SCA of the households, presumably because insurance coverage reduces risk exposure for risk-averse buyers. Table 5 also shows that interlinking IBI with credit increases the log-odds of reporting higher ScA by 1.27, while further interlinking IBI provision with credit and agricultural inputs increases the log-odds of reporting higher SWB by 2.19. All these results are significant at 1 percent level after controlling for all covariates (see column 2 in Table 5).

The IV-based 2SLS estimations of the impacts of the interlinked intervention on ScA were presented under columns 3-4 in Table 5. LATE results reveal that the overall intervention has statistically significant impact on increasing households' ScA. The LATE estimates based on the single post-treatment data show that the intervention has increased the log-odds of reporting higher ScA by 2.79. Exponentiating this, we find that participants of the interlinked intervention are by far more likely to report higher ScA than reporting lower ScA.

As we explained in previous sections, since randomized treatment dummies were used as instruments for the potentially endogenous uptake of IBI, the coefficients on IBI, IBI+ILC and IBI+ILC+AIC measures the causal effects the three components of the intervention on ScA. This result is statistically significant at 1 percent level. The estimation is also based on the 2SLS that helps to control for the biases arising from time-invariant heterogeneity. Hence, it is evident that the insurance-credit-input interlinked intervention has causally increased households' shock-copying ability.

Table 5: Impact of interlinked insurance-credit-input on shock-copying ability

Variables	ITT		LATE	
	Post treatment (single outcome)		Post treatment (single outcome)	
	(1)	(2)	(5)	(6)
IBI	1.003***	0.989***		
	(0.116)	(0.134)		
IBI+ILC	1.284***	1.269***		
	(0.175)	(0.190)		
IBI+ILC+AIC	2.180***	2.185***		
	(0.159)	(0.168)		
Uptake (=1 for uptakers; =0 for non-uptakers)			2.775***	2.785***
			(0.180)	(0.186)
Age		0.011*		0.001
		(0.006)		(0.003)
Gender		-0.563***		0.041
		(0.168)		(0.081)
Married		-0.517*		-0.060
		(0.301)		(0.140)
Education (years)		0.027		0.012
		(0.026)		(0.008)
Family size		-0.003		-0.008
		(0.019)		(0.008)
2015 drought		-0.869*		-0.067
		(0.505)		(0.218)
2016 drought		-0.941*		-0.193
		(0.542)		(0.221)
Land size		-0.008		0.002
		(0.015)		(0.005)
Saving		0.204		-0.038
		(0.192)		(0.059)
Outstanding loan		-0.195		0.037
		(0.147)		(0.048)
Credit rationed		-0.084		0.006
		(0.165)		(0.063)
Constant			0.864***	0.923***
			(0.054)	(0.296)
Observations	1,661	1,659	1,661	1,659
R-squared			0.305	0.303

6. Conclusion

Index-based insurance is increasingly recognized as a pro-poor climate risk management strategy to help protect agricultural common land. Overcoming the classic information asymmetry problems that often plague the functioning of rural financial markets, IBIs have a remarkable potential to improve common land protection and welfare. However, the uptake of IBI remains quite low at micro-level. Practical understanding on the extent to which interlinking IBI with credit and inputs can enhance the uptake and impacts of insurance is important, but yet unexplored, particularly to inform policy aimed at improving rural financial markets and adoption of land productivity enhancing high-risk high-return inputs. To improve our understanding in this regard, we conducted an RCT in which we exogenously vary the provision of the standalone IBI, IBI interlinked with credit and IBI interlinked with both credit and agricultural inputs among smallholders. The experiment is undertaken in the Ethiopian Rift Valley zone. The results of the experiment indicate that the uptake of IBI alone is very low amounting 8.8% of the total potential demand, but interlinking IBI with credit significantly increases uptake. Further interlinking IBI with both credit and agricultural input even further increases the uptake of IBI.

We estimated the causal impacts of the interlinked insurance-credit-input system on household weekly food consumption and investment in high-risk high-return agricultural inputs, using the intent-to-treat (ITT) and local average treatment effect (LATE) for both the single post-treatment and the double difference outcomes. We employed OLS, IV regressions in which actual uptake is instrumented by assignment to treatments and double differencing to overcome biases arising from time-invariant heterogeneity in estimating LATEs. First, impact estimations from the ITT effects indicate that interlinking IBI, with both credit and inputs, increases household total investment in high-risk high-return inputs by ETB 429 and ETB 659, for the single and double difference outcomes, respectively. Further, IV-based 2SLS LATE estimation results show that, the insurance-credit-input intervention has increased total investment in high-risk high-return inputs by ETB 1490, based on the single post-treatment outcome for actual adopters. Then, second, we disaggregated the total impacts of the interlinked intervention on household investment on inputs into effects on investment in chemical fertilizer and improved seed varieties. Estimated ITT effects show that the intervention increases investment in chemical fertilizer by ETB 402, for the double difference outcome. IV-based 2SLS LATE estimations also show that the interlinked intervention has increased investment in chemical fertilizer by ETB 595, for the single post-treatment outcome. Similarly, OLS-based ITT estimates indicate that interlinking IBI with credit increases household investment in improved seeds by ETB 314 and ETB 257, for the post-treatment and double difference outcomes, respectively. The IV-based 2SLS LATE estimations also show that the interlinked intervention has investment in adoption of improved seeds by ETB 895, for the single post-treatment. Third, we estimated the impact of the interlinked intervention on household weekly food consumption expenditure. From the OLS-based ITT effect estimations, we find that, for the single post-treatment outcome, interlinking IBI with credit and with both credit and inputs increases weekly consumption by ETB 76 and ETB 91, respectively. In addition, using the difference-in-difference method, estimated ITT effects show that the standalone IBI, IBI interlinked with credit and IBI interlinked with both credit and inputs, have increased the level of consumption by ETB 40, ETB 54 and ETB 96, respectively. Finally, the IV-based 2SLS LATE estimations show that the intervention has increased weekly consumption for actual adopters by ETB 292. The double difference ITT estimates also show that controlling for all covariates, interlinking IBI with both credit and input increases the land productivity by 0.42. These interventions also increase the households' shock-copying ability to protect their common land. Further, IV-based 2SLS estimations reveal that the interlinked intervention increases the log-odds of reporting higher subjective wellbeing and shock-copying ability to protect their common land by 4.11 and 2.79, respectively.

We find that the estimated impacts are justifiable for various reasons. Due to random treatment and low level of attrition in our data, the post-treatment outcomes were unbiased. In addition, the double differencing techniques are helpful to account for potential biases that may arise from time-invariant heterogeneity. Our LATE estimates are also based on the instrumental variable (IV) regressions in which assignment to treatments are used as instrument for actual uptake. The higher welfare impacts we estimated using LATE as compared with ITT are in line with theory, and this is due to the reason that LATE stand for real adopters while ITT estimates are for only being assigned to treatment irrespective of the uptake status. In general, our results point that insurance, credit and agricultural inputs can complement each other, and IBI-credit-input interlinkage can enlarge climate risk-management improvement for the protection of common land of smallholder farmers in developing countries. To successfully meet the risk management needs of smallholders who are usually credit constrained it is important to innovate and develop interlinked financial services that bear enhanced uptake and economic impacts. Previously, insurance, credit, and agricultural inputs were often offered independently of each other but their uptake and impacts are limited. This study, however, evidences that interlinking insurance, credit and inputs together could combine the advantages of all three and hence can enhance the uptake and impacts significantly. The policy-relevant message from this study is that integrating insurance, credit and agricultural inputs can help to upscale agricultural risk management options and improve risk-management strategies for the protection of common land of smallholder farmers in the world.

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