See It Grow: A randomized evaluation of digital innovations in crop insurance to increase insurance and fertilizer demand in Kenya.

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Abstract

Picture-based insurance (PBI) is an innovation designed to lower basis risk in index-based crop insurance for smallholder farmers by indemnifying insurance claims based on crop damage documented through a stream of pre- and post-damage smartphone pictures. To evaluate its impacts on insurance take-up and fertilizer use, we implemented a cluster randomized controlled trial in seven counties in Kenya. Approximately 190 villages are randomly assigned to a control group, as well as weather index-based insurance (WBI) and picture-based insurance (PBI) treatment arms, where farmers are offered free insurance trials of a standard rainfall insurance product and a similarly priced PBI product, respectively. Subsequently, farmers in these insurance treatment arms can purchase the insurance product of which they received a trial at subsidized premiums, whereas farmers in the control group are offered a standard insurance product at commercial premiums. PBI increases insurance take-up compared to WBI, especially among female farmers and those farming Arid and Semi-Arid Lands (ASALs). Both treatments increase fertilizer use compared to the control group, but this effect is most pronounced in the WBI treatment. The indemnity-based nature of PBI may disincentivize farmers to invest in crop management. We conclude that digital innovations in crop insurance that indemnity insurance claims based on visible crop losses can boost demand and have positive impacts on agricultural technology adoption, but insurance providers introducing such innovations will need to keep monitoring and managing moral hazard concerns.

Keywords: technology adoption, insurance demand, basis risk, impact evaluation, Kenya.

JEL codes: D82, G52, O13, Q12, Q14

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1. Introduction

Farmers in developing countries face a host of climate-related risks that make their incomes volatile, undermine their food security, and hamper investments in agriculture, including the adoption of higher-yielding technologies (Dercon, 2005). Risk poses a threat to livelihoods not only *ex post*, by reducing agricultural output and inducing farmers to sell their assets, keep children out of school or borrow at high rates when shocks occur (Kahan, 2008; Karlan et al. 2014; Cole et al. 2017); but also *ex ante*, even in the absence of a shock, by discouraging farmers from investing in high-return practices and technologies as they anticipate the mere possibility of agricultural income losses (Elbers et al., 2007). Climate change will only increase the frequency at which natural hazards occur (Porter et al., 2014). Innovative solutions are therefore needed to help marginalized farmers prepare for these natural hazards and better manage agricultural risks.

Although agricultural insurance has the potential to transfer some of these risks away from smallholder farmers, protect households' incomes and assets from weather shocks (Janzen and Carter, 2019; Jensen et al. 2017; Hill et al. 2019), improve access to credit, and increase investments in agriculture (Hazell et al. 2010; Farrin and Miranda, 2015; Karlan et al. 2014; Jensen et al. 2017; Hill et al. 2019), insurance supply and demand remains limited across the global south. Classic incentive problems stemming from asymmetric information, such as moral hazard and adverse selection, along with high monitoring and transaction costs, restricts the supply of indemnity-based insurance (Alderman and Haque, 2007; Santos and Barrett, 2011). Index-based insurance, introduced to lower transaction costs and solve problems associated with asymmetric information, grapple with low demand due to high basis risk (discrepancies between actual losses and insurance payouts determined by the index; Clarke, 2016) and other factors, such as product complexity combined with low financial literacy levels, liquidity constraints, and lack of trust (Gine et al. 2008; Casaburi and Willis, 2018; Hill et al. 2016, 2019).

This paper describes a randomized impact evaluation in Kenya of picture-based crop insurance (PBI), an innovative product designed to lower basis risk by indemnifying insurance claims based on visible damage detected from smartphone images of an insured crop (Ceballos et al., 2019). Reducing basis risk could increase demand and strengthen the impacts of agricultural insurance. By providing insurance providers with a stream of pre- and post-damage pictures of insured crops taken from planting to harvest, the product also reduces monitoring costs, addressing potential concerns around classic incentive problems stemming from asymmetric information (Ceballos and Kramer, 2021). Moreover, by being more participatory and easier to explain than index-based insurance, picture-based crop insurance could also improve farmer trust and product understanding, and thereby strengthening the demand for and impacts of insurance, resulting in a more commercially viable insurance solution.

We test these hypotheses using a cluster randomized controlled trial in which 191 villages spread across seven counties in Kenya were randomly assigned to a control group and two insurance treatment arms: one in which standard Weather Index-Based Insurance was marketed (WBI), and one in which farmers were offered PBI. The study included areas with historically arid and semi-arid climates, referred to as Arid and Semi-Arid Land (ASAL) counties, as well as counties with less arid climates, henceforth labeled non-ASAL counties. ASAL counties are among the most exposed to weather, and thus in greater need of financial and non-financial instruments that help farmers cope with weather-related, and especially drought-related, downward income shocks. Even so, insurance coverage rates are not dissimilar to those in less vulnerable areas of the country, and usually hover stubbornly around and below 10% of potential users.

We find that compared to the WBI treatment arm, PBI increased insurance uptake substantially. In particular, the increased appeal was observed in ASAL counties, where insurance uptake increases to around 30% for men and 40% for women, an increase in uptake that has no precedents in other studies aiming at increasing the appeal of insurance among smallholders in Africa—perhaps with the exception of interventions that delayed the payment of the premium until after harvest (Casaburi and Willis, 2018; Belissa et al., 2019). In addition, disaggregating by gender, we find that demand was particularly increased among women. Women tend to have lower financial literacy on average and may have been attracted by a product that is both easier to understand – payouts are based on the assessment of damage in the pictures by a team of experts, instead of demeaned and indexed remote sensing rainfall data – and thus to trust.

Unlike other parts of the world, where fertilizer is sometimes overutilized (e.g., in large portions of South and Eastern Asia), smallholder farmers in Sub-Saharan Africa (SSA) typically underutilize fertilizer. In this sense, fertilizer is an excellent proxy for the chronic underinvestment in farming, likely to be the leading cause for the persistent agricultural yield gap in SSA and associated with uninsured production risks (Karlan et al. 2014). Indeed, our analysis shows that fertilizer use is particularly low in ASAL countries, where those risks are markedly greater. Our study confirms that insurance has an important role to play in increasing the adoption of such farm inputs (e.g. Karlan et al., 2014; Bulte et al., 2020). We find that fertilizer use increases significantly in ASAL counties when either PBI or WBI insurance products are marketed. As expected, this increase in fertilizer use is greater among those who did insure, for which the effect is significant also in non-ASAL counties. This said, among the insured, PBI shows a somewhat muted effect on fertilizer adoption compared to WBI. This could partially be explained by the indemnity-based nature of PBI, re-introducing asymmetric information effects both in terms of adverse selection (the incentive to buy PBI insurance is greater among those who do not use complementary risk-reducing inputs) and moral hazard (as investing in using modern inputs is disincentivized by insurance). However, the risk-reducing effect of PBI still outweighs the asymmetric information effect, resulting in a positive, yet statistically insignificant, effect on fertilizer adoption.

Our study shows that PBI is far from just another small tweak in the domain of crop insurance for smallholders. Instead, it has shown a transformative potential in increasing the appeal of insurance, especially among the most vulnerable, such as farmers in ASAL counties and women farmers. This while being a product that was commercialized by our insurance partner under similar cost structures and marketing strategies to standard WBI. While we cannot rule out that some asymmetric information problems eliminated by WBI do arise again with PBI, their effect on input adoption is more than mitigated by the positive effect of relaxing the downward income risk constraint through a transparent, hands-on, easy to comprehend insurance product.

The remainder of this paper is structured as follows. The next section describes the intervention, study context, experimental design, and empirical strategy in more detail. We then turn to describing our sample and testing for balance between the experimental treatments. This is followed by a presentation of our main results, and in the final section, we conclude.

2. Methods

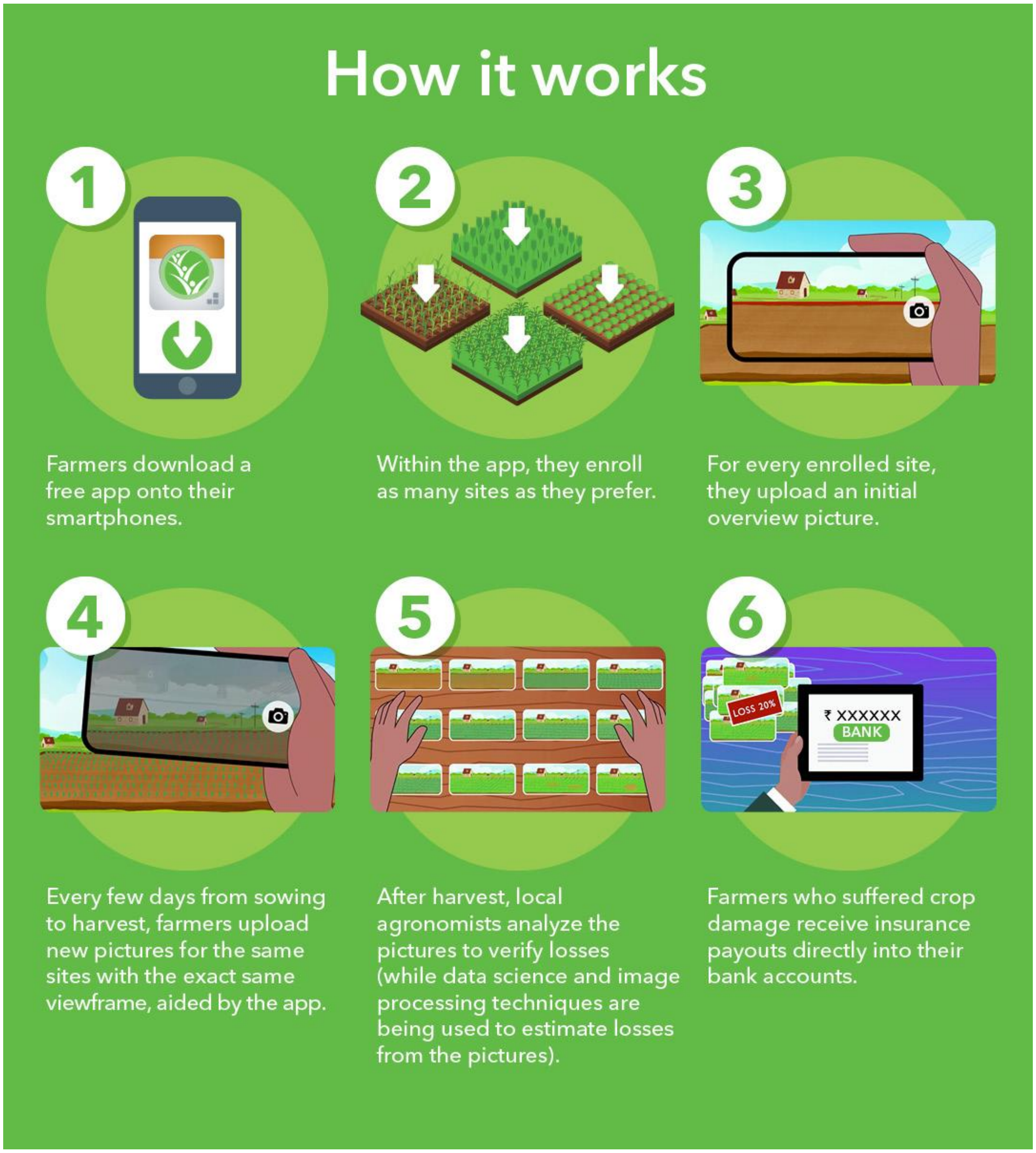
2.1. Intervention: Weather index-based and picture-based insurance

We study an insurance product developed as part of an agricultural research-for-development project that was launched mid-2019 by ACRE Africa—a service provider that works with local insurers and agricultural value chains actors to provide holistic risk management solutions including insurance for smallholder farmers—in collaboration with the Kenya Agriculture and Livestock Research Organization (KALRO), and researchers from the International Food Policy Research Institute (IFPRI) and Wageningen University. The main objective of this project was to develop a scalable approach to improve smallholder farmers' risk management through an innovative picture-based crop insurance (PBI) solution and by promoting drought-tolerant maize varieties and improved varieties of drought-tolerant crops such as sorghum and green gram.

Figure 1 illustrates how the product works. PBI uses pictures of insured crops, taken using a dedicated smartphone application (called SeeItGrow in the case of Kenya) from sowing to harvest, and always of the same portion of the plot to minimize tampering, for claims settlement. Initially, agricultural experts inspect pictures to verify crop damage, but over time, one can use deep learning to automate image processing, making the solution more scalable. The main benefit of using pictures is that it pays farmers in case of visible damage to their crops, which makes the product easier to understand, and can help reduce the basis risk—or inadequate correlation between insurance payouts and actual crop losses—that has plagued more common weather index insurance products (Clarke, 2016).

A formative evaluation in India demonstrated the feasibility of this approach and shows that severe damage can indeed be detected from smartphone images of crops (Ceballos et al., 2019). However, compared to index-based insurance, PBI coverage may reduce incentives to invest in risk prevention, since claims are settled based on pictures of insured crops, and the costs of having visibly damaged crops are partially transferred to the insurance provider. In India, applications did not find evidence of such moral hazard, or of adverse selection (Ceballos et al., 2019). Indeed, commercial insurance companies have underwritten picture-based insurance, indicating that this can be a marketable commercial insurance solution. Nonetheless, learning about the benefits of the product might occur over time, and adverse selection and moral hazard might only occur after farmers have had a few years of experience with a product.

Figure 1 – Illustration of how picture-based crop insurance (PBI) works



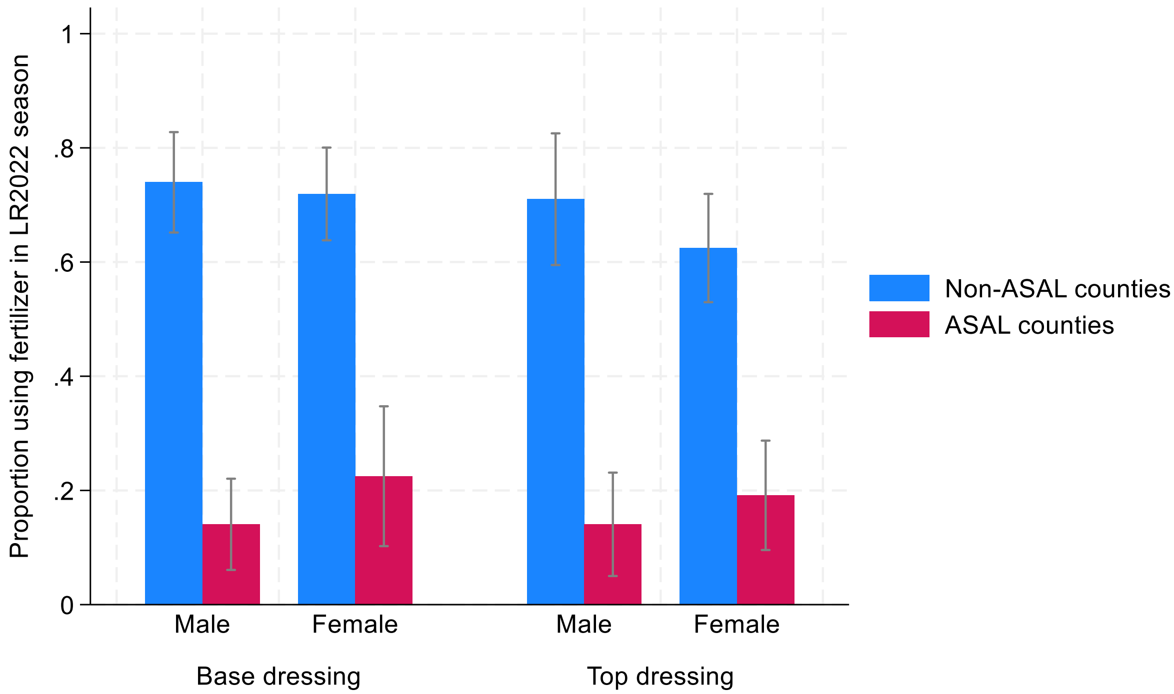
In Kenya, the distribution of the insurance product was done through so-called champion farmers, or local progressive farmers recruited to become community-based entrepreneurial service providers. In each of the 191 study villages, the insurance service provider recruited one male or female champion farmer, equipped this person with a smartphone, and trained them on how to take field images through a dedicated smartphone application. The insurance service provider also facilitated these champion farmers in selling and distributing improved seeds. Champion farmers would register up to 250 farmers with the insurance service provider. Of these registered farmers, 20 were randomly selected to receive a trial pack of an improved (drought-tolerant) sorghum or maize variety. We call these farmers project farmers, as champion farmers were sending in pictures of their plots for crop monitoring purposes.

2.2. Study context

The project was implemented in 7 counties from eastern and western Kenya with a range of agroecological zones. In eastern Kenya, this included the counties of Machakos, Makueni and Tharaka-Nithi, with largely semi-arid and arid lands (ASALs), as well as Meru and Embu, with largely mid-potential rainfall areas. The counties from western Kenya comprised of Busia and Bungoma, which largely cover mid- to high- potential rainfall areas. The project was implemented from 2019-2022, during which Kenya experienced one of the worst droughts in 40 years with its highest severity experienced since 40 years (UN News, 2022). Especially ASALs suffered severely from this drought. The insurance product targeted farmers growing maize, sorghum and green gram. These crops attracted the insurance product because of their commercial viability: maize is a staple crop for which there is a large local market; for sorghum, there is high demand among Kenya's brewing companies as raw material for brewing beer; and for green gram, there is both local and external market demand (Abodi et al., 2021; Food Business Africa, 2023; Kihoro et al., 2019).

The main outcome variables in this evaluation include insurance take-up and fertilizer use. Only 14% of control group farmers had purchased insurance at endline. Insurance coverage is low in Kenya despite several organizations, including ACRE Africa, providing insurance for smallholder farmers, and the government even having a national insurance scheme. In terms of fertilizer use, Kenya imported 792,670 metric tons of fertilizer in 2021, an indication of how much fertilizer was used by Kenya's 7.5 million smallholder farmers in that year. These comprised of DAP, NPK, CAN, Urea, NP Compounds and MOP which accounted for 91% of total fertilizer imports in 2021 (IFDC, 2022). About a quarter of the fertilizer is used for maize, either grown as a stand-alone crop or intercropped with beans. Moreover, fertilizer use in Kenya is not universal. Results from our endline survey, focusing on the control group in our study, indicate that fertilizer use was particularly low in ASAL counties (Figure 2).

Figure 2 – Fertilizer use in ASAL and non-ASAL counties in the study area.



Note: N = 791, based on endline survey data for project farmers in the control group.

2.3.Experimental design and data collection

Table 1 summarizes the experimental design. To evaluate the impacts of picture-based insurance on demand for insurance itself, and fertilizer use, we randomized 191 villages from the seven study counties into one of three treatment arms: a control group, in which no free insurance trials were provided (40% of all champion farmers); an index-based insurance treatment, in which project farmers were provided with free trials of rainfall insurance (20% of all champion farmers); and a treatment arm in which project farmers received free trials of the new picture-based insurance product (40% of all champion farmers). We randomized relatively more farmers into the control group and the PBI treatment arm because the rainfall insurance treatment mainly served to analyze the effects of PBI on insurance take-up, which is a comparison that requires a relatively smaller sample than the comparison of fertilizer use between treatment and control.[1]

The free insurance trials were provided for two subsequent seasons. A few months prior to endline, champion farmers in the two insurance treatment arms provided all farmers with an opportunity to purchase the insurance product of which they had received an insurance trial. Non-project farmers were offered insurance at actuarially fair prices. Project farmers were offered subsidized premiums, and we randomized whether these insurance premium subsidies were 80% or 20%. In the control group, champion farmers offered other insurance products developed by ACRE Africa, and there were no premium subsidies offered in this treatment arm. Importantly, this will imply that uptake rates will reflect preferences for a product that had already been experienced by our subject pool in previous years, through two seasons of free trials of either PBI or WBI. Differences in uptake between the two products will hence not be the result of a more appealing marketing strategy. As a matter of fact, the marketing strategies of our WBI and PBI arms are identical in every aspect except for the offered insurance product itself. Our 'pure' control group helps us disentagle marketing and premium subsidy effects (comparing WBI to control) from the effect of the digital innovation in insurance design (PBI vs WBI).

Across these three treatment arms, 36,307 farmers were surveyed by champion farmers at baseline, as part of the farmer registration. These baseline registration data include information on basic demographics and insurance awareness, and for a randomly selected 18,285 farmers also include more details information on education, marital status, income diversification, land use, food security, and intra-household decision-making. After fertilizer application for the Long Rains 2022 (LR2022) season, we administered a survey with 10 randomly selected project farmers per champion to measure the impacts of the two types of insurance products on insurance demand, perceptions, and agricultural investments, including fertilizer use. This was a comprehensive in-person survey administered by Innovations for Poverty Action (IPA), yielding higher-quality data than the baseline farmer registration, but due to budget constraints, we could not survey all 20 project farmers. Power calculations guided us in the choice to select 10 farmers per champion.

[1] We cross-randomized whether farmers were also offered seeds of improved (drought-tolerant) maize and sorghum varieties. We control for this treatment assignment in regression analyses, but given that this treatment assignment does not explain any of the variation in our outcome variables, we do not report on it in this paper.

Table 1 – Overview of the experimental design

Control group 40% of champions	Weather Index-Based Insurance (WBI) – 20%	Picture-Based Insurance (PBI) 40% of champions
Picture-based crop monitoring by champion farmer		
No free insurance trials	Free WBI policies for 3-4 seasons	Free PBI policies for 3-4 seasons
Other insurance products, no subsidies	WBI sold in LR2022, low vs high subsidies for project farmers	PBI sold in LR2022, low vs high subsidies for project farmers

2.4. Empirical strategy

We have two primary outcome variables: farmers' self-reported insurance take-up, and farmers' self-reported fertilizer use, both for the Long Rains 2022 season. For insurance take-up, we estimate the following equation for project farmer i with champion c (excluding champion farmers themselves from the analyses):

$$Y_{ic} = \alpha + Ins_c\beta_1 + PBI_c\beta_2 + X_{ic}\gamma + \varepsilon_{ic}$$

where Y_{ic} is our outcome variable, α a constant, Ins_c a binary variable indicating whether champion farmer c was randomly assigned to the control group ($Ins_c = 0$) or to one of the two insurance treatment arms ($Ins_c = 1$), PBI_c is a binary variable indicating whether the champion farmer was randomly assigned to the treatment arm where PBI was offered ($PBI_c = 1$) instead of either the control group of the treatment arm with WBI ($PBI_c = 0$), X_{ic} is a matrix with control variables, and ε_{ic} is our error term, which we assume is clustered at the champion level.[2] The coefficient estimates β_1 and β_2 provide the treatment effect of the WBI product and the additional effect of the PBI product, respectively. We will report the effect of WBI (β_1) and the total effect of PBI ($\beta_1 + \beta_2$) and indicate whether the effect of PBI was significantly different from the effect of WBI (that is, whether β_2 is significantly different from zero).

For fertilizer use, we will estimate Equation (1) for project farmers (excluding champion farmers themselves), whereby we can interpret estimated coefficients β_1 and β_2 as the intention-to-treat (ITT) estimators, which provide a treatment effect for the full sample, regardless of whether a farmer took up insurance. However, since not all farmers will have taken up insurance, and treatments may have influenced behavior only among those who took up the product, we will also want to estimate an average treatment effect for the treated (ATET).[3] We use a Heckman maximum likelihood selection model to correct for endogeneity in the decision to enroll in insurance. To satisfy the exclusion restriction, our selection equation includes farmers' randomly assigned premium subsidy levels (which was either a high 80% versus a low 20% discount), which we do not control for in the outcome equation.

We will also estimate extension of these models that include interactions between treatment and the farmer's gender, and in another extension, we will include an interaction term for treatment and a dummy variable indicating that a farmer is from an ASAL county.

[2] As control variables, we include county indicators, which also absorb any variation in outcome variables between ASAL and non-ASAL counties; a variable controlling for a cross-randomized seed promotion treatment; a dummy for gender; and indicators for whether the farmer reported growing maize, sorghum and green gram during the Long Rains of 2022.

[3] We opt not to estimate a local average treatment effect, whereby we would instrument insurance coverage using the randomly assigned treatment and premium subsidy levels for project farmers. Despite these variables having a significant effect on insurance take-up, they do not yield a high enough F-statistic to have a strong first stage, and the LATE estimator would be biased as a result.

3. Data

This section provides a description of the study population, the endline survey sample, and balancing of baseline characteristics across treatments. In Table 2, we start with a description of the full study population, including 18,285 and 18,022 registered farmers that we randomly assigned to be eligible and non-eligible for project activities in Columns (1) and (2), respectively, and 199 champion farmers (Column 3). In Column (4), we provide *p*-values from a test of equal means between eligible and non-eligible farmers, and Columns (5) and (6) provide similar statistics from comparisons of these two groups of farmers with champion farmers.

Table 2 – Baseline data for all registered eligible, non-eligible and champion farmers

	Eligible	**Non-eligible**	**Champion farmers**	***p*-value comparison of**		
				(1)-(2)	**(1)-(3)**	**(2)-(3)**
	(1)	(2)	(3)	(4)	(5)	(6)
Female	0.607	0.606	0.583	0.785	0.504	0.523
Owns a phone	0.965	0.962	0.984	0.199	0.122	0.077
Owns a smartphone	0.286	0.277	0.827	0.094	0.000	0.000
Youth (18-35 years)	0.228	0.225	0.331	0.679	0.002	0.002
Middle-aged (36-55 years)	0.553	0.555	0.622	0.714	0.197	0.212
Elderly (above 55 years of age)	0.219	0.220	0.047	0.964	0.000	0.000
Has ever been trained on insurance	0.321	0.313	0.598	0.225	0.000	0.000
Has ever had insurance	0.169	0.170	0.425	0.726	0.000	0.000
Lives in an ASAL county	0.397	0.407	0.422	0.100	0.281	0.507
Number of observations	18,285	18,022	199			

Notes: Eligibility was randomly assigned during baseline registration by the survey software, and for eligible farmers, a longer survey form was asked. *p*-values are derived from a regression testing for equal means between two samples, with standard errors clustered by champion farmer/village. ASAL counties include Machakos, Makueni, and Tharaka-Nithi; non-ASAL counties include Busia, Bungoma, Embu and Meru.

About 61 percent of registered farmers are female, and nearly all registered farmers own a phone. However, most phones are basic feature phones, with only 28.6 percent of eligible farmers owning a smartphone. This is why the project engaged champion farmers instead of asking insured farmers themselves to send in pictures of insured crops. At the time of baseline registration, 23 percent of farmers were considered youth (below 35 years of age), whereas 22 percent were above 55 years of age. A bit less than one third of registered farmers had ever had training on insurance, and only 17 percent reported ever having had insurance. About 40 percent of registered farmers are based in one of the three ASAL counties (Machakos, Makueni and Tharaka-Nithi).

The survey software would randomize farmers into an eligible versus non-eligible group of farmers, and for eligible farmers, a longer survey form was administered. This resulted in two very comparable groups of farmers across Columns (1) and (2), with no variables being significantly different across the two groups at the 5-percent significance level, which we apply as a threshold given that we have more than 18,000 observations in both groups. Champion farmers, on the other hand, are systematically different from other registered farmers: they are more likely to own a smartphone, even at baseline registration, when the project had not equipped them with a smartphone yet; they are significantly younger than other registered farmers; and more likely to have received insurance training and to have had insurance. Because of this, and because of their role in project implementation, we exclude champion farmers from the analyses.

Table 3 provides summary statistics for the sample of 18,285 eligible farmers, now distinguishing between those who were shortlisted by champion farmers for project activities (N = 3,473, Column 1), and the remaining 14,812 eligible registered farmers who were not shortlisted. From the 20 shortlisted farmers per champion farmer, we randomly selected a subset of 10 eligible project farmers for an endline survey (N = 1,738, Column 3). Comparing Columns (1) and (2), we find that champions shortlisted relatively more farmers from the middle age category (36-55 years of age), with relatively fewer older farmers. Champions in ASAL counties shortlisted relatively fewer farmers than champions in non-ASAL counties, reducing the proportion of farmers in ASAL counties in the shortlisted sample of project farmers.

Table 3 – Baseline data for all eligible shortlisted and non-shortlisted farmers

	Shortlisted (project farmer)	Not shortlisted	Surveyed at endline	*p*-value comparison of (1)-(2)	*p*-value comparison of (1)-(3)
	(1)	(2)	(3)	(4)	(5)
Female	0.617	0.604	0.640	0.278	0.008
Owns a phone	0.962	0.966	0.968	0.522	0.312
Owns a smartphone	0.303	0.281	0.281	0.089	0.888
Youth (18-35 years)	0.236	0.226	0.209	0.362	0.053
Middle aged (36-55 years)	0.527	0.559	0.533	0.020	0.488
Elderly (above 55 years of age)	0.237	0.215	0.258	0.081	0.005
Has ever been trained on insurance	0.318	0.322	0.335	0.928	0.023
Has ever had insurance	0.162	0.170	0.173	0.555	0.233
Lives in an ASAL county	0.356	0.407	0.360	0.046	0.132
Has non-crop income	0.531	0.591	0.520	0.005	0.028
Single	0.110	0.108	0.078	0.654	0.002
Married	0.813	0.841	0.842	0.004	0.774
Divorced or separated	0.076	0.051	0.079	0.000	0.009
Literacy	0.732	0.706	0.741	0.256	0.506
Completed primary education	0.462	0.463	0.483	0.920	0.196
Completed secondary education	0.354	0.378	0.371	0.146	0.713
Completed post-secondary education	0.089	0.071	0.070	0.027	0.479
Cultivated 0.1 - 1 acres	0.392	0.420	0.407	0.008	0.188
Cultivated 1.1 – 2.5 acres	0.244	0.249	0.244	0.952	0.720
Cultivated 2.5 – 5 acres	0.189	0.196	0.184	0.936	0.928
Cultivated more than 5 acres	0.049	0.049	0.058	0.398	0.038
Household Dietary Diversity Score	2.690	2.709	2.749	0.787	0.612
Food Consumption Score					
- 'Poor' (0 to 21)	0.641	0.628	0.622	0.507	0.659
- 'Borderline' (21.1 to 35)	0.106	0.089	0.113	0.042	0.058
- 'Acceptable' (above 35)	0.253	0.284	0.265	0.097	0.105
Decides on …					
… seed use alone	0.666	0.659	0.636	0.674	0.224
… seed use jointly with others	0.329	0.335	0.360	0.661	0.200
… finance use alone	0.656	0.646	0.625	0.854	0.353
… finance use jointly with others	0.339	0.348	0.369	0.820	0.337
… where to sell crops alone	0.652	0.649	0.619	0.537	0.144
… where to sell crops jointly with others	0.341	0.345	0.372	0.586	0.197
… how to use income alone	0.652	0.642	0.617	0.949	0.322
… how to use income jointly with others	0.343	0.352	0.377	0.890	0.303
Observations	3,473	14,812	1,738		

Notes: p-values are derived from a regression testing for equal means between two samples, with standard errors clustered by champion farmer/village. ASAL counties include Machakos, Makueni, and Tharaka-Nithi; non-ASAL counties include Busia, Bungoma, Embu and Meru.

The next set of variables are available only for eligible farmers as they completed a longer survey form. Shortlisted farmers were relatively less likely to have non-crop income. In shortlisting, champion farmers appear to have been biased towards divorced and separated farmers vis-à-vis married farmers. Shortlisted farmers were also more likely to have completed post-secondary education, to not have cultivated land in the prior season instead of cultivating 0.1 to 1 acre of land, and to have 'borderline' instead of 'acceptable' food consumption scores. Other than that, champion farmers selected a group of farmers that is representative of the full study population.

Column (5) provides *p*-values from a test for equal means between shortlisted project farmers and those who were randomly selected and consented to participate in the endline survey. The endline survey includes a relatively higher proportion of female and elderly farmers, with lower representation of male and youth farmers. Farmers who completed the endline survey were also more likely to have received insurance training, and less likely to have non-crop income. They are less likely to be single and more likely to be divorced or separated, and we see slightly higher participation rates among relatively large farmers cultivating up to 5 acres of land, and among farmers with borderline food consumption scores. In future analyses, as a robustness check, we will reweigh the sample to make the endline survey sample more similar to the overall registered sample, but since none of these differences are major, here, we present results without reweighting.

As a final sample description in this section, Table 4 summarizes farmers' baseline characteristics by treatment, to test for treatment balance. In the PBI treatment arm, farmers are relatively more likely to be female compared to the WBI treatment arm ($p < 0.10$), and compared to the control group, the PBI treatment has relatively more elderly farmers instead of youth farmers ($p < 0.10$), and more farmers that have ever received insurance training ($p < 0.05$). Besides these small differences, we find no significant differences in baseline characteristics across the three treatment arms. With a 10-percent significance level, we would expect one out of every ten tests to yield a significant result, meaning that with the 27 comparisons shown in the table below, we would expect about three comparisons to turn out significant. We conclude that the randomization has resulted in three comparable samples across the treatment arm, whereby we can attribute differences in outcome variables at endline to the interventions that varied across treatments.

Table 4 – Estimated treatment effects on endline insurance take-up

				***p*-value comparison of**		
	PBI	**WBI**	**Control**	**(1)-(2)**	**(1)-(3)**	**(2)-(3)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Female	0.674	0.583	0.619	0.063	0.131	0.418
Owns a phone	0.962	0.975	0.972	0.453	0.437	0.963
Owns a smartphone	0.266	0.258	0.308	0.981	0.255	0.342
Youth (18-35 years)	0.178	0.237	0.208	0.191	0.070	0.820
Middle aged (36-55 years)	0.549	0.515	0.548	0.593	0.896	0.393
Elderly (above 55 years of age)	0.273	0.248	0.244	0.471	0.084	0.487
Has ever been trained on insurance	0.391	0.403	0.225	0.797	0.042	0.127
Has ever had insurance	0.169	0.169	0.151	0.977	0.942	0.938
Lives in an ASAL county	0.297	0.292	0.436	0.966	0.126	0.180
Number of observations	832	472	1,042			

Notes: p-values are derived from a regression testing for equal means between two samples, with standard errors clustered by champion farmer/village. ASAL counties include Machakos, Makueni, and Tharaka-Nithi; non-ASAL counties include Busia, Bungoma, Embu and Meru.

4. Findings

4.1. Insurance take-up

Figure 3 presents insurance take-up reported by project farmers (excluding champion farmers themselves, given the higher chances of socially desirable reporting) during the endline survey. We find that providing picture-based crop insurance significantly increases insurance demand relative to providing weather index-based insurance. The effects of picture-based insurance on demand are concentrated in ASAL counties and are strongest among women smallholder farmers; and even in non-ASAL counties, we find a significant effect of providing picture-based insurance on take-up among female farmers. Whereas in the rainfall index insurance treatment, less than 20 percent of women purchased insurance, this increases to about 30 percent in the picture-based insurance treatment in non-ASAL counties, and to more than 40 percent in ASAL counties. We observe smaller effects of offering picture-based insurance on take-up among men smallholder farmers. As a result, the picture-based product increases women's insurance uptake beyond take-up rates observed among men, suggesting that this product is a gender-responsive solution.

Figure 3 – Endline insurance take-up by treatment, gender, and county type

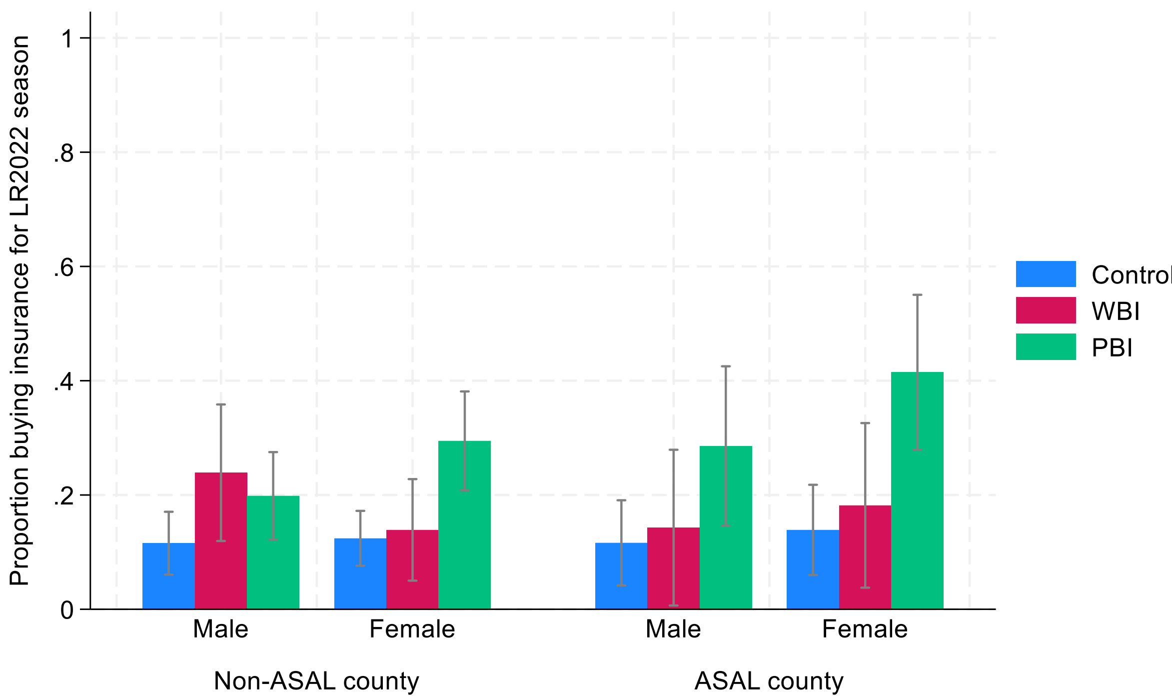


Table 5 Column (1) presents estimates of total treatment effects of WBI (β_1) and PBI ($\beta_1 + \beta_2$) from the linear probability model specified in Equation (1). On average, WBI increases insurance take-up by 6.7 percentage points ($p < 0.10$). The effect of PBI is considerably larger, increasing

insurance take-up by an economically and statistically significant 18.5 percentage points ($p < 0.01$). We find a significant increase in take-up of 10-11 percentage points among male farmers in both insurance treatments (Column 2), whereas for female farmers, only PBI significantly take-up – but by a whopping 20 percentage points (Column 3). Finally, disaggregating the sample by non-ASAL and ASAL counties (Columns 4 and 5), we find modest and statistically insignificant effects of the WBI treatment on insurance take-up, whereas the total effect of PBI is statistically significant. However, in non-ASAL counties, the marginal effect of offering PBI is not significant, unlike in ASAL counties, where PBI increases take-up by an additional 20 percentage points.

Table 5 – Estimated treatment effects on endline insurance take-up

Buys insurance for the LR2022 season	**All project farmers**	**Male farmers**	**Female farmers**	**Non-ASAL counties**	**ASAL counties**
	(1)	(2)	(3)	(4)	(5)
Total effect WBI	0.067*	0.102*	0.030	0.070	0.055
	(0.040)	(0.053)	(0.046)	(0.047)	(0.070)
Total effect PBI	0.185***	0.117***	0.217***	0.150***	0.258***
	(0.036)	(0.042)	(0.040)	(0.041)	(0.069)
N	1,804	652	1,152	1,151	653
Mean dep. variable	0.198	0.173	0.213	0.190	0.213
p-value PBI-WBI	0.011	0.190	0.001	0.126	0.024

Notes: * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$. Standard errors estimated using clustering at the champion level. Estimated using a linear probability model controlling for county effects, seed treatment, gender, and whether the farmer grows maize, sorghum and/or green gram during the Long Rains 2022 (LR2022) season. ASAL counties include Machakos, Makueni, and Tharaka Nithi; non-ASAL counties include Busia, Bungoma, Embu and Meru.

These effects are mediated by significantly improved perceptions of insurance in terms of respondents finding insurance more easily available, more trustworthy, and of higher quality when offered PBI compared to standard rainfall index-based insurance (see Table 6).

Table 6 – Estimated treatment effects on endline insurance perceptions

	Agrees (strongly) with statement that insurance product offered…							
	Is easy to understand	**Is easily available**	**Is cheap**	**Pays out in time**	**Pays out in case there are losses**	**Is sold by trustworthy insurer**	**Is of high quality**	**Is sold by trustworthy champion**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Offered insurance (β_1)	0.057	0.031	-0.014	0.051	0.036	0.039	0.05	-0.018
	(0.048)	(0.050)	(0.052)	(0.043)	(0.051)	(0.049)	(0.048)	(0.043)
Offered PBI (β_2)	0.078*	0.139***	0.122**	0.055	0.090*	0.114**	0.114**	0.098**
	(0.047)	(0.050)	(0.053)	(0.044)	(0.052)	(0.049)	(0.049)	(0.043)
N	1804	1804	1804	1804	1804	1804	1804	1804
Mean dep. variable	0.636	0.587	0.614	0.422	0.62	0.626	0.621	0.790
p-value $\beta_1 + \beta_2$	0.001	0.000	0.009	0.011	0.003	0.000	0.000	0.018

Notes: * $p < 0.10$. ** $p < 0.05$. *** $p < 0.01$. Standard errors estimated using clustering at the champion level. Estimated using a linear probability model controlling for county effects, seed treatment, gender, and whether the farmer grows maize, sorghum and/or green gram during the Long Rains 2022 (LR2022) season.

4.2. Fertilizer use

Figure 4 plots the percentage of farmers in non-ASAL and ASAL counties using fertilizer in the Long Rains 2022 season, by treatment and gender. In non-ASAL counties, fertilizer use is high, and the insurance treatments – especially the treatment in which farmers were offered picture-based insurance – have a small but noisily estimated effect on fertilizer use. In ASAL counties, on the other hand, fertilizer use is very low in the control group, especially among male farmers. Offering insurance increases fertilizer use, particularly among male farmers. Surprisingly, providing weather index-based insurance – which had similar take-up rates as the product offered in the control group – has a stronger impact on fertilizer use than providing picture-based insurance, for which take-up was significantly higher. We will turn to potential explanations for this in the next section.

Figure 4 – Endline fertilizer use by treatment, gender, and county type

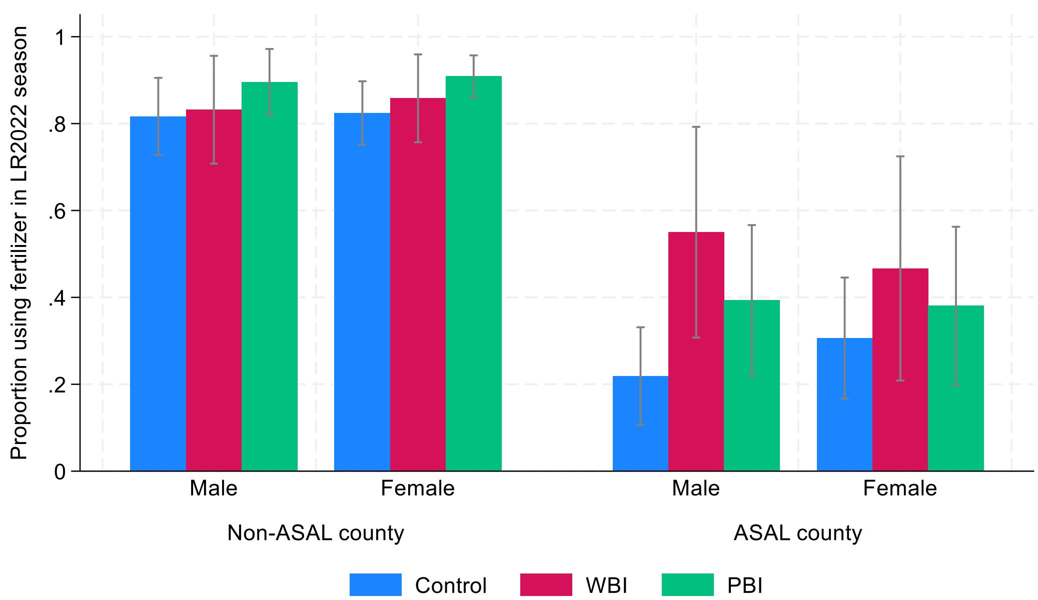


Table 7 estimates Equation (1) for all project farmers and insured farmers in Columns (1)-(2), and the Heckman selection model – using the randomly assigned premium subsidy levels in the selection equation, to satisfy the exclusion restriction – to estimate an average treatment effect on the treated in Columns (3)-(5). Column (1) shows that there is no intent-to-treat effect for the overall sample; neither WBI nor PBI significantly increase fertilizer use across the sample. However, focusing on farmers that took up insurance in Column (2), we do see that fertilizer use is higher in the WBI treatment arm than in the control group. PBI appears to offset this positive effect, which could potentially be explained by moral hazard – the indemnity-based nature of this insurance policy may have given farmers a disincentive to invest in good management practices, including fertilizer use. In Column (3), correcting for potential selection into insurance, we find even stronger effects of WBI. Here, the PBI treatment is no longer fully offsetting this positive effect, meaning that also among farmers being offered PBI, there is a positive – but statistically insignificant – effect on fertilizer use.

Columns (4) and (5) estimate a model whereby the two indicators for insurance treatment and PBI treatment are interacted with an indicator for ASAL counties in Column (4), and an indicator for female farmers in Column (5). In non-ASAL counties, fertilizer use in both insurance treatment arms is higher than in the control group, but these differences are not statistically significant. In ASAL counties, on the other hand, we find a significant increase in fertilizer use of 43.1 percentage points in the WBI treatment arm, and of 22.7 percentage points in the PBI treatment, compared to fertilizer use in the control group. Finally, Column (5) shows that the increases in fertilizer use are mainly concentrated among male farmers, and particularly those in the WBI treatment arm, also consistent with Figure 4.

Table 7 – Estimated treatment effects on endline insurance perceptions

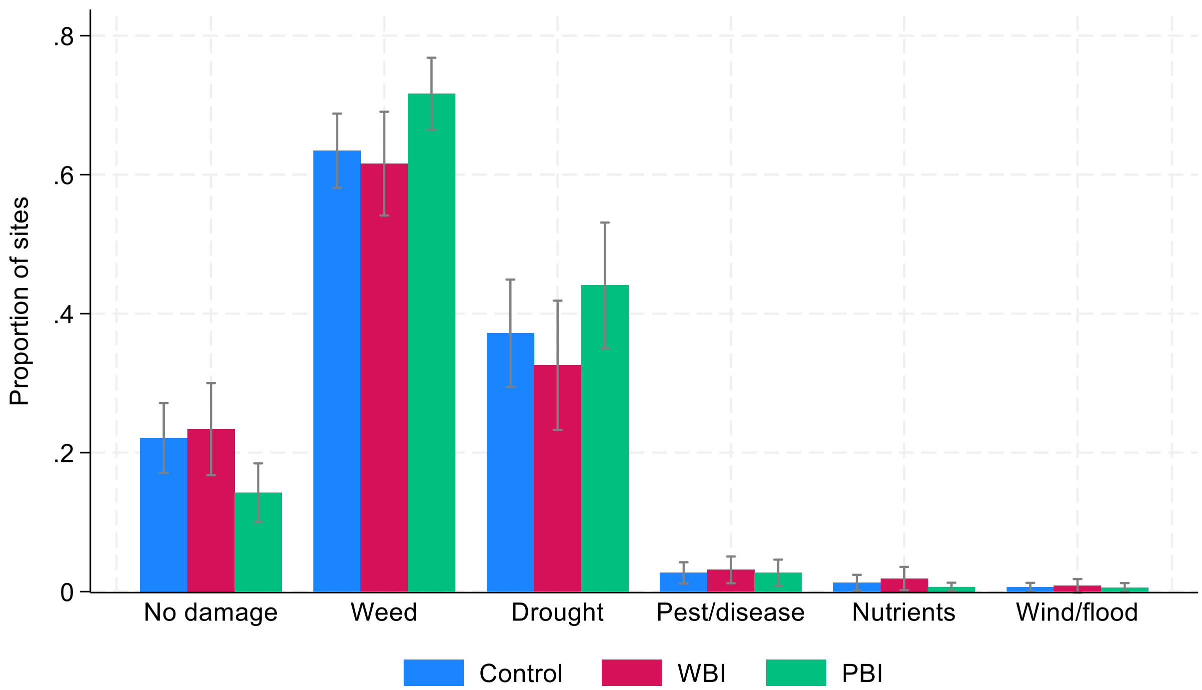
Dependent variable: Uses fertilizer	**All project farmers (LPM)**	**Insured farmers (LPM)**	**Insured farmers (Heckman)**	**Insured farmers (Heckman, by ASAL)**	**Insured farmers (Heckman, by gender)**
	(1)	(2)	(3)	(4)	(5)
Offered insurance (β_1)	0.047	0.166**	0.228***	0.130	0.282**
	(0.047)	(0.065)	(0.085)	(0.082)	(0.112)
Offered PBI (β_2)	0.008	-0.193***	-0.107	-0.066	-0.176*
	(0.047)	(0.064)	(0.081)	(0.071)	(0.100)
Offered insurance X subgroup				0.301*	-0.091
				(0.182)	(0.127)
Offered PBI X subgroup				-0.138	0.116
				(0.172)	(0.126)
N	1,785	357	1,803	1,803	1,803
Mean dep. variable	0.673	0.689	0.673	0.673	0.673
p-value $\beta_1 + \beta_2$	0.119	0.651	0.213	0.421	0.290
p-value β_1 | subgroup				0.011**	0.054*
p-value $\beta_1 + \beta_2$ | sub				0.088*	0.236

4.3. Hidden effort

One explanation for why PBI does not increase fertilizer as much as WBI is that farmers in PBI underinvest in fertilizer, because they might perceive that if their crop does not look healthy, that they will receive payouts. To explore this hypothesis in more detail, we turn to administrative data collected as part of the project implementation, and in particular, the images of crops that champion farmers took for their project farmers. We have rich data on these for the Long Rains 2021 (LR2021) season, so one year prior to the season during which we analyze insurance take-up and fertilizer use. During the LR2021 season, farmers had a free trial of insurance – WBI in the WBI treatment arm, and PBI in the treatment arm. If there is moral hazard, then it could have manifested itself in increased observations of visible damage in the PBI compared to the WBI treatment arm.

Agronomic experts assessed for all 10,455 images (from 2,472 plots) during the LR2021 season whether there was evidence of damage, and the image labels from this activity are summarized in Figure 5, where we plot the proportion of sites with various types of damage. Despite low fertilizer use, experts rarely identified nutrient deficiencies, and the probability of identifying nutritional deficiencies does not differ across treatment arms. However, experts were more likely to identify especially weed and drought damage for sites in the PBI treatment arm, and they were significantly less likely to label these sites as undamaged. One explanation for this could be that PBI champions were sending in more pictures, in the hope of increasing the chances that their farmers would be getting insurance payouts, but there is no evidence of this; the number of pictures sent in by farmers does not vary between the PBI and WBI treatment arms. It could well be that there is a hidden effort problem, and that farmers with PBI feel more secure, and less inclined to apply fertilizer or adopt good management practices compared to farmers in the WBI treatment arm. Whether such moral hazard also results in significantly higher payouts, which would be potentially problematic for the sustainability of an insurance product, is a question that we will explore in future research.

Figure 5 – Endline fertilizer use by treatment, gender, and county type



5. Conclusion

To evaluate impacts of PBI on the demand for both insurance and fertilizers, as an important indicator of agricultural technology adoption in sub-Saharan Africa, we implemented a cluster randomized controlled trial in seven counties in Kenya. We randomized villages into one of three treatment arms: a control group, a weather index-based insurance (WBI) treatment arm, and a picture-based insurance (PBI) treatment arm, where farmers were offered free insurance trials of a standard rainfall insurance product and a similarly priced PBI product, respectively. We then invited farmers in these insurance treatment arms to purchase (at randomly assigned subsidized premiums) the insurance product of which they received a trial, whereas farmers in the control group were offered a standard insurance product at commercial premiums.

We find that PBI increases insurance take-up compared to WBI, especially among female farmers and those farming Arid and Semi-Arid Lands (ASALs), but demand is also highly price sensitive. Positive effects on demand are related to improved perceptions of PBI compared to farmers' perceptions of the quality and coverage that they receive under WBI. This implies that an easy-to-understand insurance solution with low basis risk can increase demand to levels that are potentially more commercially viable, but insurance programs would still benefit from insurance subsidies to reach larger numbers of farmers. Although the use of smartphone technology could have potentially reduced interest among women farmers, who have less access to smartphones, we find that this did not deter them from taking up insurance. In fact, the use of smartphones in this innovation increases demand among women more than among men, suggesting that this ended up being a gender-responsive solution.

In ASAL counties, where control group fertilizer use is very low, when estimating the average treatment effect on the treated, both WBI and PBI increase fertilizer use compared to the control group. This effect is most pronounced in the WBI treatment and among male farmers, despite higher take-up in the PBI treatment and among female farmers. The indemnity-based nature of PBI may have disincentivized farmers to invest in crop management. We conclude that digital innovations in crop insurance that indemnity insurance claims based on visible crop losses can boost demand and have positive impacts on agricultural technology adoption, but insurance providers introducing such innovations will need to keep monitoring and managing moral hazard concerns. Moreover, it will be important to explore why insurance does not have stronger positive effects on female farmers' fertilizer use, and test, for instance, whether women face mobility-related barriers to access fertilizers, or whether they did not have the liquidity to purchase fertilizers. This is an important area for future research.

Finally, our finding that having PBI does not increase fertilizer use as much as having WBI suggests that farmers perceive improved agricultural technologies, an important risk management technology for moderate risks, to be a substitute for crop insurance, which is in theory a risk management solution for more extreme risks. Alternatively, insurance and agricultural technologies could be competing expenses for liquidity-constrained farmers. An important research question therefore remains how to design insurance products in ways that farmers perceive these products to be complementary, rather than substitutes, for other risk management instruments they might use, and if bundling such products, how to keep the bundles affordable. Relatedly, in our study, the sum insured of any insurance product provided to farmers was equal to the estimated cost of seeds, not the cost of both seeds and fertilizers or other production costs. Whether this relatively low sum insured may have prevented farmers from investing more in agricultural technologies remains another area for future research.

References

Abodi, M. A., Obare, G. A., & Kariuki, I. M. (2021). Supply and demand responsiveness to maize price changes in Kenya: An application of error correction autoregressive distributed lag approach. *Cogent Food & Agriculture, 7*(1), 1957318. https://doi.org/10.1080/23311932.2021.1957318

Alderman, H., & Haque, T. (2007). *Insurance against covariate shocks: The role of index-based insurance in social protection in low-income countries of Africa* (No. 95). World Bank Publications. http://documents.worldbank.org/curated/en/158791467990329754/Insurance-against-covariate-shocks-the-role-of-index-based-insurance-in-social-protection-in-low-income-countries-of-Africa

Belissa, T., Bulte, E., Cecchi, F., Gangopadhyay, S., & Lensink, R. (2019). Liquidity constraints, informal institutions, and the adoption of weather insurance: A randomized controlled Trial in Ethiopia. *Journal of Development Economics*, *140*, 269-278. https://doi.org/10.1016/j.jdeveco.2019.06.006

Bulte, E., Cecchi, F., Lensink, R., Marr, A., & Van Asseldonk, M. (2020). Does bundling crop insurance with certified seeds crowd-in investments? Experimental evidence from Kenya. *Journal of Economic Behavior & Organization*, *180*, 744-757. https://doi.org/10.1016/j.jebo.2019.07.006

Casaburi, L., & Willis, J. (2018). Time versus State in Insurance: Experimental Evidence from Contract Farming in Kenya. *The American Economic Review*, *108*(12), 3778–3813. https://www.jstor.org/stable/26562918

Ceballos, F., Kramer, B., & Robles, M. (2019). The feasibility of picture-based insurance (PBI): Smartphone pictures for affordable crop insurance. *Development Engineering*, *4*, 100042. https://doi.org/10.1016/j.deveng.2019.100042

Ceballos, F., & Kramer, B. (2021). The role of asymmetric information in multi-peril picture-based crop insurance: Field experiments in India. https://doi.org/10.2499/p15738coll2.134941

Clarke, D.J. (2016). A theory of rational demand for index insurance. *American Economic Journal: Microeconomics*, 8(1), pp.283-306. http://dx.doi.org/10.1257/mic.20140103

Cole, S., Giné, X., & Vickery, J. (2017). How does risk management influence production decisions? Evidence from a field experiment. *The Review of Financial Studies*, *30*(6), 1935-1970. https://doi.org/10.1093/rfs/hhw080

Dercon, S., Hoddinott, J., Woldehanna, T. (2005). Shock and consumption in 15 Ethiopian villages, 199-2004. Journal of African Economies, 14, (559-585). https://doi.org/10.1093/jae/eji022

Elbers C., Gunning J. W., and Kinsey B. (2007). Growth and Risk: Methodology and Micro Evidence. The World Bank Economic Review, 21(1): 1-20. https://doi.org/10.1093/wber/lhl008

Farrin, K., & Miranda, M. J. (2015). A heterogeneous agent model of credit-linked index insurance and farm technology adoption. *Journal of Development Economics*, *116*, 199-211. https://doi.org/10.1016/j.jdeveco.2015.05.001

Food Business Africa. (2023). Kenya Breweries Limited expands sorghum sourcing program to Murang'a County. https://www.foodbusinessafrica.com/kenya

Giné, X., Townsend, R., & Vickery, J. (2008). Patterns of rainfall insurance participation in rural India. The World Bank Economic Review, 22(3), 539-566. https://www.jstor.org/stable/40282287

Hazell, P., Poulton, C., Wiggins, S., & Dorward, A. (2010). The future of small farms: Trajectories and policy priorities. *World development, 38*(10), 1349-1361. https://doi.org/10.1016/j.worlddev.2009.06.012

Hill, R. V., Robles, M., & Ceballos, F. (2016). Demand for a simple weather insurance product in India: theory and evidence. *American Journal of Agricultural Economics*, *98*(4), 1250-1270. URL: https://www.jstor.org/stable/24739942

Hill, R. V., Kumar, N., Magnan, N., Makhija, S., de Nicola, F., Spielman, D. J., & Ward, P. S. (2019). Ex ante and ex post effects of hybrid index insurance in Bangladesh. *Journal of development economics*, *136*, 1-17. https://doi.org/10.1016%2Fj.jdeveco.2018.09.003

IFDC. (2022). Fertilizer Statistics Overview Kenya 2017 – 2021. https://api.hub.ifdc.org/server/api/core/bitstreams/7cdb863d-6abe-437c-8940-69bc0e29084c/content

Janzen, S. A., & Carter, M. R. (2019). After the drought: The impact of microinsurance on consumption smoothing and asset protection. *American Journal of Agricultural Economics*, *101*(3), 651-671. https://doi.org/10.3386/w19702

Jensen, N. D., Barrett, C. B., & Mude, A. G. (2017). Cash transfers and index insurance: A comparative impact analysis from northern Kenya. *Journal of Development Economics*, *129*, 14-28. https://doi.org/10.1016/j.jdeveco.2017.08.002

Kahan, D. (2008). *Managing risk in farming*. Rome: Food and Agriculture Organization of the United Nations. https://www.fao.org/uploads/media/3-ManagingRiskInternLores.pdf

Karlan, D., Osei, R., Osei-Akoto, I., & Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, *129*(2), 597-652. https://doi.org/10.1093/qje/qju002

Kihoro, E. M., Irungu, P., Nyikal, R., & Maina, I. N. (2019). An analysis of factors influencing farmers' choice of green gram marketing channels in Mbeere south sub-county, Kenya. https://www.researchgate.net/publication/338005755

Porter, J.R., Xie, L., Challinor, A., Cochrane, K., Howden, S., Iqbal, M., Lobell, D., Travasso, M., Netra Chhetri, N., and Garrett, K. (2014). *Food Security and Food Production Systems.* In: Field, C.B., Barros, V.R., Dokken, D.J., Mach, K.J., and Mastrandrea, M.D. (eds.), *Climate Change 2014: Impacts, Adaptation, and Vulnerability.* Working Group II

Contribution to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, 485–533 (Chapter 7). https://www.ipcc.ch/site/assets/uploads/2018/02/WGIIAR5-Chap7_FINAL.pdf

Santos, P., & Barrett, C. B. (2011). Persistent poverty and informal credit. *Journal of Development Economics*, *96*(2), 337-347. https://doi.org/10.1016/j.jdeveco.2010.08.017

UN News. (2022). Kenya: Severe drought fuels malnutrition, reduces hospital-delivery births in Turkana County; https://news.un.org/en/story/2022/12/1132047