Adoption of Weather Insurance and Household Welfare: Evidence on Consumption Smoothing and Risk-taking Behaviour in Ethiopia

Temesgen Keno Belissa

Abstract

Evidence on the welfare impacts of index-based insurance is scant. This study examines the impact of sustained uptake of index-based insurance on household consumption and investment in inputs. A two-round panel data were collected from smallholders in Ethiopia, and the difference-in-difference estimator was employed to reduce program placement and self-selection biases, arising from time-invariant unobserved heterogeneity. Results indicate that adoption of index insurance has causally increased household consumption and investment in high-risk high-return agricultural inputs. Further, accounting for the intensity of adoption, results suggest that repeated adoption of index insurance has cumulative lasting effect on household welfare.

Keywords: Weather insurance; Welfare impacts; Ethiopia; Smallholders

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1. Introduction

Increased interest is seen in recent years in studying index-based insurance (IBI) as a potential drought insurance technology that constitutes a pro-poor climate risk management strategy. However, evidence on the welfare impacts of this innovation is scant. In the absence of data on repeated observations, identification and measurement problems create the difficulty to assess the impact of an intervention implemented in a natural experimental setting. Impact estimations that rely on simple comparison of outcomes of participants with that of non-participants often suffer from selection biases. In technology adoption, one form of such bias is self-selection bias that arises from the tendency of adopters to engage in adoption decisions being motivated by their own unique characteristics like individual-specific entrepreneurial spirit. Self-selection bias results in biased impact estimates since unmeasured individual attributes of adopters may simultaneously affect participation in adoption and the outcome of adoption. Program placement bias that occurs when interventions are undertaken on non-random basis is another form of selection bias (Ravallion 2007). In IBI intervention, insurance firms may choose villages for implementation based upon characteristics that may not be observable to the researcher.

Randomized experimental designs that create exogenous variations in sub-groups of treated and controlled units may help to overcome the problems of selection biases. However, randomization alone is not a necessary and sufficient condition to capture the complete impact of an intervention. Karlan and Goldberg (2007) explain that since interventions often take long time to establish lasting effects, impact estimates based on one period of experimental or quasi-experimental data meant to randomize over potential sources of selection may not reflect the full effect of an intervention. The timing and duration of exposures is important in assessing the impact of interventions (Ravallion 2001; Ahlin and Jiang 2008; Tedeschi 2008;King and Behrman 2009; Berhane and Gardebroek 2011).

Various studies (Pitt and Khandker 1998; Coleman 1999) depend on cross-sectional data analysis techniques, and exploit program-specific designs or innovative quasi-experimental survey methods to generate control and treatment groups. Estimation techniques like Heckman correction and instrumental variable (IV) are also used to control for selection biases stemming from unobserved heterogeneity. However, these procedures still impose distributional and functional form assumptions. Furthermore, identifying a valid instrument that determines the treatment status but not the outcome variable remains an empirical challenge in IV regressions (Staiger and Stock 1997).The IV approach also ignores interactions between the treatment variable and other covariates as it assumes that the treatment variable has only a parallel shift effect (intercept effect but not slope effect) with respect to the outcome variable (Wooldridge 2002). Hence, estimating unbiased impact of an intervention that may accrue overtime requires dealing with individual, village or intervention-specific time-invariant heterogeneity, using for instance, a panel dataset. The difference-in-difference approach is a better alternative to control for time-invariant unobservable heterogeneity that may cofound with impacts (Copestake et al. 2001; Khandker 2005; Coleman 2006; Tedeschi 2008). This studyinvestigates whether adoption of IBI can provide for welfare enhancements at household level using this method. We use a two-round panel data on two welfare indicators: household consumption and investmentrisk-taking behaviour. We measure household consumption in terms of per capita weekly food consumption, annual non-food and total consumption expenditures.Similarly, we measure investment risk-taking behaviour of the households in terms of theirinvestment in high-risk high-return inputs including investment in chemical fertilizer, improved seed variety and pesticides/herbicides. First, we estimate the impact of participation at the extensive margin of IBI adoption using the difference-in-difference method. Then, we estimate the impacts of the intensity of IBI adoption at the intensive margin using a flexible specification that takes adoption cycles or years into account. Both ways show that adoption of IBI has significant welfare improvement effects in terms of increased consumption and investment in high-risk high-return agricultural inputs at household level. The impact of IBI adoption on consumption and investment in high-risk high-return inputs also increases with the frequency of IBI adoption.

The remaining sections of this chapter are organized as follows. Section 2 presents review studies on the impacts of IBI adoption. Section 3 details the study context, IBI implementation in the study area and the design of the survey. Section 4 explains the impact identification strategy employed. Section 5 presents the results. Section 6 concludes the chapter.

2. Review of micro-insurance impact studies

Barnett et al. (2008) explain that the economic returns to adoption of IBIs are potentially broad and substantial, ranging from inducing households to make more prudential investments, providing better management for consumption risk, crowding-in finance for ancillary investment and enhancing local adaptation to climate change. Corroborating this, various studies show that where effectively implemented, IBIs have welfare improvement impacts. For instance, Karlan et al. (2014) identified that lack of access to insurance is the limiting factor to investment for maize farmers in Ghana. The study revealed that smallholders who purchased IBI have a 13% more investment in agricultural inputs than others. Fuchs and Wolff (2011) assessed the impact of insurance against catastrophic drought on corn yields, area cultivated in corn, and per capita income and expenditures of smallholders in Mexico. Results indicate that where coverage is available corn yield was increased by 8%, with gains in income and expenditures. These evidences indicate that adoption of insurance induces ex-ante risk management responses. Mobarak and Rosenzweig (2013) used a randomized experiment where IBI is offered to Indian cultivators, finding that IBI helps cultivators reduce self-insurance and switch to riskier, higher-yield production techniques. Similarly, in Cai et al. (2015) it was found that insurance for sows significantly increased farmers' tendency to raise sows in south-western China, where sow production is a risky production activity with potentially large returns. In another experiment, Cai (2016) demonstrates that weather insurance induces tobacco farmers in China to increase the land devoted to this risky crop by 20%. This finding implies reduced diversification among tobacco farmers, consistent with less self-insurance. Using an experimental game method, Vargas-Hill and Viceisza (2013) indicated that insurance induces farmers in rural Ethiopia to take greater, yet profitable risks, by increasing (theoretical) purchase of chemical fertilizer. An important inference from all these evidences is that adoption of IBI can enhance prudential investment risk-taking behaviour among farm households in developing counties.

IBIs were also evidenced to have impacts on ex-post shock coping. In an experimental game conducted in China, Cheng (2014) studies the effect of offering IBI to risk-rationed households. The study reports that more than half of the risk-rationed farmers decided to apply for credit when IBI is available to them. Similarly, Giné and Yang (2009) studied an intervention where maize farmers in Malawi were offered with a choice between a loan and a loan plus insurance. The study found, however, that demand for the basic loan was 13% higher than that for the insured loan. In Carter et al. (2016), it was argued that a stand-alone insurance product does not provide additional benefits to farmers who have low collateral. The reason is that, if no formal insurance is available, only farmers with high collateral may choose not to borrow, because they do not want to put their collateral at risk. Cai (2016) also finds that insurance causes households to decrease savings by more than 30%, pointing that households were building up extra precautionary savings in order to better smooth consumption in the case of a shock. Belissa et al. (2019) examined the impact of IBI on credit rationing in Ethiopia, and found that insurance coverage is positively related to credit use. The study then goes on to examine if the change is associated with reduced demand side or supply-side rationing, finding that the changes are due to differences in supply-side credit rationing.

Adoptions of IBIs were also evidenced to reinforce the functioning of the extant social insurance mechanisms. Mobarak and Rosenzweig (2014) show that, in rural India, the existence of informal risk-sharing networks among members of a sub-caste increases demand for IBI when informal risk-sharing covers idiosyncratic losses. Belissa et al. (2019) examined whether uptake of IBI can be enhanced by postponing the premium payment towards shortly after harvest, and by marketing the product through the extant social insurance institutions known as *Iddirs* in Ethiopia. The study found that coaxing the market-based IBI with the predominant social insurance increases uptake, as compared with selling such insurance through conventional statutory channels like state-owned cooperatives. On the other hand, Fuchs and Rodriguez-Chamussy (2011) analysed the impact of insurance payouts on voter behaviour in the 2006 presidential election in Mexico. Using a regression discontinuity design with electoral section as a unit of analysis, the study questions whether insurance payouts received by farmers in the electoral section in 2005 have affected voting behaviour in favour of the incumbent political party in the subsequent 2006 election. The study finds that disaster relief buys votes. The incumbent party is estimated to have gained 8% more votes where payouts had been made prior to the election.

However, though insurance is usually targeted to smooth consumption or enhance risk-taking behaviour (Townsend et al. 1994:1995), evidences in this regard are limited. Janzen and Carter (2013) explained that access to an index-based livestock insurance (IBLI) in northern Kenya helped pastoral households to smooth their asset and consumption that constitute the two key dimensions of self-insurance. The study revealed that after the intervention, poor pastoral households are less likely to destabilize their consumption in response to drought, while those who are better off are less likely to have to compromise their accumulated assets. Insured households are observed to be less dependent on food aid and other forms of assistance, which indicates their better ability to cope with shocks. The impact of the IBLI intervention was also selective based on wealth position of the pastoral households. Studies also show that adoption of IBI enhances households' access to other financial markets. The current study provides evidences on the impact of repeated adoption of index insurance for crops on household welfare from the perspectives of consumption and production (i.e., risking taking from investment in high-risk high-return production inputs).

3. Study context, IBI intervention, survey design and data

3.1. Context

This study is undertaken in the central Rift Valley zone of the Oromia regional state in south-eastern Ethiopia. The Rift Valley zone is a semi-arid plain plateau area with a low-land agro-ecology. The pattern and intensity of rainfall exhibits considerable spatial and temporal variation, with a bimodal type of distribution. The area receives very low level of annual average rainfall. Rainfall seasons are from May to August and during October and November. Moisture stress and drought frequently causes devastating crop failure, rampant livestock mortality and herd collapse. Major droughts in the area include the 2015-16 drought which followed the historical trend of droughts during 1973-74, 1983-84, 1991-92, 1999-2000, 2005-06 and 2011-12 (Dercon 2004). Households in the area are smallholder subsistence farmers who mainly produce maize and wheat. They often face drought-induced income shocks that translate into erratic consumption patterns. Their ex-post shock coping mechanisms include reducing frequency of meals per day, distress livestock sells, reducing farm investment on chemical fertilizer and improved seed varieties, forcing pupils to withdraw from school for casual labour, renting land and family labour for local landlords and wage employment on floriculture farms of foreign investors. Future drought shock predictions in Ethiopia are pessimistic with expected rise in temperature from 23.08 to 26.92℃ (Hulme et al. 2001; Meze-Hausken 2009). As a result, the wide crop-livestock mixed farming system in arid and semi-arid areas like the Rift Valley zone were projected to transform into extensive systems to respond to the risks of climate change (Meinke and Stone 2005; Thornton et al. 2010). Hence, innovative drought risk management mechanisms like adoption of drought insurances were highly required for farm households in the area. A large proportion of the smallholders in the study area have no access to formal financial service. They also do not have access to non-traditionalrisk coping mechanisms[1].

[1]However, the functioning of indigenous social institutions is actively remarkable. Burial societies (*Iddirs*) provide social insurance services when households lose their bread winners like death of household heads or draft oxen.

3.2. IBI in the study area

To improve the resilience of households in the face of climate change, Japan International Cooperation Agency (JICA) and Oromia Insurance Company (OIC) jointly initiated the implementation of IBI for crops in the Rift Valley zone of Ethiopia in 2013. The IBI scheme was implemented in five districts including Boset, Bora, Ilfata, Adamitullu-Jido-Kombolcha (AJK) and Arsi Negele. Before the initial intervention in 2013, OIC and JICA that provides the financial support and Ethiopian Ministry of Agriculture that provides the technical support for the intervention have discussed and identified districts in which drought shocks are common in Ethiopia. Most of these districts are located in the Rift Valley zone. The partners then held a focus group discussion (FGD) with selective representative farmers from each *kebele* within each of the selected districts. Based on this discussion, many *kebeles* which have severe drought experience in the past were identified. However, then, it was found that the financial support that JICA allotted for the 2013 weather index insurance intervention was not adequate to cover all the identified drought-prone *kebeles*. Therefore, the partners randomly considered some *kebeles* for the first intervention in 2013 and rank-filed the remaining *kebeles* to be considered in subsequent interventions. IBI is often marketed and sold twice per year during April and during September, months preceding the two rainy seasons, to provide coverage against losses during the seedling and flowering stages of crop growth, respectively. Major targeted stable food crops to be insured include maize, wheat, barley and teff. However, payout is not crop-specific. OIC currently uses vegetation index crop insurance (VICI). VICI is a modified product with better quality, 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). In VICI design, NDVI is extracted at a geospatial resolution of 1km^2. 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[2].

[2] 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.In order to deal with transaction costs, it divides the geographical coverage into CPS zones. NDVI is computed for each zone at grids of 1km^2. Payout is calculated for a decal or

3.3. Survey design and data

Data used in this study were collected from smallholders in the Rift Valley zone in south-eastern Ethiopian. A two-round survey conducted with two-year intervals during 2015 and 2017 were considered in this study. Recruitment of the sample households was worked out as follows. First, we selected three districts, namely Bora, AJK and Arsi Negele, out of the five districts where OIC implemented IBI. Second, we identified a random sample of *kebeles* within the three districts, including those *kebeles* covered by IBI as well as those that OIC did not cover. Finally, sample households were randomly drawn from all these selected *kebeles*.

In the first round of survey that we conducted during January-April 2015, data were collected from a total of 1143 households, out of which 461 were adopters and 682 were non-adopters of IBIs. However, during the second round survey, we observed that adoption status was changed since some new households joined and others dropped out the adoption. We excluded these two sets of households from our analysis. Hence, we used a balanced dataset of only 149 persistent adopters and 543 never-adopters. This enables us to identify the impact of sustained uptake of IBI over the period 2015−2017. Information on household, village and IBI intervention characteristics as well as investment in agricultural inputs, consumption, use of financial services as well as village infrastructure and access to markets were collected. In addition, we collected data on uptake, the number of years of adoptionper household and payout from OIC.

The impact of IBI adoption was measured for two welfare indicators: household consumption and investment in high-risk high-return inputs. Both set of variables are continuous in nature. Household consumption is an aggregate of selected food and non-food consumption. Food items consumed both from own sources and from purchases over a period of one week were included[3].

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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 1 km^2 grid (location) specific.

[3]Food items include food grains, fruits, vegetables, milk and milk products, beef, meat and meat products, cooking oil, salt, and coffee, tea, and other leisure drinks. Non-food items include clothing and footwear, gas and fuel, schooling, health, family events, and household durables. Note that the recall period for estimating food items consumed was 7 days, and for non-food items like cloths was a year.

4. Identification strategy

We analyze the effects of sustained uptake of IBI on household welfare using the difference-in-difference method in two different ways. First, we measure the effect of adoption at the extensive margin as follows:

$$\mathrm{W_{hkjt}} = \beta_0 + \beta_1 \mathrm{IBI_h} + \beta_2 \mathrm{Post_t} + \beta_3 (\mathrm{IBI} * \mathrm{Post})_{\mathrm{ht}} + \beta_4 \mathrm{R_k} + \beta_5 \mathrm{X_h} + \beta_6 \mathrm{Strata_j} + \varepsilon_{\mathrm{hkjt}} \quad (1)$$

where W_{hkjt} is the welfare outcome of interest for household h in region k and district j at time$t$; IBI_h is an indicator for sustained uptake of IBI that equals '1' if household h is an adopter of IBI in both 2015 and 2017 but equals '0' if the household is non-adopter; $Post_t$ is an indicator that equals '1' if the observation is in 2017 and equals '0' if the observation is in 2015; R_k is an indicator that equals '1' if the household is in the initial adoption region and '0' if the household is in the expansion (subsequent phase adoption) region; X_h is a vector of covariates including households' demographic characteristics, assets and access to services as described in Appendix I; $Strata_j$ represents the three districts (one of which is excluded from the regression); and ε_{hkjt} is the error term.Second, following Berhane and Gardebroek (2011), we measure the effect of intensity of adoption of IBI at the intensive margin as follows:

$$\mathrm{W_{hkjt}} = \beta_0 + \beta_1 \mathrm{P_1} + \beta_2 \mathrm{P_2} + \beta_3 \mathrm{P_3} + \beta_4 \mathrm{P_4} + \beta_5 \mathrm{R_k} + \beta_6 \mathrm{X_h} + \beta_7 \mathrm{Strata_j} + \varepsilon_{\mathrm{hkjt}} \quad (2)$$

where $P_1 \dots P_4$ are dummies indicating one-year, two-years, three-years and four-years adoption of IBI respectively, and the other variables are as defined in eq. 1). Hence, in eq. (2), intensities of IBI adoption are represented by dummy variables for each of the number of years that the households were stayed in adoption phase.

5. Results

5.1. Characteristics of the sample households

Summary statistics on the characteristics of IBI-adopter and non-adopter households is presented in Table 5.1. IBI-adopter and non-adopter households had statistically insignificant differences in terms of their various demographic characteristics including age, gender of the household head and dependency ratio.However, compared to non-adopters, IBI-adopters were more educated and had larger family size. In terms of production assets, IBI-adopters had larger land and livestock sizes compared to non-adopter households.

Table 5.1: Summary statistics of IBI adopter and non-adopter households

Variables	Full sample		Adopters		Non-adopters		Difference in means		p-value
	Mean	SD	Mean	SD	Mean	SD	Mean	SD[a]	
Age	38.97	12.84	39.56	10.29	38.81	13.45	−0.75	0.84	0.37
Gender	0.83	0.37	0.86	0.34	0.82	0.38	−0.04	0.02	0.14
Education (years)	2.33	1.17	2.62	1.15	2.25	1.16	−0.37	0.08	0.00
Family size	6.66	2.69	7.45	3.06	6.45	2.54	−1.01	0.17	0.00
Dependency ratio	0.50	0.20	0.48	0.19	0.50	0.21	0.01	0.01	0.26
Land size in *qarxi*	8.29	8.59	10.12	14.07	7.79	6.21	−2.34	0.56	0.00
Livestock size (TLU)	9.08	7.80	10.93	10.51	8.58	6.79	−2.35	0.51	0.00
Distance from market	1.69	0.99	1.87	1.10	1.64	0.95	−0.23	0.06	0.00
Extension contact	0.95	0.23	1.00	0.06	0.93	0.25	−0.06	0.01	0.00
Investment in fertilizer	1900.99	2424.94	3067.56	3187.98	1580.88	2058.42	−1486.68	153.51	0.00
Investment in improved seed	1542.15	3360.66	3104.9	5814.00	1113.32	2070.83	−1991.58	213.22	0.00
Investment in pesticides	226.00	1262.76	555.27	2586.66	135.65	403.81	−419.61	81.83	0.00
Total investment in high-risk high-return inputs	3669.14	4983.07	6727.72	8044.12	2829.86	3265.57	−3897.86	308.66	0.00
Per capita food consumption expenditure	88.05	178.25	109.76	166.13	82.09	181.05	−27.67	11.64	0.02
Per capita non-food consumption expenditure	1896.43	4000.30	2445.65	5537.43	1745.72	3449.41	−699.93	261.02	0.01
Per capita total consumption expenditure	6088.49	10556.83	7856.27	10840.61	5603.41	10430.41	−2252.85	687.95	0.00

[a] $SD_{differenceinmeans} = \sqrt{\frac{SD_1^2}{N_1} + \frac{SD_2^2}{N_2}}$

Our descriptive statistic results also show that IBI-adopters travel more distance to access markets and, also make more frequent contact with extension agents as compared with non-adopter households.Table 5.1 also shows that IBI-adopter and non-adopter households have significant differences in terms of the outcome variables. Compared to non-adopters, IBI-adopters have made much more investment in total high-risk high-return agricultural inputs. On disaggregated terms, adopters have made much more investment in chemical fertilizer, improved seed varieties and pesticide/herbicides as compared with non-adopters. Similarly, there are statistically significant differences between IBI-adopter and non-adopter households in their per capita consumption. As shown in Table 5.1, on average, IBI-adopters have higher per capita weekly food consumption and higher per capita total annual consumption than IBI non-adopters. The difference in per capita non-food consumption between IBI-adopters and non-adopters is also statistically significant, showing that adopters have higher levels of consumption than non-adopters.

In general, Table 5.1 reveals that IBI-adopter and non-adopter households were observed to have statistically meaningful differences in some characteristics as well as outcome variables. These differences in characteristics between the two groups necessitate controlling for these variables in our subsequent impact estimate regressions. Similarly, the observed differences in outcome variables provide us with indications about the impacts. However, this measure of differences did not take into account the role of other covariates. As such these results are not adequate to causally infer the impact of IBI adoption on the welfare of adopter households. Hence, more rigorous estimates that take the role of other covariates into account were provided and discussed in the subsequent sections.

5.2. Effects of participation in IBI adoption on household welfare

Table 5.2 presents the impact of IBI adoption on household production behaviour. Estimated results were reported for value of high-risk high-return inputs, chemical fertilizer, improved seed variety and herbicide/pesticide, with and without controlling for potential covariates. Since we are primarily interested to measure the welfare impact of IBI adoption, we include only household observables that may systematically correlate with selection. Moreover, since time-invariant characteristics are removed by the within transformation, only time-varying variables were included in our estimation procedure. Demographic characteristics including age, gender and level of education of the household head as well as family size and dependency ratio are considered.

Table 5.2: Impacts of IBI adoption on household production behaviour (difference-in-difference) estimates

Variables	(1) Total value of high-risk high-return inputs	(2) Total value of high-risk high-return inputs	(3) Value of fertilizers used	(4) Value of fertilizers used	(5) Value of improved seed	(6) Value of improved seed	(7) Value of pesticides used	(8) Value of pesticides used
Uptake of IBI	1,625.34***	968.72	1,142.66***	753.73**	190.90	-48.58	291.78	263.57
	(592.29)	(590.28)	(338.53)	(305.66)	(147.57)	(178.53)	(284.00)	(294.78)
Post	1,216.21***	1,194.02***	119.10	98.48	1,046.43***	1,048.38***	50.68**	47.16**
	(207.30)	(215.74)	(134.73)	(138.88)	(138.78)	(142.99)	(22.13)	(23.31)
IBI*Post	4,545.06***	4,566.57***	688.03*	707.14*	3,601.35***	3,605.20***	255.68	254.23
	(661.50)	(667.04)	(380.56)	(382.76)	(636.76)	(640.93)	(296.18)	(300.49)
Region		107.85		173.46		-73.38		7.77
		(235.73)		(174.18)		(150.45)		(49.93)
Age		9.64		8.09		-0.40		1.94
		(12.40)		(5.53)		(10.00)		(1.70)
Sex		-97.56		-243.71		218.05		-71.91*
		(239.21)		(159.84)		(149.55)		(42.42)
Education		520.52***		343.78***		118.06*		58.68
		(125.33)		(76.81)		(60.97)		(46.13)
Family size		129.25*		37.02		84.96		7.27
		(74.59)		(31.90)		(67.44)		(12.93)
Dependency ratio		542.49		85.59		315.88		141.02
		(584.36)		(283.49)		(432.45)		(139.76)
Land size		42.93**		34.75***		11.15		-2.97
		(17.48)		(8.20)		(9.61)		(4.80)
TLU		82.07***		52.32***		30.98***		-1.23
		(17.81)		(11.23)		(10.90)		(3.95)
Distance from market		-126.15		-88.34		-13.54		-24.26
		(113.59)		(68.14)		(67.64)		(19.88)
Extension contact		-256.98		-255.36		-26.71		25.09
		(504.10)		(361.00)		(222.10)		(46.50)
District1		704.98		1,081.79***		-647.29**		270.48
		(435.70)		(264.00)		(320.27)		(275.18)
District2		-150.91		279.73*		-388.53		-42.11
		(390.44)		(142.24)		(353.73)		(55.42)
Constant	2,221.75***	-1,029.53	1,521.33***	-484.10	590.11***	-414.03	110.31***	-131.41
	(135.28)	(1,000.37)	(108.38)	(600.32)	(65.66)	(668.21)	(16.29)	(241.53)
Observations	1,384	1,384	1,384	1,384	1,384	1,384	1,384	1,384
R-squared	0.19	0.23	0.07	0.16	0.18	0.20	0.02	0.03

Note: *** p<0.01, ** p<0.05, * p<0.1 Robust standards errors, clustered at *Iddir* level are in brackets. Estimations follow OLS regressions based on eq. (5.1).

Land size and size of the livestock owned by the household were also controlled for, since these productive assets may also affect the level of the outcome indicators. In anticipation that OIC might have targeted accessible villages in terms of infrastructure, we included proxies, distance from the market and frequency of extension contact, as two sets of controls. Moreover, we controlled for spatial variations by including district dummies in the regressions.The full estimate results based on the difference-in-difference show that adoption of IBI has a significant positive effect on household investment in high-risk high-return agricultural inputs for adopters as compared with non-adopters. After controlling for potential selection on unobservables, household investment in high-risk high-return agricultural inputs has increased by ETB 4,567 for IBI-adopters, compared to non-adopters (see Column 2 in Table 5.2). Disaggregating these results, Table 5.2 indicates adoption of IBI have statistically significant impact on increasing investment in improved seed variety, but not on investment in chemical fertilizer and pesticide/herbicide. With the full estimate including all covariates, uptake of IBI increases investment in improved seed varieties by ETB 3,605. The results are statistically significant at 1 percent level. Note that the double-differencing estimation procedure reduces the risk of selection bias.

Two causal mechanisms can be proposed. First, household can pursue intensification with increased investment on insured farms with the expectation that increase in productivity provides for a higher return. Second, households can increase their investment in inputs as they expect that payout from the insurance firm can well commensurate their investment. Table 5.2 also shows that certain control variables, namely education of the household, land size and number of livestock owned by the household have statistically significant positive effect on investment in high-risk high-return inputs.

Table 5.3 presents the results of double difference estimates of the impact of IBI adoption on household food, non-food and total consumption, with and without controlling for potential covariates. The full estimate with covariates indicates that adoption of IBI increases household per capita weekly food consumption expenditure by ETB 48 (see Column 2 in Table 5.3). Similarly, per capita annual consumption is increased by ETB 3,006 for IBI-adopters than non-adopters (see Table 5.3 under Column 6 for the details).

Table 5.3 also shows that consistent with theory, our estimation also shows household consumption decreases with increase in dependency ratio and family size, and consumption increases with household assets like increase in number of livestock owned.

Table 5.3: Impacts of IBI adoption on household consumption (difference-in-difference estimates)

Variables	(1) Per capita food consumption expenditure	(2) Per capita food consumption expenditure	(3) Per capita non-food consumption expenditure	(4) Per capita non-food consumption expenditure	(5) Per capita total consumption expenditure	(6) Per capita total consumption expenditure
Uptake of IBI	3.69	1.36	602.83*	605.46*	757.92*	626.43
	(2.80)	(5.31)	(314.22)	(358.62)	(447.12)	(577.18)
Post	87.30***	88.00***	794.86***	822.29***	4,254.87***	4,317.88***
	(12.25)	(12.76)	(181.65)	(184.92)	(691.05)	(713.09)
IBI*Post	47.95**	48.28**	194.19	197.97	2,989.86**	3,006.83**
	(22.09)	(22.42)	(538.15)	(538.57)	(1,241.46)	(1,255.42)
Region		23.82		457.47*		1,510.19*
		(14.86)		(258.71)		(841.72)
Age		-0.55*		-18.49		-40.86**
		(0.32)		(11.17)		(20.16)
Sex		6.77		84.42		598.32
		(17.05)		(303.58)		(961.95)
Education		2.36		328.92**		363.62
		(3.83)		(135.07)		(239.86)
Family size		-11.13***		-291.01***		-814.24***
		(1.36)		(37.41)		(91.69)
Dependency ratio		-93.40**		-2,891.37***		-7,246.75***
		(37.47)		(795.03)		(2,250.66)
Land size		-0.13		-11.73		-8.42
		(0.35)		(8.15)		(21.94)
TLU		1.01**		29.16**		92.02**
		(0.49)		(14.34)		(36.81)
Distance from market		1.47		30.15		88.28
		(3.77)		(138.69)		(252.42)
Extension contact		-15.10		-394.72		-700.08
		(23.91)		(480.11)		(1,251.45)
District1		21.43		1,393.29***		1,878.41**
		(14.06)		(429.42)		(862.40)
District2		-6.02		604.42**		311.33
		(12.74)		(256.08)		(744.78)
Constant	38.44***	155.45***	1,348.29***	3,744.05***	3,475.98***	10,815.80***
	(1.42)	(29.50)	(76.22)	(978.22)	(215.95)	(2,063.67)
Observations	1,384	1,384	1,384	1,384	1,384	1,384
R-squared	0.08	0.16	0.02	0.15	0.06	0.19

Note: *** p<0.01, ** p<0.05, * p<0.1 Robust standards errors, clustered at *Iddir* level are in brackets. Estimations follow OLS regressions based on eq. (5.1).

5.3. Effects of intensity of IBI uptake on household welfare

An important follow-up question is that we address in this section is the extent to which the impact of IBI adoption varies with the intensity and frequency of repeated adoptions. Instead of mere participation in IBI adoption, in this case, indicators were assigned, for the number of years that each household has been involved in IBI adoption phase. Table 5.4 provides the estimated results of this model for the first category of outcome indicators related to investment in high-risk high-return inputs. Again note that the double-differencing estimation procedure reduces the risk of selection bias. Results in Table 5.4 show once again that IBI adoption has a significant impact on household investment in high-risk high-return agricultural inputs. Interestingly, Table 5.4 shows that the magnitude of the impact of IBI adoption increases with increase in frequency (years) of adoption.

Controlling for all covariates, adoption of IBI for two years have increased total investment in high-risk high-return agricultural inputs by ETB 2248 (See Column 2 in Table 5.4). Further, three- and four-years of adoption of IBI have increased total investment in high-risk high-return inputs by ETB 5,562 and ETB 4,746 (both with $p = 0.00$). Table 5.4 also show that for individual input components, two-, three- and four-yearsof adoption of IBI increase investment in chemical fertilizers by ETB 852, ETB 1643 and ETB 1597, respectively. These results are statistically significant at 1% level controlling for all covariates (See Column 4 in Table 5.4). Similarly, controlling for all covariates, two-, three- and four-yearsof adoption of IBI were observed to increase the respective investment in improved seed variety by ETB 1,296, ETB 2,757 and ETB 2,653, and the investment in pesticide/herbicide by ETB 100, ETB 1162 and ETB 495, respectively.

Next, the impact of repeated IBI adoption on per capita consumption is presented in Table 5.5. Overall results reveal that the impact of IBI adoption on household per capita food and total consumption increases with the number of years of adoption. Three- and four-years of adoption were indicated to increase household per capita weekly food consumption expenditure by ETB 73 and 52, respectively. Three-years of adoption was also indicated to increase per capita total consumption expenditure by ETB 4080. As their income increases, households may spend more on basic consumption items (e.g., food) at first, followed by investment in high-risk high-return inputs (e.g., purchase of chemical fertilizer, improved seed varieties and use of pesticide/herbicides). And, then, households may invest in other consumption items (e.g., health, education or clothing).

Table 5.4: The impact of intensity of IBI adoption on household production behaviour (difference-in-difference estimates)

Variables	(1) Total value of high-risk high-return inputs	(2) Total value of high-risk high-return inputs	(3) Value of fertilizers used	(4) Value of fertilizers used	(5) Value of improved seed	(6) Value of improved seed	(7) Value of pesticides used	(8) Value of pesticides used
Two-years adoption	2,684.45***	2,247.66***	1,009.46***	851.91***	1,574.55***	1,296.25**	100.43***	99.50***
	(570.20)	(576.57)	(215.51)	(198.14)	(501.92)	(501.66)	(30.34)	(32.31)
Three-years adoption	6,014.70***	5,561.76***	1,985.18***	1,642.89***	2,842.10***	2,756.59***	1,187.43*	1,162.28**
	(1,135.43)	(1,068.79)	(417.34)	(340.28)	(486.31)	(499.20)	(601.01)	(567.05)
Four-years adoption	5,353.53***	4,745.78***	2,031.89***	1,596.95**	2,900.51**	2,653.42***	421.14***	495.42***
	(1,108.31)	(1,077.15)	(609.82)	(652.40)	(1,124.40)	(998.81)	(114.14)	(139.20)
Region	480.97**	74.68	422.67***	168.05	-27.18	-103.93	85.48***	10.56
	(212.89)	(225.95)	(157.90)	(169.99)	(128.90)	(143.94)	(20.07)	(47.42)
Age		20.38*		9.46*		8.50		2.42
		(11.30)		(5.53)		(9.29)		(1.48)
Sex		-76.97		-227.34		202.74		-52.37
		(237.55)		(163.03)		(145.53)		(35.07)
Education (years)		589.40***		354.52***		170.92***		63.96
		(112.88)		(74.00)		(58.53)		(43.18)
Family size		94.75		30.59		63.23		0.93
		(70.44)		(31.75)		(64.31)		(11.62)
Dependency ratio		681.82		101.69		444.14		135.98
		(542.55)		(289.28)		(399.16)		(118.80)
Land size		41.94**		34.90***		9.44		-2.40
		(17.75)		(8.20)		(9.63)		(4.54)
TLU		76.23***		50.54***		27.64**		-1.95
		(19.00)		(11.84)		(11.38)		(3.87)
Distance from the market		-151.38		-94.96		-25.47		-30.95
		(108.81)		(68.12)		(64.27)		(20.28)
Extension contact		-414.28		-273.43		-159.64		18.80
		(490.15)		(355.06)		(217.33)		(38.41)
District1		302.93		983.28***		-822.36***		142.01
		(406.89)		(272.48)		(274.01)		(207.69)
District2		-414.92		214.88		-524.61*		-105.19**
		(351.45)		(138.97)		(309.67)		(49.07)
Constant	2,518.07***	-344.30	1,306.89***	-383.69	1,130.95***	65.87	80.24***	-26.49
	(167.99)	(943.90)	(107.31)	(582.73)	(102.57)	(639.59)	(14.50)	(192.65)
Observations	1,384	1,384	1,384	1,384	1,384	1,384	1,384	1,384
R-squared	0.12	0.17	0.08	0.16	0.07	0.09	0.05	0.05

Note: *** p<0.01, ** p<0.05, * p<0.1 Robust standards errors, clustered at *Iddir* level are in brackets. Estimations follow OLS regressions based on eq. (2).

Table 5.5:The impact of intensity of IBI adoption on household per capita consumption (difference-in-difference estimates)

Variables	(1) Per capita weekly food consumption expenditure	(2) Per capita weekly food consumption expenditure	(3) Per capita non-food consumption expenditure	(4) Per capita non-food consumption expenditure	(5) Per capita total consumption expenditure	(6) Per capita total consumption expenditure
Two-years adoption	-7.52	6.35	344.08	709.31	159.68	1,078.49
	(13.75)	(11.70)	(538.17)	(546.54)	(974.34)	(883.74)
Three-years adoption	52.02	72.75**	-125.82	309.69	2,662.60	4,079.79**
	(31.65)	(30.04)	(343.41)	(330.25)	(1,736.97)	(1,632.62)
Four-years adoption	39.34	52.17**	1,665.21	1,837.99	4,707.73	5,289.44*
	(32.50)	(24.38)	(1,892.54)	(1,682.33)	(3,379.24)	(2,744.59)
Region	47.20***	22.39	977.05***	429.27	3,040.52***	1,414.87*
	(9.93)	(14.88)	(165.14)	(261.75)	(576.22)	(844.40)
Age		-0.08		-13.85		-16.14
		(0.30)		(10.78)		(18.63)
Sex		5.21		67.58		546.16
		(16.74)		(300.02)		(941.90)
Education (years)		5.05		356.11**		509.76**
		(3.77)		(137.50)		(238.23)
Family size		-12.28***		-297.35***		-872.66***
		(1.36)		(37.90)		(88.80)
Dependency ratio		-85.97**		-2,793.35***		-6,832.89***
		(36.10)		(770.86)		(2,169.34)
Land size		-0.19		-12.84		-11.90
		(0.30)		(8.50)		(19.64)
TLU		0.90*		25.87		81.20**
		(0.51)		(16.12)		(39.66)
Distance from the market		0.98		27.98		58.43
		(3.81)		(145.18)		(260.76)
Extension contact		-24.20		-487.27		-1,168.34
		(23.85)		(481.02)		(1,250.64)
District1		13.36		1,430.96***		1,495.78*
		(13.65)		(468.35)		(857.42)
District2		-11.99		570.21**		-41.07
		(12.57)		(278.18)		(748.17)
Constant	51.49***	197.31***	1,112.35***	4,080.90***	3,632.39***	12,879.73***
	(3.59)	(30.60)	(77.35)	(1,012.38)	(225.87)	(2,091.72)
Observations	1,384	1,384	1,384	1,384	1,384	1,384
R-squared	0.02	0.09	0.02	0.14	0.03	0.13

Note: *** p<0.01, ** p<0.05, * p<0.1 Robust standards errors, clustered at *Iddir* level are in brackets. Estimations follow OLS regressions based on eq. (2).

Hence, it is likely that the cumulative effect of repeated adoption of IBI on household welfare is in line with the usual spending patterns of households as their income increases.

6. Conclusion

This study evaluates the impact of IBI adoption on two categories of welfare indicators: household consumption and investment in high-risk high-return inputs. The study used a two-round panel data collected from smallholders in the Rift Valley zone of south-eastern Ethiopia. IBI adoption in the area has lasted four years before this study, so that lasting welfare effects can be established. Self-selection and program placement biases often complicate causal attributions of welfare improvements to rural interventions. The study employs difference-in-difference techniques to reduce selections based on time-invariant unobservables. The results indicate that adoption of IBI has significantly increased both investment in high-risk high-return inputs and per capita household consumption expenditure, which are important indicators of welfare in the study area. A flexible specification of the double difference estimator that takes the frequency of adoption into account has also shown that investment in high-risk high-return inputs as well as per capita household consumption were increased with the frequency of IBI adoption. Repeated cycles of adoption, however, do matter to achieve significant welfare impacts from IBI adoption. Both methods strongly suggest that adoption of IBI in this specific Rift Valley zone of east Africa has been useful in terms of the measured household welfare outcomes. These findings have a number of implications. First, they show that the effect of IBI adoption on household welfare can be multidimensional and may not be fully captured by just a single household welfare outcome indicator. Second, the results also indicate that it takes time before the effect of IBI adoption on consumption or investment in high-risk high-return inputs is fully materialized. Therefore, impact estimates that rely on a single household welfare indicator and focus only on one cycle or year of IBI adoption may underestimate the potential welfare gains that can be achieved overtime. Future research should focus on larger longitudinal database with increase in both the number of years and units of observations. Finally, an important implication of these results for microinsurance firms like OIC is that IBI-adopter households should be encouraged not only to participate in adoption once, but also to sustain their uptake by renewing the IBI policy, and by remaining for longer periods in adoption phase in order to realize the full potentials in welfare gains.

Appendix I: Variable type and definition

Variables	**Variable type and definition**
Age	Continuous, age of the household head in years
Gender	Dummy, gender of the household head, 1= male headed 0 = female headed
Education (years)	Continuous, household head's level of education in years of schooling
Family size	Continuous, number of household members in the family
Dependency ratio	Continuous, ratio of dependents[1] in a family to family size
Land size in *qarxi*	Continuous, household's land holding, measured in a local unit called qarxi, where 1 qarxi = 0.25 hectares
Livestock size (*TLU*)	Continuous, number of livestock owned by a household measured in standard tropical livestock units (TLU)[2]
Distance from market	Continuous, distance from household's residence to market measured in walking hours
Extension contact	Dummy, equal to 1 for households that frequently make contact with extension agents; 0 for others
Investment in fertilizer	Continuous, value of household's investment in fertilizer in ETB
Investment in improved seed	Continuous, value of household's investment in improved seed varieties in ETB
Investment in pesticides/herbicides	Continuous, value of household's investment in pesticides/herbicides in ETB
Total investment in high-risk high-return inputs	Continuous, value of household's total investment in high-risk high-return agricultural inputs in ETB
Per capita food consumption expenditure	Continuous, value of household's annual per capita food consumption expenditure in ETB
Per capita non-food consumption expenditure	Continuous, value of household's annual per capita non-food consumption expenditure in ETB
Per capita total consumption expenditure	Continuous, value of household's total annual per capita food consumption expenditure in ETB

[1]Family dependents were counted as household members with age less than 15 years (preschool children) and those with age greater than 65

[2] 1 TLU = 1*cow or ox = 0.75*heifer = 0.34*calf = 1.1*horse = 0.7*donkey = 0.13*adult sheep or goat = 0.013*chicken (Storck and Doppler1991).

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