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See It Grow

A Randomized Evaluation of a Digital Innovation to Improve Crop Insurance Contract Design

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Abstract

Insurance has great potential to increase productive investments, but agricultural insurance markets remain thin, in part because asymmetric information limits the viability of indemnity-based contracts. This paper evaluates a digital innovation—picture-based insurance (PBI)—that uses smartphone images of insured crops to indemnify crop damage. Through a cluster randomized trial in seven counties in Kenya, we compare subsidized PBI to subsidized weather index-based insurance (WBI) and to a control group offered unsubsidized WBI. We find that moving from index-based to indemnity-based insurance substantially increases take-up, particularly among women and farmers in drought-prone areas, indicating that innovations in contract design can broaden coverage in inclusive ways. Insurance coverage significantly increases fertilizer use in both treatments, confirming that uninsured risk constrains agricultural investment. However, despite higher take-up, PBI increases total fertilizer use as much as WBI. Using a Heckman selection model to correct for endogenous adoption, we show that this is not only due to incentive effects but also to multidimensional selection: PBI attracts farmers who, in the absence of insurance, would have invested less in fertilizer. After adjusting for this compositional change, differences in fertilizer use per farmer enrolled in WBI and PBI are not statistically significant. We conclude that higher take-up rates of digital indemnity-based insurance may not automatically translate into proportionally larger farm investments, but since increased coverage is concentrated among the relatively more vulnerable, it may contribute to complementary objectives such as inclusivity, equity, and resilience. Contract design and targeting, therefore, remain central to effective insurance product development.

Keywords: Technology adoption, insurance, basis risk, asymmetric information, Kenya

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1. Introduction

Insurance allows households and firms to undertake risky but productive investments (Leland, 1972; Sandmo, 1971). Historically, insurance has its roots in long distance (maritime) trade: early marine markets in Antwerp and London developed underwriting, pricing and intermediation practices that expanded what was economically feasible under uncertainty (Kelly et al., 2021; Puttevils and Deloof, 2017). These innovations typically offered protection against risks while mitigating asymmetric information issues and reducing transaction costs. Port arrival and departure logs and standardized reporting requirements limited scope for ex-post moral hazard; organizations such as Lloyd's Register (founded as a Society in 1760, with the first register published in 1764) provided independent assessments of ship quality and maintenance that addressed ex-ante moral hazard; and actuarial methods based on empirical loss data helped discipline pricing and adverse selection (Kelly et al., 2021). Since then, insurance markets have found various solutions to asymmetric information, resulting in the current proliferation of various insurance products across the world, protecting households' and firms' assets as well as incomes from shocks.

One domain in which insurance markets seem to be still far from complete is agriculture. Agricultural insurance has long been promoted as a cornerstone of risk management, with the potential to improve farmers' access to credit, expand investments and production, and increase profitable technology adoption (Carter et al., 2017; Kramer et al., 2021). Yet, with the exception of the US, only a minority of farmers are sufficiently insured (European Investment Bank, 2025; U.S. Department of Agriculture, 2024; Vyas et al., 2021). In large middle-income countries such as India and China, rural insurance covers roughly one-third and about one-tenth of total agricultural area, respectively, despite substantial public premium subsidies; and in many lower-income settings, including much of Sub-Saharan Africa and parts of Latin America, agricultural insurance remains substantially lower with most schemes confined to small pilot programs or narrow value chains (Harfuch and Lobo, 2021). Hill et al. (2025) estimate that one fifth of the world's population is at high risk from climate-related hazards, with the highest exposure in Africa south of the Sahara. Weather shocks, pests and diseases, and price volatility continue to threaten farm incomes and investments, especially in the Global South.

Theoretical and empirical research attributes the limited spread of insurance coverage in LMICs to asymmetric information and associated incentive failures that are intrinsic to insurance markets. Indemnity-based products, which pay out based on an assessment of actual losses, face moral hazard and adverse selection, raising premiums and limiting coverage (Carter et al., 2017; Kramer et al., 2021). By contrast, index-based products link payouts to objectively measured indices such as rainfall or vegetation to mitigate monitoring problems, asymmetric information, reduce costs, and increase speed of claims processing. Across low- and middle-income settings, risk reduction through this second-best solution has been shown to increase farm investments, input use, and technology adoption (Cole et al., 2013; Hill et al., 2019; Karlan et al., 2014). Yet, as Carter et al. (2017) note, despite extensive experimentation, "take-up has been disappointingly low without large and sustained subsidies", in part due to basis risk, that is, the mismatch between index outcomes (and thus payouts) and actual farm losses. As a result of basis risk, farmers may not receive a (full) insurance payment when experiencing damage, or receive a payment in the absence of farm losses. This undermines the credibility of an insurance product, suppressing trust and demand (Jensen et al., 2017; Kramer et al., 2025; Vosper and Cecchi, 2021). Distance to weather stations on which weather indices are based, serving as a proxy for basis risk, have indeed been associated with lower adoption (Vargas Hill et al., 2016; Wairimu et al., 2016). Recent advances in index insurance design have therefore attempted to improve insurance indices and reduce basis risk through satellite remote sensing, although farmer comprehension of satellite-based contracts and tangibility of claims processing remains a major issue (De Leeuw et al., 2014; Nguyen et al., 2025).

This paper evaluates the effects of picture-based insurance, a digital solution to expand agricultural insurance coverage in low- and middle-income countries (LMICs), on insurance take-up and productive risk taking in agriculture. Picture-based insurance uses smartphone pictures of insured crops to overcome challenges typically related to monitoring costs in indemnity-based insurance—whilst improving contract credibility, comprehension and trust compared to index-based insurance. In a near-surface remote sensing study in India, Ceballos et al. (2019) show that agricultural experts can identify severe crop damage from a stream of farmer-provided pre- and post-damage pictures of their crops with greater accuracy than common weather indices and area yield indices. They argue that the use of images offers a middle ground between the high costs of indemnity products, and basis risk-prone index insurance products. Image-based claims settlement makes contracts more intuitive and closely tied to realized damage, and can easily be blended with machine learning and artificial intelligence technologies to reach cost-effective scales. At the same time, determining payouts based on actual damage could reintroduce adverse selection and moral hazard, problems stemming from information asymmetries that plagued indemnity-based insurance in the first place.

An important question, then, is to what extent picture-based insurance helps expand insurance coverage, and thereby encourages investments as a form of productive risk taking, or whether impacts are muted due to selection and incentive problems. We explore three potential mechanisms through which innovations in contract design may influence insured farmers' fertilizer investments. First, farmers may invest more in costly inputs if a change in contract design improves their insurance *perceptions and trust* that the product reduces their risk exposure. A second mechanism influencing investment behavior is the *incentive* effect of insurance. Increased insurance take-up may lead to productive risk taking and increased investments, or to moral hazard, where insurance weakens incentives to invest in productivity-enhancing inputs that could minimize observed losses. Third, a change in insurance contract design may influence the nature of *selection*. A change from index to indemnity coverage may attract farmers with different propensities to invest. For instance, more risk averse and less empowered farmers—who tend to face greater barriers to invest in risk management and productive input use more broadly (Nshakira-Rukundo et al., 2021; Phiri et al., 2020)—may not want to enroll in a standard weather index-based insurance, out of concerns over the repercussions of poor product quality. Reduced basis risk and transparency may encourage especially these farmers to enroll in picture-based insurance, thereby changing the nature of selection and the potential impacts on investments.

Building on this insight, we examine how insurance contract design affects not only adoption and investment behavior, but also the composition of adopters and their subsequent investment behavior. Through a large-scale randomized field experiment in 191 villages in rural Kenya, we compare a standard weather index-based insurance (WBI) product with picture-based insurance (PBI), a digital indemnity contract that links payouts to pre- and post-damage photographs documenting the extent and cause of crop damage. Villages were randomly assigned to be offered WBI or PBI, with exogenous within-village variation in insurance premium subsidies, versus a control group. This design allows us to study how moving from an index trigger to plot-specific verification influences both insurance take-up, including who buys insurance, and how adopters invest. We show that PBI increases take-up, and that both types of contracts increase fertilizer use, especially among the insured. However, despite higher take-up, we observe fairly similar effects on total fertilizer use regardless of whether a farmer is offered the indemnity-based PBI contract or the index-based WBI contract. Exploring whether this reflects incentive effects or a shift in the composition of insured farmers, we find that changes in contract design indeed do influence which type of farmers enroll in insurance. Once these selection effects are taken into account, indemnity-based insurance increases fertilizer use per farmer enrolled as much as index-based insurance.

Our findings contribute to three strands of economic research. First, we contribute to the knowledge base of how the design of agricultural insurance influences take-up and investments (Sibiko, 2016; Vosper and Cecchi, 2021). We show that moving from an index-based to an indemnity-based contract improves insurance take-up substantially, meaning that farmers value the reduction in basis risk. We find a positive effect of both insurance products on fertilizer investments, but per person insured, indemnity-based insurance increases investments less than index-based insurance. Second, by delving into the mechanisms behind these results, we extend the literature on how asymmetric information may influence behavior in insurance markets. We document that changes in contract design are associated with changes in observed investment behavior among the insured not only through incentive effects, but also by reshaping the composition of participants. In doing so, we provide experimental evidence that agricultural insurance markets can exhibit multidimensional selection, extending the insights of Finkelstein and McGarry (2006) to a developing-country production setting. Third, we speak to the literature on gender and empowerment, such as Phiri et al. (2020); Sheremenko and Magnan (2015), as we show that digital innovations resulting in more transparent and inclusive contract designs disproportionately attract women, who tend to have lower instrumental and intrinsic agency, with implications for welfare targeting. Together, these results caution against interpreting higher adoption as evidence of greater efficiency. Innovations that expand participation may simultaneously change who participates and how they respond.

The remainder of the paper proceeds as follows. Section 2 describes the experimental design and implementation. Section 3 provides an overview of our sample, while section 4 presents results on insurance take-up, fertilizer use, and mechanisms. Section 5 concludes with the broader implications for insurance market design and welfare targeting.

2. Methods

2.1 Intervention: Weather index- 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. The PBI product was offered for maize, which is the main crop grown and consumed across Kenya; and for sorghum and green gram, which are drought-tolerant crops that farmers tend to grow on a more commercial basis than maize.

Figure 1 illustrates how this PBI solution works. To monitor crop growth and damage for insurance claims settlement, the solution uses pictures of insured crops, taken using a dedicated smartphone application (called SeeItGrow in the case of Kenya) at regular intervals from sowing to harvest, and always of the same portion of the plot to minimize tampering. During project implementation, agricultural experts inspect pictures to verify crop damage, but as more images labeled with indicators of crop damage have become available, insurers have started using deep learning models to automate image processing, and implement the solution at larger scale. The main benefit of using pictures is that it pays farmers in case of visible damage to their crops, making the product easier to understand and helping to reduce the basis risk—that is, the inadequate correlation between insurance payouts and actual crop losses—that has hindered the adoption of 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 can reduce incentives to invest in risk prevention, since claims are settled based on pictures of insured crops, and the costs of having visibly damaged

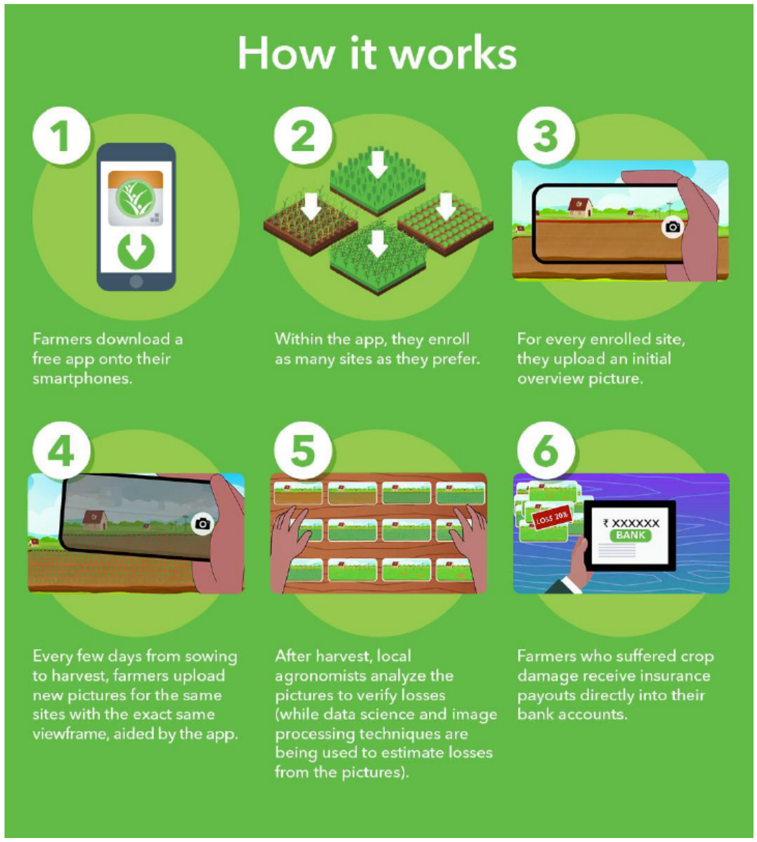

Figure 1: Illustration of how picture-based crop insurance (PBI) works

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 PBI, indicating that this can be a marketable insurance solution. Nonetheless, farmers learn about the benefits of the product over time, and prolonged experience with indemnity-based insurance could change the nature of selection and incentive effects. In fact, as being insured in itself is expected to increase farming efforts and investments, incentive effects can be either positive or negative compared to an index-based insurance product that, by design, is unaffected by information asymmetries. For this reason, in the present study, we provide farmers with several seasons of product experience, and then study outcomes under PBI both compared to a control group and to a group that was offered a standard, commercially available weather index-based insurance (WBI) product.

In Kenya, the distribution of the insurance product was done through so-called champion farmers, which are 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 seeds of improved varieties. Champion farmers would register up to 250 farmers with the insurance service provider to establish a census of farmers to market insurance, seeds, and other agricultural risk management services. Half of registered farmers were randomly assigned to be eligible for current project activities, and champion farmers were asked to shortlist 20 eligible farmers for picture-based crop monitoring activities.[1] For these farmers, henceforth referred to as project farmers, champion farmers would send in pictures of farmers' plots for crop monitoring purposes. All project farmers also received a free maize or sorghum seed sample; and as part of the intervention in our treatment arms, project farmers received free trials of an insurance product for one acre of land.

2.2 Study context

The project was implemented in 7 counties in eastern and western Kenya, covering a range of agroecological zones. In eastern Kenya, the study included the counties of Machakos, Makueni and Tharaka-Nithi, focusing on subcounties with largely semi-arid and arid lands (ASALs), as well as mid-potential rainfall areas from areas of Meru and Embu. The counties from western Kenya included Busia and Bungoma, which largely cover mid- to high- potential rainfall areas. The project was implemented from 2019 to 2022, during which Kenya experienced one of the worst droughts in 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, as well as fertilizer use and costs. Only 14% of farmers in our control group—our counterfactual—had purchased insurance at endline (Figure 2, Panel A). 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.

Fertilizer investments are a commonly used measure of productive risk-taking under uncertainty. In 2021, Kenya imported 792,670 metric tons of fertilizer, an indication of how much fertilizer

[1] Appendix Table A2 shows that shortlisted farmers differ from the overall pool of registered farmers in several ways. Shortlisted farmers are slightly younger and less likely to fall in the oldest age group, more likely to report ownership of smartphones, and they are less likely to have ever bought insurance. They also show small but statistically significant differences in food consumption scores, amount of land cultivated, and decision-making indicators—suggesting they are somewhat better off or more engaged in farm management than non-shortlisted farmers. Whilst this is a consideration to keep in mind when thinking about external validity, it does not affect our internal validity. Shortlisting was done before champions were assigned to treatment, and treatment will therefore not have influenced the types of characteristics on which champions shortlisted farmers.

was used by Kenya's 7.5 million smallholder farmers in that year. DAP, NPK, CAN, Urea, NP Compounds and MOP accounted for 91% of these fertilizer imports (IFDC, 2022). About a quarter of this 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 Panel B).

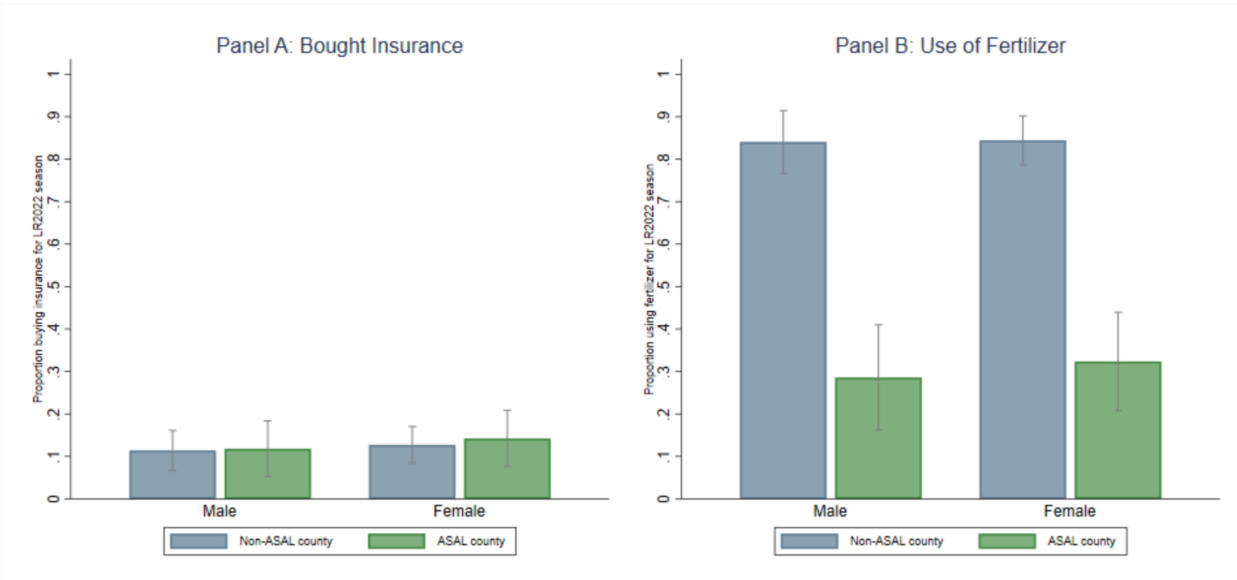

Figure 2: Counterfactual insurance take-up and fertilizer use

2.3 Experimental design and data collection

Table 1 summarizes the experimental design. Our aim was to evaluate the impacts of a change in insurance contract design (moving from index-based to picture-based indemnity-based coverage) on demand for insurance, the composition of the insured pool of farmers, and fertilizer use. To that end, 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); a weather index-based insurance (WBI) treatment arm, in which project farmers received free trials of rainfall insurance (20% of all champion farmers); and a treatment arm in which project farmers received free trials of the new indemnity-based picture-based insurance (PBI) product (40% of all champion farmers). We randomly assigned relatively more champions and farmers to the control and PBI treatment arms, since the WBI treatment mainly served to analyze the effects of PBI on insurance take-up. That comparison requires a relatively smaller sample than the comparison of fertilizer use between treatment and control.[2]

[2]We cross-randomized an intervention aiming to improve access to high-quality seed. Champion farmers across all treatment arms were tasked with marketing seeds of widely available maize and sorghum varieties,

Table 1: Overview of the experimental design

<table>
<tr><th>Control group
40% of champions</th><th>Weather index insurance
20% of champions</th><th>Picture-based insurance
40% of champions</th></tr>
<tr><td colspan="3">Picture-based crop monitoring by champion farmer until LR22</td></tr>
<tr><td>No free insurance trials</td><td>Free WBI in SR20/LR21/SR21</td><td>Free PBI in SR20/LR21/SR21</td></tr>
<tr><td rowspan="2">WBI sold in LR22 with
no subsidies</td><td>WBI sold in LR22 with</td><td>PBI sold in LR22 with</td></tr>
<tr><td colspan="2">20% vs 80% subsidy for project farmers</td></tr>
</table>

Notes: SR and LR stand for Short Rains and Long Rains, respectively, with 20, 21 and 22 representing the years 2020, 2021 and 2022. WBI and PBI stand for weather index-based and picture-based insurance.

Project farmers received their free insurance trials for three subsequent seasons in the WBI and PBI arms, as seen in Figure 3.[3] Uptake of free insurance trials was universal across project farmers in the WBI and PBI arms, as there were no administrative requirements for farmers to enroll; project farmers were automatically insured. We therefore do not study demand during the three seasons with free insurance trials. However, a few months prior to endline, champion farmers in all treatment arms (including the control group) provided all farmers with an opportunity to purchase insurance. In the control group and the WBI arm, farmers were offered WBI, whereas in the PBI arm, the PBI product was offered. Most farmers, including all farmers in the control group and non-project farmers in the WBI and PBI arms, were offered these insurance products at actuarially fair premiums, without additional subsidies. Project farmers in the WBI and PBI treatment arms received insurance premium subsidies, and we randomized at the farmer level whether these subsidies were 80% or 20%, creating exogenous within-village variation in premiums that project farmers were asked to pay.

Across all three treatment arms, champions were tasked with picture-based crop monitoring for project farmers, and also the marketing strategies in our WBI and PBI treatment arms are identical in every aspect. The only aspect that was different between these two arms was the offered insurance product itself, along with associated payout experiences from the first and second season (payouts from the third season had not yet been made due to administrative delays in insurance claim settlement, as shown in Figure 3). Thus, differences in uptake rates between WBI and PBI will reflect preferences for a product, rather than experiences with picture-based crop monitoring or a more appealing marketing strategy in one of the two treatment arms. Importantly, our 'pure'

and in the cross-randomized treatment, also of improved (drought-tolerant) varieties. Seed sales were low, though. Our regressions control for this cross-randomized treatment, but it does not explain any of the variation in our outcome variables, and we do not focus on this intervention in this paper.

[3]The Long Rains 2020 season was a pilot season with implementation only for champion farmers, because of the COVID-19 pandemic-related mobility restrictions at that time.

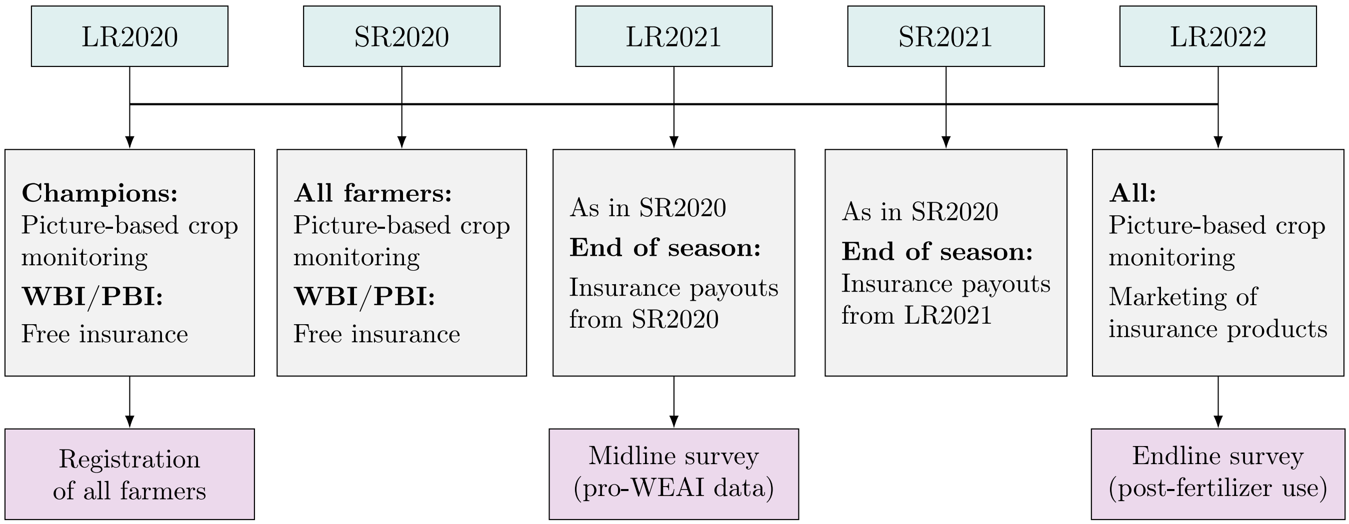

Figure 3: Timeline of Experiment and survey rounds
Notes: SR and LR refer to Short Rains and Long Rains, respectively. WBI and PBI stand for weather index-based and picture-based insurance. The pro-WEAI is the project-level Women's Empowerment in Agriculture Index.

control group helps us disentangle the effects of marketing through free insurance trials and premium subsidies (comparing WBI to control) from the effect of the digital innovation in insurance contract design (comparing PBI to WBI).

Champion farmers registered in total 36,307 farmers at the beginning of the study. These baseline registration data include information on basic demographics and insurance awareness, and for the randomly selected 50% of farmers who would be eligible for project activities (or 18,285 farmers), the data also include more detailed information on education, marital status, income diversification, land use, food security, and intra-household decision-making. From those randomly selected farmers, champions shortlisted about 20 project farmers each, as described above. After one season of implementation, around April 2021, Innovations for Poverty Action (IPA) administered a phone survey with these project farmers.[4] At that time, impacts were expected to be minimal, given that farmers had not yet received any insurance payouts, and perception data from this survey show that farmers were not fully aware of what type of insurance coverage they had through the free trials.[5] The phone survey included the project-level Women's Empowerment in Agriculture Index (pro-WEAI), which produces three measures of empowerment: instrumental, intrinsic, and collective agency (Malapit et al., 2019). After farmers had applied fertilizer for the Long Rains 2022 (LR2022) season (in July 2022), IPA enumerators administered a more comprehensive in-

[4]In-person surveys were not feasible in 2021 because of mobility restrictions related to the COVID-19 pandemic.

[5]This, in fact, prompted ACRE Africa to provide additional training to champion farmers and strengthen implementation.

person survey with 10 randomly selected project farmers per champion.[6] Through this survey, we measure the impacts of the two types of insurance products on insurance demand, perceptions, and agricultural investments, including fertilizer use.

2.4 Empirical strategy

Our primary outcomes are insurance take-up, fertilizer use, and out-of-pocket expenditures on fertilizer. Contract design can influence investments in costly inputs, such as fertilizer, through three channels. First, moving from WBI to PBI may increase insurance take-up, particularly among farmers with concerns around basis risk in WBI, by improving product quality and trust in insurance (Kramer et al., 2025); and making products more transparent and enhancing understanding (Timu and Kramer, 2023). Increased insurance coverage, not only in absolute terms, but also in terms of improved *perceptions*, can reduce perceived risk in agricultural production, and thereby increase fertilizer use. Second, contract design may affect the nature of *selection*, that is, influence who chooses to buy insurance, for example by drawing in poorer or less empowered farmers (who are less likely to invest in fertilizer) under PBI than under WBI. Third, it may alter how much insured farmers invest once they are covered, by changing *incentives* to use productivity-enhancing inputs. To disentangle these effects, we first estimate intent-to-treat (ITT) effects of exposure to each insurance design and then correct for endogenous adoption using a Heckman selection model that exploits the randomized premium subsidy as an exclusion restriction.

The ITT specification measures how assignment to each contract affects insurance and fertilizer outcomes; which, in the case of fertilizer use, is regardless of which farmers ultimately purchase insurance:

$$\mathrm{Y}_{ic} = \alpha + \beta_1 \, \mathrm{WBI}_c + \beta_2 \, \mathrm{PBI}_c + \mathbf{X}'_{ic}\delta + \varepsilon_{ic}, \tag{1}$$

where Y_{ic} is a binary variable indicating whether farmer i in cluster c purchased insurance during the Long Rains 2022 season, whether the farmer used inorganic fertilizer in that season, or a continuous variable indicating the natural logarithm of the total amount spent on inorganic fertilizer during the Long Rains of 2022. We regress these outcome variables on WBI_c and PBI_c, our two treatment indicators (with the control group being the omitted category), and $\mathbf{X}_{ic}$. The vector $\mathbf{X}_{ic}$ includes variables selected using a LASSO procedure to avoid overfitting. The resulting set of controls is used in all specifications, including both the ITT and subsequent Heckman selection models. Coefficients β_1 and β_2 capture average intent-to-treat treatment effects of WBI and PBI relative to control. The difference between these two coefficients represents the effects of changes in contract design. All regressions include county fixed effects and cluster-robust standard errors at the village level. Predicted insurance take-up and fertilizer use plotted in Sections 4.1 and 4.2 are all derived from this ITT specification in Equation 1.

[6] 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.

Because farmers self-select into insurance, ITT estimates for fertilizer use in Equation 1 may mask heterogeneous behavioral responses. A naïve regression restricted to adopters would be biased if unobserved traits, such as risk preferences, optimism, or entrepreneurial ability, influence both the decision to insure and fertilizer investment. One option to correct for this bias would be to use instrumental variables (IV) and estimate local average treatment effects (LATE) of purchasing WBI and PBI, by instrumenting these purchases with the randomly assigned contract type in a two-stage least squares framework, as described in Appendix C. In practice, the effect of WBI on insurance take-up is only moderate, and the first stage is weak in several strata, limiting precision and potentially even biasing our second-stage estimates (Heckman, 1979; Puhani, 2000).

Because of the limitations associated with using instrumental variables when the first stage is weak, we turn to a Heckman selection model to estimate to estimate average treatment effects on the treated.[7] This approach allows us to jointly estimate the effects of WBI and PBI treatments on insurance purchase decisions, and the effects of both treatments on fertilizer investments among insured farmers. To correct for non-random insurance purchases when estimating effects on fertilizer use, this model exploits the randomized subsidy (which was either 80% or 20% for project farmers in the WBI and PBI arms) as an exclusion restriction. Specifically, we estimate the Heckman selection model using full-information maximum likelihood (FIML), which includes a selection equation that models the latent probability of insurance purchase as the following probit model,

$$\text{Insure}^*_{ic} = \mathbf{Z}'_{ic}\pi + u_{ic}, \qquad \text{Insure}_{ic} = 1\{\text{Insure}^*_{ic} > 0\}, \tag{2}$$

where $\mathbf{Z}_{ic}$ includes the two contract-type indicators (WBI and PBI), whether a farmer was offered the high (80%) premium subsidy level (as opposed to the 20% premium subsidy), and the post-LASSO control vector $\mathbf{X}_{ic}$ defined previously. The outcome equation models fertilizer investment among those who purchase insurance as

$$\text{Fert}_{ic} = \alpha + \beta_1 \text{WBI}_c + \beta_2 \text{PBI}_c + \mathbf{X}'_{ic}\delta + \eta_{ic}. \tag{3}$$

where $\mathbf{X}_{ic}$ includes the same post-LASSO selected covariates. Estimation of these two equations is conducted jointly using FIML under the assumption that the error terms (u_{ic}, η_{ic}) follow a bivariate normal distribution with correlation ρ.

The coefficients β_1 and β_2 now measure the average effects of WBI and PBI on fertilizer use among insured farmers after accounting for selection bias—which is our estimate of the average treatment effect on the treated (ATET) for each contract. The FIML procedure reports a parameter that allows us to test for selection: ρ, which is the correlation in error terms of selection and outcome equations. A statistically significant `rho` indicates that unobserved characteristics jointly influence insurance adoption and fertilizer use, making the selection correction relevant. The sign of ρ reveals

[7] Nonetheless, Appendix C, estimating IV-based LATE estimates, replicates our main results.

whether insured farmers are, on average, positively selected (unobservables that increase insurance take-up also increase fertilizer use) or negatively selected (unobservables that increase insurance take-up reduce fertilizer use).

Three features make the Heckman estimator well suited to our context. First, the randomized premium subsidy provides a natural exclusion restriction. Conditional on contract type and baseline characteristics, high premium subsidies increase the probability of purchasing insurance in the selection equation, without affecting fertilizer use in the outcome equation. This exclusion is justified by the relative scale of the subsidy variation compared to fertilizer costs during the study period. In principle, the money saved by spending less on insurance could have been used for fertilizer. However, the difference in high and low insurance premium subsidies (80% of KES 200 versus 20% of KES 200, or KES 120) was only a fraction of the total cost of a bag of fertilizer, even more so as fertilizer prices peaked during the Long Rains 2022 season.[8] Second, unlike IV methods that depend on a strong first stage, the Heckman FIML uses information from both adopters and non-adopters, improving estimator efficiency. The Heckman FIML produces selection-corrected ATET estimates for the effects of WBI and PBI on fertilizer use among the insured. Third, the FIML directly provides insights on selection, by reporting the correlation between unobservable characteristics driving both insurance take-up and fertilizer use, which is important given our interest in whether the nature of selection changes as a result of a shift in product design.

3. Data

3.1 Descriptive statistics and balance across treatment arms

This section provides a description of the study sample at baseline, balancing of baseline characteristics across treatments, and determinants of participation in the endline survey. First, in Table 2, we start with a description of project farmers, based on the data champion farmers collected for all farmers they wished to register into the project at the beginning of the study. At that time, they had not yet been assigned to any treatment arm, and we would not expect to observe imbalances across treatments. To test this assumption, we compare descriptive statistics for project farmers in the control (column 1), the WBI treatment (column 2) and the PBI group (column 3).[9]

Around 60% of the sample is female, closely resembling the demographics of rural areas in Kenya, as men have often migrated to cities to generate off-farm income. Nearly all farmers have their

[8] Peaks in fertilizer prices were driven by the COVID-19 pandemic's impact on production, increased international oil and natural gas prices, and the conflict in Russia-Ukraine. Kenya did not implement a widespread, general subsidy program until September 2022, at which point the price was reduced to a maximum of KES 3,500 per 50kg bag under the subsidy. Before this subsidy, market prices were significantly higher, sometimes reaching up to KES 7,500 (Anyango, 2022; Mather et al., 2022).

[9] We also have baseline registration data for champion farmers, but are leaving them out from the analysis given their role in project implementation.

own phone, but at the time of baseline registration, less than one third of project farmers owned a smartphone, necessitating the involvement of champion farmers in sending images for picture-based crop monitoring. The median project farmer is between 35 and 55 years of age, with around one quarter of respondents being considered youth farmers (under the age of 35), and another quarter being over 55 years of age. Although around one third of farmers had been trained on insurance at some point, only about 15% had ever taken up insurance. Household dietary diversity scores suggest that the average farmer consumes less than 3 food groups on average, and food consumption scores (FCS) suggest high food insecurity in the area. However, follow-up data suggest that this may also have been a data quality issue as champion farmers are not well-trained enumerators.

When asked how much land farmers cultivated, more than 10% said that they had not cultivated any land in the previous season, and among the remaining project farmers who did cultivate land, the modal farmer cultivated less than one acre (roughly 40%). Nearly 25% of respondents cultivated between 1 and 2.5 acres, another 20% cultivated between 2.5 and 5 acres, and very few (about 5%) cultivated more than 5 acres. Champion farmers also asked project farmers about household decision-making practices at the time of baseline registration. Most project farmers indicated that they took decisions on what seeds to use, how to finance production, where to sell the produce, and how to spend their income, by themselves (62 to 68%, depending on the type of decision), as opposed to taking these decisions jointly, or not having a say in the decision-making process at all.

In the final three columns, we test for balance across treatment arms. For each baseline variable, we estimate simple linear regressions of that variable on treatment arm indicators and county fixed effects, with standard errors clustered by champion farmer, and we report the p-value from the corresponding test of equality between treatment arms. Randomization of registered farmers ended up in very similar groups. Most variables are balanced across treatment arms, without significant differences, with a few exceptions, as would be expected when testing multiple hypotheses: in the PBI treatment, farmers are more likely to be female than in the control group (65% versus 60%, $p < 0.10$); and PBI farmers are more likely to have been ever trained on insurance (38.5% versus 28.3%, $p < 0.10$). We correct for these small imbalances by including control variables for gender and pre-baseline exposure to insurance training. To assess how representative the evaluation sample is relative to the broader population of farmers engaged in the study, we refer readers to Appendix Tables A1 and A2.[10]

[10] Appendix Table A1 compares the full pool of registered farmers at baseline across treatment arms and shows that, on average, these groups were well balanced. Appendix Table A2 then contrasts the evaluation sample to those who were shortlisted and with other eligible but non-shortlisted farmers. While both groups are broadly similar, shortlisted farmers are slightly older, more likely to have cultivated land, and display greater signs of food insecurity.

Table 2: Baseline characteristics of project farmers at baseline

	Control	WBI	PBI	*p*-value		
Variable	Mean (1)	Mean (2)	Mean (3)	PBI–C (4)	WBI–C (5)	PBI–WBI (6)
Female	0.600	0.592	0.651	0.811	0.085*	0.173
Owns a phone	0.957	0.967	0.966	0.275	0.667	0.720
Owns a smartphone	0.334	0.267	0.321	0.177	0.758	0.449
Age $\leq$ 35	0.231	0.257	0.231	0.807	0.878	0.618
Age 36 - 55	0.546	0.507	0.520	0.369	0.298	0.977
Age $\geq$ 56	0.223	0.236	0.249	0.455	0.188	0.549
Attended insurance training	0.283	0.340	0.385	0.618	0.091*	0.462
Ever bought insurance	0.160	0.146	0.162	0.802	0.946	0.796
Household Dietary Diversity	2.458	2.785	2.811	0.324	0.397	0.952
FCS - poor	0.663	0.647	0.638	0.730	0.824	0.890
FCS - borderline	0.104	0.086	0.109	0.532	0.833	0.365
FCS - acceptable	0.233	0.267	0.252	0.523	0.884	0.772
Did not cultivate land	0.140	0.120	0.112	0.414	0.334	0.799
Land cultivated < 1 acre	0.359	0.395	0.412	0.826	0.573	0.857
Land cultivated 1 - 2.5 acres	0.244	0.233	0.249	0.988	0.784	0.859
Land cultivated 2.6 - 5 acres	0.204	0.198	0.190	0.640	0.798	0.966
Land cultivated > 5 acres	0.053	0.054	0.037	0.995	0.638	0.564
Decides on seed use alone	0.683	0.675	0.663	0.980	0.538	0.566
Decides on input financing alone	0.682	0.634	0.656	0.498	0.463	0.912
Decides on sales output alone	0.681	0.623	0.652	0.425	0.447	0.977
Decides on income use alone	0.667	0.633	0.668	0.687	0.851	0.795
Observations	1,630	615	1,336			

Notes: Means of baseline characteristics for project farmers by treatment arm: picture-based insurance (PBI), weather index-based insurance (WBI) and the control group. Columns 4–6 present p-values from tests of equal means between arms, derived from regressions of the baseline variable on an indicator for treatment arm and county fixed effects using only observations in the control and WBI arm in column (4), observations in the control arm and PBI arm in column (5), and observations in the WBI arm and PBI arm in column (6).

3.2 Empowerment measures

We conjecture that empowerment is an important prerequisite for farmers to be able to both purchase insurance and use fertilizer. During April 2021, we collected phone survey data allowing us to construct the project-level Women's Empowerment in Agriculture Index (pro-WEAI), which is a survey module that covers various domains of empowerment: instrumental, intrinsic, and collective agency (Malapit et al., 2019). To measure instrumental agency ("power to"), the index measures: (i) the extent to which a respondent has input in household decision-making over production; (ii) their control over income; (iii) access to and control of assets; (iv) access to and control over financial instruments; (v) freedom from time constraints (measured through a 24-hour recall of time allocation); and (vi) mobility, which influences access to markets and services. Intrinsic agency ("power within") is measured by asking respondents about: (i) their autonomy in income decisions; (ii) their rejection of domestic partner violence; and (iii) their perceived self-efficacy. Collective agency ("power with") is measured as a respondent's membership and participation in different types of groups within the community, including farmer and savings groups.

For each respondent, we construct standardized scores for these three domains of empowerment, as well as an aggregated score across the three domains (the so-called 3DE score). First, we construct respondent-specific measures of the ten indicators underlying pro-WEAI, and standardize these ten indicators to have mean zero and unit variance in the entire sample (including men and women respondents). For each domain of empowerment, we then average across the standardized components of the underlying indicators for that domain, to form indicators of intrinsic, instrumental, and collective agency. We re-standardize each agency indicator, from which we build an aggregate empowerment score as the equal-weighted mean of the three subindices (referred to as the 3DE score in pro-WEAI resources), which again we standardize to have a mean of zero and a standard deviation of one. Due to this standardization, the coefficients for these indices can be interpreted as changes associated with an increase of one standard deviation in intrinsic, instrumental, or collective agency; or in overall empowerment across the three domains. Not all observations can be matched to the midline survey; for respondents without empowerment data, we impute missing values, and we include a dummy variable in regressions to indicate that values were imputed.

Table 3 reports mean values of the overall agency index and its three domains, along with clustered standard errors, by treatment arm. Panel A presents results for all farmers. Panels B and C split the sample by gender. In the full sample, we do not detect statistically significant differences among any of the pro-WEAI indices across treatment arms. The same pattern holds when we look separately at women and men. Moreover, across all treatment arms, women have lower intrinsic and instrumental agency than men, and also their aggregate empowerment scores are lower than those among men. However, women have higher collective agency than men, as they are more likely to be part of farmer groups and other collectives in their communities. Because of this heterogeneity in agency for women and men, we mainly use the separate agency scores instead of the overall index in our

Table 3: Pro-WEAI agency indices by treatment arm

	Control		WBI		PBI		*p*-value		
	Mean	SE	Mean	SE	Mean	SE	PBI–WBI	PBI–Ctrl	WBI–Ctrl
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Panel A: All project farmers									
Overall agency	0.075	0.061	-0.019	0.075	-0.085	0.0786	0.679	0.456	0.749
Intrinsic agency	0.054	0.054	-0.042	0.085	-0.046	0.068	0.222	0.268	0.830
Instrumental agency	0.065	0.067	0.052	0.096	-0.112	0.079	0.467	0.490	0.927
Collective agency	0.021	0.056	-0.046	0.099	-0.001	0.062	0.248	0.789	0.435
Observations	704		317		556				
Panel B: Women									
Overall agency	0.041	0.067	-0.046	0.095	-0.132	0.089	0.980	0.482	0.637
Intrinsic agency	-0.057	0.070	-0.161	0.107	-0.129	0.079	0.623	0.500	0.959
Instrumental agency	-0.052	0.077	-0.068	0.109	-0.206	0.093	0.990	0.996	0.920
Collective agency	0.186	0.058	0.142	0.117	0.088	0.075	0.638	0.539	0.445
Observations	435		194		383				
Panel C: Men									
Overall agency	0.131	0.084	0.024	0.099	0.019	0.115	0.850	0.896	0.988
Intrinsic agency	0.236	0.057	0.145	0.110	0.140	0.102	0.328	0.571	0.988
Instrumental agency	0.254	0.088	0.242	0.135	0.094	0.104	0.585	0.481	0.949
Collective agency	-0.245	0.082	-0.343	0.116	-0.198	0.087	0.219	0.308	0.937
Observations	269		123		173				
Panel D: ASAL									
Overall agency	0.432	0.053	0.293	0.099	0.422	0.121	0.347	0.864	0.114
Intrinsic agency	0.272	0.058	0.169	0.072	0.173	0.110	0.807	0.377	0.429
Instrumental agency	0.349	0.091	0.229	0.132	0.365	0.130	0.220	0.524	0.213
Collective agency	0.185	0.066	0.149	0.127	0.249	0.076	0.402	0.573	0.519
Observations	315		98		173				
Panel E: Non-ASAL									
Overall agency	-0.213	0.063	-0.158	0.083	-0.313	0.069	0.252	0.295	0.618
Intrinsic agency	-0.121	0.073	-0.136	0.113	-0.144	0.081	0.209	0.469	0.569
Instrumental agency	-0.165	0.079	-0.026	0.125	-0.328	0.068	0.100	0.169	0.392
Collective agency	-0.111	0.079	-0.133	0.127	-0.113	0.075	0.394	0.972	0.597
Observations	389		219		383				

Notes: Table reports means and clustered standard errors (SE) of the mean for project-level Women's Empowerment in Agriculture Index (pro-WEAI) domains by treatment arm. WBI: Weather index-based insurance. PBI: Picture-based insurance. *p*-values come from linear regressions of each index on treatment indicators (with county fixed effects and standard errors clustered at the champion farmer level), testing equality of means between the indicated arms.

main estimations. Finally, Panels D and E show considerably higher empowerment scores in counties with semi-arid lands compared to higher rainfall areas across all domains of empowerment.

3.3 Attrition in the endline survey

Of the full sample of 20 project farmers registered by champions at baseline, in 2019-2020, 49% participated in the endline survey a full 2 years later. This is in part by design; we randomly sampled on average only 10 of the 20 project farmers per champion for the endline survey. However, in case not all 10 sampled farmers could be found, the remaining project farmers could be used as replacements, introducing potential for selective attrition. To explore this further, Appendix Table A3 presents the marginal effects from a probit model that estimates the probability of participating in the endline survey as a function of baseline characteristics for the full sample. We control for indicators of treatment and county fixed effects, though coefficients on treatment indicators are not shown.

Column (1) reports results for the model without treatment interactions. Attrition is indeed systematically related to a number of baseline characteristics. All else equal, women are 5.5 percentage points more likely to participate in the endline survey than men. The few farmers without phone are 17 percentage points less likely to be re-interviewed, while those with smartphone are 6.6 percentage points less likely to participate. Attrition is significantly higher among the youth (35 years of age or younger) than among the elderly (55 years and above; omitted category). Farmers who had ever bought insurance before the start of the project are about 6.8 p.p. more likely to participate in the endline survey. Attrition is lower among farmers who cultivated more than 5 acres of land at baseline (omitted category) than among farmers with smaller areas of land cultivated, including farmers who did not cultivate at all.

We also find differences in average attrition rates across treatment arms. WBI farmers were 5.4 percentage points more likely to be surveyed than control farmers, while PBI farmers were 2.8 percentage points less likely compared to the control group to complete the endline survey. These differences with the control group are not significant, but a formal test marginally fails to reject the null that WBI and PBI have equal attrition rates ($p = 0.095$). Columns (2)-(4) explore whether the predictors of attrition vary by treatment arm. This is done by interacting all baseline covariates with treatment indicators in a single model. The joint χ^2 test reported at the bottom of the table rejects the null of the interaction terms being jointly insignificant ($p = 0.077$ for WBI and $p = 0.054$ for WBI). This suggests heterogeneity in the determinants of attrition.

To correct for this differential attrition across treatment arms, our analyses will reweigh the sample using the inverse probability of participating in the endline survey, as estimated from the probit regressions presented in Table A3. This means that farmers with characteristics that are relatively less likely to be represented in the endline survey receive a higher weight. Such reweighting of observations based on their inverse probability weights is a common strategy to correct for potential selection on observables (Fitzgerald et al., 1998).

4. Results

In this section, we present the main results in three steps. We begin with the effects of WBI and PBI on the adoption of insurance and fertilizer for the aggregate sample. We then explore heterogeneity in these intent-to-treat (ITT) effects for different types of farmers. We show that effects of PBI on insurance take-up are more pronounced among women, but that effects on fertilizer use are largest among men, especially in the WBI treatment arm. While differences in observed changes in fertilizer use may reflect incentive differences across contract types, they may also arise from differential selection into PBI, which in our case could be considered inclusive market expansion of individuals who are less likely to use fertilizer in the first place.

This motivates our third step, which is to estimate the effects of WBI and PBI using Heckman selection models, whereby we correct for potential selection in insurance when estimating effects of contract type conditional on purchasing insurance. Both sets of estimates (ITT and Heckman selection-corrected models) are worth describing in their own regard. The ITT estimates help assess the aggregate effects of providing WBI and PBI, which provides policymakers with insights on effectiveness for the targeted study population. The Heckman selection-corrected models estimate impacts conditional on purchasing insurance, as an average treatment effect on the treated (ATET).

4.1 Treatment effects on insurance take-up

We begin by analyzing how prior exposure to subsidized insurance contracts affects subsequent market demand for insurance. At the start of the Long Rains 2022 season, a few months before the endline survey, all respondents were approached by their champion farmer with the offer to purchase insurance; at subsidized premiums for project farmers in WBI and PBI villages, and at full, unsubsidized rates for any other farmers, including those in the control group. The type of product offered varied by treatment: farmers in WBI villages could buy the weather-based index contract of which they had received free trials for the two previous seasons; farmers in PBI villages could buy the picture-based index contract for which they had previously received free trials; and in control villages, farmers could purchase the standard WBI product (of which they had previously not received free trials). Differences between treatments therefore capture how prior exposure and subsidies (WBI versus control) and contract design (WBI versus PBI) influence insurance demand.

Figure 4 plots insurance take-up by treatment arm, estimated using Equation (1), which includes county fixed effects and cluster-robust standard errors.[11] We display the predicted share of farmers purchasing insurance, along with 90% confidence intervals. Because the control group could purchase unsubsidized WBI, we observe some take-up (13%) in this treatment arm. Past exposure to WBI through free insurance trials, combined with premium subsidies, increases the probability of purchasing insurance by 7 percentage points to about 20%. Among farmers offered a low (20%) versus high (80%) subsidy, uptake increases to about 18% and 21% but this difference is not statistically significant. However, PBI take-up is significantly higher than WBI take-up among farmers receiving the high subsidy ($p = 0.027$), and marginally higher among those receiving the low subsidy ($p = 0.071$).

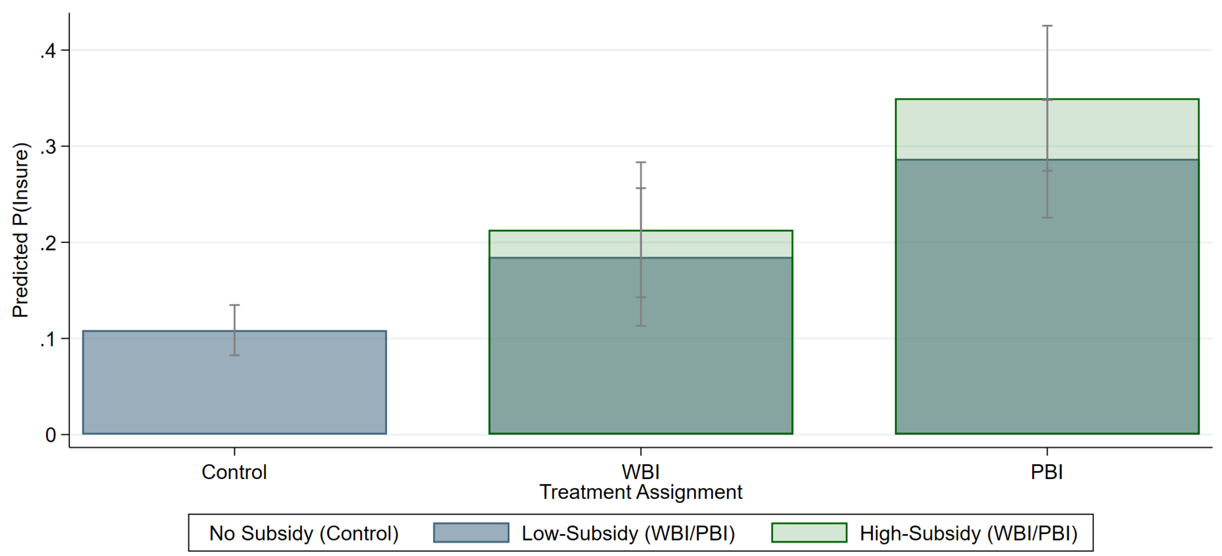

Figure 4: Insurance uptake by contract type and subsidy level

Villages assigned to PBI achieved a significantly higher take-up rate of 29% under the low-subsidy and 35% under the high subsidy. In other words, assignment to PBI increases take-up by roughly 17 percentage points relative to the control group and by about 10 percentage points relative to WBI. This is a strong behavioral effect of insurance product design. To explore what might explain this result, Table 4 compares farmers' subjective evaluations of insurance across treatment arms. We focus on eight endline perception outcomes and a summary standardized index. Each item reflects a distinct construct, including ease of understanding, affordability, trust, and perceived quality.

The results point to strong, positive perception effects for PBI that mirror the take-up results, with a robust favorable shift in the perception index by 0.278 standard deviations as a result of PBI.

[11] Appendix Table A4 presents the regression results corresponding to Figures 4-8, for insurance take-up (Column 1), fertilizer use (Column 2), and fertilizer expenditures (Column 3). This table starts with between aggregate treatment effects (Panel A), but also presents treatment effect heterogeneity by region (Panel B) and by gender (Panel C).

Assignment to PBI significantly increases agreement across nearly all dimensions, with especially large improvements in perceived availability (18.6 pp), trust (15.6 pp), and quality (17.2 pp). PBI farmers seem to find the product easier to understand (+14.1 pp) and are more likely to expect a payout (+12.1 pp). Assignment to WBI had no statistically significant effect on any perception category. This lack of movement in subjective evaluation helps explain the relatively muted effect of free WBI trials on demand. Unlike WBI, the design of PBI appears to successfully address trust and transparency barriers that the standard WBI product does not.

Table 4: Endline perceptions of crop insurance characteristics

	Index (1)	Understand (2)	Available (3)	Cheap (4)	Timely (5)	Expect payout (6)	Trust (7)	Quality (8)	Champion (9)
WBI	0.063	0.060	0.028	-0.021	0.046	0.033	0.040	0.065	-0.002
	(0.091)	(0.050)	(0.056)	(0.059)	(0.045)	(0.055)	(0.050)	(0.051)	(0.047)
PBI	0.278***	0.141***	0.186***	0.131***	0.093**	0.121***	0.156***	0.172***	0.085**
	(0.070)	(0.040)	(0.045)	(0.042)	(0.041)	(0.043)	(0.042)	(0.042)	(0.036)
Control mean	0.016	0.601	0.536	0.597	0.388	0.588	0.585	0.572	0.780
N	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577	1,577

Notes: Column (1) presents a standardized summary index of the eight insurance-related perceptions from Columns (2)-(9). These eight items were measured through a series of statements on insurance to which respondents could agree a lot, agree, disagree, or disagree a lot. Each dependent variable equals one if the respondent agrees or strongly agrees with the statement and zero otherwise. Statements related to understanding the contract (2), availability when needed (3), affordability (4), timely payouts (5), expected payouts in case of damage, that is, limited basis risk (6), trust in the insurer (7), perceived quality (8), and relationship with the champion farmer (9). Coefficients are estimated using Equation (1), including county fixed effects and LASSO-selected controls. Standard errors clustered at the champion level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

This is consistent with the hypothesis that a more credible and transparent verification mechanism for insurance payouts (using photographic evidence of crop damage) reduces perceived basis risk, improves trust in the insurance product and its provider, and thereby strengthens demand for insurance. This pattern follows broader experimental evidence that contract credibility, not price alone, remains the central barrier to adoption (Carter et al., 2017; Kramer et al., 2025; Vosper and Cecchi, 2021). At the same time, these differences in take-up of WBI and PBI imply that the composition of insured farmers may differ across contract types, with potential implications for how insurance affects productive risk taking.

4.2 Treatment effects on fertilizer use

From the participation patterns, we next turn to our second question: whether being offered insurance, and variation in contract design, translates into higher fertilizer use, our main measure of productive risk-taking under uncertainty in this paper. Figure 5 presents fertilizer use by treatment, based on estimates of the ITT model in Equation 1. The outcome variable equals one if the farmer reported applying any inorganic fertilizer during the Long Rains 2022 season, after having been offered to purchase insurance (WBI or PBI, depending on treatment arm) at subsidized premiums. As before, we plot the outcome variable as a proportion, this time the share of farmers using fertilizer, along with 90% confidence intervals.

Overall, fertilizer use is high, with 67% of farmers using any type of inorganic fertilizer in the control group. However, this is masking low use in semi-arid areas (see Section 2), to which we will return below. On average, being offered either form of insurance increases the probability of fertilizer use by 8–10 percentage points (Panel A). In terms of fertilizer expenditures, we are observing a similar increase, with more pronounced effects that are statistically significant (Panel B). In other words, increased experience with insurance combined with premium subsidies slightly raises the share of farmers using fertilizer, and their total spending on fertilizer. The relatively small observed impacts on fertilizer use at the extensive margin could be related to a large share of farmers already using fertilizer in the control group; evidence from previous agricultural insurance evaluations with sufficiently high take-up has shown more pronounced effects on input use in settings where counterfactual input use was low (Cole et al., 2013; Hill et al., 2019; Karlan et al., 2014).

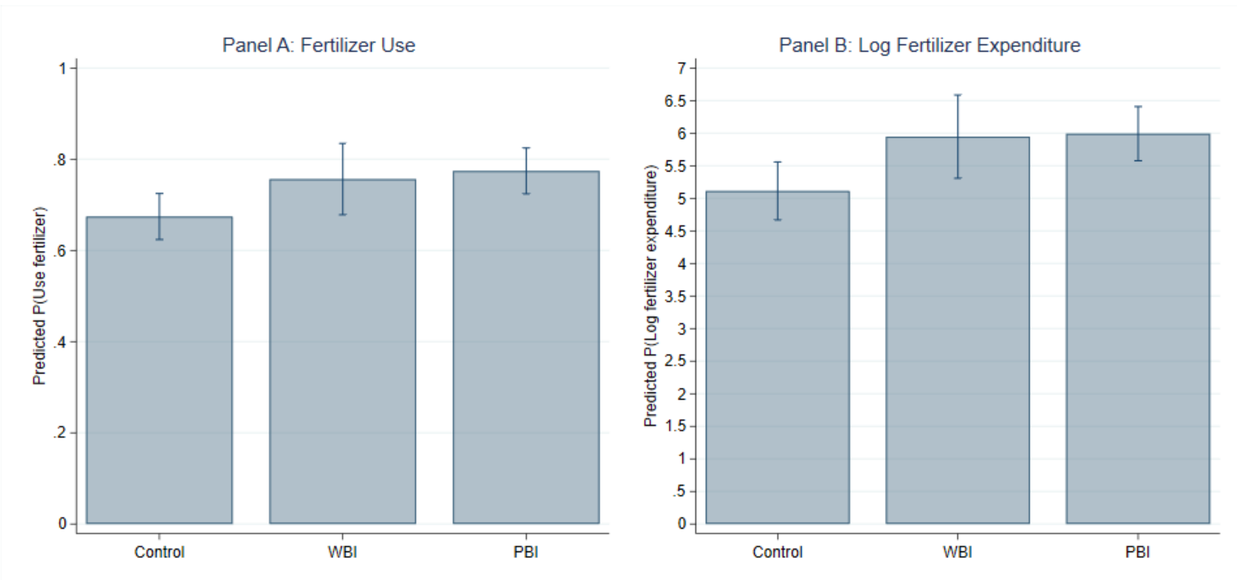

Figure 5: Fertilizer use and log fertilizer expenditure by contract type

If reducing downside risk relaxes farmers' main constraint to using fertilizer, we expect larger effects of PBI than WBI on fertilizer use, given that insurance take-up is considerably larger among farmers offered the PBI contract, and because even conditional on take-up, farmers with PBI coverage may have greater trust than those with WBI coverage in their insurance coverage to pay out–and being able to recuperate at least some of their investments–in case of crop damage. However, in Figure 5, we do not find major differences by contract type, with our model predicting fertilizer to be used by 76% of farmers in WBI villages, and a very similar 77% in PBI villages (Panel A); and also very similar levels of fertilizer expenditures in these two sets of villages (Panel B). Confidence intervals for WBI and PBI overlap substantially, so we cannot statistically distinguish either extensive- or intensive-margin effects of PBI on fertilizer use.

The picture changes when we condition on actual insurance take-up. Figure 6 plots predicted fertilizer use and log expenditure in Panels A and B, respectively, again using the specification noted in Equation 1, but now restricting the sample to insured farmers. Among control farmers who choose to buy (unsubsidized) WBI, the predicted share of farmers using fertilizer is close to 67%, similar to the predicted levels of fertilizer use in the aggregate sample. In the WBI treatment arm, insured farmers have significantly higher rates of fertilizer use, with our model predicting 90% of farmers to use fertilizer, and we also observe significantly higher levels of expenditures. By contrast, farmers who took up insurance in the PBI treatment use fertilizer at rates closer to 73%, which is closer to fertilizer use in the control group. The gap of nearly 20 percentage points between the WBI and PBI treatment arms is statistically significant, as is the gap in fertilizer expenditures between these two treatment arms. This is very different from what we observe for the full sample of farmers in Figure 5, where we did not condition on insurance adoption.

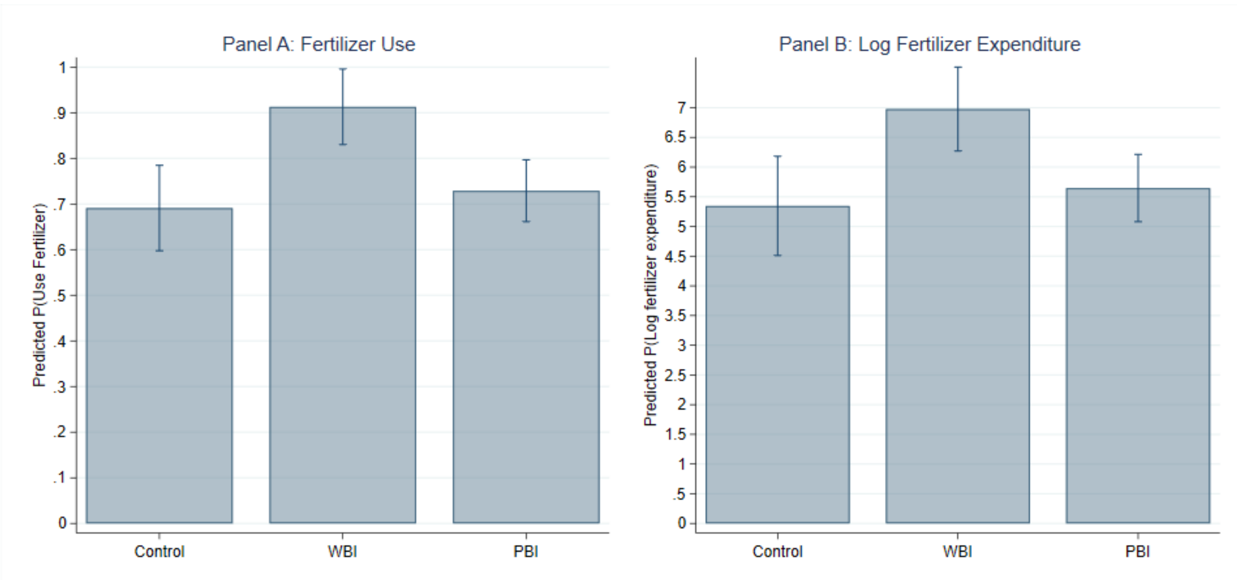

Figure 6: Fertilizer use and log fertilizer expenditure among the insured

4.3 Impact heterogeneity by gender and region

There are two possible explanations for why farmers with PBI coverage are less likely to use fertilizer than farmers with WBI coverage. The first explanation relates to moral hazard under PBI: farmers who purchase PBI may invest less in fertilizer because the indemnity-based nature of PBI coverage weakens their incentives to invest in risk-reducing inputs. The second explanation relates to selection effects: PBI may attract a different type of farmer, who is more vulnerable to weather risk, more liquidity-constrained, and less empowered–and therefore would have invested less in fertilizer even in the absence of insurance–compared to the type of farmers who tend to enroll in WBI.

To explore these mechanisms further, we first analyze impact heterogeneity by gender and region. Panel A in Figure 7 plots predicted shares of farmers purchasing insurance by treatment arm for men and women. Both genders increased their take-up of insurance in response to being offered PBI, but the relative increase is markedly larger among women: for them, predicted insurance take-up rises to roughly one third under PBI, compared with a control mean in the mid-teens, while the corresponding increase for men is more modest. In fact, the absolute gain in demand from switching from WBI to PBI is roughly twice as large for women as for men. This pattern is consistent with evidence that women tend to be more risk-averse and face greater informational constraints in decision making (Phiri et al., 2020; Sheremenko and Magnan, 2015). However, these patterns alone cannot explain why fertilizer use is lower among insured farmers offered PBI than for those offered WBI. Predicted fertilizer use is as high for women as for men, with limited gender differences in estimated treatment effects (Panel B in Figure 7).

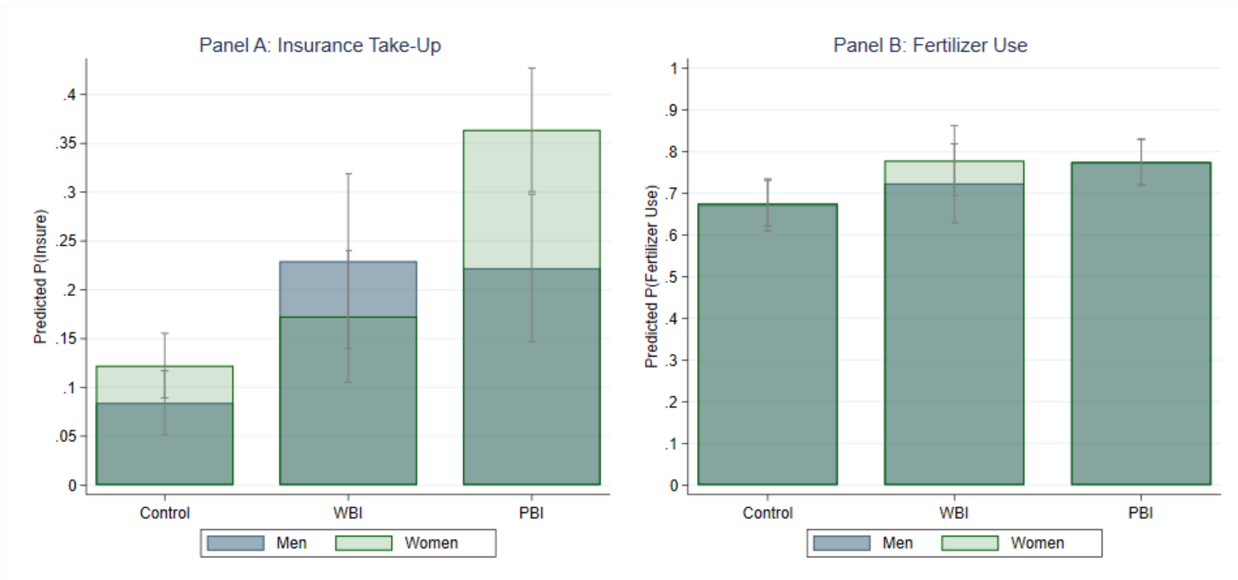

Figure 7: Insurance take-up and fertilizer use by gender

Regional heterogeneity further demonstrates the inclusivity of an indemnity-based insurance contract in terms of take-up. Panel A in Figure 8 shows that predicted take-up in the PBI treatment arm was highest in counties with arid and semi-arid lands (ASALs). ASALs are characterized by the greatest weather volatility and lowest insurance penetration across Kenya. In these areas, the PBI treatment increased the probability of purchasing insurance by more than 20 percentage points relative to the control, compared to about 10 percentage points in non-ASAL areas. The WBI product, in contrast, generated much smaller and statistically insignificant changes across both ASALs and non-ASAL areas. This, combined with ASAL areas being characterized by low fertilizer use (Panel A in Figure 8), suggests that a change in contract design from index- to indemnity-based coverage influences the nature of selection: PBI crowds in farmers from ASAL areas, who are less likely to invest in costly inputs.

These patterns partially explain why we observe lower fertilizer use among insured farmers in the PBI treatment compared to insured farmers in the WBI treatment. Indeed, in non-ASAL areas where fertilizer use is high to begin with, we do observe a stronger effect of PBI on fertilizer use. In semi-arid areas, we find the opposite: although both insurance treatments increase fertilizer use, WBI has more pronounced effects than PBI, even though Panel B in Figure 8 presents ITT effects, including both insured and uninsured farmers. In other words, PBI broadened the composition of insurance beneficiaries to include households that would not enroll in standard index-based insurance, many of whom–at least in ASAL areas–might not have been able to take up insurance coverage even under an index-based contract. At the same time, WBI does increase fertilizer use more in these regions than PBI, meaning that we cannot rule out some modest incentive effects of WBI at the extensive margin.

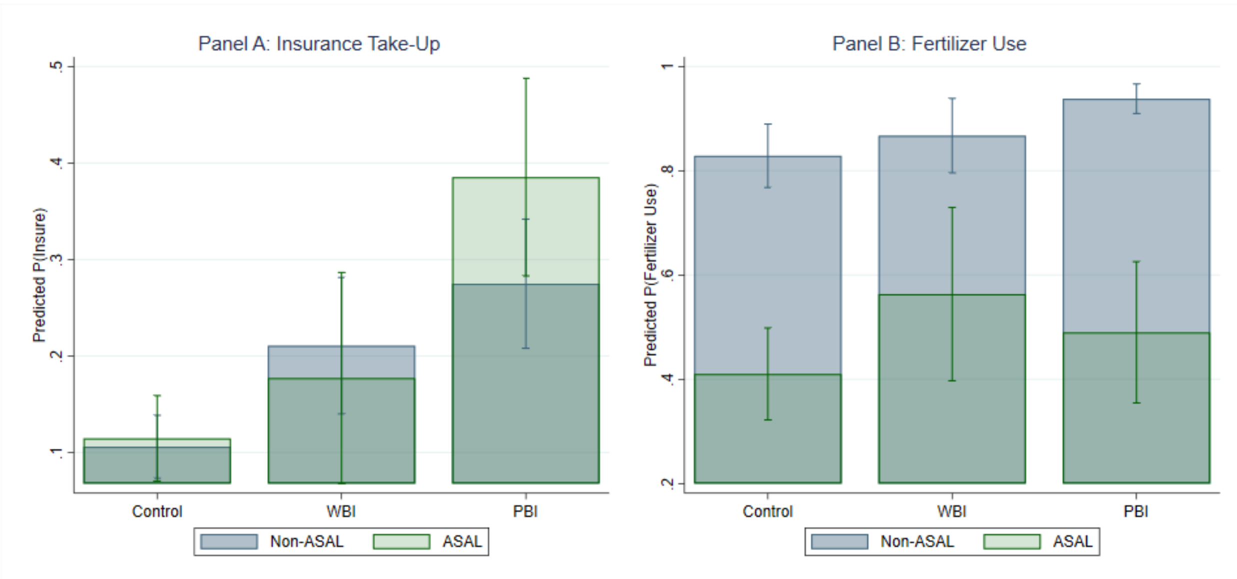

Figure 8: Insurance take-up and fertilizer use by region

A next question is whether selection on gender and by region is driven by gender or regional differences in other characteristics related to both insurance take-up and fertilizer use, such as risk aversion, liquidity constraints, and empowerment. To explore this further, we first use Appendix Figures in Section B to show that empowerment is not evenly distributed across the sample. Farmers who purchased insurance tend to report higher levels of agency, particularly along the instrumental dimension, than farmers who did not purchase insurance. This suggests that even among relatively disadvantaged groups, such as women or farmers in ASAL regions, those with more decision-making power and control over productive assets are more likely to buy insurance. This difference is however less pronounced in the PBI treatment arm, suggesting that PBI does attract a pool of relatively less empowered individuals.

These differences are also reflected in the estimates of Equation (2), which models the probability of a farmer taking up insurance, and serves as the selection equation of the Heckman model. We present these estimates in Appendix Table A6), which interacts our agency measures with treatment status to predict both insurance take-up and fertilizer investment.[12] We find that higher instrumental agency is positively associated with insurance take-up in the WBI treatment, while intrinsic agency is positively associated with take-up in the PBI treatment. These results suggest that agency influences who selects into insurance, and that contract design moderates this relationship. At the same time, as discussed in Section 4.1, PBI appears to crowd in a larger share of farmers from ASAL regions and lower-empowerment groups, indicating that more trusted insurance contracts may help overcome some of the barriers to participation faced by more vulnerable populations.

4.4 Selection-corrected effects of insurance on fertilizer investment

A final strategy we use to distinguish behavioral effects from compositional sorting is by presenting the ATET based on estimates of the outcome equation (3) for the two-equation Heckman selection model described in Section 2.4. The outcome equation captures fertilizer use among those who insure. The randomized premium subsidy enters only the selection equation. We assume that it shifts insurance purchase incentives without directly affecting post-insurance fertilizer behavior, providing an exclusion restriction that helps identify the model. We discussed earlier that savings from the high as opposed to the low subsidy were only a fraction of total fertilizer costs, and therefore unlikely to influence fertilizer purchases directly.

Table 5 presents outcome equation estimates across three outcome variables. Columns (1)-(3) are for binary fertilizer use, Columns (4)-(6) show log fertilizer expenditure unconditional on fertilizer use, and Columns (7)-(10) present the log fertilizer expenditure conditional on fertilizer use. The model estimated in Panel A includes no interaction terms and presents aggregate effects, while Panels B and C estimate models that include interaction terms for treatment and either region (Panel B) or gender (Panel C), allowing treatment effects to vary by region (non-ASAL versus ASAL) and gender (male versus female). All models control for a set of LASSO-specified covariates (see Appendix Table A6 and county fixed effects. Further, we weight observations by inverse probability weights to correct for selective attrition on observed characteristics, based on predicted participation in the endline survey from Appendix Table A3. Standard errors are clustered by champion farmer.

Column (1) presents estimates of the outcome equation of the Heckman model, Equation (2), for fertilizer use in the full sample of farmers enrolled in insurance. Panel A, focusing on aggregate effects in the pooled sample, shows that assignment to WBI increases the probability of fertilizer use by 31 percentage points ($p < 0.05$), while assignment to PBI increases use by 23 percentage points ($p = 0.13$). We cannot reject the null hypothesis that these average treatment effects on the treated (ATET) of WBI and PBI are equal ($p = 0.460$).

[12] Among the full set of agency-by-treatment interaction terms included as candidates, only a subset were selected by the LASSO procedure and appear in the final model. Appendix Table A6 reports only these selected terms.

Table 5: Average Treatment Effect on the Treated (ATET) (Heckman Selection Model)

	Fertilizer use (binary variable)	Log fertilizer expenditures (unconditional)	(conditional)
	All farmers	All farmers	Fertilizer users
	(1)	(2)	(3)
Panel A: Outcome Equation Main Effects			
Treatment effect of WBI	0.309**	1.949**	0.154
	(0.097)	(0.656)	(0.355)
Treatment effect of PBI	0.229	0.954	-0.037
	(0.155)	(0.721)	(0.416)
Rho	0.766	0.367*	0.035
	(0.233)	(0.095)	(0.794)
p-value WBI = PBI	0.460	0.116	0.487
Panel B: Regional Heterogeneity (Total Effects)			
Treatment effect of WBI in ASAL regions	0.614***	3.470***	-0.928
	(0.159)	(1.331)	(0.647)
Treatment effect of PBI in ASAL regions	0.402***	1.979	-0.169
	(0.148)	(1.391)	(0.582)
Treatment effect of WBI in non-ASAL regions	0.164**	1.048*	0.494
	(0.078)	(0.626)	(0.386)
Treatment effect of PBI in non-ASAL regions	0.144*	0.241	-0.075
	(0.077)	(0.631)	(0.465)
Rho	0.795***	0.350	0.042
	(0.007)	(0.164)	(0.785)
p-value WBI = PBI in ASAL regions	0.162	0.255	0.201
p-value WBI = PBI in non-ASAL regions	0.764	0.111	0.468
Panel C: Gender Heterogeneity (Total Effects)			
Treatment effect of WBI for women	0.307***	2.020**	0.390
	(0.103)	(0.823)	(0.551)
Treatment effect of PBI for women	0.187	0.689	0.039
	(0.156)	(0.746)	(0.510)
Treatment effect of WBI for men	0.333**	2.042*	-0.129
	(0.129)	(0.855)	(0.583)
Treatment effect of PBI for men	0.274**	1.526	-0.133
	(0.129)	(0.983)	(0.523)
Rho	0.734	0.365*	0.057
	(0.195)	(0.062)	(0.600)
p-value WBI = PBI for women	0.355	0.092*	0.462
p-value WBI = PBI for men	0.527	0.115	0.994
Observations	1576	1577	1089
Control group mean dependent variable	0.600	4.580	7.788

Notes: Estimates of Equation (3) on the insured, correcting for selection into insurance using Equation (2), whereby receiving a high subsidy serves as the exclusion restriction. For fertilizer expenditures, we use $\log(X+1)$ instead of $\log(X)$ to accommodate zeros. Rho is the estimated correlation of residuals from selection and outcome equations. All models control for LASSO-selected covariates and county fixed effects. Standard errors clustered at champion level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel B estimates the ATET by region. Consistent with earlier findings, we find much larger treatment effects in ASAL areas. WBI increases fertilizer use by 61 percentage points among the insured in ASAL regions ($p < 0.01$), while PBI increases it by 40 points ($p < 0.01$). These are substantially larger than the estimated effects in non-ASAL regions, where the corresponding effects are 16 percentage points under WBI ($p < 0.05$) and 14 percentage points under PBI ($p < 0.10$). However, differences across contract types are not statistically significant. Moreover, selection is correlated with fertilizer use, with a correlation of $\hat{\rho} = 0.795$ ($p < 0.01$).

In Panel C, we analyze heterogeneity by gender. We find that WBI significantly increases fertilizer use by 33 percentage points among men ($p < 0.05$) and by 31 points among women ($p < 0.01$). PBI has slightly smaller ATETs for both genders, increasing fertilizer use by 27 percentage points among men ($p < 0.05$) and 19 percentage points among women (not significant). However, also when allowing for heterogeneity by gender, the differences across contract design are not statistically significant. The correlation between residuals of the selection and outcome equations is of similar magnitude as in Panels A and B, but not statistically significant.

Columns (2)–(3) turn to fertilizer spending. Column (2) presents the ATET among the insured across the full sample, unconditional on fertilizer use. We find large and significant increases in fertilizer investment in Panel A, where assignment to WBI increases fertilizer expenditures by a significant 195 percent ($p < 0.05$). Enrolling in PBI increases fertilizer expenditures by a lower 95 percent. Although this is not statistically significantly, it also not significantly different from the effect of WBI ($p = 0.116$). Selection effects matter also in this specification, with a correlation of 0.37 in residuals from selection and outcome equations ($p < 0.10$). When examining treatment heterogeneity in expenditure outcomes in Panels B and C, we find that especially WBI increases fertilizer spending in ASAL regions, with smaller—but not significantly different—ATET effects of PBI. WBI also increases fertilizer spending among both men and women, again with smaller effects observed for PBI. For women, the difference in effects of WBI and PBI is marginally significant ($p < 0.10$), and we find evidence of selection influencing the outcome also in this specification, with a correlation between residuals of 0.365 ($p < 0.10$).

In Column (3), we present estimated ATETs conditional on fertilizer use. Unconditional on use, effects are larger in magnitude than the binary adoption effects, suggesting that insurance not only affects the decision to use fertilizer but also the intensity of use. However, in Column (3), once conditioning on fertilizer use, these treatment effects are smaller and no longer statistically significant, indicating that insurance affects fertilizer investment mainly at the extensive margin.

Taken together, Table 5 points to a consistent picture. Across specifications, we find evidence of a modest selection bias, with residuals between selection and outcome equations being correlated—although the correlation for fertilizer use is significant only when we interact treatment with region, suggesting that a large share of the selection is driven by a differential response to contract type in semi-arid versus higher-rainfall areas. Conditional on taking up insurance, we find large and positive effects of both index-based and indemnity-based insurance on extensive margin fertilizer use after correcting for this selection bias, especially in semi-arid areas. Moreover, tests of equal treatment effects of WBI versus PBI indicate that an indemnity-based insurance contract–which is associated with higher and more inclusive take-up–does not significantly reduce effects on fertilizer use among the insured compared to index-based insurance. By contrast, when focusing on fertilizer expenditures, women increase investments in fertilizer more when they enroll in WBI, but this difference is small and significant only at the 10% level.

5. Conclusion

This paper examined whether a digital indemnity-based innovation in crop insurance–picture-based insurance (PBI)–can overcome key frictions that have long constrained agricultural insurance markets in LMICs. Using a randomized controlled trial implemented in 191 villages across 7 counties in Kenya, we experimentally compare PBI to a standard weather index-based insurance (WBI) product. Based on intent-to-treat and selection-corrected estimates of the average treatment effect on the treated, we provide three central insights into how contract design shapes both insurance take-up and agricultural investment.

First, moving from an index-based to an indemnity-based contract substantially increases insurance take-up. Farmers value the reduction in basis risk and the ability to verify losses through photographic evidence. Importantly, this expansion in adoption is also inclusive: the largest gains emerge among women farmers and those living in drought-prone semi-arid areas, which have traditionally been underserved by insurance markets, and are most exposed to weather risk. This underscores that contract design matters: more transparent and credible indemnity mechanisms bring in precisely those farmers who stand to gain the most from effective agricultural risk management tools.

Second, higher take-up of insurance translates into greater agricultural investment. Both ITT and selection-corrected ATET estimates indicate that both WBI and PBI coverage increases fertilizer use, consistent with the idea that uninsured risk is a constraint on technology adoption. These investment responses arise even under indemnity-based PBI coverage, where classical theory would predict incentive failures due to adverse selection and incentive effects. Instead, our results show that farmers respond productively to both index-based and improved indemnity-based insurance coverage by adopting modern inputs, rather than strategically by reducing investments to increase the likelihood of insurance claims.

Third, once we correct for endogenous selection into insurance, the apparent differences between WBI and PBI in fertilizer use largely disappear. The indemnity-based contract does not reduce fertilizer use among the insured, nor does it generate meaningful incentives to reduce fertilizer use compared to index-based insurance. The one exception arises in terms of fertilizer expenditures for women. There, even after accounting for selection, we find a marginally significant difference in the average treatment effect on the treated across contract types, with women's fertilizer spending increasing less when enrolling in PBI than when enrolling in WBI. Understanding these incentive effects requires more in-depth understanding of women's ability to invest more in fertilizer both at extensive and intensive margins in response to insurance, which remains an area for future research.

Although PBI broadens participation, especially among women and farmers in semi-arid regions, our evidence indicates that it does not selectively attract farmers based on any single observable characteristic that simultaneously influences fertilizer use, such as risk preferences, liquidity constraints, or empowerment. Instead, the change in the composition of the insured appears to be driven by a broader, multidimensional bundle of traits. Neither standard measures of risk and time preferences nor the three domains of the project-level Women's Empowerment in Agriculture Index (pro-WEAI) consistently predict insurance take-up once we account for gender and regional differences. This aligns with theories of multidimensional selection in insurance markets, where unobserved combinations of risk exposure, trust, experience, and intra-household decision-making jointly determine both the demand for insurance and subsequent investment behavior. In our context, PBI seems to reduce barriers to enrollment that disproportionately prevented farmers across several of these dimensions simultaneously, rather than along any single axis, contributing to a more diverse risk pool without strongly reshaping it along any one observable characteristic.

Taken together, these findings highlight that innovations in contract design can substantially expand insurance coverage, especially among vulnerable populations, whilst inducing higher productive investments at the same time. Yet, they also caution that expanding participation changes the composition of the insurance pool, such that aggregate investment effects may not scale proportionally with adoption. Incentive effects under indemnity-based coverage appear limited. These results suggest that digital indemnity mechanisms like picture-based insurance can help close longstanding gaps in agricultural insurance markets, provided that insurers and policymakers remain attentive to heterogeneity in both risk exposure and baseline investment capacity across farming environments.

These findings carry several implications for the design and scaling of agricultural insurance in settings with high basis risk and low trust in formal insurance markets. First, improvements in contract credibility—here achieved through near-surface remote sensing via smartphone images—can deliver sizeable and inclusive increases in take-up even without heavy price subsidies. Second, because expanded take-up does not automatically translate into proportionally larger investment impacts, policymakers should avoid using take-up as the sole metric for program success. Instead, understanding who is being drawn into the risk pool, and under what baseline constraints, is essential. Third, the limited evidence of moral hazard under PBI suggests that indemnity-based innovations may be viable and scalable in smallholder settings, provided they are paired with clear verification protocols and low-cost digital monitoring. Taken together, these insights suggest that contract design reforms, rather than further subsidies, may offer the most promising path to making agricultural insurance both more effective and more equitable.

Finally, our results highlight that while insurance can relax an important barrier to fertilizer investment—exposure to uninsured risk—it is only one of several constraints that farmers face. Low fertilizer use in semi-arid regions, even among the insured, suggests that other factors – such as liquidity constraints, limited access to inputs, agronomic uncertainty, and weak extension services – may continue to suppress productive investment. This underscores the need to address multiple constraints simultaneously, and thus the value of bundling insurance with complementary innovations, such as input credit, improved varieties of in-demand crops, timely extension advice, or digital tools for crop management. Insurance can play a catalytic role, but its impacts on technology adoption will be largest when embedded in broader, multi-faceted approaches that tackle both risk and the structural barriers that shape farmers' investment decisions.

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A. Appendix Tables and Figures

Table A1: Baseline characteristics of shortlisted registered farmers

	Control	WBI	PBI	p-value		
Variable	Mean (1)	Mean (2)	Mean (3)	PBI–Ctrl (4)	WBI–Ctrl (5)	PBI–WBI (6)
Female	0.600	0.565	0.632	0.196	0.015**	0.194
Owns a phone	0.958	0.967	0.972	0.330	0.753	0.410
Owns a smartphone	0.308	0.232	0.283	0.334	0.326	0.058*
Age $\leq$ 35	0.218	0.251	0.229	0.581	0.850	0.466
Age 36 - 55	0.559	0.547	0.548	0.390	0.433	0.821
Age $\geq$ 56	0.224	0.201	0.223	0.827	0.306	0.542
Attended insurance training	0.244	0.396	0.377	0.040**	0.957	0.140
Ever bought insurance	0.162	0.153	0.184	0.798	0.463	0.608
Household Dietary Diversity Score	2.638	2.727	2.775	0.639	0.934	0.629
FCS - poor	0.622	0.618	0.645	0.757	0.677	0.697
FCS - borderline	0.105	0.073	0.085	0.504	0.488	0.311
FCS - acceptable	0.273	0.309	0.270	0.995	0.471	0.445
Did not cultivate land	0.096	0.110	0.086	0.707	0.936	0.976
Land cultivated < 1 acre	0.394	0.411	0.439	0.573	0.474	0.760
Land cultivated 1 - 2.5 acres	0.244	0.220	0.265	0.589	0.596	0.843
Land cultivated 2.6 - 5 acres	0.201	0.198	0.185	0.936	0.510	0.580
Land cultivated > 5 acres	0.065	0.062	0.025	0.057*	0.123	0.943
Decides on seed use alone	0.685	0.622	0.648	0.226	0.655	0.194
Decides on finance production alone	0.677	0.603	0.633	0.168	0.639	0.135
Decides on sales output alone	0.678	0.602	0.637	0.197	0.602	0.144
Decides on income use alone	0.672	0.602	0.631	0.191	0.671	0.174
Observations	8,119	3,097	7,069			

Notes: Means of baseline characteristics for farmers randomly selected during baseline registration to be eligible to participate in project activities by treatment arm: the control group, weather index-based insurance (WBI), and picture-based insurance (PBI). Columns 4–6 present p-values from tests of equal means between arms, derived from regressions of the baseline variable on an indicator for treatment arm and county fixed effects, using only observations from the control and WBI arms in (4), control and PBI arms in (5), and WBI and PBI arms in (6). FCS stands for Food Consumption Score. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Baseline characteristics of shortlisted and non-shortlisted farmers

	Shortlisted	Not Shortlisted	Difference
	Mean	Mean	p-value
	(1)	(2)	(3)
Female	0.618	0.604	0.137
Owns a phone	0.962	0.966	0.284
Owns a smartphone	0.317	0.278	0.000***
Age $\leq$ 35	0.235	0.226	0.230
Age 36 - 55	0.530	0.558	0.002***
Age $\geq$ 56	0.235	0.216	0.012**
Attended insurance training	0.331	0.319	0.160
Ever bought insurance	0.158	0.172	0.056*
Household Dietary Diversity Score	2.645	2.721	0.101
FCS - poor	0.651	0.625	0.004***
FCS - borderline	0.103	0.089	0.012**
FCS - acceptable	0.246	0.286	0.000***
Did not cultivate land	0.126	0.087	0.000***
Land cultivated < 1 acre	0.385	0.421	0.000***
Land cultivated 1 - 2.5 acres	0.244	0.249	0.496
Land cultivated 2.6 - 5 acres	0.197	0.194	0.619
Land cultivated > 5 acres	0.048	0.049	0.719
Decides on seed use alone	0.675	0.657	0.038**
Decides on how to finance production alone	0.665	0.644	0.018**
Decides on sales output alone	0.661	0.647	0.112
Decides on income use alone	0.662	0.640	0.013**
Observations	3,578	14,707	

Notes: Sample includes farmers who were randomly selected at the time of baseline registration to be eligible to participate in project activities. "Shortlisted" refers to those who were shortlisted by champion farmers for project activities, including picture-based crop monitoring. Column (3) presents p-value from tests of equal means between those who were shortlisted from Column (1) and those who were not from Column (2). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Attrition: Marginal effects of baseline characteristics on endline participation

	Dependent variable: Participated in endline (=1)			
	Full Sample (1)	Main effects (2)	WBI $\times X$ (3)	PBI $\times X$ (4)
Female	0.055***	0.047**	0.043	0.073**
	(0.018)	(0.022)	(0.044)	(0.030)
Owns a phone	0.170***	0.282***	0.179	0.045
	(0.052)	(0.069)	(0.113)	(0.092)
Owns a smartphone	-0.066***	-0.062**	-0.110**	-0.074*
	(0.023)	(0.030)	(0.045)	(0.042)
Age ≤35	-0.090***	-0.086**	-0.077	-0.105***
	(0.026)	(0.042)	(0.055)	(0.041)
Age 36–55	-0.028	-0.031	-0.065	-0.006
	(0.022)	(0.034)	(0.052)	(0.033)
Attended insurance training	0.043	0.010	0.080	0.046
	(0.034)	(0.048)	(0.051)	(0.059)
Ever bought insurance	0.068*	0.086	0.045	0.072
	(0.039)	(0.054)	(0.045)	(0.067)
FCS - poor	-0.035	0.009	-0.304***	0.039
	(0.048)	(0.068)	(0.107)	(0.075)
FCS - borderline	0.023	0.099**	-0.099	-0.021
	(0.040)	(0.049)	(0.103)	(0.065)
Household Dietary Diversity	-0.005	0.011	-0.053***	-0.001
	(0.010)	(0.016)	(0.018)	(0.015)
Did not cultivate land	-0.203***	-0.237**	-0.052	-0.186*
	(0.061)	(0.098)	(0.123)	(0.104)
Land cultivated < 1 acre	-0.099*	-0.088	0.021	-0.150*
	(0.053)	(0.084)	(0.120)	(0.087)
Land cultivated 1–2.5 acres	-0.102**	-0.164**	-0.054	-0.055
	(0.048)	(0.079)	(0.119)	(0.079)
Land cultivated 2.6–5 acres	-0.114**	-0.179**	-0.070	-0.052
	(0.047)	(0.081)	(0.098)	(0.077)
Decides on seed use alone	-0.032	0.013	-0.093	-0.023
	(0.046)	(0.064)	(0.105)	(0.061)
Decides how to finance production alone	0.021	0.059	-0.014	-0.004
	(0.046)	(0.063)	(0.094)	(0.081)
Decides on sales output alone	-0.023	-0.151**	0.185**	-0.030
	(0.047)	(0.073)	(0.083)	(0.067)
Decides on income use alone	-0.021	0.016	-0.086	-0.003
	(0.053)	(0.080)	(0.116)	(0.093)
p-value Joint χ^2 (Treatment $\times X$)		.	0.077	0.054
p-value WBI = PBI	0.095			

Notes: Table reports average marginal effects from two probit models with county fixed effects: a pooled model, including main effects of WBI and PBI (marginal effects described in text but not shown here) in Column (1); and one interacting baseline characteristics with treatment arms in Columns (2)–(4). Marginal effects of baseline covariates for the control are shown in Column (2), and their interaction with WBI and PBI in Columns (3) and (4), respectively. Standard errors in parentheses are clustered by champion farmer. FCS stands for Food Consumption Score. $^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$.

Table A4: Intent-to-Treat effects on insurance take-up and fertilizer investment

	Buys insurance	Uses fertilizer	Log fertilizer expenditures	
			Unconditional	Conditional
	All farmers	All farmers	All farmers	Fertilizer users
	(1)	(2)	(3)	(4)
Panel A: Outcome Equation Main Effects				
Assigned to WBI	0.088*	0.082	0.833	0.302
	(0.040)	(0.056)	(0.466)	(0.186)
Assigned to PBI	0.204***	0.100*	0.879*	0.106
	(0.038)	(0.044)	(0.374)	(0.173)
p-value WBI = PBI	0.020**	0.754	0.921	0.283
Panel B: Regional Heterogeneity (Total Effects)				
WBI in ASAL	0.063	0.153	0.934	-0.106
	(0.071)	(0.114)	(0.907)	(0.533)
PBI in ASAL	0.271	0.080	0.454	-0.205
	(0.068)	(0.099)	(0.742)	(0.351)
WBI in non-ASAL	0.105*	0.039	0.763	0.438**
	(0.048)	(0.056)	(0.498)	(0.161)
PBI in non-ASAL	0.169***	0.109**	1.107**	0.196
	(0.045)	(0.041)	(0.411)	(0.198)
p-value WBI = PBI in ASAL	0.023**	0.577	0.630	0.832
p-value WBI = PBI in non-ASAL	0.256	0.131	0.431	0.178
Panel C: Gender Heterogeneity (Total Effects)				
WBI for men	0.145*	0.051	0.884	0.501
	(0.058)	(0.068)	(0.607)	(0.291)
PBI for men	0.138**	0.102*	1.042*	0.221
	(0.050)	(0.051)	(0.457)	(0.275)
WBI for women	0.050	0.103	0.800	0.167
	(0.045)	(0.060)	(0.473)	(0.207)
PBI for women	0.242***	0.100**	0.784**	0.032
	(0.042)	(0.047)	(0.393)	(0.197)
p-value WBI = PBI for women	0.001***	0.962	0.973	0.529
p-value WBI = PBI for men	0.919	0.452	0.791	0.288
Observations	1577	1547	1577	1089
Control group mean	0.128	0.600	4.580	7.788

Notes: Table presents ITT effects of weather index-based insurance (WBI) and picture-based insurance (PBI) on outcome variables shown in column headers estimated using Equation (1), controlling for a set of LASSO-selected covariates (for which coefficients are presented in Table A5) and county fixed effects. Standard errors in parentheses are clustered at the champion level, and observations are reweighted to account for attrition. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Full LASSO Covariates across ITT Specifications (Insurance and Fertilizer)

	Buys insurance	Uses fertilizer	Log fertilizer expenditures Unconditional	Conditional
	All farmers	All farmers	All farmers	Fertilizer users
	(1)	(2)	(3)	(4)
Seed treatment	-0.018	-0.021	-0.115	-0.066
	(0.032)	(0.040)	(0.339)	(0.155)
Female respondent	0.060*	0.011	-0.145	-0.272
	(0.024)	(0.021)	(0.186)	(0.142)
Age: 36 to 55 years old	-0.027	0.014	0.202	0.299*
	(0.029)	(0.025)	(0.243)	(0.143)
Single	-0.001	0.117*	0.208	-0.038
	(0.054)	(0.049)	(0.499)	(0.345)
Married	0.083*	0.054	0.404	0.092
	(0.036)	(0.043)	(0.376)	(0.264)
No formal education	-0.087**	-0.168**	-1.231*	-0.057
	(0.029)	(0.063)	(0.501)	(0.285)
Has non-farm income	-0.024	0.053	0.310	-0.115
	(0.027)	(0.028)	(0.234)	(0.145)
Cultivates 1.01–2.5 acres	0.025	0.010	-0.045	-0.125
	(0.031)	(0.034)	(0.294)	(0.160)
Cultivates 2.6–5 acres	0.011	-0.076	-0.825*	-0.337
	(0.038)	(0.053)	(0.411)	(0.244)
Intrinsic Agency × PBI	0.037	-0.014	0.034	0.128
	(0.019)	(0.017)	(0.148)	(0.119)
Collective Agency × WBI	0.017	0.011	0.231	0.185
	(0.022)	(0.021)	(0.168)	(0.107)
Instrumental Agency × WBI	0.038*	0.066	0.556*	0.152
	(0.019)	(0.034)	(0.259)	(0.119)
Observations	1577	1547	1577	1089

Notes: This table reports coefficients on the full set of LASSO-selected controls in the ITT specifications shown in Table A4. All specifications include county fixed effects and observations are reweighted to correct for attrition on observable characteristics. Standard errors clustered at the champion level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Selection and Outcome Equation Controls Across Fertilizer Outcomes

	Fertilizer use (binary)		Log fertilizer expenditures (unconditional)		(conditional)	
	All farmers		All farmers		Fertilizer users	
	Selection (1)	Outcome (2)	Selection (3)	Outcome (4)	Selection (5)	Outcome (6)
High subsidy = 1	0.181		0.179		0.071	
	(0.093)		(0.106)		(0.112)	
Seed treatment	-0.072	-0.099	-0.064	-0.410	-0.095	0.411
	(0.120)	(0.058)	(0.122)	(0.455)	(0.144)	(0.316)
Female respondent	0.234*	0.124	0.238*	0.052	0.195	-0.744*
	(0.093)	(0.074)	(0.094)	(0.372)	(0.111)	(0.317)
Age $\geq$ 35	-0.132	0.042	-0.125	0.363	-0.074	-0.057
	(0.114)	(0.058)	(0.114)	(0.526)	(0.120)	(0.423)
Single	-0.131	-0.025	-0.089	-1.980	-0.157	-1.423
	(0.258)	(0.101)	(0.259)	(1.096)	(0.284)	(0.919)
Married	0.320*	-0.010	0.323*	-0.771	0.184	-0.219
	(0.149)	(0.135)	(0.152)	(0.728)	(0.173)	(0.254)
No formal education	-0.406**	-0.252**	-0.392**	-0.936	-0.351	0.982*
	(0.145)	(0.096)	(0.146)	(0.758)	(0.198)	(0.388)
Has non-farm income	-0.095	-0.036	-0.084	0.024	-0.103	0.258
	(0.099)	(0.052)	(0.100)	(0.410)	(0.112)	(0.270)
Land 1.01–2.5 ac	0.103	0.080	0.096	0.365	0.116	-0.155
	(0.115)	(0.062)	(0.115)	(0.453)	(0.140)	(0.315)
Land 2.6–5 ac	0.062	-0.016	0.057	-0.264	-0.069	0.170
	(0.140)	(0.092)	(0.141)	(0.633)	(0.179)	(0.369)
Intrinsic agency × PBI	0.125*	0.001	0.119*	-0.085	0.089	-0.067
	(0.060)	(0.035)	(0.060)	(0.245)	(0.065)	(0.147)
Collective agency × WBI	0.054	-0.044	0.068	-0.032	0.076	0.491**
	(0.090)	(0.052)	(0.089)	(0.326)	(0.105)	(0.157)
Instrumental agency × WBI	0.153*	0.135*	0.151*	0.948**	0.196	0.066
	(0.072)	(0.065)	(0.074)	(0.366)	(0.103)	(0.142)
Observations	1,576	1,576	1,577	1,577	1,089	1,089
Selected (insured)	325	325	326	326	238	238

Notes: This table presents, for each dependent variable, two specifications: a selection equation based on Equation (2), and an outcome equation based on Equation (3). We control for county fixed effects and the set of LASSO-selected covariates from this table, as well as main effects for WBI and PBI (for which marginal effects are shown in Table 5). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B. Appendix Figures: Pro-WEAI by insurance take-up

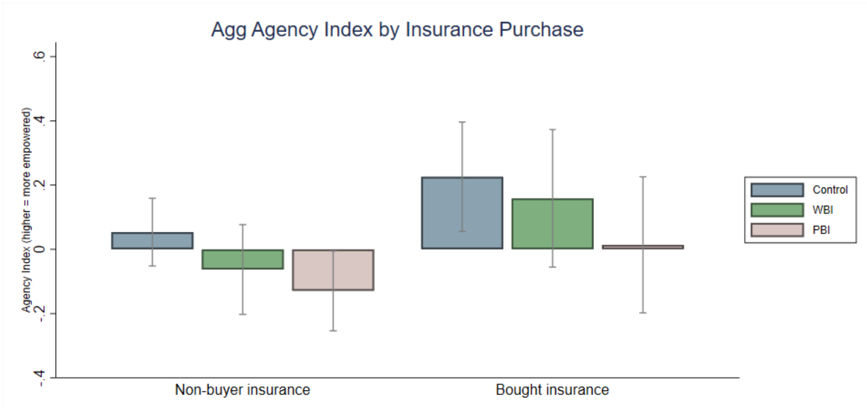

Figure B1: Aggregate agency index

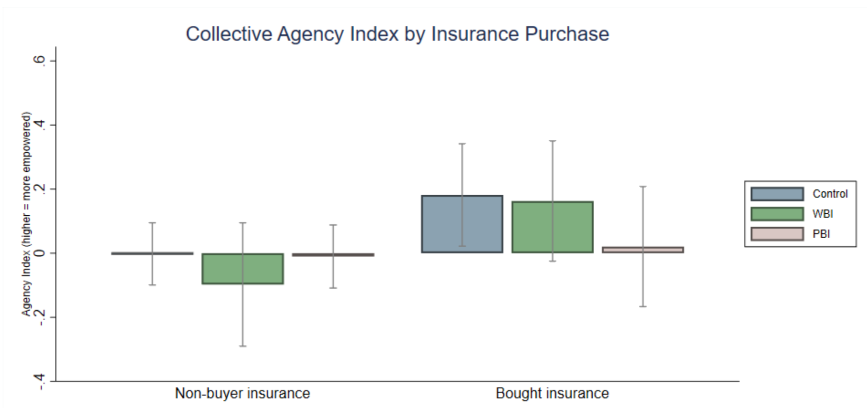

Figure B2: Collective agency index

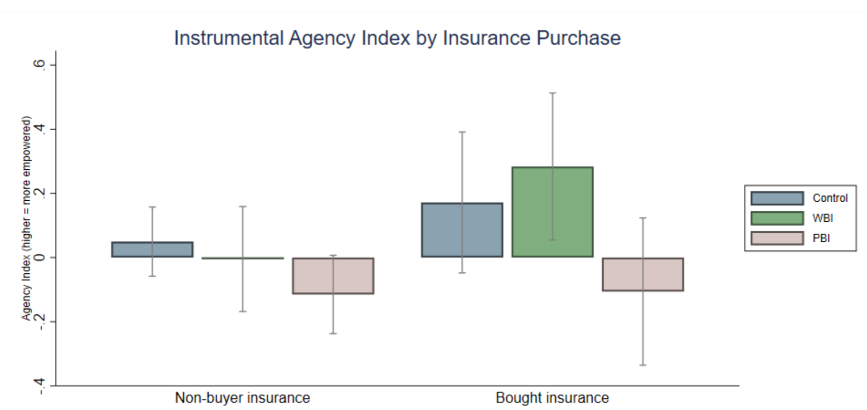

Figure B3: Instrumental agency index

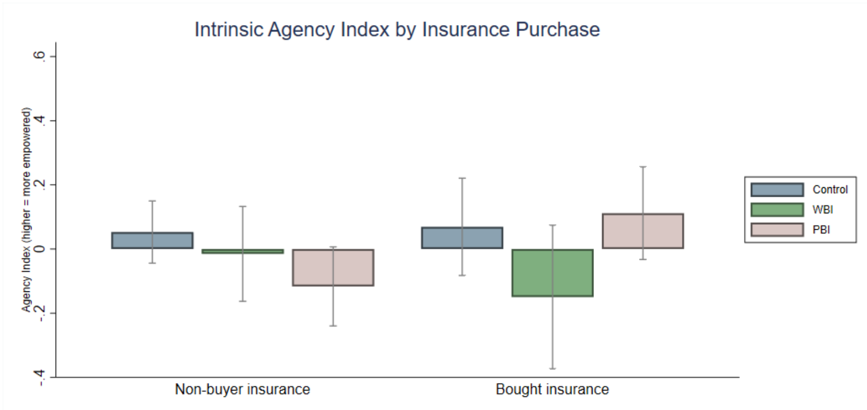

Figure B4: Intrinsic agency index

C. Instrumental Variables (IV) approach

C.1 Empirical strategy

Because insurance take-up is imperfect, we complement our main Intent-to-Treat approach with an instrumental variables specification that identifies the local average treatment effect (LATE) of being insured on fertilizer use among farmers whose insurance decision is induced by exogenous variation in treatment assignment ("compliers"). Let D_i indicate whether farmer i purchased insurance. We estimate the following two-stage least squares (2SLS) model:

$$D_{ic} = \pi_0 + \pi_1 Z_{ic} + X_{ic}'\pi + \delta_c + u_{ic} \tag{4}$$

$$Y_{ic} = \beta_0 + \beta_1 \widehat{D}_{ic} + X_{ic}'\beta + \zeta_c + \eta_{ic} \tag{5}$$

Here, D_{ic} indicates actual insurance take-up of farmer i with champion c, $\widehat{D}_{ic}$ is predicted take-up based on Equation (4), Z_{ic} is the instrument used to estimate the first stage, X_i is a matrix that includes covariates selected through a LASSO, δ_c and $zeta_c$ are county fixed effects, and u_i and η_i represent residuals of these selection and outcome equations, with clustering by champion farmer. Under the usual IV assumptions (relevance, i.e. $\pi_1 > 0$, exclusion, i.e., conditional on Z_{ic}, X_{ic}, δ_c and ζ_c, the residuuals u_{ic} and η_{ic} are not correlated, and monotonicity), our estimate for β_1 recovers the LATE.

We estimate this model for two types of instruments: random assignment to the contol group, versus either the WBI or PBI treatment, which introduces exogenous variation in the probability of enrolling in insurance between villages; and random individual-level assignment to either a high subsidy in the WBI or PBI treatment versus a low or zero subsidy in the same treatment or control group, respectively. For both instruments, we implement (4)–(5) separately for each insurance product by restricting the sample to the relevant treatment arm (either WBI or PBI) and the control group. We report first-stage diagnostics alongside 2SLS estimates. When the first stage is weak, we interpret 2SLS results cautiously and emphasize the reduced-form ITT estimates.

C.2 Results

Table C1 reports LATE estimates across binary and continuous fertilizer outcomes, both unconditional and conditional on any use. Columns (1)–(4) show the LATE on fertilizer take-up. The WBI instrument yields a large point estimate (0.93) but with a weak first stage (F = 4.29), suggesting caution in interpretation. The PBI instrument is statistically significant and more precisely estimated (0.49, $p < 0.05$, F = 38.31). The high-subsidy IV for WBI also produces a large estimate (0.94) but with a weaker instrument (F = 2.45); for PBI, the estimate is 0.83 (not statistically significant), with moderate instrument strength (F = 10.61).

Columns (5)–(8) present LATE estimates on log fertilizer expenditure, unconditional on whether the farmer uses fertilizer. Point estimates are again large—9.39 for WBI and 4.38 for PBI, with PBI statistically significant at the. As before, the WBI estimate is imprecise, with a weak instrument (F = 4.29). The high-subsidy IVs yield similar effects (11.51 for WBI, 6.46 for PBI), though these are not significant and rely on weaker instruments (F = 2.40 and 10.30, respectively).

Columns (9)–(12) restrict the sample to fertilizer users. The LATEs are smaller at 2.58 (WBI), 0.53 (PBI), and 3.29 (WBI subsidy), none statistically significant. First-stage F-statistics are again strongest for PBI (F = 14.87) and weakest for WBI (F = 2.58). These results suggest that insurance purchase, especially under the PBI design, influences fertilizer behavior. However, the WBI and high-subsidy instruments are weak in most specifications, making those estimates less reliable. We therefore emphasize the ITT and Heckman selection results, where identification is stronger and more robust.

Table C1: LATE (2SLS) Estimates of the Impact of Insurance Purchases

	Binary: Adoption				Unconditional: Fertilizer Expenses				Conditional: Fertilizer Expenses			
Instrument type	Village-level		Individual subsidy		Village-level		Individual subsidy		Village-level		Individual subsidy	
	WBI	PBI	WBI	PBI	WBI	PBI	WBI	PBI	WBI	PBI	WBI	PBI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Purchased Insurance	0.925	0.485*	0.942	0.831	9.390	4.375*	11.513	6.461	2.578	0.525	3.289	-0.226
	(0.675)	(0.237)	(0.905)	(0.425)	(6.255)	(2.096)	(9.257)	(3.621)	(1.990)	(0.917)	(2.189)	(1.312)
LASSO Controls												
Seed Treatment	-0.033	-0.021	-0.034	-0.016	-0.230	-0.111	-0.344	-0.245	0.081	-0.054	0.046	-0.091
	(0.054)	(0.048)	(0.056)	(0.054)	(0.425)	(0.407)	(0.468)	(0.435)	(0.234)	(0.198)	(0.245)	(0.203)
Female Respondent	0.004	0.011	0.004	0.007	0.020	-0.145	0.005	-0.211	0.061	-0.272	0.077	-0.245
	(0.036)	(0.021)	(0.037)	(0.025)	(0.334)	(0.186)	(0.342)	(0.215)	(0.302)	(0.142)	(0.311)	(0.165)
Age $\geq$ 35	0.058	0.013	0.057	0.011	0.366	0.204	0.352	0.188	-0.052	0.307	-0.063	0.320
	(0.062)	(0.045)	(0.063)	(0.051)	(0.526)	(0.435)	(0.563)	(0.488)	(0.425)	(0.320)	(0.465)	(0.342)
Single	0.073	0.117	0.073	0.110	0.165	0.208	0.150	0.195	0.081	-0.038	0.092	-0.045
	(0.082)	(0.049)	(0.083)	(0.055)	(0.835)	(0.499)	(0.852)	(0.522)	(0.345)	(0.345)	(0.355)	(0.360)
Married	-0.030	0.054	-0.031	0.052	-0.402	0.404	-0.415	0.395	-0.082	0.092	-0.095	0.088
	(0.103)	(0.043)	(0.105)	(0.048)	(1.025)	(0.376)	(1.045)	(0.395)	(0.264)	(0.264)	(0.275)	(0.278)
No Formal Education	-0.176	-0.168**	-0.177	-0.165	-0.923	-1.231*	-1.048	-1.350	0.985	-0.057	1.012	-0.045
	(0.092)	(0.063)	(0.095)	(0.071)	(0.758)	(0.501)	(0.833)	(0.585)	(0.388)	(0.285)	(0.402)	(0.302)
Has non-farm Income	0.083	0.053	0.084	0.058	0.303	0.310	0.315	0.342	0.258	-0.115	0.274	-0.118
	(0.043)	(0.028)	(0.045)	(0.032)	(0.410)	(0.234)	(0.442)	(0.254)	(0.270)	(0.145)	(0.284)	(0.151)
Land 1.01-2.5 acres	-0.040	0.010	-0.040	0.008	-0.210	-0.045	-0.225	-0.055	0.105	-0.125	0.115	-0.130
	(0.053)	(0.034)	(0.054)	(0.038)	(0.425)	(0.294)	(0.445)	(0.315)	(0.145)	(0.160)	(0.155)	(0.170)
Land 2.6-5 acres	-0.158*	-0.076	-0.158*	-0.072	-1.670**	-0.825*	-1.722**	-0.827	-0.694	-0.337	-0.695	-0.343
	(0.065)	(0.053)	(0.066)	(0.063)	(0.518)	(0.411)	(0.554)	(0.425)	(0.378)	(0.244)	(0.388)	(0.255)
Intrinsic agency	-	-0.029	-	-0.042	-	-0.114	-	-0.192	-	0.105	-	0.124
$\times$PBI	-	(0.020)	-	(0.028)	-	(0.164)	-	(0.223)	-	(0.122)	-	(0.125)
Collective agency	-0.011	-	-0.011	-	-0.042	-	-0.075	-	0.104	-	0.090	-
$\times$WBI	(0.027)	-	(0.028)	-	(0.238)	-	(0.275)	-	(0.123)	-	(0.129)	-
Instrumental agency	0.034	-	0.034	-	0.242	-	0.184	-	0.068	-	0.043	-
$\times$WBI	(0.035)	-	(0.039)	-	(0.284)	-	(0.357)	-	(0.132)	-	(0.138)	-
F-stat First Stage	4.288	38.307	2.454	10.605	4.288	38.307	2.404	10.297	2.583	14.868	2.053	7.152
Observations	1000	964	1000	964	1021	983	1021	983	712	665	712	665

Notes: Local Average Treatment Effects (LATE) estimated via two-stage least squares (2SLS), using as instruments either village-level treatment assignment (WBI or PBI versus control group) in Columns (1)-(2), (5)-(6), and (9)-(10), and the individually assigned high (80%) subsidy offer (versus 20% or 0% subsidy in WBI/PBI and control arms, respectively) in Columns (3)-(4), (7)-(8), and (11)-(12). Standard errors clustered at champion level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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