NBER WORKING PAPER SERIES

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

Stephen R. Boucher
Michael R. Carter
Jon Einar Flatnes
Travis J. Lybbert
Jonathan G. Malacarne
Paswel Marenya
Laura A. Paul

Working Paper 29234
http://www.nber.org/papers/w29234

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
September 2021, Revised February 2022

This study was made possible through the generous support of the American people through the United States Agency for International Development Cooperative Agreement No. AID-OAA-L-12-00001 with the BASIS Feed the Future Innovation Lab. The contents are the responsibility of the authors and do not reflect the views of the US Government. We thank seminar participants at the University of Maryland, University of California, Davis, the University of San Francisco and Wageningen University for valuable comments. We also thank our respondents and our commercial partners. The projects activities in both countries were ruled Exempt under Category 2 by the IRB at the University of California, Davis. Project numbers: 905582-1 (Mozambique), 905584-1 (Tanzania). Tanzania research permits issued by the Tanzanian Commission on Science and Technology, No. 2016-83-NA-2015-272, No. 2017-106-NA-2015-272, and No. 2018-237-NA-2015-272. This RCT was registered in the American Economic Association Registry for randomized controlled trials under trial numbers 2700 and 2702. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Bundling Genetic and Financial Technologies for More Resilient and Productive Small-scale Agriculture
Stephen R. Boucher, Michael R. Carter, Jon Einar Flatnes, Travis J. Lybbert, Jonathan G. Malacarne, Paswel Marenya, and Laura A. Paul
NBER Working Paper No. 29234
September 2021, Revised February 2022
JEL No. O12,O55,Q12,Q14,Q16

ABSTRACT

We utilize a multi-year randomized controlled trial spanning two African countries to explore whether complementarities between two risk management technologies–stress tolerant seeds and index insurance–can promote a more resilient, higher productivity small farm sector. We find that, by themselves, drought tolerant maize seeds mitigate the adverse impacts of mid-season drought, while farmers with access to both drought tolerant seeds and index insurance show greater resilience and intensify production in seasons following a shock. Our findings showcase important complementarities between these risk mitigating technologies and the crucial role learning plays in tapping their benefits to small farmers.

Stephen R. Boucher
University of California, Davis
boucher@primal.ucdavis.edu

Michael R. Carter
Department of Agricultural and
Resource Economics
University of California, Davis
One Shields Avenue
Davis, CA 95616
and NBER
mrcarter@ucdavis.edu

Jon Einar Flatnes
Chr. Michelsen Institute
Jekteviksbakken 31
5006 Bergen
Norway
joneinar.flatnes@cmi.no

Travis J. Lybbert
Agricultural and Resources
Economics University of
California, Davis
1 Shields Avenue
Davis, CA 95616
tlybbert@ucdavis.edu

Jonathan G. Malacarne
The University of Maine
jonathan.malacarne@maine.edu

Paswel Marenya
ICRAF House
UN Avenue, Girgiri
Nairobi, Kenya
p.marenya@gmail.com

Laura A. Paul
Department of Applied
Economics & Statistics
531 South College Avenue
Newark, DE 19716
lpaul@udel.edu

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 productivity and resilience 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 this experiential learning is that farmers who do not directly experience the benefit of these technologies begin almost immediately to dis-adopt 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 shocks damage their current farm income; that even moderate shocks have persistent effects, reducing future income as farm households become decapitalized as they cope with the income reduction; and, that severe shocks overwhelm households' consumption smoothing capacity and compromise both 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 productivity-depressing effect of uninsured risk on productivity and investment by smallholder farmers is well-established in the literature. For example, see Morduch (1995); Rosenzweig and Binswanger (1992); Carter and Lybbert (2012).

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) provides encouraging evidence that highlights this potential. The authors find that flood tolerant rice varieties not only provided Indian farmers significant protection against yield loss from this weather shock, 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 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,

[2] In a study of drought tolerant maize varieties in Ugansa, 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 the authors do not provide information on the full distribution of flood length, they note that 24% of

the drought tolerant (DT) maize varieties studied here protect against moderate mid-season drought, but remain vulnerable to severe mid-season drought as well as early and late season drought and the 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

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 insurance subsidies.

are likely to overwhelm the protection provided by drought tolerant seeds. Limiting the insurance coverage to those extreme, tail end 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 the local seed varieties retained from previous harvests that most plant. 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

[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, small-holder farmers who do not participate in a structured value chain, such as those in our study population, tends to be very low.

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 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, we provide evidence that this excess mitigation effect is driven by treated farmers who experience the protection provided by DT seeds and insurance 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 the index insurance contract. Section 3 describes the research design created by the randomized controlled trial and the vagaries of growing conditions across the study areas. The section analyzes some baseline imbalance problems in detail and motivates the paper's reliance on both ANCOVA and difference-in-differences estimation methods. Section 4 presents the key econometric results, beginning with the analysis of the impact of the experimental and natural treatments (lagged and contemporaneous shocks) on maize yields. To help decipher the revealed pattern of excess yield loss mitigation, the section goes on to analyze the impact of the treatments and lagged shocks on the allocation of resources to maize production (input expenditures and land). A similar analysis is applied to household food insecurity. In Section 5, we discuss our results from the perspective of learning and explore 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 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's 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 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

[10] In 2010, the Syngenta Foundation for Sustainable Agriculture, in partnership with UAP Insurance and Safaricom, launched a microinsurance program called Kilimo Salama, which offered farmers the option to insure their seeds against drought. Also in Kenya, the multinational seed company SeedCo offered their drought tolerant seed variety with a similar replacement guarantee. Farmers who activated the SeedCo guarantee received a mobile money reimbursement when a rainfall index indicated early season drought. While unstudied, the seeming success of these programs informed our decision to bundle seed with insurance.

costly loss verification.[11] The contract designed for this study was intended to complement the partial protection provided 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,[12] with a payout being triggered if there was less than 70-100 mm of rainfall 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 a satellite-measured vegetative growth (Normalized Difference Vegetation Index, NDVI) and estimated full-season rainfall to predict area yields.[13] Payments were triggered by this index when predicted area-yield dropped below 60% of the historical average.

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, what has come to be known as the basis risk problem.[14] In an effort to further 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.

[11] Hazell (1992) offers several striking examples of conventional loss-adjusted contracts where the insurance provider cannot cost-effectively verify losses, with national insurance programs from the 1980s paying out 2-5 times the premiums collected.

[12] 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.

[13] 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 combination 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.

[14] For further discussion of the basis risk problem, see Clarke (2016), Carter et al. (2017) and Jensen and Barrett (2017). Benami and Carter (2021) define and decompose basis risk into idiosyncratic and design risk.

If more than 30% of farmers registered a complaint, a crop-cut audit was conducted using novel imaging software (Makanza et al., 2018), with replacement seeds issued if average yield as estimated by the crop-cut was indeed below the trigger. The data summarized in Figures 5 and 6 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.[15]

For purposes of implementation, study villages (see Section 3) were divided into insurance zones (35 in Tanzania and 13 in Mozambique), which were determined 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 standalone 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.[16] 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.

[15]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.

[16]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.

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 in that 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.[17] As shown in Section 3, when we pool the data across countries and districts, this research strategy was successful in the sense that across the study's three years, we were able to observe mid-season droughts and severe yield losses across both countries.

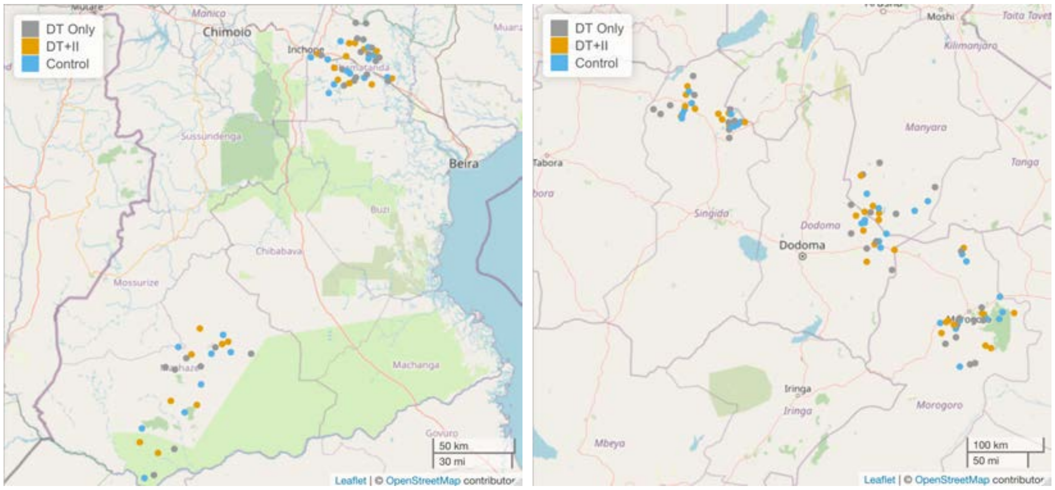
3.1 The Randomized Control Trial

The maps in Figure 1 display the randomization strategy that was implemented in all study districts in both countries.[18] After identifying a set of study communities in each district in each country, communities were matched into triplets based on having

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

[18]After the initial district selection, the research team visited each district and worked with extension agents, local farmers, and village leaders to understand the culture and practices of maize production in the areas. Using maps of the areas and local knowledge, a set of feasible communities was identified. For the purpose of this study, feasible meant that a community was located in a maize growing area of the district, the community was accessible (though perhaps with difficulty) even during the rainy season, and the community was as insulated as possible from other study communities in the district in order to minimize the risk of informational spillovers between treatment and control communities. The set of communities also had to be acceptable to the projects' local partners – particularly the seed companies and organizations involved in the marketing treatment.

Figure 1: Geographic Diversification and Matched Triplet Randomization



(a) Mozambique (b) Tanzania

Base map and data are from OpenStreetMap and OpenStreetMap Foundation.

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, 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, 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 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 proceeding the beginning of the study. While we cannot fully rule out that 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,[19] climate conditions and market access to create triplets, each consisting of one non-VBA and two VBA communities. Starting with a feasible non-VBA community (control), the two best-matched VBA communities were selected, ensuring that the resulting triplet was unique. 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.[20] Study households were individually invited to the training sessions, and other community members were also welcome to participate. Training sessions provided information on the DT trait, as well as information on the 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).[21] Non-study households who attended the training were given smaller (100-250 gram) packets. Communities were sufficiently isolated to prevent DT seeds spreading into control areas.

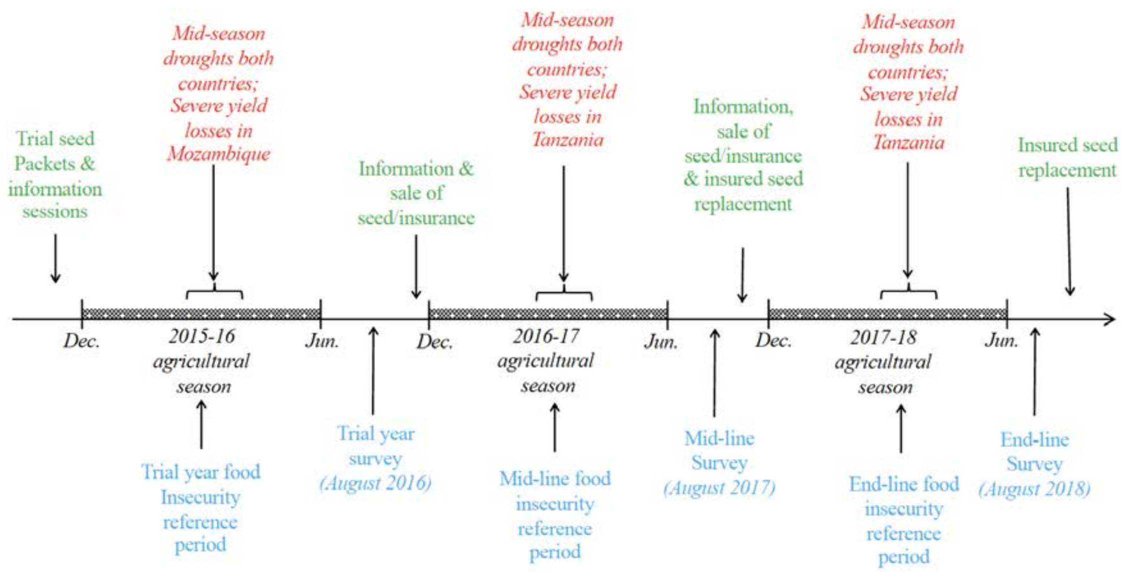
In communities assigned to the bundled DT-II treatment, participants were also given information on the insurance contract prior to the 2016-17 season. The information covered the group nature of the payout decision, the possibility of positive and negative basis risk events, and the nature, timing, and documentation requirements of payouts. Seeds offered for sale in these villages came only bundled with the index

[19]The soil data was taken from the Africa Soils Information Service.

[20]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.

[21]At standard planting densities, the free packets would have allowed the farmer to plant 0.04 to 0.08 hectares. The average farmer planted a total of 2 hectares of maize at baseline.

Figure 2: Timeline for RCT & Natural Experiment



insurance. The insurance, which was not subsidized, raised the price of the seeds by approximately 20%.[22] 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 would replace 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.

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.[23] 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

[22]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.

[23]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.

controls during the trial pack year.[24]

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, administrative complications with the VBA program in 2016/17 prompted our seed company partners to establish their own network of local sales agents as a preferred distribution alternative for the remainder of the project.

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 importantly on stochasticity that is outside the control of researchers (see Rosenzweig and Udry, 2020), this RCT about the value of risk mitigation was itself risky. While we could randomize the offer of DT seeds and the DT-II bundle across villages and control other key dimensions of the design as described in this section, the realization of the shocks that are central to our research question was entirely out of our control. In what follows, we will focus on two kinds 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 note 12) is less than 200 millimeters during the time period 40 and 80 days after planting (200 mm is the amount of water

[24]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%.

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 kind 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 60% 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 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 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. In the two subsequent seasons, between 5 and 12% of farmers suffered severe yield losses. Mid-season droughts afflicted 38% to 51% of farmers in these two seasons, respectively. Figure 2 records the seasons and locations in which these shocks primarily occurred. The bottom panel of Table 1 shows that this natural 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.

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 for household i in in randomization cluster s:

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

where α_s is a vector of randomization cluster or triad fixed effect, and S_{is} and I_{is} are, respectively, binary indicators of treatment 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.[25]

Table 1 displays the results from this balance analysis. Particularly noteworthy is the baseline imbalance in yields between the control and the treatment groups, with the treatment groups averaging a statistically significant 159 additional kilograms of production per-hectare compared to the control group.[26] This gap is slightly smaller for households that also received the insurance treatment (14 kg/hectare), but this difference between the two treatment groups is not statistically, or otherwise, significant. This 145-159 kg yield gap is larger than what we would expect from the yield packets alone (see footnote 24). We also see that treatment households appear to be better off economically as judged by their food security and poverty probability scores, although other wealth indicators (area planted) show no differences. 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.[27]

[25]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 and is balanced across treatment assignment.

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

[27]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-

Table 1: Regression Analysis of Baseline Balance by Experimental Treatment

Dependent Variable	Baseline Control Mean	Offered DT Seed, S_{ivt} Coef.	(Std. Err.)	Offered Insurance, I_{ivt} Coeff.	(Std. Err.)
Maize Cultivation					
Maize Yield (kg/hectare, winsorized)	399	159	(40)	-14	(39)
Seed Fertilizer Expend ($US PPP, winsorized)	39.9	1.5	(3.3)	1.6	(3)
Maize Area Planted (hectares)	2.1	-0.03	(0.1)	-0.02	(0.1)
Demographics & Wealth					
Education of Farmer (years)	2.3	0.10	(0.054)	0.06	(0.06)
Area Cultivated (hectares)	4.2	-0.03	(0.3)	-0.5	(0.26)
Poverty Probability Score (%)	58.7	-4.6	(1.4)	0.9	(1.3)
Food Insecurity Score	25.0	-4.8	(1.4)	2.9	(1.58)
Drought & Yield Shocks					
Mid-season Drought (%)	74.3	0.06	(0.03)	0.02	(0.03)
Yield Shock (%)	39.8	-0.02	(0.03)	0.03	(0.022)
Observations	1047	978		949	

As with the regressions reported in Tables 3 and 4, these
regressions include cluster fixed effects and the additional control variables listed in those tables.

The source of this baseline yield imbalance can be traced to two of the six districts within Tanzania (Singida and Iramba). The Mozambique 2015/16 crop year suffered extreme drought, which would have been expected to suppress any trial packet effect as many farmers in both treatment and control groups reported zero maize output for that year. The imbalance in Tanzania in excess of what could be expected from the trial seed packs could reflect a mix of differences in agricultural potential between treatment and control areas, especially if the VBA program had been endogenously placed in higher potential areas. It could also reflect the impact of the VBA program itself, and/or differential baseline weather in the treatment versus control areas.[28]

To better understand the source of this imbalance, we utilized the same NDVI-based biomass growth information used for the insurance yield index over the 2002-2018 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.[29] As mentioned earlier, treated households

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.

[28]While in Mozambique matched treatment and control areas were always quite close to each other geographically, 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.

[29]Specifically, we measure cumulative NDVI over the maize growing season. Across all areas in

do not devote more area to maize (or other crops), as might be expected if they were located in higher potential areas. Next, we restricted our focus to treatment areas[30] 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 2016. There is, however, no difference in NDVI between treatment and control areas in Singida district, suggesting that perhaps the trial packs and VBA interventions were driving the yield imbalance.

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 an impact of the trial packets and/or the VBA agents. 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 FIPS 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 econometric analysis to follow, we will take a two-pronged approach, estimating both ANCOVA and Difference-in-Differences (DiD) models. To the extent

Tanzania, the mean NDVI measure is 67.8 for control and 66.0 for treatment areas (p-value for difference is 0.49). For the Singida district the difference is 1.8 (favoring the control areas), whereas in Iramba the difference in NDVI measures is 3.9, favoring the treatment areas (p-values for both differences are about 0.30).

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

that the yield imbalance in the quasi-baseline year was the short-lived result of either the trial packs themselves, better weather in control areas or of the VBA sales agents, then the DiD will over-correct and lead to conservative estimates of program impacts. In this case, the ANCOVA results would be the preferred, lower variance estimator. On the other hand, if the imbalance reflects a permanent and persistent feature of the control areas, then the DiD estimates would be preferred as the ANCOVA impact estimates would be upwardly biased. As we shall see, with one important exception, the results are consistent across the two estimation approaches.

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. Net compliance for both treatments hovered around 50% at midline, but fell to 42% and 44% by endline for the DT and DT-II treatments, respectively. 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, 41%-50% of households had experienced a mid-season drought in the preceding year. Exposure to lagged yield shocks at endline ranged between 6% and 12%. Experimentally treated households that were also treated by nature with these shocks at midline had an opportunity to observe the risk management technologies in action and learn about them. Foreshadowing later discussion in Section 5, note that conditional on receiving a shock in the midline year, endline compliance rates are higher by about 10 percentage points.

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

Table 2: Compliance and Key Outcome Variables by Experimental Treatment

	Experimental Assignment		
	Control	*DT Seeds*	*DT & Insurance*
Midline			
Compliance & Shocks			
Technology Adoption (%)	3.6	54.3	48.2
Mid-season Drought (%)	38.5	40.7	41.6
Yield Shock (%)	12.1	8.5	6.0
Lagged (baseline) Mid-drought (%)	74.5	77.6	80.4
Lagged (baseline)Yield Shock (%)	40.4	34.8	37.5
Outcome Variables			
Maize Yield (kg/hectare)	535	776	756
Seed fertilizer Expend ($USPPP)	42.1	72.5	75.5
Maize Area Planted (hectares)	2.0	1.8	2.3
Food Insecurity Score	25.6	22.8	22.8
Midline Observations	**996**	**917**	**902**
Endline			
Compliance & Shocks			
Technology adoption (%)	5.3	49.5	41.9
Adoption Conditional on Lagged Mid-drought (%)	6.0	56.0	50.0
Adoption Conditional on Lagged Yield Shock (%)	4.2	54.8	48.9
Mid-season Drought (%)	51.5	51.2	48.7
Yield Shock (%)	4.9	10.3	3.8
Lagged (midline) Mid-drought (%)	41.2	50.2	48.5
Lagged (midline)Yield Shock (%)	12.3	8.0	6.1
Outcome Variables			
Maize Yield (kg/hectare)	544	719	706
Seed fertilizer Expend ($USPPP)	38.1	93.4	77.3
Maize Area Planted (hectares)	2.0	2.1	2.1
Food Insecurity Score	10.3	8.3	8.8
Endline Observations	**964**	**914**	**864**

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 things on household food security, giving us a deeper look into household coping and risk management strategies.

4.1 Yield Effects

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

(1)

$$\begin{aligned} y_{ist} = &[\beta_1 d_{ist} + \beta_2 z_{ist}] + \left[\beta_3 d_{is(t-1)} + \beta_4 \left(d_{is(t-1)} \times E_{ist}\right) + \beta_5 z_{is(t-1)} + \beta_6 \left(z_{is(t-1)} \times E_{ist}\right)\right] + \\ &S_{is}\left[\delta_0 + \delta_t E_{ist} + \delta_1 d_{ist} + \delta_2 \left(d_{ist} \times E_{ist}\right) + \delta_3 \left(d_{is(t-1)} \times E_{ist}\right)\right] + \\ &I_{is}\left[\gamma_0 + \gamma_t E_{ist} + \gamma_1 \left(z_{is(t-1)} \times E_{ist}\right)\right] + \\ &[\alpha_0 y_{is0} + \alpha_E E_{ist} + \alpha_1' x_{is0} + \nu_s] + \varepsilon_{it} \end{aligned}$$

where y_{ist} measures maize yields for household i in randomization triad s in year t, and 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. The first two terms in the first row of equation 1 capture the contemporaneous impact 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.[31] Because compliance rates and adoption intensity changed from midline to endline (Table 2), we allow the impact of the treatments to differ by year. Differences in farmer response to treatment could 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 to be positive if insurance crowded in more intensive input use than the DT seeds alone. That same term could be negative if 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 is a randomization cluster fixed effect.

Table 3 reports the estimates of this ANCOVA regression model and an analogous difference in differences version.[32] Figure 3 displays the 95% confidence interval estimates for the ANCOVA results on shocks and the mitigating impacts of the risk management treatments.[33] We will focus primarily on the ANCOVA results and

[31]In principle, 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.

[32]As can be gleaned from Table 3, we write the DiD model using treatment assisgnment to control for baseline differences and the interaction between treatment assignment and a post-treatment dummy variable to identify impacts.

[33]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:

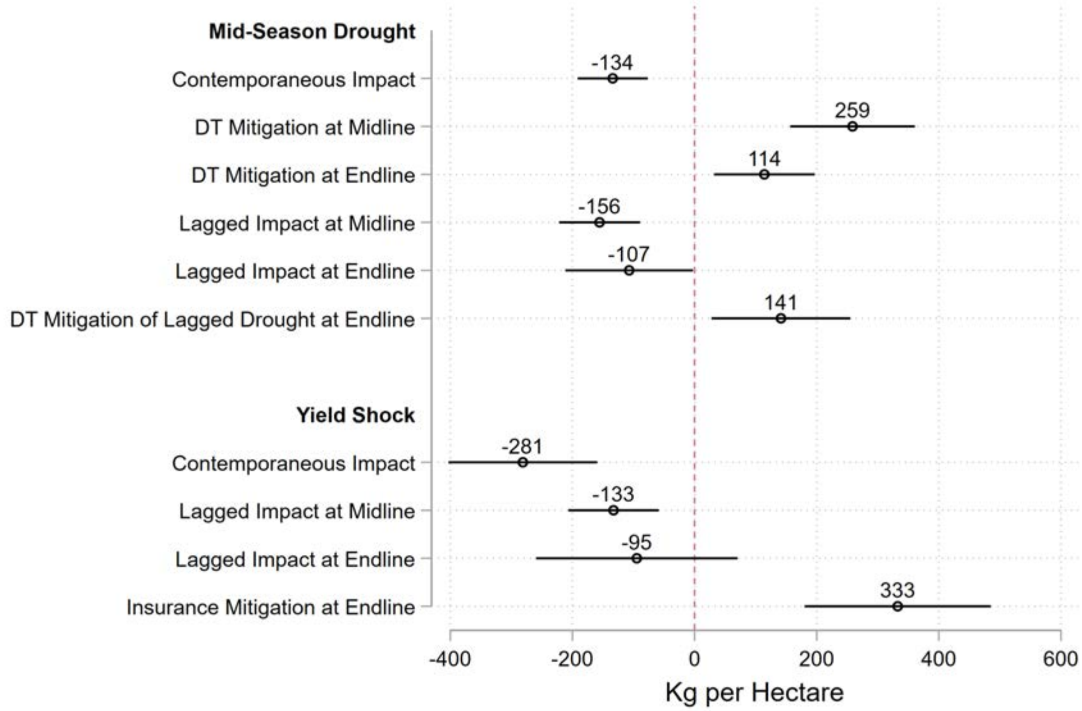
- Contemporaneous mitigation effects of DT on a drought shock at midline: $\delta_1 + \delta_0$
- Contemporaneous mitigation effects of DT on a drought shock at endline: $\delta_1 + \delta_2 + \delta_0 + \delta_t$

Table 3: Maize Yields

Explanatory Variables [for DiD]	ANCOVA Coef.	ANCOVA Std. Err.	DiD Coef.	DiD Std. Err.
Impact of Shocks				
Mid-season Drought, d_{ist}	-134.0	35.0	-78.6	32.0
Yield Shock, z_{ist}	-281.2	74.1	-183.5	46.4
Lagged Mid-season Drought, $d_{is(t-1)}$	-155.6	40.3	-159.8	41.0
$d_{is(t-1)} \times$ Endline, E_{ist}	48.5	77.1	-75.0	78.8
Lagged Yield Shock, $z_{is(t-1)}$	-132.6	45.1	-55.5	34.3
$z_{is(t-1)} \times E_{ist}$	38.0	117.2	-53.4	101.5
Mitigation Impacts of DT Seed Treatment, S_{it}				
S_{is} [$S_{is} \times post$]	77.0	40.4	33.3	64.9
$S_{is} \times E_{ist}$	-97.5	54.0	-137.3	55.8
$S_{is} \times d_{ist}$ [$S_{is} \times d_{ist} \times post_t$]	181.7	56.8	93.1	62.4
$S_{is} \times d_{ist} \times E_{ist}$	-46.9	62.3	-27.0	64.1
$S_{is} \times d_{is(t-1)} \times E_{ist}$	162.0	71.2	227.2	75.8
Mitigation Impacts of Insurance Treatment, I_{it}				
I_{is} [$I_{is} \times post_t$]	-13.1	44.7	-23.9	70.0
$I_{is} \times E_{ist}$	-51.4	64.8	-37.8	65.2
$I_{is} \times z_{is(t-1)} \times E_{ist}$	417.7	94.8	358.2	115.3
Control for Baseline Differences				
S_{is}	–	–	121.1	47.8
I_{ist}	–	–	6.9	51.5
Intercepts & Control Variables				
Baseline Yields	0.22	0.02	–	–
Midline time effect ($post_t$)	–	–	90.5	48.6
Endline time effect, E_{ist}	-108.3	53.5	64.8	47.8
Cluster fixed effects	Included		Included	
Other controls	Included		Included	
Number of Observations	5568		8542	

Other controls: Household Head Age and Education, Poverty Prob. & Intercropping
Standard errors clustered at the village level

Figure 3: Yield Shocks and Mitigation Impacts (ANCOVA Estimates)



discuss DiD 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 550 kg/hectare, implying that the contemporaneous impact of drought and yield shocks amount to yield losses of 25% and 50%, respectively. As is clearly visible in the table and figure, both kinds of shocks have lagged impacts on future yields. The one-year lagged impact of yield shocks is between 33% and 46% the level of the contemporaneous impact, whereas the point estimate of the lagged impact of drought shocks indicate continuing strong, negative impacts.[34] The lingering yield effects indicate that absent risk management tools,

- Mitigation effect of DT on lagged drought at endline: $\delta_3 + \delta_0 + \delta_t$
- Mitigation effect of insurance on lagged yield shock at endline: $\gamma_1 + \delta_0 + \delta_t + \gamma_0 + \gamma_t$

[34] The magnitude of the lagged effect of drought shocks appear surprisingly large, although the interval estimates contain many values that are more in line with the expected range.

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 33). As can be seen in Figure 3, the coefficients on the seed treatment indicate that the DT technology effectively mitigates the yield loss otherwise brought on by a mid-season drought.[35] 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, as would be expected given that the seeds mitigate the initial impact of a drought shock.

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 negative but statistically insignificant effect on contemporaneous yields, but mitigates the lingering effects of lagged yield shocks by a substantial and statistically significant 333 kg/ha. This point estimate is three times larger than the estimated impact of lagged yield shocks. For now, we refer to this as “excess mitigation.” We explore possible mechanisms responsible for this empirical pattern in Section 5 below.

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 77 kg/ha yield bump (about a 15% yield 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. The next section discusses changes in input use at the extensive and intensive margins to help understand this endline difference.

As discussed in Section 3.3, quasi-baseline yields are unbalanced between treatment and control groups. While there is some evidence that this may simply be the

[35]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.

result of bad luck rather than systematic differences, we cannot rule out systematic differences between treatment and control groups. The DiD estimates in Table 3 are arguably preferable given this uncertainty. The primary difference between the DiD and ANCOVA estimates is that the former reveal smaller impacts of the DT seed treatment. Mechanically, this is not surprising given that the DiD estimation requires impacts above and beyond the baseline imbalance in order to register an impact (note that the estimated coefficient of the seed treatment in baseline is 121 kg/ha). As can be seen in the table, the DiD results cast doubt on whether or not the DT seeds have a normal-year yield effect (the point estimate drops from 77 kg/ha to a statistically insignificant 33 kg/ha). The estimated contemporaneous drought mitigation effects of the DT seed treatment also diminish in magnitude and lose statistical significance. Interestingly, the DiD estimates continue to indicate that the DT seeds mitigate the lagged effects of mid-season droughts. The other results, including the impact of shocks and the mitigation effects of the insurance treatment are largely unaffected by the shift to the DiD estimation method.

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 current year's shock and thus cannot be influenced by contemporaneous shocks that occurred during the growing season. We thus adapt regression model 1 and estimate the following ANCOVA ITT specification:

$$
\begin{aligned}
r_{ist} = {} & \left[\theta_1 d_{is(t-1)} + \theta_2 \left(d_{is(t-1)} \times E_{ist}\right) + \theta_3 z_{is(t-1)} + \theta_4 \left(z_{is(t-1)} \times E_{ist}\right)\right] + \\
& S_{is}\left[\lambda_0 + \lambda_t E_{ist} + \lambda_1 \left(d_{is(t-1)} \times E_{ist}\right)\right] + \\
& I_{is}\left[\rho_0 + \rho_t E_{ist} + \rho_2 \left(z_{is(t-1)} \times E_{ist}\right)\right] + \\
& \left[\tau_0 r_{is0} + \tau_t E_{ist} + \tau_1' x_{is0} + \nu_s\right] + \varepsilon_{it}
\end{aligned} \tag{2}
$$

Table 4: Maize Input Expenditures & Area Cultivated

	Maize Input Expenditures		Maize Area	
Explanatory Variables	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*
Impact of Shocks				
Lagged Mid-season Drought, $d_{is(t-1)}$	-2.2	9.5	0.0	0.1
$d_{is(t-1)} \times$ Endline, E_{ist}	-36.7	13.3	-0.12	0.15
Lagged Yield Shock, $z_{is(t-1)}$	9.2	10.9	-0.07	0.17
$z_{is(t-1)} \times E_{ist}$	-63.8	38.0	-0.56	0.32
Mitigation Impacts of DT Seed Treatment, S_{is}				
S_{is}	23.9	7.3	-0.21	0.12
$S_{is} \times E_{ist}$	-11.7	11.0	0.34	0.17
$S_{is} \times d_{is(t-1)} \times E_{ist}$	78.2	18.9	-0.07	0.17
Mitigation Impacts of Insurance Treatment, I_{is}				
I_{is}	1.6	6.9	0.55	0.16
$I_{is} \times E_{ist}$	-28.1	18.6	-0.62	0.20
$I_{is} \times z_{is(t-1)} \times E_{ist}$	146.3	78.4	1.47	0.46
Intercepts & Control Variables				
Baseline Dependent Variable	0.42	0.14	0.42	0.10
E_{ist}	19.4	9.1	0.09	0.12
Cluster fixed effects	Included		Included	
Other controls	Included		Included	
Number of Observations	5568		5568	

Other controls: Household Head Age and Education, Predicted Poverty Prob. & and Intercropping Indicator
Standard errors clustered at the village levels.

The resource allocation outcome variable r_{ist} will either be total (not per-hectare) expenditures on maize inputs (measured in \$US PPP; see footnote 27) 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 employed in the yield regression 1 and include only lagged shock terms that can affect current year resource allocation decisions. DiD estimates are shown in Appendix Table A1.

Table 4 displays the results from specification 2.[36] Consistent with the impact of lagged shocks on yields discussed in Section 4.1, Table 4 and Figure 4 show that lagged

[36] We focus only on the ANCOVA results as expenditure and area cultivated variables were well-balanced at baseline. Appendix Table A1 reports the results from running a difference-in-differences specification on equation (2). As can be seen, the results are extremely similar to the ANCOVA results.

drought and severe, covariate yield shocks dampen the allocation of inputs to maize, especially in the endline period.[37] 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.[38] Midline drought shocks are estimated to reduce input expenditures by \$38, whereas the DT treatment following a midline yield shock boosts expenditures by more than double that amount (\$90). Similar excess mitigation is revealed with yield shocks and exposure to insurance: Midline yield shocks reduce endline expenditures by an estimated \$54, whereas the insurance treatment following that shock boosts spending by \$132. 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).

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 \$24, whereas those receiving the combined seed-insurance treatment increases input spending by almost an identical amount (\$26). However, farmers who did not experience midline shocks are estimated to retreat from the novel risk management technologies and reduce their expenditures. In contrast, households that experienced shocks in the midline substantially boosted their expenditures on seeds and fertilizers.

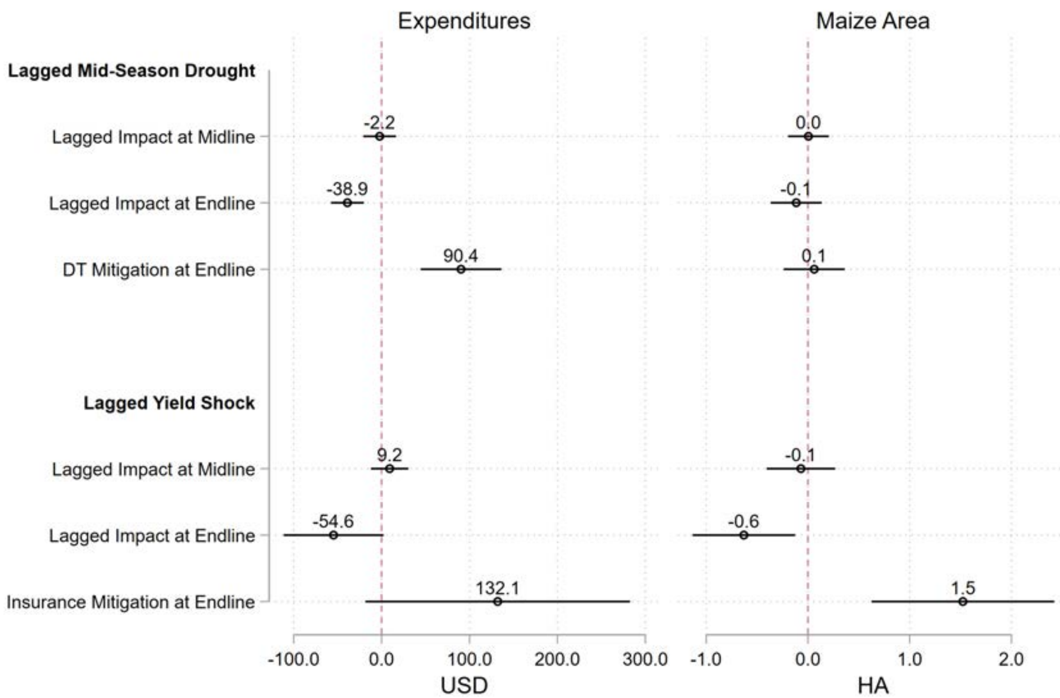
The results on area planted to maize parallel these findings on input spending. While drought shocks seem to have little impact on area planted to maize, severe, covariate yield shocks in the midline are estimated to have reduced maize cultivation by 0.63 hectares, a drop of just over 25% given that control group farmers on average plant 2 hectares of maize. Severe yield shocks not only reduce future yield as discussed

[37]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.

[38]The mitigation effects of the treatment are defined analogously to those describe in footnote 33. Using the notation in equation 2, the mitigation effects are:

- Mitigation effect of DT on lagged drought at endline: $\lambda_1 + \lambda_0 + \lambda_t$
- Mitigation effect of insurance on lagged yield shock at endline: $\rho_2 + \lambda_0 + \lambda_t + \rho_0 + \rho_t$

Figure 4: Shocks and Resource Allocation (ANCOVA Estimates)



above, they also reduce area planted. The insurance treatment has an estimated mitigation effect of 1.41 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 35%. 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, whereas those who did experience shocks continue with expanded maize area.

4.3 Food Insecurity

To test the effect of the risk management technologies on household welfare, we examine their impact on food consumption of households using the continuous Household Food Insecurity Access Scale (HFIAS) measure.[39] Because of the reference periods

[39]To construct the continuous HFIAS, households were asked about the frequency and severity of food insecurity coping strategies that they employed during a typical week during the hungry

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, we thus employ regression model 2 as it explores the connection between currently reported data on lagged yield shocks.

Table 5 again presents results from both an ANCOVA specification and a DiD specification. As Table 1 reveals, baseline food insecurity was higher in control than in treatment areas, making the DiD estimates the more conservative choice. There is little evidence that mid-season drought shocks affect food security. Given earlier estimates that mid-season droughts reduce yields by some 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. These larger shocks seem to overwhelm household's ability to smooth consumption. 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 5.78 points (95% interval estimate is 0.9-10.7), whereas the insurance treatment mitigation effect is -7.98 (-15.4 - -0.6). In other words, insurance seems to almost exactly offset the negative impact of yield shocks of consumption without inducing the additional mitigation seen in the case of inputs and yields.

season. The index itself is defined as 1*(# days less preferred foods) + 2*(# days limit variety) +3*(# days reduce meals for children + # days reduce meals for women + # days reduce meals for men) + 4*(# days no food in house + # days no food for 24 hours). The measure runs from 0 (no food insecurity) to a maximum value of 146 (see Coates et al. 2007 for details).

Table 5: Food Insecurity

	ANCOVA		DiD	
Explanatory Variables	Coef	Std Err	*Coef.*	*Std. Err.*
Impact of Shocks				
Lagged Mid-season Drought, $d_{is(t-1)}$	-0.17	1.82	0.87	1.36
$d_{is(t-1)}\times$ Endline, E_{ist}	0.88	2.23	2.31	2.11
Lagged Yield Shock, $z_{is(t-1)}$	-0.04	1.94	-3.26	1.31
$z_{is(t-1)} \times E_{ist}$	5.82	3.22	8.16	2.05
Mitigation DT Seed Treatment, S_{is}				
$S_{is} \times Post_{ist}$	-1.81	1.74	2.19	2.66
$S_{is} \times E_{ist}$	-0.39	2.16	0.17	2.11
$S_{is} \times d_{is(t-1)} \times E_{ist}$	1.98	1.57	0.80	1.59
Mitigation Impacts of Insurance Treatment, I_{is}				
$I_{is} \times Post$	-0.13	1.71	-2.69	2.65
$I_{is} \times E_{ist}$	1.45	2.13	1.33	2.13
$I_{is} \times z_{is(t-1)} \times E_{ist}$	-7.10	3.77	-6.95	2.71
Control for Baseline Differences				
S_{is}			-4.04	1.67
I_{is}			2.83	1.70
Intercepts & Control Variables				
Baseline Dependent Variable	0.10	0.01		
Mid-line Time Effect			1.03	1.93
End-line Time Effect,E_{ist}	-16.4	1.92	-16.9	1.94
Cluster fixed effects		Included		
Other controls		Included		
Number of Observations	5568		8542	

Other controls: Household Head Age and Education, Predicted Poverty Prob. & and Intercropping Indicator
Standard errors clustered at the village levels.

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. It is further evident in differential endline compliance visible in Table 2. Similar to results from an insurance program in China (Cai et al., 2020), endline compliance with treatment assignment was about 10 percentage points higher for treated farmers that experience mid-season droughts and severe yield shocks, a differential largely driven by the increasing non-compliance by farmers who did not experience shocks.

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 and γ_1. 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 would naturally 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 further investment and risk-taking (Ikegami et al., 2019). Alternatively, if resilience is the ability of households to recover from a shock and return to pre-shock levels of production and well-being, such an explanation for excess mitigation might be labelled "resilience-plus," as it seems to imply that 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 to learning. One alternative explanation is that the shock realizations made information on shocks more salient or "available" (to use the term of Kahneman, 2011), leading them 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. Specifically, we can test if a shock in the quasi-baseline year encouraged mid-line adoption of the drought tolerant seeds and insurance technologies by modifying regression model 2 to see if treatment group farmers in midline purchased more inputs or cultivated more area in response to baseline (pre-treatment) shocks.

In Appendix Table A2, we show 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 those in Cai et al. (2020), cannot fully rule out salience effects in the endline since farmers in the mid-line 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 and γ_1 explains the estimated excess mitigation, we might still wonder if this learning is durable, or if decays over time without frequent reenforcement. Unfortunately, the duration of this study does not permit an answer to this question.

As another alternative explanation for the excess mitigation we observe, one specific feature of the insurance we bundled with DT seeds may have amplified farmers' excess mitigation response. Specifically, in the wake of a triggering event the seed-insurance bundle delivered free replacement seed to farmers prior to planting in the next maize 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). Such a payout timing effect is distinct from resilience plus as defined above. 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, which effectively payout their biological indemnities at harvest, show nearly the same degree of excess mitigation with input expenditures as farmers in the insurance treatment.

Our multi-year, spatially-diversified experimental design generates a host of insights related to experience and learning in the context of risk mitigating technologies with stochastic benefits. At least part of the excess mitigation we see in our results seems to emerge from farmers learning and responding to greater protection with increase investment. In this paper, we see empirical glimmers of this resilience-plus and hints of the learning dynamics on which it is based. Both deserve deeper and dedicated research.

6 Conclusion

This study reinforces the growing body of evidence that documents how uninsured risk can expose 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 hope that thoughtfully-designed and appropriate risk management tools can 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.[40] Strikingly, after farmers experienced the benefits of these

[40] Despite some imbalances created by imperfections in the study's randomization scenario, the

technologies in the wake of what could have been a painful welfare shock, they intensified their investment, leading to further gains, exhibiting what might be termed 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.

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.

primary results concerning mitigation of shocks survives a statistically more conservative difference-in-differences estimation method. Unclear is whether drought tolerant seeds offer a yield benefit in years with normal weather patterns.

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, Alain de Janvry, Elisabeth Sadoulet, and Alexandros Sarris, "Index Insurance for Developing Country Agriculture: A Reassessment," *Annual Review of Resource Economics*, 2017, *9*, 421–438.

_ 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.

Clarke, Daniel J, "A Theory of Rational Demand for Index Insurance," *American Economic Journal: Microeconomics*, 2016, *8* (1), 283–306.

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 and Christopher Barrett, "Agricultural Index Insurance for Development," *Applied Economic Perspectives and Policy*, 2017, *39* (2), 199–219.

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).

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.[41] The field trials do nonetheless signal that the varieties produced and released[42] 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

[41] 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.

[42] 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 5 uses the recall data to backcast the performance of the two indices in Mozambique (Figure 6 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 contradct 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 (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 (actual zone-year yields lower than 60% of normal) in Mozambique, with only 3 out of 14 bad years being misclassified. However, in the Figure 6 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 5: The Accuracy of the Fail-safe Index Insurance Contracts

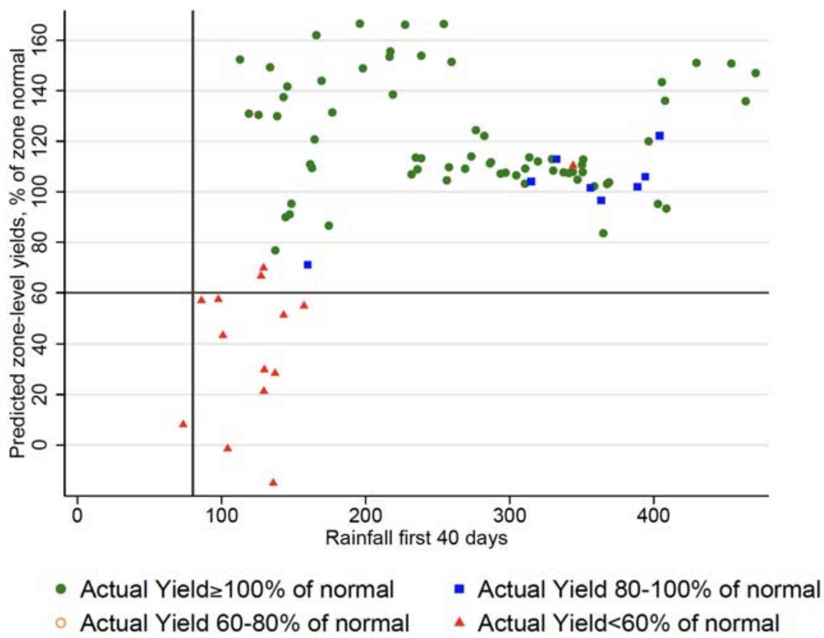
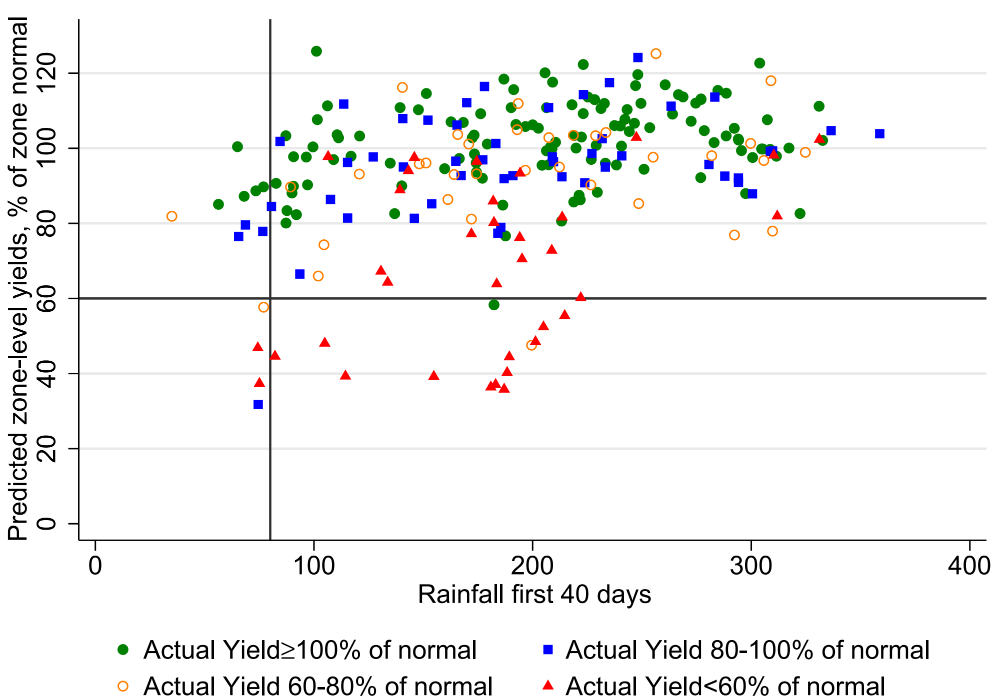


Figure 6: Tanzania



Appendix 3: Tables and Figures

Table A1: DiD Estimates for Spending, Area and Food Security

	Maize Input Expenditures		**Maize Area**	
Explanatory Variables	*Coef.*	*Std. Err.*	*Coef.*	*Std. Err.*
Impact of Shocks				
Lagged Mid-season Drought, $d_{is(t-1)}$	12.5	4.4	0.02	0.08
$d_{is(t-1)} \times$ Endline, E_{ist}	-36.8	10.0	0.02	0.16
Lagged Yield Shock, $z_{is(t-1)}$	-20.4	5.6	-0.22	0.09
$z_{is(t-1)} \times E_{ist}$	-17.7	19.2	-0.43	0.28
Mitigation DT Seed Treatment, S_{ist}				
$S_{ist} \times Post_{ist}$	24.8	7.2	-0.09	0.11
$S_{ist} \times E_{ist}$	-10.0	10.9	0.36	0.17
$S_{ist} \times d_{is(t-1)} \times E_{ist}$	76.2	18.0	-0.14	0.19
Mitigation Impacts of Insurance Treatment, I_{ist}				
$I_{ist} \times Post$	0.9	8.4	0.52	0.19
$I_{ist} \times E_{ist}$	-27.3	18.4	-0.64	0.22
$I_{ist} \times d_{is(t-1)} \times E_{ist}$	142.3	83.3	2.11	0.71
Control for Baseline Differences				
S_{ist}	-0.9	5.1	-0.08	0.12
I_{ist}	1.8	5.2	-0.01	0.13
Intercepts & Control Variables				
Mid-line Time Effect	6.2	4.1	-0.12	0.08
End-line Time Effect, E_{ist}	16.9	6.5	-0.14	0.10
Cluster fixed effects	Included		Included	
Other controls	Included		Included	
Number of Observations	8542		8542	

Other controls: Household head age and education; Predicted poverty probability; and Intercropping Indicator. Standard errors clustered at the village levels

Table A2: 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.