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BUNDLING GENETIC AND FINANCIAL TECHNOLOGIES FOR MORE RESILIENT AND PRODUCTIVE SMALL-SCALE AGRICULTURE

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ABSTRACT

Utilizing a multi-year, spatially diversified randomized controlled trial spanning two African countries, this paper explores whether bundled genetic and financial technologies can boost the resilience and productivity of small-scale farmers who are exposed to significant risk. The analysis shows that both moderate droughts and more severe yield losses undermine the resilience of control group households, and that these shocks have long-lasting effects as they decapitalize households who invest less in years following these shocks. Severe yield shocks also increase hunger and food insecurity. The genetic technology— drought tolerant seeds—provides significant protection against moderate drought events and mitigates the long-term drop in farm productivity seen in the control group. The financial technology—satellite-based index insurance —offsets the long-term consequences of severe yield losses that are not mitigated by the drought tolerant seeds. Finally, the analysis shows that farmers who experienced shocks and saw both technologies in action subsequently increase their agricultural investment at both the extensive and intensive margins. The technologies thus not only allow farmers to return to their pre-shock positions, but also allow them to move toward higher expected incomes. Unfortunately, this apparent experiential learning cuts both ways. Farmers who did not experience the efficacy of the risk management technologies backed away from using them in the following season. Our findings thus showcase important complementarities between genetic and financial risk mitigating technologies as well as the challenge of inducing sustained uptake of technologies that only occasionally reveal their benefits.

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1 Introduction

Economic resilience can be defined as a household's ability to absorb a shock with minimal damage to current and future economic well-being. This paper reports the results of a multi-year, spatially diversified randomized controlled trial of a novel bundle of genetic and financial technologies designed to boost the resilience and productivity of small holder farm households. Drawing on earlier conceptual work that proposed bundling complementary financial and genetic technologies to cost-effectively enhance the resilience of small farm households (Lybbert and Carter, 2015), this paper is the first to estimate the impact of such a bundle on farmer resilience and productivity. We find that these technologies–index insurance and drought tolerant seeds–not only boost households' economic resilience, but also generate a resilience dividend in the form of intensified agricultural investment that occurs after farmers experience the technologies in action. Consistent with other work on technologies that generate stochastic benefits (Cai et al., 2020), we also find that the unfortunate flip side of experiential learning is that farmers who do not directly experience the benefit of these technologies begin to disadopt them.

In addition to identifying the state-contingent impact of these technologies on adopting households, our unique research design allows us to gauge the short and medium term impact of shocks on the study's control group households. These control households are anything but resilient. The econometric analysis shows that even moderate shocks, which reduce current farm income by some 25%, have persistent effects by decapitalizing control households and reducing their future income. More severe shocks, which reduce farm income by more than 50%, appear to overwhelm these households' consumption smoothing capacity and compromise both their future productivity and food security. Unsurprisingly, the agricultural productivity of control group households is low, consistent with the hypothesis that their vulnerability to shocks inhibits investment in technologies that could increase household income in most, but not all, years.[1]

[1]The negative impact of uninsured risk on productivity and investment by smallholder farmers is well-established in the literature (e.g., (Morduch, 1995; Rosenzweig and Binswanger, 1992; Carter

The biological insurance embedded in the genetic technology of stress tolerant seeds and the financial insurance of index-based insurance technologies can independently mitigate shocks and crowd-in additional investment. At the same time, each technology has acknowledged but distinct limitations. The bundle we design and test aims to exploit complementarities between the two technologies that emerge from their respective strengths and limitations.

Stress tolerant seed varieties bred to withstand abiotic weather shocks like drought or flood are among the new genetic technologies that potentially improve the resilience of smallholder farmers. Emerick et al. (2016) provide evidence that highlights this potential. The authors find that flood tolerant rice varieties not only provided Indian farmers significant protection against yield loss from floods, but also gave them confidence to intensify investment in productivity-enhancing practices and inputs.[2] Stress tolerant varieties are a particularly attractive innovation because of their low marginal cost. While breeding these varieties demands substantial upfront investments in lab work and field trials, once stress tolerant varieties are developed they can be multiplied and distributed to farmers with little or no additional cost relative to improved, non-stress tolerant varieties.[3] Farmers may consequently pay little or no price premium to access these stress tolerant varieties compared to purchasing non-tolerant but otherwise comparable improved varieties.[4] Yet, these promising varieties offer farmers protection against only a limited range of production shocks. The flood tolerant rice variety studied by Emerick et al. (2016) provides protection against flood events that last no more than 15 days (Dar et al., 2013), but succumbs like other rice varieties to longer periods of flooding.[5] Similarly, the drought tolerant

and Lybbert, 2012)).

[2]In a study of drought tolerant maize varieties in Uganda, Simtowe et al. (2019) find that those who use drought tolerant seeds enjoy higher and more stable yields and appear to invest more in maize at both extensive and intensive margins.

[3]In the specific case of the drought tolerant maize varieties studied here, the cost of varietal development were paid by philanthropic capital that financed the multi-year, CIMMYT-led Drought Tolerant Maize for Africa initiative.

[4]However, for farmers that usually plant unimproved local seed varieties (which is the majority of farmers in our sample), the shift to an improved, stress tolerant variety represents a substantial increase in up-front investment.

[5]In the first year of the Emerick et al. (2016) impact evaluation, approximately 40% of sample farmers experienced flooding, with an average length of submerged fields of roughly 5.5 days. While

(DT) maize varieties studied here protect against moderate mid-season drought, but remain vulnerable to other kinds of drought as well as to other biotic and abiotic stresses that can, in the extreme, drop maize yields to zero.

The limited protection–effectively, single peril coverage–of stress tolerant varieties reflects the simple fact that plant breeders face biological constraints that limit how much and what types of stress these new varieties can withstand. In contrast, insurance contracts can be flexibly engineered to cover extreme shocks that overwhelm the stress tolerance that can be bred into seeds. The last decade has seen numerous efforts to develop index insurance contracts that offer reliable protection to smallholder farmers without the necessity of costly individual yield loss measurement and verification. Similar to the Emerick et al. (2016) study, the impact evaluation literature shows that index insurance can both protect farmers from the worst consequences of drought and other shocks and can induce them to increase investment at both the intensive and extensive margins.[6] This work also reveals significant limitations to index insurance. Unless carefully designed, index insurance is prone to failure. It also tends to be expensive (often sold at prices that are more than 150% of the actuarially fair price), and, consequently, smallholder farmers are often reluctant to purchase it unless it is either heavily subsidized, or can be financed as part of a value chain finance package.[7]

For this study, we bundled single peril, drought tolerant maize seeds with a "fail-safe" index insurance contract that protects farmers against the severe loss events that are likely to overwhelm the protection provided by drought tolerant seeds. Limiting

the authors do not provide information on the full distribution of flood length, they note that 24% of treatment households did not re-plant the flood tolerant variety in the second year of the evaluation and that the primary reason was harvest failure due to flooding for longer than 14 days.

[6]A handful of studies have established that insurance coverage increases on-farm investment for a variety of crops and across different countries, usually in the range of 15-30% compared to uninsured, control households (see Cai, 2016, Elabed and Carter, 2018, Hill et al., 2019, Jensen et al., 2017, Karlan et al., 2014, Mobarak and Rosenzweig, 2013, and, Stoeffler et al., 2021). In the wake of shocks, index insurance has been shown to protect households, reducing reliance on costly coping strategies (Janzen and Carter, 2018 and Jensen et al. 2017) and avoiding decapitalization of farm activities (Bertram-Huemmer and Kraehnert, 2017; Hill et al., 2019; Stoeffler et al., 2021).

[7]Casaburi and Willis (2018), Elabed and Carter (2018) and Stoeffler et al. (2021) study instances in which insurance has been successfully marketed through tightly integrated value chains for sugar cane and cotton. Outside of value chains, Karlan et al. (2014) and McIntosh et al. (2020) find little insurance take-up without subsidies.

the insurance coverage to these extreme events holds in check the cost of insurance protection. Providing additional protection via the bundling of insurance with improved, stress-tolerant seeds may be especially important to incentivize farmers to adopt improved seeds in lieu of local seed varieties. Because of the significantly higher cost of improved seeds, this transition from local to improved seeds exposes the farmer to greater financial risk; the single peril protection of DT seeds alone may be insufficient to induce this increased investment.[8] To explore the efficacy of this bundle, we carried out a multi-year randomized controlled trial that offered farmers the opportunity to purchase drought tolerant (DT) maize varieties, either as seeds alone, or as seeds bundled with an index insurance contract that protected farmers' investment in the DT varieties.[9] The RCT itself was spatially diversified (within and across countries) in order to increase the likelihood of observing different types of shocks during the study period. Nature cooperated with the study as 58% and 18% of the observations across the three years of the study experienced mid-season drought events and more severe, covariate yield shocks, respectively.

Several findings emerge from our analysis. First, the resilience of control households is significantly undermined by the two types of shocks we study. Mid-season drought and more severe yield shocks reduce within-season maize yields by 25% and 50%, respectively. The effects of these shocks persist and prevent farmers in the control group from returning to pre-shock yield levels in the year following the shock. A mid-season drought reduces average yields in the following year by roughly the same magnitude as the within-season impact; while the delayed impact of a severe yield shock is roughly one-third of the within-season impact. Second, we find that DT varieties provide significant protection against mid-season drought as they completely

[8]Most farmers in our sample do not purchase complementary inputs such as fertilizers or pesticides. Seeds thus represent the primary on-farm investment. The transition from local to improved varieties would require at least a five- to ten-fold increase in input expenditures per hectare planted (from about 13 USD per-hectare when local seeds are used to 63 - 100 USD when improved seeds are used).

[9]We chose not to offer an insurance-only arm for two reasons. First, the insurance provider did not have a cost-effective mechanism to indemnify insured households. Second, and relatedly, evidence cited above shows that take-up of index insurance among low income, smallholder farmers who do not participate in a structured value chain, such as those in our study population, tends to be very low.

mitigate both the within-season and lagged yield losses associated with mid-season drought events. Third, the addition of index insurance significantly strengthens farmers' resilience, including food security in the face of yield shocks. Bundling index insurance with the DT varieties raised yields in the year following a covariate yield shock by 60%, more than offsetting the adverse contemporaneous impact of this severe shock. Fourth, this excess mitigation effect is driven by treated farmers who experience the protection provided by DT seeds and insurance and subsequently intensified their investment in productive inputs. Finally, we find that treated farmers who did not experience a shock were more likely to scale back their investment in the following year.

The remainder of this paper is organized as follows. Section 2 provides an overview of the two technologies that feature in this analysis, drought tolerant seeds and index insurance. Section 3 describes the research design and analyzes baseline imbalance problems and our strategy to address the imbalance.Section 4 presents the key econometric results, analyzing of the impact of the experimental and natural treatments (lagged and contemporaneous shocks) on maize yields, resource allocation and food insecurity. In Section 5, we discuss our results from the perspective of learning and alternative explanations. Finally, Section 6 concludes with reflections on the specific challenge of learning about risk management technologies, which by definition only occasionally reveal their benefits to farmers.

2 The Risk Mitigation Technologies

The two risk mitigation technologies that lie at the heart of this study are DT maize varieties and a complementary index insurance contract designed to protect farmer investment in the event of severe yield loss. While several commercial partners have bundled index insurance and seeds,[10] Bulte et al. (2020) is the only study we know

[10]In 2010, the Syngenta Foundation for Sustainable Agriculture offered farmers the option to insure their seeds against drought. The multinational seed company SeedCo subsequently offered a similar product. While never formally evaluated, the reported success of these programs informed our decision to bundle seed with insurance.

that examines the impact of bundling seed with insurance. In contrast to the Bulte et al. (2020) study, which finds that free insurance enhances the adoption of certified seeds, this study offered a bundle of drought tolerant seeds and insurance that was intended to leverage the risk management complementarities between the genetic and financial technologies in a way that would result in a commercially viable product.

Mid-season drought stress disrupts pollination and grain formation, and thus represents a significant risk to maize producers. Paul (2021) uses farmer field trial data from the International Maize and Wheat Improvement Center (CIMMYT) to show that even moderate mid-season drought stress can decrease yields by 20% for non-DT, improved maize varieties. To reduce this risk, plant breeders in the Drought-Tolerant Maize for Africa (DTMA) program used conventional (non-GMO) breeding techniques to select for varieties less susceptible to mid-season drought (CIMMYT, 2012). Using observational data and a variety of econometric strategies, Gebre et al. (2021), Wossen et al. (2017) and Simtowe et al. (2019) find risk reduction effects similar to Paul (2021) for farmers who use DT seeds in Tanzania, Nigeria and Uganda. Additional detail on DT varieties is given in Appendix 1.

The second component of this study's risk mitigation package is index insurance. By basing payouts on an index that is correlated with farmers' yield losses but cannot be influenced by individual farmer behavior, index insurance avoids the pitfalls of conventional indemnity insurance, including moral hazard, adverse selection and costly loss verification. The contract designed for this study was intended to complement the partial protection provided by DT seeds and was based on two indices. The first is an early-season rainfall deficit index based on estimated rainfall during the 40-day plant germination and establishment phase,[11] with a payout being triggered if less than 70-100 mm of rainfall fell during this period, with the specific level depending on the insurance zone. The second is a multi-peril, satellite-based area-yield index based on a calibrated model that used a combination of satellite-measured vegetative growth (Normalized Difference Vegetation Index, NDVI) and estimated full-season rainfall

[11]Rainfall was estimated using Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data (Funk et al., 2015). A separate estimate was created for each household based on its GPS location and its reported planting date.

to predict area yields.[12] Payments were triggered by this index when predicted area-yield dropped below about 65% of the historical average, with the exact trigger value set separately for each community in order to equalize the price of insurance across all locations.

The early-season rainfall deficit trigger was included in the contract in part to ease communication to farmers about the risks, like early season drought, not covered by DT seeds. The satellite-based area yield index was intended to be the workhorse for the insurance contract, covering the array of risks not covered by the single peril DT seeds.

Despite its advantages, many index insurance contracts have failed to reliably detect and cover losses incurred by farmers, which has come to be known as the basis risk problem. In an effort to reduce basis risk, the contract developed for this project included the conditional or "fail-safe" audit proposed by Flatnes and Carter (2016). Under the audit clause of the contract, insured farmers were invited to submit a complaint if the contract did not trigger, but they believed it should have. If more than 30% of farmers registered a complaint, a crop-cut audit was conducted using novel imaging software (Makanza et al., 2018), with insurance payouts issued if average yield, as estimated by the crop-cut, was indeed below the trigger. The data summarized in Figures A1a and A1b in Appendix 2 were used to evaluate the expected additional payments that audits might trigger, and that additional cost was rolled into the premium for the commercial insurance contract.[13]

For purposes of implementation, study villages (see Section 3) were divided into insurance zones (35 in Tanzania and 13 in Mozambique), which were determined

[12]The model was calibrated to annual average zone-level yields reported by farmers. Given the lack of preexisting data on farmer yields, the project solicited historical yield data going back up to 10 years from 1,852 farmers in Tanzania and 1,348 farmers in Mozambique. These data were aggregated to a zone-year level, yielding a total of 223 zone-year combinations in Tanzania and 90 zone-year combinations in Mozambique. A variety of candidate remote sensing measures were explored, with the combination rainfall and NDVI chosen as giving the best statistical yield prediction.

[13]The sense of the research team was that farmers were reluctant in general to report exceptions to the satellite estimate, even though efforts were made to make reporting as simple as possible (*e.g.*, in Mozambique, a toll-free SMS line was established that farmers could use to report exceptions to the satellite readings). In the second year, government extension agents were asked to check the satellite estimate. While several insurance payouts were triggered based on audits, additional work is required to make the audit process work better.

based on size and agro-ecological features, and typically included 2-3 neighboring study villages. To address the challenge of low demand for stand-alone index insurance observed in many index insurance programs, we chose to bundle the insurance with DT seed and did not offer a stand-alone insurance product (see footnote 10). Households in the insurance treatment group were offered a bundle of DT seeds and insurance. Insurance payouts took the form of replacement seeds delivered in the next planting season.[14] In principle, the multi-peril contract could have have been set to cover the cost of other inputs or even the full value of the lost harvest. However, to keep the cost of the insurance low, the project offered only this basic level of coverage. On average, the insurance increased the price of seed by 20%, reflecting both the relatively high level of risk and the commercial loadings added to the actuarially fair price of the insurance.

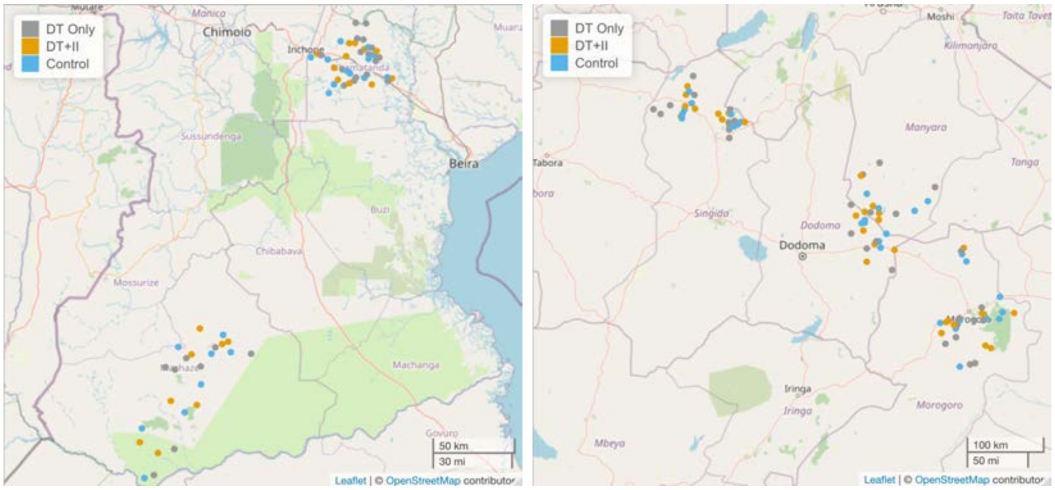
3 Research Design

Learning about technologies that can only display their benefits during infrequent, bad years is challenging for both farmers and researchers (Cai et al., 2020 and Lybbert and Bell, 2010). To increase the probability of observing mid-season droughts and other shocks that could be used to test the risk mitigation effects of the DT seeds and the DT-II bundle, we designed a geographically diversified study that spanned two countries and multiple regions within each country. We focussed on regions that were likely to benefit from the DT technology because maize was a dominant crop and farmers were exposed to moderate to severe drought risk. We then utilized the Princeton University African Drought and Flood Monitor to assess the correlation in weather outcomes between regions, selecting regions that tended to be drought-affected in different years.[15] As we shall see, this strategy for selecting districts proved

[14]The total sum insured for a farmer planting maize at the recommended seeding rate, was thus about 75-100 USD. While this sum is perhaps modest, many study farmers traditionally planted only local seeds, meaning the shift to the improved DT varieties represented a large increase in their agricultural investment at risk.

[15]In Tanzania, the provinces of Singida, Iramba, Kongwa, Kiteto, Morogoro and Mvomero were identified as suitable for the project. In Mozambique, three districts in the provinces of Manica (Machaze district, Tambara district) and Zambezia (Morrumbala district) were initially chosen.

Figure 1: Geographic Diversification and Matched Triplet Randomization



(a) Mozambique (b) Tanzania

Base map and data are from OpenStreetMap and OpenStreetMap Foundation.

successful in the sense that across the study's three years, we were able to observe mid-season droughts and low-frequency severe yield losses across both countries.

3.1 The Randomized Control Trial

The maps in Figure 1 display the randomization strategy that was implemented in the selected study districts in both countries. After identifying a set of study communities in each district in each country, communities were matched into triplets based on having similar agro-ecological (*e.g.*, being located in a river valley) and economic characteristics (access to roads and proximity to larger urban centers). One community of each matched triplet was then assigned to one of the three experimental groups: control, DT seeds only or the DT-II bundle. Within each study community, a random sample of 20 maize-growing households was selected from a community list.

In Mozambique, community assignment was carried out randomly, with one member of each triplet allocated to control and the two treatments. In Tanzania, various logistical constraints led to a more complex implementation process. In that country,

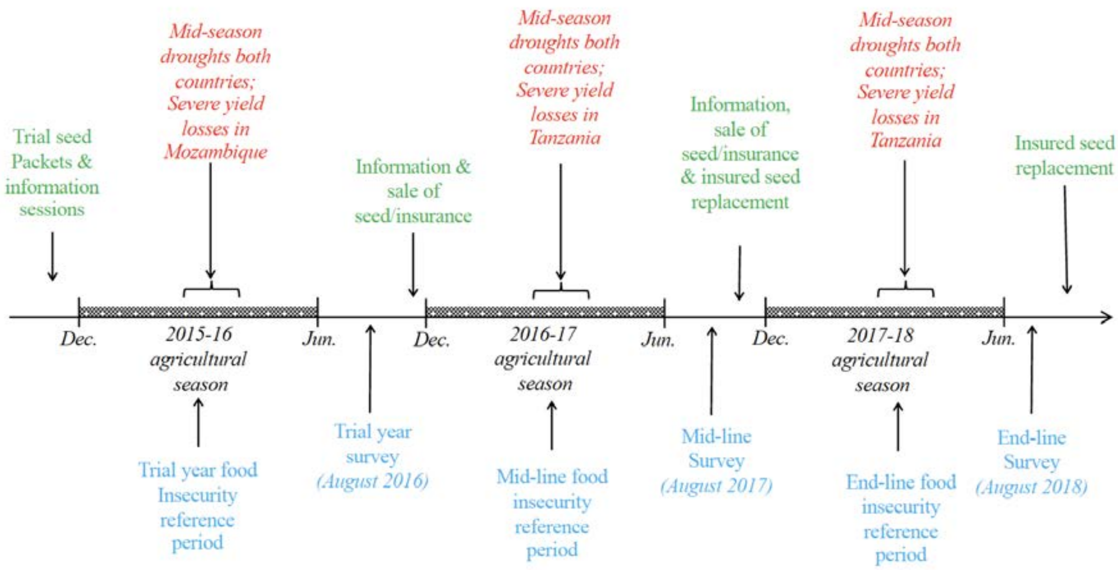
Because of civil unrest, travel to Zambezia and Northern Manica became unsafe, and we had to drop both Morrumbala and Tambara districts form the study, replacing them with Nhamatanda district in Sofala province.

we initially decided to offer DT seeds and the DT-II bundle through village-based agricultural input dealers (VBAs) established by an international NGO. While this strategy was attractive to insurance and seed company partners (who lacked a presence in the study areas for engaging directly with farmers), we discovered that the NGO's expansion plan in the study area was less robust than expected, and that we would be unable to randomize new communities between control and VBA-mediated treatment status. Instead, for treatment communities, we ultimately had to rely on a predetermined set of communities where VBAs had been introduced in the year preceding the study. While we cannot fully rule out the possibility that the NGO may have selected VBA communities based on characteristics unobservable to us that correlate with productivity, the NGO assured us that they did not rely on any such selection criteria (see Section 3.3 for more on these concerns). In order to identify suitable control communities in Tanzania, we used matching methods based on soil quality, climate conditions and market access to create triplets, each consisting of one non-VBA and two VBA communities. With the triplets created, the two VBA communities were randomly allocated across the DT seed and the bundled DT seed-insurance treatments.

Figure 2 displays the stages of the RCT as implemented in both countries. Prior to the 2015/16 agricultural season, training sessions in all treatment communities were organized in cooperation with CIMMYT, local seed and insurance company partners and local government agricultural extension officers.[16] Study households were individually invited to the training sessions, and other community members were also welcome to participate. The training sessions provided information on the DT trait, as well as recommended planting density and fertilization for the different varieties. Study households were given a trial seed packet (1 kg in Mozambique and 2 kg in Tanzania). Non-study households who attended the training were given smaller

[16]In Tanzania, the project worked with three seed companies (Iffa Seed Company, Suba Agro and Meru Agro) that produced hybrid DT varieties. Only one company was assigned to sell seeds in each treatment village. In Mozambique, the project worked with Phoenix Seeds, which produces DT open pollinated varieties (OPVs), and Klein Karoo, which produces hybrid DT varieties. Seeds from both companies were offered for sale in all treatment villages. The price of the hybrid varieties was roughly triple that of the OPV variety.

Figure 2: Timeline for RCT & Natural Experiment



(100-250 gram) packets. No further DT seeds (nor any insurance) were made available in what we will call this quasi-baseline year. Communities were sufficiently isolated to prevent DT seeds spreading into control areas.

In communities assigned to the bundled DT-II treatment, participants were also given information on the insurance contract prior to the second, 2016-17 season. The information session included a description of the two indexes with an emphasis that the index values, and thus insurance payouts, reflect average conditions in the community as opposed to the individual farmer's losses. Farmers were also informed of the possibility of basis risk events and the nature, timing, and documentation requirements of payouts. Seeds offered for sale in these villages came only bundled with the index insurance. The insurance, which was not subsidized, raised the price of the seeds by approximately 20%.[17] Insurance premiums collected from the sale of insured seeds were paid directly by the seed companies to the insurance companies. In the case that the insurance was triggered, the seed company partners replaced insured seed (for planting in the next season), with the insurance company in turn compensating the seed company for the value of the seeds provided.

[17] In Tanzania, the index insurance contract described above was underwritten and sold by UAP Insurance Tanzania, whereas Hollard Moçambique Companhia de Seguros sold the product in Mozambique. Both companies worked with SwissRe as a reinsurance partner.

As shown in Figure 2, the first survey was administered after the 2015/16 trial seed packet year. Unfortunately, resource and time constraints did not allow us the luxury of a pure baseline year followed by a pure learning year.[18] We therefore treat the learning or trial pack year as a quasi-baseline. We recognize that the seed packets given to treatment farmers could slightly unbalance the sample across treatment and control groups. We calculate that the amount of seed given away in trial packets could have generated no more than a 12% yield differential between treatment and controls during the trial pack year.[19]

Following the quasi-baseline year and at the initiation of the 2016/17 (midline) and 2017/18 (endline) seasons, training sessions were again held in treatment communities (see the Figure 2 timeline). While no further trial packets were distributed, seeds were made available for purchase in the treatment villages. In the Tanzania sites, complications with the VBA program in 2016/17 prompted the seed companies to establish their own network of local sales agents.

Follow-up surveys were administered after the two treatment seasons, 2016/17 and 2017/18. In both countries, the research team trained local enumerators in the use of tablets and participated in field testing the survey instrument prior to its launch. The same survey instrument was used in both countries in order to facilitate comparisons across the two countries, and contained modules on agricultural practices and outcomes, household asset ownership, credit access, food security, household expenditures, and attitudes toward risk.

3.2 Natural Weather Experiment

Like all research that hinges on stochasticity that is outside the control of researchers (see Rosenzweig and Udry, 2020), this RCT about the value of risk mitigation was

[18]Based on their experience, the seed company partners indicated that uptake of a new seed would be minimal until farmers had the opportunity to experiment at small scale and learn about the new variety for one season.

[19]The average farmer in our sample uses just over 25 kg of maize seed a year, mostly comprised of low yielding local seeds. Assuming that (i) the 2 kg seed packet of the improved DT seeds replaced 2 kg of the local seeds; and, (ii) that the improved seeds yield 250% of the amount of the local seed, then we would expect the seed packet to boost trial year yields of the control group by 12%.

itself risky. While we could randomize the offer of DT seeds and the DT-II bundle across villages, the realization of shocks was entirely out of our control. In what follows, we will focus on two types of shocks. The first are the mid-season drought events that DT varieties were bred to mitigate. We will say that a mid-season drought event occurs when cumulative rainfall (as estimated by the CHIRPS data described in footnote 11) is less than 200 millimeters during the time period between 40 and 80 days after planting (200 mm is the amount of water that conventional maize needs during the mid-season stage for healthy growth and development). Each farmer reported their own maize planting date, and the drought measure was calculated for each farmer using this reported planting date and their GPS location.

The second type of shock we study are yield losses that are sufficiently severe that they would trigger an indemnity payment under the index insurance contract described in Section 2. As mentioned in that section, yields estimated by the satellite model to be about 65% or less of the long term average for the insurance zone triggered payment. In the discussions to follow, we will simply refer to such a triggering event as a "yield shock," keeping in mind that this term means a severe yield loss that was likely caused by stresses beyond mid-season drought. Note that these shocks are determined at the level of the insurance zone (roughly a 3-village area).

Table 2 below reports the frequency with which nature delivered these shocks across the different seasons of the study. The quasi-baseline season was disastrous across most of the Mozambique study sites, with many farmers losing their entire crop (see the figures in the table for lagged yield shocks in the midline year). In the two subsequent seasons, between 4 and 12% of farmers suffered severe yield losses. Mid-season droughts afflicted 39% to 52% of farmers in these two seasons, respectively. Figure 2 records the seasons and countries in which these shocks primarily occurred.

3.3 Experimental Balance

In order to gauge the balance of trial packet year characteristics across the different RCT groups, we run the following regression for quasi-baseline characteristic c_{is} for household i in randomization cluster, triad, s:

$$c_{is} = \alpha_s + \alpha_1 S_{is} + \alpha_2 I_{is} + \varepsilon_{is}$$

where α_s is a vector of triad fixed effects, and S_{is} and I_{is} are, respectively, binary indicators of assignment to DT seed (whether insured or not) and to the DT-II bundle treatment. The latter variable thus picks up any additional imbalance associated with the insurance treatment above and beyond that associated with the seed treatment. For the estimation, we clustered standard errors at the village level. Only observations included in the final regression sample for the analysis in Section 4 are included in this analysis.[20]

Table 1 displays the results from this balance analysis. As can be seen in the bottom panel of the table, the natural weather experiment resulted in balanced exposure to shocks across the different treatment groups, with the exception that the DT seed only treatment group was 6 percentage points more likely to experience a mid-season drought than the control group. Given that we are able to control for these events in the regression models to follow, we are not concerned by this imbalance in weather outcomes, which is unlikely to be related to any other farm or farmer characteristics, especially given the matched triplet randomization strategy described above.

While nature was relatively cooperative with the study design (to the distress of farmers), we do observe some imbalance in the controlled part of our experiment. As can be seen in Table 1, baseline food insecurity is significantly different between control communities and communities offered uninsured seeds. Food insecurity is not statistically different between control communities and treatment communities offered insured seeds. There is also baseline imbalance in yields between the control and both treatment groups, with the treatment groups averaging a statistically signif-

[20] We eliminated all observations that were missing any data needed for the later ANCOVA or difference-in-differences regressions. The resulting data set is not a balanced panel in that in a few cases, a household might be missing, say, midline data, perhaps because the household did not cultivate maize in the midline year. The panel is also partially unbalanced because of attrition, which was approximately 4.5% between each survey round. Attrition is balanced across treatment assignment.

Table 1: Regression Analysis of Baseline Balance by Experimental Assignment

	Full Sample			Trimmed Sample		
Dependent Variable	**Baseline Control Mean**	**DT Seed, S_{ivt}** *Coef. (Std. Err.)*	**Insurance, I_{ivt}** *Coeff. (Std. Err.)*	**Baseline Control Mean**	**DT Seed, S_{ivt}** *Coef. (Std. Err.)*	**Insurance, I_{ivt}** *Coeff. (Std. Err.)*
Outcome Variables						
Maize Yield (kg/hectare, winsorized)	399	159***	-14	291	36.3	6.8
		(40)	(39)		(31.1)	(37.8)
Seed Fertilizer Expend ($US PPP, winsorized)	38.9	1.5	1.6	35.0	-0.6	1.6
		(3.3)	(2.7)		(3.6)	(2.8)
Maize Area Planted (hectares)	2.1	-0.03	-0.02	2.4	-0.04	-0.002
		(0.1)	(0.1)		(0.13)	(0.14)
Food Insecurity Score	25.0	-4.8***	2.9	26.6	-3.2**	2.2
		(1.4)	(1.6)		(1.6)	(1.9)
Demographics & Wealth						
Education of Farmer (years)	2.3	0.10*	0.06	2.2	0.04	0.1
		(0.05)	(0.06)		(0.07)	(0.07)
Area Cultivated (hectares)	4.2	0.03	-0.5*	4.4	0.23	-0.53
		(0.25)	(0.26)		(0.29)	(0.32)
Poverty Probability Score (%)	58.7	-4..6***	0.9	59.1	-3.4**	1.0
		(1.4)	(1.3)		(1.5)	(1.5)
Drought & Yield Shocks						
Mid-season Drought (%)	74.3	6.1*	2.4	76.4	8.1***	1.1
		(3.2)	(3.4)		(3.0)	(3.9)
Yield Shock (%)	39.8	-1.7	2.6	48.9	-2.2	3.3
		(2.8)	(2.2)		(3.6)	(2.8)
Observations	1047	978	949	853	782	756

***, ** & * indicate statistical significance at the 1%, 5% & 10% level, respectively.
Other controls are Cluster Fixed Effects, Household Head Age and Education, Poverty Prob. & Intercropping
Standard errors clustered at the village level

icant 145-159 additional kilograms of production per-hectare compared to the control group.[21] There is no significant difference between the two treatment groups. This baseline yield difference is larger than what we would expect from the yield packets alone (see footnote 19). We also see that treatment households appear to be better off economically as judged by poverty probability scores, although another wealth indicator (area planted) shows no difference. Expenditures on maize seeds (including the approximately $3 value of trial seed packets in the quasi-baseline year), fertilizer and other inputs are only insignificantly larger in the seed treatment groups.[22]

The source of the baseline yield imbalance can be traced to two of the six districts within Tanzania (Singida and Iramba). Possible explanations of this imbalance include differences in agricultural potential between treatment and control areas, es-

[21] Yields were winsorized at the 99th percentile. These winsorized yields are used here and throughout the econometric analysis.

[22] A fixed set of local prices were used to value seed and other inputs that were purchased. Retained seeds were valued at the average consumer price for maize. Local currency values were converted to $US using PPP exchange rates. The expenditure aggregate is thus a fixed-price, quantity index. To eliminate the undue influence of outliers, we transformed total input expenditures into a per-hectare measure. The per-hectare measure was then winsorized at the the 99th percentile. The winsorized per-hectare measures were then transformed back into total expenditures by multiplying each observation by reported maize area.

pecially if the VBA program had been endogenously placed in high-potential areas. It could also reflect the impact of the VBA program itself, and/or differential baseline weather in the treatment versus control areas.[23]

To better understand the source of this imbalance, we utilized the NDVI-based biomass growth information used for the insurance yield index over the pre-intervention 2002-2016 period to gauge the long-term agricultural potential of treatment and control areas. In no case are the long-term average NDVI measures statistically different between treatment and control areas.[24] As mentioned earlier, treated households do not devote more area to maize (or other crops), as might be expected if they were located in high-potential areas. Next, we restricted our focus to treatment areas[25] and measured maize yields based on farmer recall for the decade preceding the intervention. In the problematic Iramba and Singida districts, mean yields in the quasi-baseline year were 117-121% of normal, suggesting that these two areas experienced relatively favorable conditions. Other districts in Tanzania had close to average yields during the quasi-baseline period. Finally, we examined the NDVI measures for 2016 specifically. In the case of the Iramba district, the cumulative NDVI measure was higher in treatment than in control areas (with the difference being significant at the 11% level), suggesting that treatment areas may have experienced relatively good weather in the 2015-2016 season. There is, however, no difference in NDVI between treatment and control areas in Singida district.

While this analysis is not entirely satisfying, it does suggest that there are unlikely to be large differences in agricultural potential between treatment and control areas. Much less clear is whether the imbalance observed in the 2016 quasi-baseline was the result of random variation in growing conditions or if it reflected the endogenous

[23]In Mozambique, matched treatment and control areas were always quite close to each other geographically, while, in Tanzania, greater variability in terrain as well presence of the pre-existing VBA program sometimes meant that matched pairs were some distance apart, making it more likely that weather differences could occur.

[24]Specifically, we measure cumulative NDVI over the maize growing season, masking out areas that are not growing maize. Across all areas in Tanzania, the mean NDVI measure indicates slightly higher average biomass growth in control than in treatment areas. The cumulative NDVI measure is 62.3 for control and 60.3 for treatment areas.

[25]Unfortunately, we do not have the same recall yield measures for control villages.

placement of the VBA agents in more favored areas. Because the seed companies shifted to their own in-house seed sales representatives after the quasi-baseline year due to concerns with the viability of the VBAs, we consider it unlikely that the VBA program *per se* gave treatment villages an advantage that increased over time. More likely, any direct advantages of the VBA program that are evident in the baseline would have dissipated over time. On the other hand, if the quasi-baseline yield imbalance reflects the impact of endogenous placement of the VBA program in higher productivity areas, then we would expect the yield difference to persist, but not grow, over time.

In the analysis to follow, we will take a multi-pronged approach to dealing with the challenges presented by these baseline imbalances and their possible causes. Each approach has its benefits and costs. Under the assumption that the imbalance was driven by once-off, random weather differences, or the fleeting impact of the VBA program, an econometric approach that relies on ANCOVA estimation would be both unbiased and statistically efficient. On the other hand, if the imbalance reflects a persistent, fixed difference between treatment and control areas, then difference-in-differences estimation would be preferred.

Finally, and most simply, we can trim our sample of the two districts in Tanzania from which the imbalance emanates. The 3 rightmost columns of Table 1 repeat the balance test for this trimmed sample. Trimming the sample eliminates the problematic difference in baseline yields. It also reduces but does not fully eliminate the significant difference in baseline food insecurity. While in many ways trimming would seem to be the least dependent on assumptions, it is also the most expensive as it reduces the sample size by almost 20%. Looking at Table 2, trimming also has a somewhat outsized effect on the fraction of the population that suffered the drought and yield shocks. Like the reduction in overall sample size, this reduced variation in a key explanatory variable would be expected to make it harder to detect effects. In the analysis to follow, we will employ all of these different approaches, emphasizing ANCOVA estimation for outcome variables that are balanced by trimming, and difference-in-differences estimation for the food insecurity measure.

4 Regression Model and Results

In this section, we present the specifications we use to estimate the impact of access to DT seeds and the DT-II bundle on various farm and household outcomes. As a precursor, we first summarize in Table 2 dimensions in the data that are particularly relevant to these specifications, including experimental compliance, shock exposure and changes in key outcome indicators. Compliance for both treatment groups was roughly 50% at midline (54.3% and 48.2% for the DT and DT-II groups respectively), but fell five to six percentage points at endline (49.5% and 41.9% for the DT and DT-II groups respectively). A small fraction, roughly 4%, of control households planted DT seeds. Although the experimental treatments were implemented uniformly, how farmers actually experienced these treatments likely varied according to their exposure to shocks during the study, introducing a source of treatment heterogeneity within treatment groups. At endline, roughly 40% of households had experienced a mid-season drought in the preceding year. Exposure to lagged yield shocks at endline ranged between 6% and 12%.

Table 2 also reports the fractions of households that experienced contemporaneous mid-season drought and severe yield shocks. Nature in effect complied with the study's diversified strategy, generating ample variation to observe the efficacy of the DT seeds in farmers' fields. Finally, the table also illustrates the mean levels of the four key outcome variables that this section examines. Given the heterogeneity in treatment generated by the variable exposure to natural shocks, the unconditional means shown in the table are not necessarily that informative. In the econometric analysis that follows, we will first explore the impact of the shocks on maize yields and the ability of the two experimental treatments to mitigate their immediate and lagged effects. We will then dig deeper and look at how shocks and treatments interact to influence farmers' allocation of resources (cash spent on maize inputs and area devoted to maize production). Finally, the last part of this section explores the impact of these same factors on household food security, giving us a deeper look into household coping and risk management strategies.

Table 2: Compliance and Key Outcome Variables by Experimental Treatment

	Full Sample			**Trimmed Sample**		
	Control	*DT Seeds*	*DT & Insurance*	Control	*DT Seeds*	*DT & Insurance*
Midline						
Compliance & Shocks						
Technology Adoption (%)	3.6	54.3	48.2	3.7	50.8	44.4
Mid-season Drought (%)	38.5	40.7	41.6	24.3	25.1	26.0
Yield Shock (%)	12.1	8.5	6.0	8.7	10.7	7.6
Lagged (baseline) Mid-drought (%)	74.4	77.3	79.9	76.6	81.0	82.6
Lagged (baseline)Yield Shock (%)	40.4	34.8	37.5	49.8	43.9	47.5
Outcome Variables						
Maize Yield (kg/hectare)	535	776	756	479	585	587
Seed fertilizer Expend ($USPPP)	42.1	72.5	75.5	37.7	58.4	68.7
Maize Area Planted (hectares)	2.0	1.8	2.3	2.2	2.0	2.6
Food Insecurity Score	25.6	22.8	22.8	26.4	25.9	25.4
Midline Observations	**996**	**917**	**902**	**808**	**726**	**712**
Endline						
Compliance & Shocks						
Technology adoption (%)	5.3	49.5	41.9	4.5	44.7	37.8
Mid-season Drought (%)	51.5	51.2	48.7	45.2	42.0	41.8
Yield Shock (%)	4.9	10.3	3.8	2.0	7.7	2.2
Outcome Variables						
Maize Yield (kg/hectare)	544	719	706	526	611	585
Seed fertilizer Expend ($USPPP)	38.1	93.4	77.3	34.0	75.1	66.2
Maize Area Planted (hectares)	2.0	2.1	2.1	2.2	2.3	2.4
Food Insecurity Score	10.3	8.3	8.8	11.0	9.6	10.2
Endline Observations	**964**	**914**	**864**	**785**	**727**	**682**

4.1 Yield Effects

Our primary ANCOVA ITT specification for maize yields at the farm level is as follows:

(1)

$$
\begin{aligned}
y_{ist} = {} & \left[\beta_1^y d_{ist} + \beta_2^y z_{ist}\right] + \left[\beta_3^y d_{is(t-1)} + \beta_4^y \left(d_{is(t-1)} \times E_{ist}\right) + \beta_5^y z_{is(t-1)} + \beta_6^y \left(z_{is(t-1)} \times E_{ist}\right)\right] + \\
& S_{is} \times \left[\delta_0^y + \delta_E^y E_{ist} + \delta_1^y d_{ist} + \delta_2^y \left(d_{ist} \times E_{ist}\right) + \delta_3^y \left(d_{is(t-1)} \times E_{ist}\right)\right] + \\
& I_{is} \times \left[\gamma_0^y + \gamma_E^y E_{ist} + \gamma_1^y \left(z_{is(t-1)} \times E_{ist}\right)\right] + \\
& \left[\alpha_0^y y_{is0} + \alpha_E^y E_{ist} + \alpha_1^{y\prime} x_{is0} + \nu_s^y\right] + \varepsilon_{it}^y
\end{aligned}
$$

where y_{ist} measures maize yields for household i in randomization triad s in year t, d_{ist} is a binary indicator for mid-season drought, z_{ist} is the same for severe yield shocks and E_{ist} is a time dummy variable taking on the value of 1 for the endline time period. S_{is} and I_{is} are the two treatment variables, taking value 1 if the household resides in a community assigned to the DT seed only and the bundled DT-II treatments respectively. The first two terms in the first row of equation 1 capture the contemporaneous impact of the two types of shocks, while the second set of terms in that row capture any lingering effects of prior shocks (e.g., if prior year shocks decapitalize the farmer and reduce their ability to invest in maize inputs). Because lagged shocks can only shape treatment effects at endline, we include additional interactions between lagged shocks and the indicator for the endline period (E_{ist}) rather than imposing the restriction that the lagged effects are the same in both midline and endline years.

The terms in the second row capture the ITT effects of being offered DT seeds in both normal years as well as in mitigating the impact of contemporaneous and lagged mid-season drought shocks.[26] Because compliance rates and adoption intensity changed from midline to endline (Table 2), we allow the impact of the treatments to

[26] We do not expect the DT seeds by themselves to mitigate yield shocks once we control for their impact on mid-season drought. In results available from the authors, we include a full set of interactions between the DT seed treatment and severe yield shocks. With a single exception, none of the many estimated coefficients are close to being statistically significant and their inclusion has virtually no effect on the estimated coefficients of the other included variables.

differ by year. Differences in farmer response to treatment could also be evident at both extensive and intensive margins, an issue to which we return below.

The third row in equation 1 captures the additional effect of insurance on yields in normal years as well its ability to mitigate any lingering effect of prior year yield shocks. We would expect γ_0^y to be positive if insurance generated an ex-ante crowding in of more intensive input use than the DT seeds alone. That same term could be negative if, instead, the higher cost of insured seeds led to a less intensive use of DT seeds by liquidity-constrained farmers who were only offered the more expensive insured DT seeds. Finally, the fourth row contains baseline yields, time effects and variables that were unbalanced at baseline between treatment and control groups (see Table 1). The term ν_s^y is a randomization triad fixed effect.

Table 3 reports the estimates of this ANCOVA regression model for both the full sample and the trimmed sample, which excludes the two districts in Tanzania that account for the yield imbalance at baseline. Figure 3 displays the 95% confidence interval estimates for the impacts of the two shocks and the mitigating impacts of the risk management treatments.[27] We will focus primarily on the full sample results and discuss the trimmed sample results where they tell a different story.

The coefficients in the top portion of Table 3 display the impact of drought and yield shocks on farmers, unmitigated by DT seeds or insurance. Both types of shocks have substantial impacts on maize yields, contemporaneously and in future years. Yields for the control group average around 540 kg/hectare, implying that the contemporaneous impact of drought and yield shocks amount to yield losses of 25% and 50%, respectively. In the trimmed sample, the impacts of the two shocks are somewhat smaller, representing yield losses of 18% and 36% of mean yield for control

[27]The mitigation effect of a treatment is defined as the difference in expected yields between a treated and a non-treated household given a shock. Using the notation in equation 1, the mitigation effects are defined as follows:

- Contemporaneous mitigation effects of DT on a drought shock at midline: $\delta_1^y + \delta_0^y$
- Contemporaneous mitigation effects of DT on a drought shock at endline: $\delta_1^y + \delta_2^y + \delta_0^y + \delta_E^y$
- Mitigation effect of DT on lagged drought at endline: $\delta_3^y + \delta_0^y + \delta_E^y$
- Mitigation effect of insurance on lagged yield shock at endline: $\gamma_1^y + \delta_0^y + \delta_t^y + \gamma_0^y + \gamma_E^y$

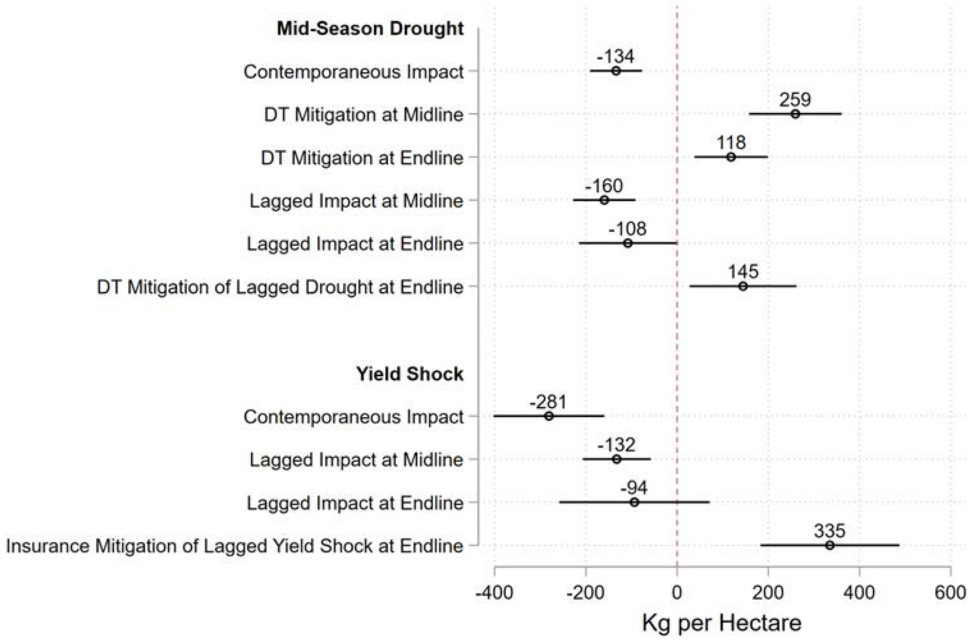
Table 3: ANCOVA Estimates of Maize Yields

	Full Sample		Trimmed Sample	
Explanatory Variables	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*
Impact of Shocks				
Mid-season Drought, d_{ist}	-133.8***	34.6	-89.6**	32.4
Yield Shock, z_{ist}	-281.0***	73.9	-180.9*	72.4
Lagged Mid-season Drought, $d_{is(t-1)}$	-159.5***	41.5	-175.4***	41.5
$d_{is(t-1)} \times$ Endline, E_{ist}	51.6	79.8	165.5	86.9
Lagged Yield Shock, $z_{is(t-1)}$	-132.4**	45.4	-114.2*	45.5
$z_{is(t-1)} \times E_{ist}$	38.8	116.5	107.5	138.1
Mitigation Impacts of DT Seed Treatment, S_{it}				
S_{is}	76.1	40.7	66.2	41.5
$S_{is} \times E_{ist}$	-92.6	53.2	-59.1	51.9
$S_{is} \times d_{ist}$	183.2**	57.1	14.0	56.7
$S_{is} \times d_{ist} \times E_{ist}$	-48.4	62.2	79.3	56.6
$S_{is} \times d_{is(t-1)} \times E_{ist}$	161.1*	72.5	60.9	76.0
Mitigation Impacts of Insurance Treatment, I_{it}				
I_{is}	-13.0	44.8	3.3	46.9
$I_{is} \times E_{ist}$	-52.2	65.0	-81.1	59.4
$I_{is} \times z_{is(t-1)} \times E_{ist}$	416.7***	94.8	380.4***	102.7
Intercepts & Control Variables				
Baseline Yields	0.22***	0.02	0.2***	0.03
Endline time effect, E_{ist}	-111.0*	55.0	-134.1*	57.7
Number of Observations	5568		4459	

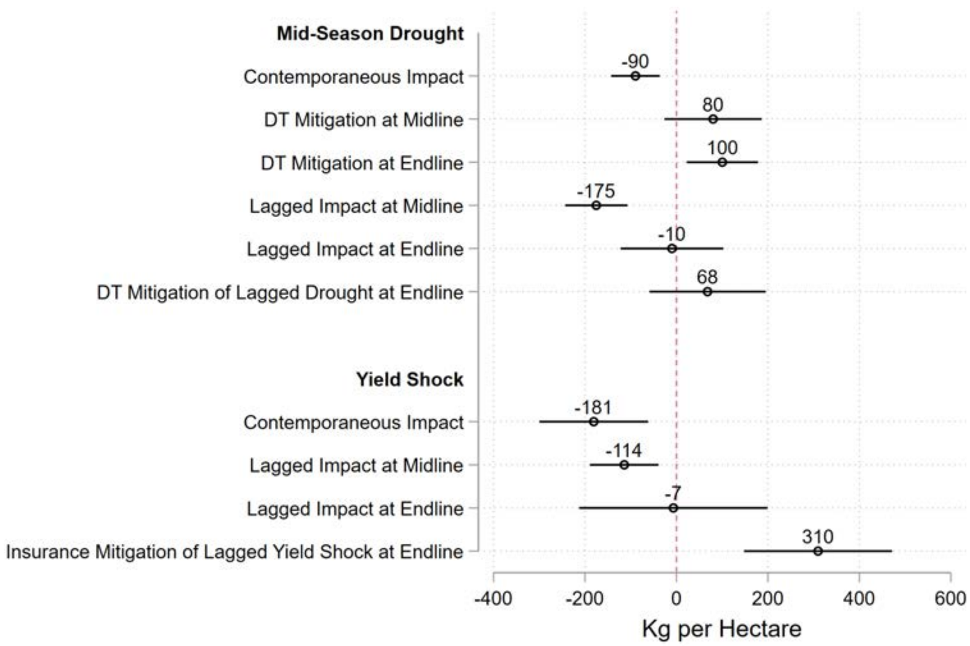
See notes for Table 1

Figure 3: Yield Shocks and Mitigation Impacts

(a) Full Sample



(b) Trimmed Sample



farmers.

Both kinds of shocks also have impacts on future yields. A yield shock experienced during the baseline season reduced yields at midline by 132 kg/ha, roughly 47% of the contemporaneous impact of this same shock. The impact at endline (of a midline yield shock) was still large in magnitude, 94 kg/ha, but the point estimate was not significantly different from zero. The lagged impacts of mid-season drought are of similar magnitude. The lingering yield effects of these weather shocks indicate that absent risk management tools, maize farmers are not resilient and that their yields fail to return to pre-shock yield levels, even a year after the shock.

The second block of coefficients in Table 3 combine to identify the mitigating effect of the DT seed technology (see footnote 27). As reflected by the point estimates of 259 and 118 kg/ha in Figure 3a, the DT technology effectively mitigates the yield loss otherwise brought on by a mid-season drought.[28] The estimated mitigation effects are modestly smaller for the endline year, but still quite substantial relative to the impact of the shock. We also see that the DT seed treatment eliminates the lingering effects of drought in future years (145 kg/ha point estimate in Figure 3a), as would be expected given that the seeds mitigate the initial impact of a drought shock. The mitigation effects of DT seeds in the trimmed sample are similar although, as discussed above, the loss of information reduces our precision, with the result that the point estimate at midline (80 kg/ha) is not significantly different from zero.

The third block of Table 3 allows us to identify the additional impact of the insurance treatment on maize yields. The estimates indicate that the insurance treatment has a small negative but statistically insignificant effect on contemporaneous yields but, as shown in Figure 3a, mitigates the lingering effects of lagged yield shocks by a substantial and statistically significant 335 kg/ha. This point estimate is more than three times larger than the estimated impact of lagged yield shocks at endline (94 kg/ha). For now, we refer to this as "excess mitigation." We explore possible mechanisms responsible for this empirical pattern in Section 5 below.

[28] Note that nature's treatment (weather shocks) have full compliance whereas compliance for our marketing treatments is roughly 50%. The mitigation effects presented here are intent to treat and thus understate the mitigation effect on adopters.

Finally, the seed treatment variable (S_{is}) by itself identifies the normal year (no shocks) effects of the DT seed treatment. Under the ANCOVA specification, this impact is a marginally significant yield increase of 76 kg/ha at midline (about a 15% increase). This yield bump is in line with the findings of Paul (2021) discussed in Section 2 above, but well-below expectation from seed breeders' experiment station trials. Indeed, that normal year yield bump disappears in endline, as shown by the coefficient of the interaction term between treatment and the endline dummy variable (-92.6). The next section discusses changes in input use at the extensive and intensive margins to help understand this endline difference.[29]

4.2 Resource Allocation Effects: Inputs and Land

In an effort to further unpack the impacts of the seed and insurance treatments, this section explores the impacts of these treatments on households' *ex ante* resource allocation decisions, namely their investment in maize inputs (seeds and fertilizers) and area cultivated in maize. Note that these are decisions taken prior to the realization of the current year's shock and thus cannot be influenced by shocks that occurred during the growing season. We thus adapt regression model 1 and estimate the following ANCOVA ITT specification for *ex ante* input decisions:

$$\begin{aligned} r_{ist} = {} & \left[\beta_3^r d_{is(t-1)} + \beta_4^r \left(d_{is(t-1)} \times E_{ist}\right) + \beta_5^r z_{is(t-1)} + \beta_6^r \left(z_{is(t-1)} \times E_{ist}\right)\right] + \\ & S_{is} \times \left[\delta_0^r + \delta_E^r E_{ist} + \delta_3^r \left(d_{is(t-1)} \times E_{ist}\right)\right] + \\ & I_{is} \times \left[\gamma_0^r + \gamma_E^r E_{ist} + \gamma_1^r \left(z_{is(t-1)} \times E_{ist}\right)\right] + \\ & \left[\alpha_0^r r_{is0} + \alpha_E^r E_{ist} + \alpha_1^{r\prime} x_{is0} + \nu_s^r\right] + \varepsilon_{it}^r \end{aligned} \tag{2}$$

The resource allocation outcome variable r_{ist} will either be total expenditures on maize inputs (measured in \$US PPP; see footnote 22) or hectares planted to maize. Note that the total expenditure variable will reflect changes at both the intensive and extensive margins of cultivation. The explanatory variables are a subset of those

[29] Difference-in-differences results–available upon request to the authors–paint a largely similar picture of impacts.

Table 4: ANCOVA Estimates of Maize Input Expenditures & Area Cultivated

	Full Sample				Trimmed Sample			
	Maize Inputs		**Maize Area**		**Maize Inputs**		**Maize Area**	
Explanatory Variables	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*
Impact of Shocks								
Lagged Mid-season Drought, $d_{is(t-1)}$	-1.5	9.5	0.0	0.1	-5.0	13.8	-0.03	0.15
$d_{is(t-1)} \times$ Endline, E_{ist}	-32.0**	14.0	-0.10	0.16	-42.1**	16.8	-0.24	0.23
Lagged Yield Shock, $z_{is(t-1)}$	2.3	9.1	-0.08	0.17	3.3	15.4	-0.12	0.19
$z_{is(t-1)} \times E_{ist}$	-57.6	36.1	-0.56*	0.31	-52.1	63.6	-0.62	0.42
Mitigation Impacts of DT Seed Treatment, S_{is}								
S_{is}	23.7***	7.2	-0.21*	0.12	16.3**	7.8	-0.26*	0.13
$S_{is} \times E_{ist}$	-11.3	11.0	0.31*	0.17	-7.4	12.4	0.37*	0.19
$S_{is} \times d_{is(t-1)} \times E_{ist}$	83.1***	20.1	-0.02	0.18	102.6***	38.0	0.05	0.27
Mitigation Impacts of Insurance Treatment, I_{is}								
I_{is}	1.9	7.0	0.55***	0.16	9.2	7.7	0.69***	0.20
$I_{is} \times E_{ist}$	-28.8	18.8	-0.62***	0.20	-29.1	22.9	-0.81***	0.25
$I_{is} \times z_{is(t-1)} \times E_{ist}$	144.0*	78.1	1.47***	0.46	128.9	78.4	1.60***	0.47
Intercepts & Control Variables								
Baseline Dependent Variable	0.42***	0.13	0.42***	0.10	0.4***	0.2	0.43***	0.1
E_{ist}	14.9*	8.6	0.07	0.12	10.3	9.9	0.03	0.15
Number of Observations	5568		5568		4463		4463	

See notes for Table 1

employed in the yield regression 1 and include only lagged shock terms that can affect current year resource allocation decisions. As we did for the yield regression, we present results for both the full and trimmed sample. Since these two outcome variables were well balanced at baseline, we focus our interpretation on the full sample results.

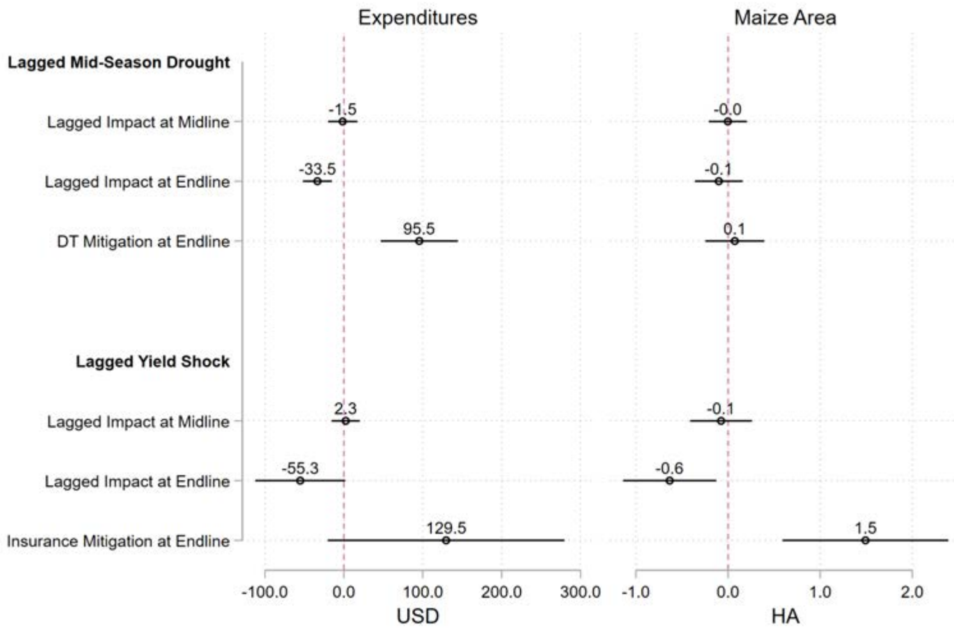
Table 4 displays the results from specification 2. Consistent with the impact of lagged shocks on yields discussed in Section 4.1, Table 4 and Figure 4 show that lagged drought and severe, covariate yield shocks dampen the allocation of inputs to maize in the endline period.[30] Mitigation effects, which can only be measured at endline, show that both the DT seed and the insurance treatment exhibit the same excess mitigation pattern noted above.[31] Midline drought shocks are estimated to

[30]Baseline shocks, which occurred primarily in Mozambique, were so severe that many farmers produced nothing, forcing many to enter the market the following season to purchase seeds. In addition, there is some evidence of external aid entering to support households in the wake of the 2015/16 drought (see Section 4.3).

[31]The mitigation effects of the treatment are defined analogously to those describe in footnote 27. Using the notation in equation 2, the mitigation effects are:

- Mitigation effect of DT on lagged drought at endline: $\delta_0^r + \delta_E^r + \delta_3^r$
- Mitigation effect of insurance on lagged yield shock at endline: $\delta_0^r + \delta_E^r + \gamma_0^r + \gamma_E^r + \gamma_1^r$.

Figure 4: Shocks and Resource Allocation (ANCOVA Estimates for Full Sample)



reduce input expenditures by $33.5, whereas the DT treatment following a midline yield shock boosts expenditures by more than double that amount ($95.5). Similar excess mitigation is revealed with yield shocks and exposure to insurance: Midline yield shocks reduce endline expenditures by an estimated $55, whereas the insurance treatment following that shock boosts spending by $129.5. Because the measure is total expenditures on maize seeds and fertilizer, it is possible that this increase in spending could reflect changes at the intensive margin (inputs per-hectare) or at the extensive margin (area planted). These findings point toward the mechanisms that underlie the results in the prior section, which showed that both mid-season droughts and more severe yield shocks have yield effects that linger into the future. Apparently, these shocks at least partially de-capitalize the farming operation or otherwise discourage continued investment in maize farming.

Further clues into this pattern can be gleaned by looking at the coefficients on the treatments in the endline period (Table 4). In the midline period, households receiving the DT treatment boosted expenditures by $23.7, whereas those receiving the combined seed-insurance treatment increases input spending by almost an identical amount (\$25.6 = \$23.7 + \$1.9). However, farmers who did not experience midline shocks are estimated to retreat from the novel risk management technologies and reduce their expenditures. Farmers in the DT and DT-II treatment groups who did not experience a midline shock reduce their expenditures at endline by \$11.3 and \$28.8 respectively, although neither point estimate is significantly different from zero. In contrast, households that experienced shocks in the midline substantially boosted their expenditures on seeds and fertilizers.

The results on area planted to maize parallel these findings on input spending. While drought shocks seem to have little impact on area planted to maize, severe yield shocks at midline are estimated to have reduced endline maize cultivation by 0.6 hectares, a drop of just over 25% given that control group farmers on average plant 2 hectares of maize. Severe yield shocks not only reduce future yield as discussed above, they also reduce area planted. The insurance treatment has an estimated mitigation effect of 1.5 hectares, more than offsetting the decrease in area. This additional mitigation implies that following a shock and demonstration of the benefits of insurance, farmers boosted maize cultivation by about 67%. While large, this increase is in line with the literature on the impact of insurance on *ex ante* investment behavior (see footnote 6 above). However, at endline, farmers who did not experience midline yield shocks dial back the area expansion (-0.62 coefficient in Table 4), whereas those who did experience shocks continue with expanded maize area.

In order to put these impact results in perspective, Table 5 uses the estimated coefficients from Table 4 to calculate the predicted endline *levels* of resource allocation under different scenarios.[32] The top row presents predicted endline values for control households when the midline season was normal, whereas the estimates in the second row are for control farmers who faced a severe yield shock during the midline season. Following a weather-induced shock, a resilient household would have maintained similar on-farm investment levels. A comparison across the first two rows shows that control households in our research context are far from resilient, with

[32]We calculate predicted values using mean values of the triad fixed effects, ν_s^r,and the mean values for the control households of the baseline covariates r_{is0} and x_{is0} from equation 2.

Table 5: Two Technologies Promote Resilience and Resilience-plus

	Predicted Endline Levels		
	Input Expenditures (PPP USD)	*Maize Area (Ha)*	*Expenditures per Hectare*
Control Household $(S_{is}, I_{is} = 0)$			
No Midline Yield Shock	59.0	2.1	27.8
Midline Yield Shock	3.7	1.5	2.5
Households Offered Insured Seeds $(S_{is}, I_{is} = 1)$			
No Midline Yield Shock	44.5	2.1	20.7
Midline Yield Shock	133.3	3.0	44.7

input expenditures collapsing and maize area falling by roughly 30%.

The third and fourth rows of Table 5 row presents predicted endline investment levels for households in the insured seed (DT-II) treatment group depending on whether they did or did not experience a yield shock at midline. A comparison of rows 1 and 4 shows that farmers in the DT-II treatment group more than recover from the shock in the subsequent year. That is, not only are these treated households resilience in the sense that they get back to where they counterfactually would have been without the shock and without the insurance treatment, they are predicted to increase total expenditures by \$74.3 and maize area by 0.9 hectares relative to this counterfactual scenario. Input intensity increases by 60% or \$16.9 per hectare compared to the no-shock, control scenario. Note that this increase in input intensity is consistent the significant yield increase discussed in section 4.1 above. Importantly, this increased input intensity is applied over a 50% larger area cultivated. We label this behavior that exhibits more than resilience as "resilience-plus."

Also apparent in Table 5 is the strong contrast between households in the treatment group who did and did not experience shocks in the midline year. Households that did not receive a midline yield shock allocate slightly less inputs to maize production than do the control households that were not shocked. Section 5 will return to discuss the meaning of this very different behavior of treated households that did and did not experience shocks.

4.3 Food Insecurity

The analysis so far indicates that control households cope with weather shocks by reducing investment in future production, suggesting a conventional pattern of consumption smoothing in which the wealth used to finance future agricultural investment is drawn down to cope with the immediate implications of income losses. The two risk management technologies studied here are estimated to cut short this reduction in future investment and income. This section takes the next steps to see if there is any further sign that shocks also spillover and reduce consumption, as would be signaled by an increase in food insecurity.

To test the effect of the risk management technologies on household consumption, we employ the continuous Household Food Insecurity Access Scale (HFIAS) measure, in which higher numbers indicate greater insecurity (see Coates et al., 2007). Because of the reference periods used in the survey (see Figure 2), food insecurity information solicited in the midline (endline) refers to consumption that was potentially driven by yield shocks in the baseline (midline) production period. To explore the impact of shocks on food insecurity and the efficacy of insurance and DT seeds in mitigating these adverse impacts, we maintain the spirit of regression model 2 which explores the connection between a currently reported outcome variable and lagged yield shocks. However, because the baseline imbalance in food insecurity did not fully disappear when trimming the sample (Table 1), we run the following statistically more conservative Difference-in-Differences regression model:

$$
\begin{aligned}
f_{ist} = & \left[\beta_3^f d_{is(t-1)} + \beta_4^f \left(d_{is(t-1)} \times E_{ist}\right) + \beta_5^f z_{is(t-1)} + \beta_6^f \left(z_{is(t-1)} \times E_{ist}\right)\right] + \\
& [S_{is} \times Post_{ist}] \times \left[\delta_0^f + \delta_E^f E_{ist} + \delta_3^f \left(d_{is(t-1)} \times E_{ist}\right)\right] + \\
& [I_{is} \times Post_{ist}] \times \left[\gamma_0^f + \gamma_E^f E_{ist} + \gamma_1^f \left(z_{is(t-1)} \times E_{ist}\right)\right] + \\
& \left[\alpha_S^f S_{is} + \alpha_I^f I_{is} + \alpha_p^f Post_{ist} + \alpha_E^f E_{ist} + \alpha_1^{f\prime} x_{is0} + \nu_s^f\right] + \varepsilon_{it}^f
\end{aligned}
$$

Table 6 presents estimation results for both the full and trimmed samples. As can be seen, there is little evidence that mid-season drought shocks affect food security

Table 6: Difference-In-Differences Estimates of Food Insecurity

	Full Sample		Trimmed Sample	
Explanatory Variables	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*
Impact of Shocks				
Lagged Mid-season Drought, $d_{is(t-1)}$	0.56	1.37	0.18	1.70
$d_{is(t-1)} \times$ Endline, E_{ist}	2.46	2.11	0.078	2.47
Lagged Yield Shock, $z_{is(t-1)}$	-3.39**	1.32	-4.33***	1.40
$z_{is(t-1)} \times E_{ist}$	8.17***	2.01	9.82***	2.50
Mitigation DT Seed Treatment, S_{is}				
$S_{is} \times Post_{ist}$	2.23	2.65	2.36	3.18
$S_{is} \times E_{ist}$	-0.29	2.07	-1.89	2.41
$S_{is} \times d_{is(t-1)} \times E_{ist}$	2.36	1.55	3.72	1.91
Mitigation Impacts of Insurance Treatment, I_{is}				
$I_{is} \times Post$	-2.70	2.64	-2.39	3.15
$I_{is} \times E_{ist}$	1.27	2.11	1.77	2.50
$I_{is} \times z_{is(t-1)} \times E_{ist}$	-7.49***	2.64	-7.52**	3.03
Intercepts & Control Variables				
S_{is}	-4.08**	1.67	-2.69	1.96
I_{is}	2.86*	1.69	2.53	2.03
Midline Time Effect ($post_t$)	1.10	1.93	1.16	2.23
Endline Time Effect,E_{ist}	-16.98***	1.92	-16.93***	2.31
Number of Observations	8630		6919	

See notes for Table 1

in the following year. Given earlier estimates that mid-season droughts may reduce yields by as much as 25%, and that these yield reductions spillover into reduced investment in maize the following season, the lack of an impact on food insecurity is consistent with a model of consumption smoothing in which households hit by mid-season drought managed to protect their consumption levels after the drought and spread the costs into future years.

In contrast, severe covariate yield shocks increase food insecurity, at least for shocks that took place during the midline year and are reflected in the endline data.[33] These more severe shocks seem to overwhelm households' ability to smooth consump-

[33] The only baseline severe yield shocks in our data occurred in Mozambique, where many farmers produced nothing. Substantial internationl flows of food aid entered Mozambique following this disastrous year, perhaps obscuring food insecurity impacts.

tion.[34] The pattern of larger effects visible in the endline year is consistent with the pattern on input spending in which we see that it was midline shocks that had the largest effect on next season's spending on maize input. Calculations akin to those that underlie Figure 4 show that midline yield shocks increased food insecurity by 4.78 points (compared to average index value of 25), with a 95% interval estimate of (0.9, 8.7). The insurance treatment is estimated to offset this impact of shocks, with an estimated mitigation effect of -8.2 points, with a 95% interval estimate of (-13.3, 3.1).

5 Excess Mitigation and Resilience Plus

Section 4.2 shows that treated farmers who experienced shocks and therefore witnessed the two risk reduction technologies in action subsequently deepened their investment in them, while other treated farmers began turning away from them. This is evident in differential "excess mitigation" among treated farmers who, after a midline shock, increase their maize yield, input use and area planted beyond pre-shock levels. In contrast, treatment farmers who did not experience shocks largely revert to the behavior of the untreated control group that also avoided shocks.[35] A plausible interpretation of these results is that farmers used the realization of shocks to learn about the key mitigation parameters in equation 1, δ_1^y and γ_1^y. If farmers began with the sort of technology skepticism exhibited by the Mozambican farmers studied by Carter et al. (2021), experiencing first-hand protection in the wake of shocks might lead them to update their perception of these parameters. Thus, what we observe empirically as excess mitigation in the results above could reflect farmers learning about these new risk mitigating technologies and then, with new-found confidence, increasing on-farm investments. In this sense, excess mitigation may be a manifestation of what some authors label as "positive moral hazard," meaning that risk reduction induces

[34] Using the data employed in this paper, Malacarne and Paul (2022) show that drought events similarly impact a dietary diversity measure of food security.

[35] Cai et al. (2020) find similar behavior in their analysis of an insurance program in China where farmers, who did not experience shocks, retreated from purchasing insurance.

further investment and risk-taking (Ikegami et al., 2019). If resilience is the ability of households to recover from a shock and return to pre-shock levels of production and well-being, the excess mitigation we see here might be labelled "resilience-plus." Once they learn that the technologies generate resilience, farmers further intensify investments and reap a productivity boost as a result.

We cannot, however, entirely rule out other explanations beyond learning. One alternative explanation is that the shocks made information on the likelihood of shocks more salient or "available" (to use the term of Kahneman, 2011), leading farmers to increase their subjective probabilities that shocks occur. While this availability or salience argument is most typically applied to low frequency natural disasters (see the Gallagher (2014) analysis of the purchase of flood insurance), we can test for salience effects for the relatively high frequency shocks relevant to our study. By modifying regression model 2, we can test if a shock in the quasi-baseline year encouraged midline adoption of the drought tolerant seeds and insurance technologies. Appendix Table A1 shows that inclusion of these terms has no explanatory power, suggesting that risk salience was not operative in explaining midline resource allocation patterns. This finding, which mirrors Cai et al. (2020), cannot fully rule out salience effects in the endline since farmers in the midline were likely more liquidity constrained than endline farmers and perhaps unable to act upon their updated perceptions of the probability of shocks. Nonetheless, given that mid-season droughts occur once every 2-3 years, and that severe yield shocks are 1-in-5-year events (as opposed to the 1-in-50-year flood events studied by Gallagher (2014)), it seems unlikely that the finding of excess mitigation is explained by an availability bias or salience effect. Even if learning about the key parameters δ_1^y and γ_1^y explains the estimated excess mitigation, we might still wonder if this learning is durable, or if it decays over time without frequent reenforcement. Unfortunately, the duration of this study does not permit an answer to this question.

Another alternative explanation of our excess mitigation is rooted in the fact that insurance payouts were delivered in-kind (as replacement seeds) at the beginning of the next season. In contrast to cash payouts made at harvest time, this delivery mechanism may have solved a commitment problem for farmers and thereby increased the investment of (timely) insurance proceeds into productive inputs (Duflo et al., 2011). While our study is unable to test whether at-harvest cash payouts would have diminished the extent of excess mitigation, we can conclude with confidence that payout timing does not entirely explain the excess mitigation pattern we observe. Specifically, farmers with access only to DT seeds receive their biological "indemnities" at harvest, not at the beginning of the next season. These farmers exhibit excess mitigation that is similar to that shown by farmers with the insurance treatment.

6 Conclusion

This study reinforces the growing body of evidence that documents how uninsured risk exposes individuals and households to shocks with persistent effects that can reverberate for years after the shock has passed. We find that production shocks that occurred across our multi-year, multi-country study areas reduced both the current and future well-being of control households. In coping with losses that reduced their primary income source by 25% to 50%, these households reduced future spending on agricultural inputs and, in the case of severe yield shocks, experienced significant increases in hunger as well.

Against this dreary backdrop, our results provide evidence that thoughtfully-designed and appropriate risk management tools reduce the risk burden in synergistic ways. Specifically, our results suggest that a genetic technology (drought-tolerant maize seeds) bundled with a financial technology (fail-safe index insurance) effectively mitigated both the immediate and longer term consequences of the shocks they were designed to offset.[36] Strikingly, after farmers experienced the benefits of these technologies in the wake of what would otherwise have been a painful welfare shock, they intensified their investment, leading to further gains, exhibiting what might be termed

[36]Despite some imbalances created by imperfections in the study's randomization scenario, the primary results concerning mitigation of shocks survives statistically more conservative approaches, including sample trimming and a difference-in-differences estimation method. Unclear is whether drought tolerant seeds offer a yield benefit in years with normal weather patterns.

resilience-plus. That is, not only did the risk management technology mitigate the impact of the shocks, but farmers' experiential learning gave them the confidence to subsequently intensify their investments.[37]

Unfortunately, experiential learning cuts both ways. Farmers who did not experience the efficacy of the risk management technologies backed away from using them in the following season. This finding parallels results in Cai et al. (2020), where experiential learning about index insurance was the *sine qua non* for its continued purchase, and Emerick et al. (2016), which found farmers who did not experience floods backed off the purchase of flood tolerant rice seeds, but those who did, intensified their use of the seeds. These findings about the adoption fragility of technologies that offer only occasional, or stochastic, benefits stands in marked contrast to the finding reported in Carter et al. (2021) that a once-off subsidy for improved seeds and fertilizer sparked a rapid and continued uptake of that technology which spread across the communities of those who received the subsidies. Subsidy schemes or other tools to promote the sustained adoption of technologies that offer infrequent, stochastic benefits have yet to be developed.

Stepping back, this study illustrates the potential of risk management technologies designed to create resilience and improved standards of living in smallholder farmer communities. The distinct complementarities between genetic and financial technologies provide a compelling logic for bundling the two, and the results of this analysis provide evidence that such a bundle offers a new generation of cost-effective risk management products that target those who now suffer from frequent uninsured shocks and the persistent welfare penalties they can trigger. This study's evidence of resilience-plus effects encouragingly suggests it may be possible to replace the weighty dynamic burden of risk with productivity- and welfare-enhancing risk management tools.

[37]While the evidence points towards a learning explanation, Section 5 discusses alternative explanations, not all of which can be definitively ruled out.

References

Benami, Elinor and Michael R. Carter, "Can Digital Technologies Reshape Rural Microfinance? Implications for Savings, Credit, Insurance," *Applied Economic Perspectives and Policy*, 2021, *43*, 1196–1220.

Bertram-Huemmer, Veronika and Kati Kraehnert, "Does Index Insurance Help Households Recover from Disaster? Evidence from IBLI Mongolia," *American Journal of Agricultural Economics*, 2017, *100* (1), 145–171.

Bulte, Erwin, Francesco Cecchi, Robert Lensink, Ana Marr, and Marcel van Asseldonk, "Does bundling crop insurance with certified seeds crowd-in investments? Experimental evidence from Kenya," *Journal of Economic Behavior Organization*, 2020, *180*, 744–757.

Cai, Jing, "The impact of insurance provision on household production and financial decisions," *American Economic Journal: Policy*, 2016, *8* (2), 44–88.

_ , Alain de Janvry, and Elisabeth Sadoulet, "Subsidy Policies and Insurance Demand," *American Economic Review*, 2020, *110* (8), 2422–2453.

Carter, Michael R and Travis J Lybbert, "Consumption versus asset smoothing: testing the implications of poverty trap theory in Burkina Faso," *Journal of Development Economics*, 2012, *99* (2), 255–264.

Carter, Michael R., Rachid Laajaj, and Dean Yang, "Subsidies and the African Green Revolution: Direct Effects and Social Network Spillovers of Randomized Input Subsidies in Mozambique," *American Economic Journal: Applied Economics*, 2021, *13* (2), 206–229.

Casaburi, Lorenzo and Jack Willis, "Time versus State in Insurance: Experimental Evidence from Contract Farming in Kenya," *American Economic Review*, 2018, *108* (12), 3778–3813.

CIMMYT, "The Drought Tolerant Maize for Africa project: Six years of addressing African smallholder farmers' needs. The Drought Tolerant Maize for Africa project: Six years of addressing African smallholder farmers' needs.," *CIMMYT, Nairobi: Brief*, 2012.

Coates, Jennifer, Anne Swindale, and Paula Bilinsky, "Household Food Insecurity Access Scale (HFIAS) for Measurment of Food Access: Indicator Guide," Technical Report, US Agency for International Development 2007.

Dar, Manzoor H, Alain De Janvry, Kyle Emerick, David Raitzer, and Elisabeth Sadoulet, "Flood-tolerant rice reduces yield variability and raises expected yield, differentially benefitting socially disadvantaged groups," *Scientific reports*, 2013, *3*, 3315.

Duflo, Esther, Michael Kremer, and Jonathan Robinson, "Nudging Farmers to Use Fertilizer: Theory and Experimental Evidence from Kenya," *American Economic Review*, October 2011, *101* (6), 2350–90.

Elabed, Ghada and Michael Carter, "Ex-Ante Impacts of Agricultural Insurance: Evidence from a Field Experiment in Mali," 2018.

Emerick, Kyle, Alain de Janvry, Elisabeth Sadoulet, and Manzoor H Dar, "Technological Innovations, Downside Risk, and the Modernization of Agriculture," *American Economic Review*, 2016, *106* (6), 1537–1561.

Fisher, Monica, Tsedeke Abate, Rodney Lunduka, Woinishet Asnake, Yoseph Alemayehu, and Ruth B Madulu, "Drought tolerant maize for farmer adaptation to drought in sub-Saharan Africa: Determinants of adoption in eastern and southern Africa," *Climatic Change*, 2015, *133* (2), 283–299.

Flatnes, Jon Einar and Michael R Carter, "Fail-Safe Index Insurance Without the Cost: A Satellite Based Conditional Audit Approach," 2016.

Funk, Chris, Pete Peterson, Martin Landsfeld, Diego Pedreros, James Verdin, Shraddhanand Shukla, Gregory Husak, James Rowland, Laura

Harrison, Andrew Hoell, and Joel Michaelsen, "The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes," *Scientific Data*, 2015, *2* (1), 1–21.

Gallagher, Justin, "Learning about an infrequent event: evidence from flood insurance take-up in the United States," *American Economic Journal: Applied Economics*, 2014, pp. 206–233.

Gebre, Girma Gezimu, Harriet Mawia, Dan Makumbi, and Dil Bahadur Rahut, "The impact of adopting stress-tolerant maize on maize yield, maize income, and food security in Tanzania," *Food and Energy Security*, 2021, *10* (4), e313.

Hill, R. V., N. Kumar, N. Magnan, S. Makhija, F. de Nicola, D. J. Spielman, and P. S. Ward, "Ex ante and ex post effects of hybrid index insurance in Bangladesh.," *Journal of Development Economics*, 2019, *136*, 1–17.

Ikegami, Menuenobu, Michael R Carter, Christopher B. Barrett, and Sarah A Janzen, "Poverty Traps and the Social Protection Paradox," in Christopher B. Barrett, Michael R. Carter, and Jean-Paul Chavas, eds., *The Economics of Poverty Traps*, University of Chicago Press, 2019, chapter 6, pp. 223–256.

Janzen, Sarah A and Michael R Carter, "After the Drought: The Impact of Microinsurance on Consumption Smoothing and Asset Protection," *American Journal of Agricultural Economics*, 2018.

Jensen, Nathaniel D, Christopher B Barrett, and Andrew G Mude, "Cash Transfers and Index Insurance: A Comparative Impact Analysis from Northern Kenya," *Journal of Development Economics*, 2017, *129*, 14–28.

Kahneman, Daniel, *Thinking, Fast and Slow*, Farrar, Straus and Giroux, 2011.

Karlan, Dean, Robert Osei, Isaac Osei-Akoto, Christopher Udry et al., "Agricultural Decisions after Relaxing Credit and Risk Constraints," *The Quarterly Journal of Economics*, 2014, *129* (2), 597–652.

Lobell, David B, George Azzari, Marshall Burke, Sydney Gourlay, Zhenong Jin, Talip Kilic, and Siobhan Murray, "Eyes in the Sky, Boots on the Ground: Assessing Satellite-And Ground-Based Approaches to Crop Yield Measurement and Analysis in Uganda," *American Journal of Agricultural Economics*, 2020, *102* (1), 202–219.

Lybbert, Travis J. and Adrian Bell, "Stochastic Benefit Streams, Learning, and Technology Diffusion: Why Drought Tolerance is Not the New Bt," *AgBioForum*, 2010, *13* (1).

Lybbert, Travis J and Michael R. Carter, "Bundling Drought Tolerance and Index Insurance to Reduce Rural Household Vulnerability to Drought," in "Risk, Resources and Development: Foundations of Public Policy," Elsevier Press, 2015.

Makanza, R., M. Zaman-Allah, J. Cairns, J. Eyre, J. Burgue no, A. Pacheco, C. Diepenbrock, C. Magorokosho, A. Tarekegne, and M. K. Olsen, "High-throughput method for ear phenotyping and kernel weight estimation in maize using ear digital imaging," *Plant Methods*, 2018, *14* (1).

Malacarne, J.G. and L.A. Paul, "Do the benefits of improved management practices to nutritional outcomes "dry up" in the presence of drought? Evidence from East Africa," *Food Policy*, 2022, p. 102332.

McIntosh, Craig, Shukri Ahmed, and Alexandros Sarris, "The Impact of Commercial Rainfall Index Insurance: Experimental Evidence from Ethiopia," *American Journal of Agricultural Economics*, 2020, *102* (4), 1154–76.

Mobarak, Ahmed Mushfiq and Mark R Rosenzweig, "Informal Risk Sharing, Index Insurance, and Risk Taking in Developing Countries," *American Economic Review*, 2013, *103* (3), 375–80.

Morduch, Jonathan, "Income Smoothing and Consumption Smoothing," *The Journal of Economic Perspectives*, 1995, *9* (3), 103–114.

Paul, Laura A, "Heterogeneous and Conditional Returns from DT Maize for Farmers in Southern Africa," *European Review of Agricultural Economics*, 2021, *48* (5), 1224–1248.

Rosenzweig, Mark R and Christopher Udry, "External validity in a stochastic world: Evidence from low-income countries," *The Review of Economic Studies*, 2020, *87* (1), 343–381.

_ **and Hans P Binswanger**, "Wealth, weather risk, and the composition and profitability of agricultural investments," *Economic Journal*, 1992, *103* (416), 56–78.

Rovere, Roberto La, Tahirou Abdoulaye, Genti Kostandini, Zhe Guo, Wilfred Mwangi, John MacRobert, John Dixon, Roberto La Rovere, Tahirou Abdoulaye, Genti Kostandini, Zhe Guo, Wilfred Mwangi, John MacRobert, John Dixon, Roberto La Rovere, Tahirou Abdoulaye, Genti Kostandini, Zhe Guo, Wilfred Mwangi, John MacRobert, and John Dixon, "Economic, Production, and Poverty Impacts of Investing in Maize Tolerant to Drought in Africa: An Ex-Ante Assessment," *The Journal of Developing Areas*, 2014, *48* (1), 199–225.

Simtowe, Franklin, Emily Amondo, Paswel Marenya, Dil Rahut, Kai Sonder, and Olaf Erenstein, "Impacts of drought-tolerant maize varieties on productivity, risk, and resource use: Evidence from Uganda," *Land Use Policy*, 2019, *88*, 104091.

Stoeffler, Q., M. Carter, C. Guirkinger, and W. Gelade, "The spillover impact of index insurance on agricultural investment by cotton farmers in Burkina Faso," *World Bank Economic Review*, 2021.

Wossen, Tesfamicheal, Tahirou Abdoulaye, Arega Alene, Shiferaw Feleke, Abebe Menkir, and Victor Manyong, "Measuring the impacts of adaptation strategies to drought stress: The case of drought tolerant maize varieties," *Journal of Environmental Management*, 2017, *203*, 106–113.

Zaman-Allah, M, P H Zaidi, S Trachsel, J E Cairns, M T Vinayan, and K Seetharam, "Phenotyping for abiotic stress tolerance in maize heat stress: a field manual," 2016.

For Online Publication

Appendix 1: Drought Tolerant Maize Varieties

The development of improved stress tolerant crops (*e.g.,* flood tolerant rice and drought tolerant maize) has been a major focus of international organizations seeking to increase yields and decrease agricultural risk around the world. As part of the Drought-Tolerant Maize for Africa (DTMA) program, the International Maize and Wheat Improvement Center (CIMMYT) developed over 100 drought tolerant maize varieties (CIMMYT, 2012). To create these improved varieties, breeders selected for synchronized maize plant silking and tasseling, thereby reducing the problem of mid-season drought stress disrupting pollination and grain formation. Genetic selection and breeding took place through experiment station trials which were conducted during dry seasons of the year using irrigation. Withholding irrigation water allowed breeders to simulate real world, mid-season drought stress.

To isolate varieties able to maintain productivity in the presence of mid-season drought, breeders induced mid-season drought stress by limiting irrigation immediately before and during the pollination period (Zaman-Allah et al., 2016) while maintaining optimal irrigation levels during all other phases of plant growth. In these managed drought trials, the DT varieties exhibited up to a 137% yield advantage relative to comparable non-DT, improved varieties (Fisher et al., 2015). Under non-drought conditions, DT varieties maintained a more modest 10% yield advantage over the non-DT comparison varieties (Rovere et al., 2014).

To further test the value of the DT varieties, CIMMYT implemented farmer field trials in East, West and Southern Africa to see if the benefits displayed by DT varieties under highly controlled experiment station conditions carried over to farmers' fields and uncontrolled weather conditions. Farmers participating in the field trials were typically commercial farmers who used agronomist-recommended levels of inputs, like fertilizer. These farmers then ran comparison tests in their own fields of DT against non-DT, improved varieties. In a recent analysis that combined the field trial data with satellite-based estimates of rainfall patterns in the test area, Paul (2021) finds that on average, DT varieties boost yields by 7% under normal rainfall conditions and by 15% under moderate, mid-season drought pressure. This first figure is similar to the experiment station findings, but the latter is much more modest, perhaps reflecting the fact that nature rarely deals up a mid-season drought in isolation from other problems.[38] The field trials do nonetheless signal that the varieties produced and released[39] by the DTMA breeding program offer farmers protection against the specific peril of mid-season drought.

While these results are encouraging, whether or not the DT protection observed in the controlled conditions of experiment station trials and on the uncontrolled field trials with commercial farmers translates into protection for Africa's many small-scale, semi-subsistence farmers, who use little or no complementary inputs, remains an open question. Learning how much of this DT yield protection transfers from these trials to the less favorable conditions that prevail throughout the agricultural sector throughout Sub Saharan Africa is important. Filling this knowledge gap is one aim of our analysis.

Appendix 2: Fail-safe Index Insurance for Drought Tolerant Maize

As discussed in Section 2, the basis risk problem is the Achilles heal of index insurance. When basis risk is high, index insurance contracts are essentially lottery tickets that provide little or no protection against the risks the insurance is intended to cover. Making matters worse, the payment of the insurance premium adds to losses in an

[38]Paul (2021) summarizes other studies that have examined this same field trial data. While these studies vary widely in terms of whether and how they control for weather conditions, they generally point to yield gains on farmer fields that are substantially more modest than the experiment station results. Using conditional quantile estimation, Paul also shows that the impacts are similar in percentage terms for lower producing observations found in the lower quantiles of the conditional yield distribution.

[39]CIMMYT provided the starting or foundation seed stock to local companies across the continent. The companies then multiply the starting stock on their own farms, and then package, seek regulatory certification, and market the seeds under their own brands.

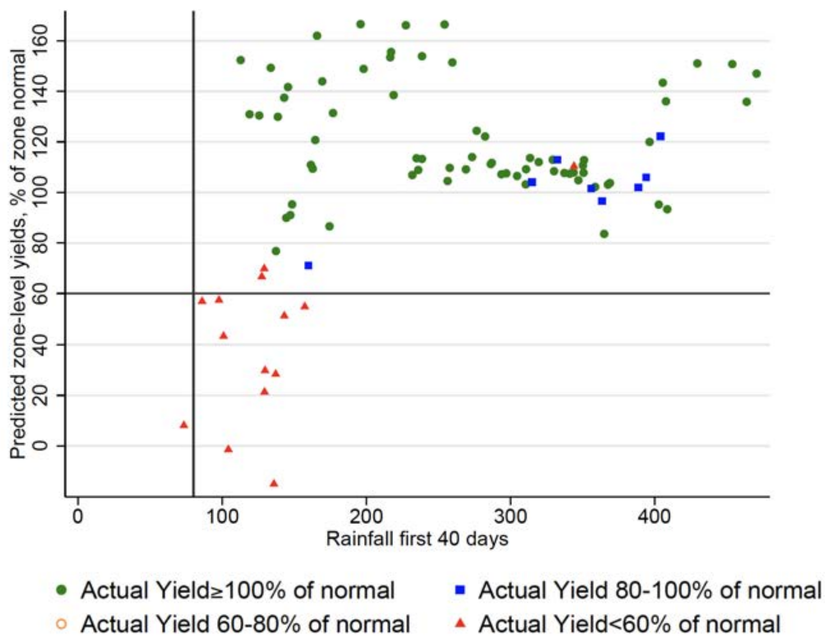
uncovered year, leaving vulnerable populations worse off with insurance than they would be without insurance.

While basis risk can never be completely eliminated (see the risk decomposition in Benami and Carter, 2021), estimating and minimizing the basis risk associated with candidate indices is a critical step in the design of a high quality index insurance contract. This estimation can be a difficult and expensive exercise, however, because the requisite farmer- or field-level yield data with sufficient cross-sectional and time series dimensions are rare, especially in sub-Saharan Africa. In order to address this challenge, we asked farmers in our sample to recall maize yields for the 10 years prior to the baseline survey. While farmer self-reported yield recall data is unreliable (Lobell et al. (2020)), averaging across all farmers in an insurance area eliminates some of the noise and allowed us to estimate the level of basis risk associated with a number of alternative, satellite-based indices.

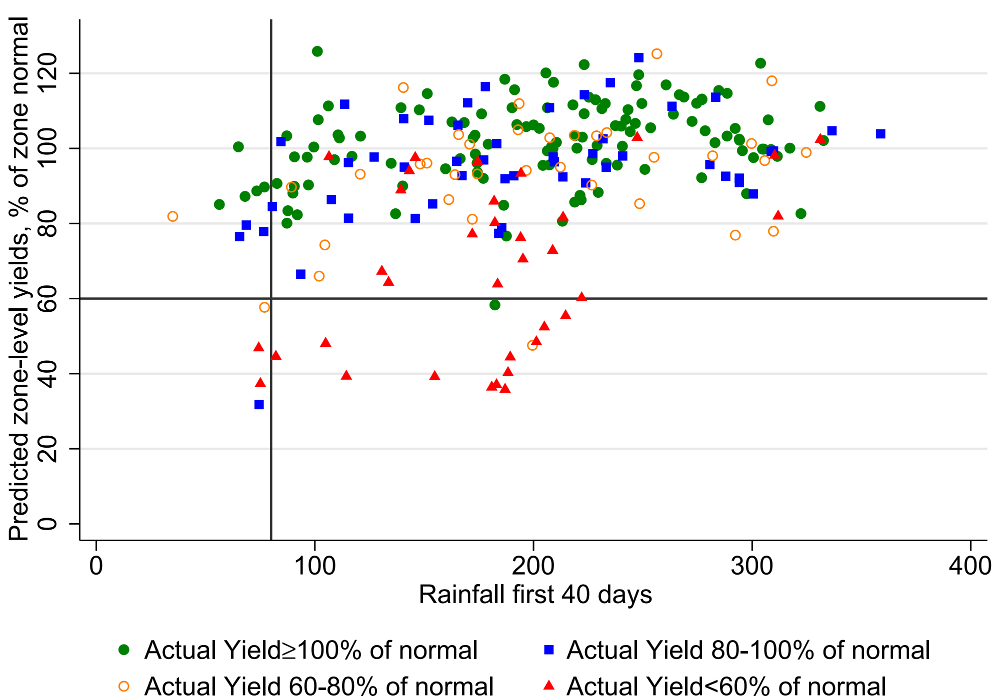
Figure A1a uses the recall data to backcast the performance of the two indices in Mozambique (Figure A1b displays the analogue graph for Tanzania). Each marker on the graph represents actual zone-year average yields, as reported by farmers, plotted against the early-season rainfall index (x-axis) and the end-of-season yield index (y-axis). Trigger levels (the index value below which the contradict issues a payment) for the two insurance indices are superimposed as straight lines. Negative basis risk events (when farmers experienced insurable losses but would not have been compensated by the contract) are signaled by (red) triangles in the northeast quadrant of the space. Payouts would have been triggered in any of the other 3 quadrants. The contract classifies almost all good years (defined here as actual zone-year yields greater than 80% of normal) correctly, with the contract triggering a payout in only 2 zone-years with good yields, both of which are in Tanzania. Moreover, the model does a good job classifying bad years (defined here as actual zone-year yields lower than about 65% of normal) in Mozambique, with only 3 out of 14 bad years being misclassified. However, in the Figure A1b graph for Tanzania, only 15 out of 35 bad years would have triggered a payout. This 57% failure rate of the core satellite-based index highlights the continuing imperfection of even this multi-index insurance contract.

Figure A1: Fail Safe Index Insurance Contracts

(a) Mozambique



(b) Tanzania



Appendix 3: Risk Salience Test

Table A1: Testing for Risk Salience Effects of Shocks on Maize Input Expenditures

	Maize Input Expenditures	
Explanatory Variables	*Coef.*	*Std. Err.*
Impact of Shocks		
Lagged Mid-season Drought, $d_{is(t-1)}$	-3.4	13.1
$d_{is(t-1)} \times$ Endline, E_{ist}	-35.7	16.1
Lagged Yield Shock, $z_{is(t-1)}$	19.0	12.2
$z_{is(t-1)} \times E_{ist}$	-73.8	39.4
Risk Salience Effects		
$S_{ist} \times d_{is(t-1)}$	0.583	13.7
$I_{ist} \times z_{is(t-1)}$	-29.8	11.7
Mitigation Impacts of DT Seed Treatment, S_{ist}		
S_{ist}	23.9	12.0
$S_{ist} \times E_{ist}$	-12.16	15.5
$S_{ist} \times d_{is(t-1)} \times E_{ist}$	78.1	22.5
Mitigation Impacts of Insurance Treatment, I_{ist}		
I_{ist}	12.1	10.1
$I_{ist} \times E_{ist}$	-39.1	20.8
$I_{ist} \times z_{is(t-1)} \times E_{ist}$	176.6	81.7
Intercepts & Control Variables		
Baseline Dependent Variable	0.42	0.14
E_{ist}	22.5	11.5
Cluster fixed effects	Included	
Other controls	Included	
Number of Observations	5568	

Other controls: Household head age and education, predicted poverty probability, and intercropping indicator.
Standard errors clustered at the village levels.