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ABSTRACT

Risk often inhibits on-farm investment by smallholder farmers. Recent evidence indicates that index insurance and stress tolerant seeds can separately and partially offset this risk effect. In this study, we explore whether the complementarities between these two risk management technologies can be harnessed to underwrite a resilient, high productivity small farm sector. Utilizing a multi-year randomized control trial that spanned two countries and exploits natural variation in weather shocks, we find that drought tolerant maize seeds mitigate the impact of mid-season drought. Compared to farms in control villages, where shocks have persistent effects that reduce future investment and productivity, those with access to both drought tolerant seeds and multi-peril index insurance show greater resilience and immediately bounce back from shocks. Experiential learning is key to realizing this resilience effect: Farmers who experienced shocks intensify their subsequent use of the technologies and exhibit what we call resilience-plus, while those who did not experience shocks disadopt. Together these findings showcase important complementarities between these risk mitigating technologies and the crucial role learning plays in tapping their potential stochastic and dynamic benefits to small farmers.

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1 Introduction

In the absence of effective tools to manage risk, shocks in one period can reverberate far into the future by distorting subsequent production and consumption decisions, amplifying the welfare losses associated with the initial shock. This burden of uninsured risk is perhaps clearest, most compelling and best understood empirically among smallholders who rely on rainfed farming. Ample evidence shows that uninsured risk leads smallholder households to forego risky but profitable investments and to engage in costly coping strategies that compromise future income-generating capacity in the wake of shocks.[1] This work has motivated the search for risk management technologies that improve the resilience of these households and encourage them to invest more in their own productivity and future living standards.

We employ a multi-country, multi-year randomized control trial (RCT) to test the efficacy of a package of two risk management technologies—stress tolerant seed varieties and index insurance—intended to boost the resilience and productivity of smallholder maize farmers in Sub-Saharan Africa. The control group for this study testifies to the magnitude of the underlying risk management problem. Maize production is a large fraction of real household income,[2] and yet yields are highly variable and average well below one ton per-hectare in environments where it is profitable in expectation to adopt technologies that could easily double or triple that average yield number.

Data from the RCT reveal that mid-season drought events, which occur with relatively high frequency, reduce control group farmer yields by some 25%. The more severe and less frequent covariate yield shocks observed in our study reduce yields by 50%.[3] Both types of shocks are estimated to have lingering effects that persist into the next year as farmers reduce investment in maize inputs, and perhaps in area cultivated following a shock. In the case of covariate yield shocks, food insecurity rises the year following a shock by nearly 50%, signaling that these households also rely on coping strategies that jeopardize family nutrition and health. These households are clearly not resilient as shocks compromise both their current and future economic well-being.

[1] For example, see Morduch (1995); Rosenzweig and Binswanger (1992); Carter and Lybbert (2012).

[2] Our data do not allow us to calculate full family income, but we do know that over a third of surveyed families rely exclusively on maize production as their source of income.

[3] Precise definitions of these shocks are given in section 3.2 below.

Stress tolerant seed varieties bred to withstand abiotic weather shocks like drought or flood are among the new technologies that potentially improve the resilience of smallholder farmers. Encouraging evidence highlights this potential. Emerick et al. (2016), for example, finds that flood tolerant rice varieties not only protected Indian farmers against the worst consequences of a shock, but also gave them confidence to intensify their investment in productivity-enhancing inputs. Stress tolerant varieties are a particularly attractive innovation because of their very 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 non-tolerant varieties.[4] Farmers may consequently pay little or no price premium to access these stress tolerant varieties compared to purchasing other improved varieties. However for the majority of the farmers in our sample, who rely on local seed varieties retained from the previous harvest, a shift to stress tolerant varieties represents a large increase in investment.

Despite the low marginal costs of producing stress tolerant seeds, they offer farmers protection against only a limited range of the shocks that they confront. The flood tolerant rice variety studied by Emerick et al. (2016) provides protection against flood events that last no more than 15 days (Dar et al. 2013), but succumbs like other rice varieties to longer periods of flooding.[5] Similarly, the drought tolerant (DT) maize varieties studied here protect against mid-season drought, but remain vulnerable to early and late season drought in addition to the other biotic and abiotic stresses that afflict other maize varieties (see Section 2.1). This limited or single peril protection reflects the fact that plant breeders face biological

[4]This marginal cost advantage is especially pronounced for smallholder farmers in developing countries since much of the fixed cost of developing these varieties is either covered by public research entities, often with support from private firms (e.g., the multi-year, CIMMYT-led Drought Tolerant Maize for Africa), or by private firms that intend to recoup this investment in more lucrative developed country markets and provide preferential access to their stress tolerant traits for farmers in Africa (e.g., the public-private partnership led by the nonprofit African Agricultural Technology Foundation, "Water Efficient Maize for Africa" initiative). Since these stress tolerant traits are generally added to improved seed varieties, accessing these new varieties does require farmers to purchase new seed rather than reusing their saved seed from previous seasons, but the retail markup of these improved stress tolerant varieties over comparable improved but not stress tolerant varieties is minimal (or zero).

[5]In the year of the Emerick et al. (2016) impact evaluation, some study farmers experienced floods which fortunately lasted only 14 days. Had the flood waters not receded at that time, the results of the study would likely have been quite different.

constraints that limit how much and what types of stress these new varieties can withstand.

The narrow single-peril protection offered by stress tolerant seeds raises an adoption dilemma for smallholder farmers - especially those who would normally re-use their own saved seed to avoid purchasing new seeds. It also raises intriguing possibilities for financial instruments designed to pick up where the stress tolerant traits leave off. Bundling with such an instrument could provide smallholder farmers more comprehensive risk mitigation and more effectively reduce the welfare burden of uninsured risk. Index insurance offers a compelling instrument for this purpose. The last decade has seen numerous efforts to develop index insurance contracts that can 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 a primary limitation to index insurance, it is expensive (often sold at prices that are more than 150% of the actuarially fair price), and 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.

The logic behind bundling stress tolerant seeds and index insurance, which was first elucidated by Lybbert and Carter (2015), stems from important differences between these risk management technologies.[7] The strengths and weaknesses of the two suggest strong

[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] Lybbert and Carter (2015) use a conceptual framework along with some simulation to illustrate this logic. More recent work has focused on empirically characterizing DT seeds and exploring this kind of bundling. Awondo et al. (2020) focus on many of the same DT maize varieties that feature in our study and use CIMMYT on-farm trial data to predict yields under different rainfall conditions. Building on this statistical characterization of DT maize yields, they then explore rainfall indexes to complement the coverage offered by DT. Their simulation results emphasize how sensitive the optimal calibration of the rainfall index is likely to be to agroecological and climatic conditions due to their strong effect on the performance of the DT trait. Several recent studies have demonstrated this complementarity and farmer demand for the resulting protection in the context of DT rice and weather index insurance in Bangladesh (Patrick S. Ward and Minocha, 2020) and Odisha, India (Patrick S. Ward and Minocha, 2020, Ward et al., 2020).

complementarities. In contrast to the narrow single-peril nature of stress tolerant protection, the design of index insurance contracts is not limited by the biological constraints faced by plant breeders; in theory, index insurance can offer farmers multi-peril protection against any combination of losses. On the other hand, whereas the marginal cost of producing and distributing the biological protection embedded in stress tolerant varieties (albeit narrow and single-peril) is near zero, the same is not true for index insurance. Even after the fixed costs of contract design have been assumed, the marginal cost of offering this protection to farmers (i.e., the premium) can be significant. In a well-designed bundle of stress tolerant seeds and index insurance, the seeds can provide inexpensive protection against their named peril, while the design flexibility of index insurance can, in principle, be fine-tuned to offer multi-peril protection to cover risks not covered by the stress tolerant seeds.

In this study, we create and test a prototype DT Maize Seed-Index Insurance bundle (DT-II) using an RCT that offered farmers the opportunity to purchase drought tolerant (DT) maize varieties, either as seeds alone, or as seeds bundled with a modest fail-safe index insurance contract that protected farmers' investment in the DT varieties. 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. The impacts of these events on the control group have already been summarized above. Key findings from the RCT are that:

- DT seeds fully protect farmers against within-season yield losses of the single peril of mid-season drought;

- In the year following a mid-season drought, farmers who planted DT seeds not only avoid the lingering effects of the drought experienced by control farmers, but their yields more than bounce back, exhibiting "excess mitigation," as they further intensify their on-farm investment;

- While index insurance does not eliminate yield losses, it does mitigate the impact of severe, covariate yield shocks (that dampen productivity of DT seeds) on yields, on-farm investment and household food insecurity in the following year, thereby complementing the protection conferred by the DT seeds and,

- Similar to the DT seed technology, the insurance creates excess mitigation as treated farmers increase on-farm investment and planted area in the year following a severe yield shock.

- Farmers who did *not* experience mid-season droughts or severe yield shocks tend to dis-adopt the resilience promoting technologies, a finding that is consistent with results reported in Cai et al. (2020).

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. Finally, Section 5 concludes with reflections on the specific challenge of learning about risk management technologies, which by definition only occasionally reveal their benefits to farmers.

2 Drought Tolerant Seed and Index Insurance

This section offers a more detailed overview of the two constituent risk management technologies that underlie this evaluation, drought tolerant maize varieties and an index insurance contract designed to protect farmer investment in the event of severe yield loss. This overview provides clearer motivation for the specific DT-II bundle we test in this work and sets the stage for interpreting the results that emerge from the analysis.

2.1 Single-Peril Drought Tolerant Maize Seeds

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. During the decade-long 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 midseason 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.

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 (forthcoming) 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.[8] The field trials do nonetheless signal that the varieties produced and released[9] 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. This uncertainty over the real world efficacy of DT seeds also limited our ability to finely tune an insurance contract to match DT's putative protection against mid-season drought.

2.2 Multi-Peril Index Insurance to Complement DT Seeds

Index insurance has been proposed as a financial instrument to mitigate the risk that confronts smallholder farmers. By basing payouts on an objective index that is correlated with farmers' yield losses but cannot be influenced by individual farmer behavior, index insurance avoids the pitfalls of conventional indemnity insurance, including moral hazard, adverse selection and costly loss verification.[10] 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.[11] When basis risk is high, index insurance contracts are

[8]Paul (forthcoming) 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.

[9]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.

[10]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.

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

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

While basis risk can never be completely eliminated, 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.

The contract we ultimately designed for this project included the following two indices:

1. 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.

2. 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.

[12]Rainfall was estimated using Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) data (Funk et al., 2015). An 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.

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. Ideally, as discussed by Lybbert and Carter (2015), this contract would have been fine-tuned so as not to cover losses, which, absent DT seeds, would have been caused by mid-season drought events. However, as discussed in section 2.1, the efficacy of DT seeds in farmers' fields was unknown at the time this study was initiated. Without clear evidence on DT efficacy we chose not to design an index that covered everything except losses caused by mid-season drought events. The second index described above was thus left as a full, multi-peril clause, intended to cover all substantial yield losses irrespective of cause. As will be seen in the analysis below, mid-season drought events on average caused yield losses of an estimated 25%, an amount well below the multi-peril yield trigger.

Figure 1 uses the recall data to backcast the performance of the two indices in Mozambique (the analogue graph for Tanzania is included as appendix Figure A1). Each marker 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 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 A1 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.

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

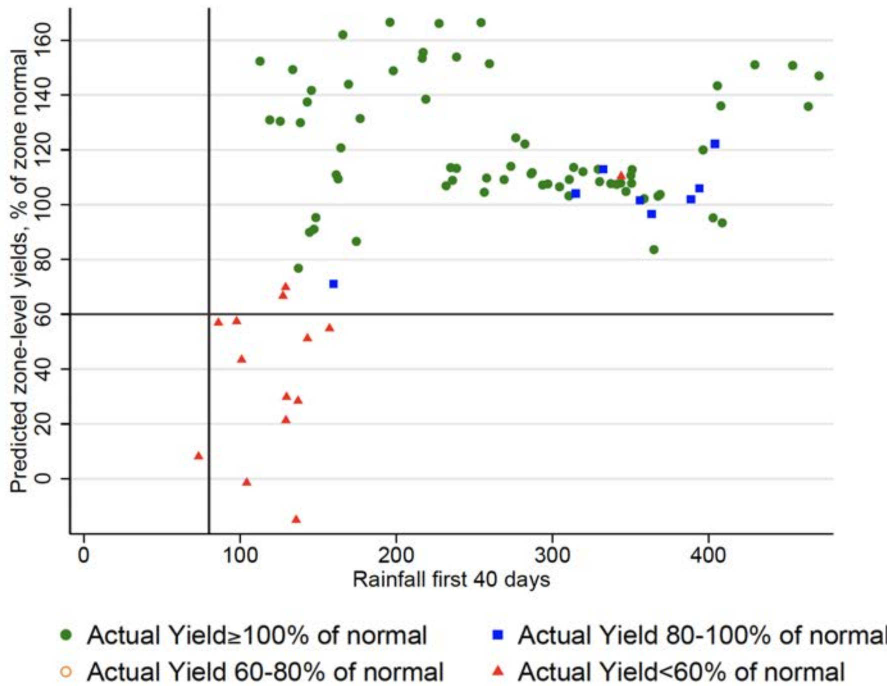


Figure 1: The Accuracy of the Fail-safe Index Insurance Contracts

clause of the contract, insured farmers were invited to submit a complaint if the contract did not trigger, but they believed it should have. If more than 30% of farmers registered a complaint, a crop-cut audit was conducted using novel imaging software ((Makanza et al., 2018)), with replacement seeds issued if average yield as estimated by the crop-cut was indeed below the trigger. The data summarized in Figure 1 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.[14]

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

[14]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.

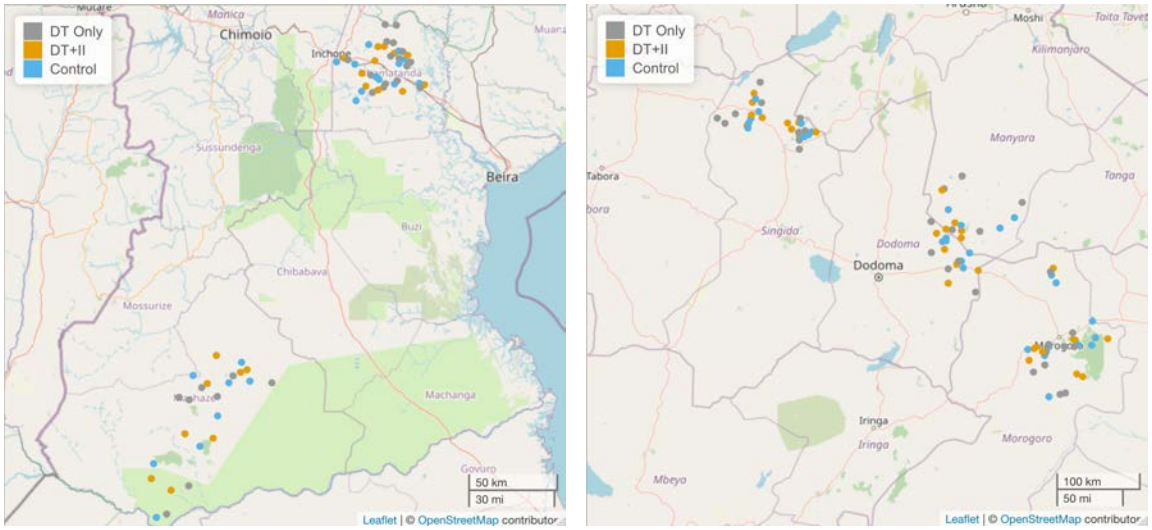
insurance product. Households in the insurance treatment group were offered a bundle of DT seeds and insurance. The payoff structure was set such that any payment triggered would cover replacement seeds to be delivered in the next planting season.[15] In principle, the multi-peril contract could have have been set to cover the cost of other inputs or even the full value of the lost harvest. However, to keep the cost of the insurance low, the project offered only this basic level of coverage. On average, the insurance increased the price of seed by 20%, reflecting both the relatively high level of risk and the commercial loadings added to the actuarially fair price of the insurance.

3 Research Design

Learning about technologies that can only display their benefits during infrequent, bad years is challenging for both farmers and researchers (see 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 the districts were exposed to moderate to severe drought risk. On the advice of DTMA colleagues, we eliminated areas from the study where drought risk was so severe that even drought tolerant maize seed would be unlikely to be successful. 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.[16] As shown below, 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.

[15] The total sum insured for a farmer planting maize at the recommended seeding rate, was thus about $US75-100. 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.

[16] 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.



(a) Mozambique (b) Tanzania

Figure 2: Geographic Diversification and Matched Triplet Randomization
(Base map and data from OpenStreetMap and OpenStreetMap Foundation)

3.1 The Randomized Control Trial

The maps displayed in Figure 2 display the randomization strategy that was implemented in all study districts in both countries.[17] After identifying a set of study communities in each district in each country, communities were matched into triplets based on having similar agro-ecological (*e.g.*, being located in a river valley) and economic characteristics (access to roads and proximity to larger urban centers). One member 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 farm households were 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

[17]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.

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 the NGO Farm Input Promotions Africa (FIPS). 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 FIPS' expansion plan in the study area was less robust than we expected and that we would be unable to randomize new communities between control and VBA-mediated treatment status. Instead, the research 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 FIPS may have selected VBA communities based on characteristics unobservable to us that correlate with productivity, FIPS 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,[18] climate conditions and market access to create triplets, each consisting of one non-FIPS and two FIPS 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 3 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.[19] Study households were individually invited to the training sessions, and other community members were also welcome to participate. Training information included 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).[20] Non-study house-

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

[19]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.

[20]At standard planting densities, the free packets would have allowed the farmer to plant 0.04 to 0.08

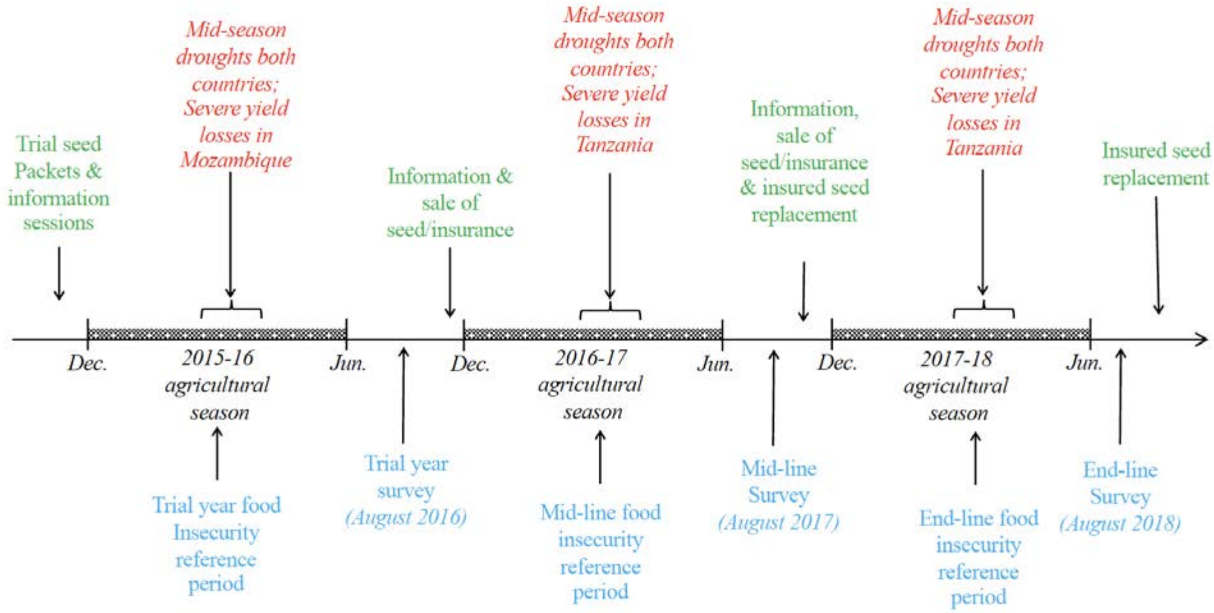


Figure 3: Timeline for RCT & Natural Experiment

holds who attended the training were given smaller (100-250 gram) packets. Villages were sufficiently isolated to prevent DT seeds spreading into control communities.

In villages 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 insurance. The insurance, which was not subsidized, raised the price of the seeds by approximately 20%.[21] Insurance premiums collected from the sale of insured seeds was 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 3, 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

hectares. The average farmer planted a total of 2 hectares of maize at baseline.

[21] 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.

pure baseline year followed by a pure learning year.[22] 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 estimate that the amount of seed given away in trial packets could have generated no more than a 12% yield differential between treatment and controls during the trial pack year.[23]

Following the quasi-baseline year and at the initiation of the 2016/17 and 2017/18 seasons, training sessions were again held in treatment communities (see the Figure 3 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 FIPS 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 the 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 to 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

[22]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.

[23]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%.

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 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 2.2. 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 3 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:

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

where α_t is a vector of 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.[24]

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 perhectare compared to the control group.[25] 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 23). 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.[26]

[24]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.

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

[26]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

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	

***, ** & * indicate statistical significance at the 1%, 5% & 10% level, respectively.
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 Tanzania, and especially 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.[27]

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

using PPP exchange rates. The expenditure aggregate is thus a fixed-price, quantity index. To eliminate the undue influence of outliers, we transformed total input expenditures into a per-hectare measure. The per-hectare measure was then winsorized at the the 99th percentile. The winsorized per-hectare measures were then transformed back into total expenditures by multiplying each observation by reported maize area.

[27]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.

areas.[28] As mentioned earlier, treated households 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[29] 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 trial pack 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 is 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 that the

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

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

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 test 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 mid-season droughts 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. Their experience may also have made risk management technologies more salient to them. For both these reasons, we might expect their endline behavior to be rather different than those who did not experience such shocks (see, for example, Cai et al. (2020) and Emerick et al. (2016)). Households also had differential exposure to lagged shocks at midline, but this heterogeneity did not offer the same learning opportunity since these lagged shocks were experienced during the quasi-baseline year prior to full access to DT seeds and the DT-II bundle. Such lagged shocks could have, however, increased the salience of drought risk independent of these learning effects. In this way, we expect that important heterogeneity in learning and behavior is hidden behind the modest decline in the simple compliance rates in this table. The specifications we introduce in this section test this hypothesis specifically.

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

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

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}

Table 2: Compliance and Key Outcome Variables by Experimental Treatment

	Experimental Assignment		
	Control	*DT Seeds*	*DT & Insurance*
Midline			
Compliance & Shocks			
DT adoption (%)	3.6	54.3	48.2
Insurance Adoption (%)	0	0	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 ($USPPP)	42.1	72.5	75.5
Maize Area Planted (hectares)	2.0	1.8	2.3
Food Insecurity Score	25.6	22.8	22.8
Midline Observations	**996**	**917**	**902**
Endline			
Compliance & Shocks			
DT adoption (%)	5.3	49.5	41.9
Insurance Adoption (%)	0	0	41.5
Mid-season Drought (%)	51.5	51.2	48.7
Yield Shock (%)	4.9	10.3	3.8
Lagged (midline) Mid-drought (%)	41.2	50.2	48.5
Lagged (midline)Yield Shock (%)	12.3	8.0	6.1
Outcome Variables			
Maize Yield (kg/hectare)	544	719	706
Seed fertilizer Expend ($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**

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.[30] 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 good 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.[31] Figure 4 displays the 95% confidence interval estimates for the ANCOVA results on shocks and the mitigating impacts of the risk management treatments.[32] We will focus primarily on the ANCOVA results and discuss DiD results where

[30]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.

[31]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.

[32]The mitigation effect of a treatment is defined as the difference in expected yields between a treated and

Table 3: Maize Yields

	ANCOVA		DiD	
Explanatory Variables [for DiD]	*Coef.*	*Std. Err.*	*Coef.*	*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_{ist}				
S_{ist} [$S_{ist} \times post$]	77.0*	40.4	33.3	64.9
$S_{ist} \times E_{ist}$	-97.5*	54.0	-137.3**	55.8
$S_{ist} \times d_{ist}$ [$S_{ist} \times d_{ist} \times post_t$]	181.7***	56.8	93.1	62.4
$S_{ist} \times d_{ist} \times E_{ist}$	-46.9	62.3	-27.0	64.1
$S_{ist} \times d_{is(t-1)} \times E_{ist}$	162.0**	71.2	227.2***	75.8
Mitigation Impacts of Insurance Treatment, I_{ist}				
I_{ist} [$I_{ist} \times post_t$]	-13.1	44.7	-23.9	70.0
$I_{ist} \times E_{ist}$	-51.4	64.8	-37.8	65.2
$I_{ist} \times z_{is(t-1)} \times E_{ist}$	417.7***	94.8	358.2***	115.3
Control for Baseline Differences				
S_{ist}	–	–	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	

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

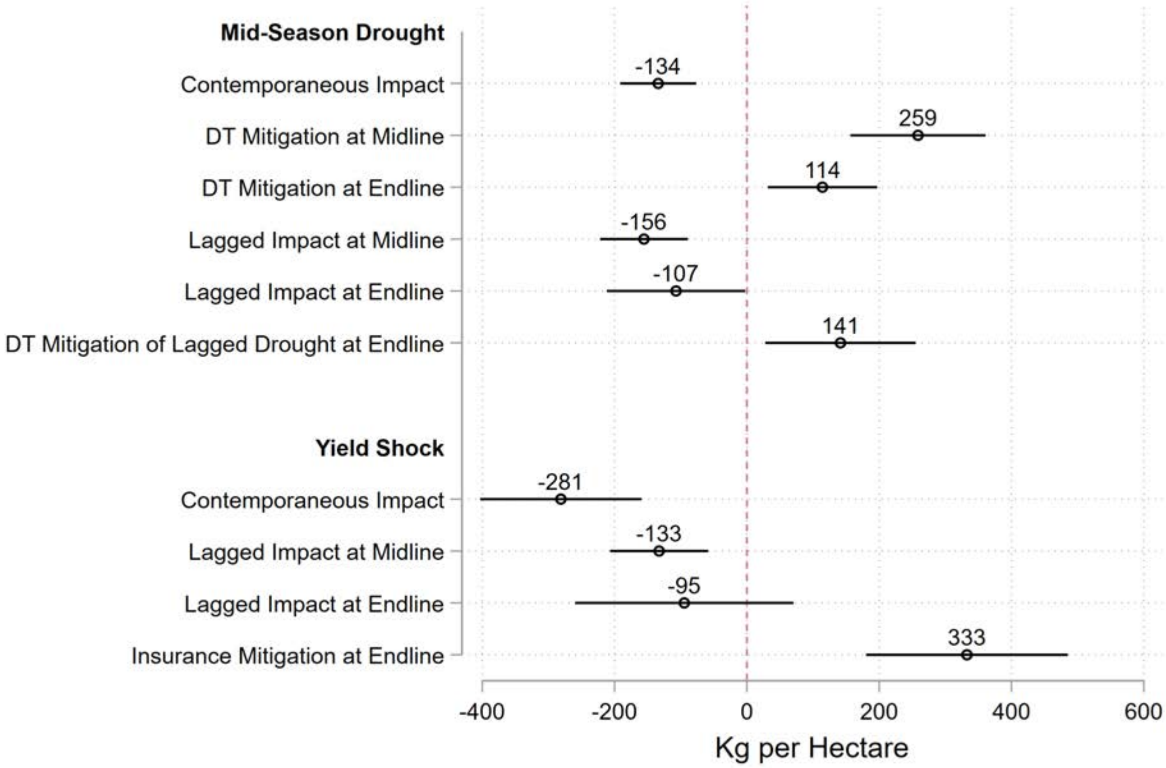


Figure 4: Yield Shocks and Mitigation Impacts (ANCOVA Estimates)

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. As can be seen, both types of shocks have substantial impacts on maize yields, both 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

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: $\delta_1 + \delta_2 + \delta_0 + \delta_t$
- 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: $\gamma_1 + \delta_0 + \delta_t + \gamma_0 + \gamma_t$

46% the level of the contemporaneous impact, whereas the point estimate of the lagged impact of drought shocks indicate continuing strong, negative impacts.[33] The lingering yield effects indicate that absent risk management tools, maize farmers are not resilient and that their yields fail to return to pre-shock yield levels, even a year after the shock.

The second block of coefficients in Table 3 combine to identify the mitigating effect of the DT seed technology (see footnote 32). As can be seen in Figure 4, the coefficients on the seed treatment indicate that the DT technology effectively mitigates the yield loss otherwise brought on by a mid-season drought. 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. However, the point estimate of the impact of the insurance treatment on mitigating the lingering effects of lagged yield shocks is substantial and statistically significant 333 kg/ha. This point estimate is several times larger than the estimated impact of lagged yield shocks. Foreshadowing later analysis, this estimated "excess mitigation" may reflect learning effects that occurred when yield shocks allowed households to learn about the reliability of the insurance contract, inducing subsequent intensification of use of the technology. If we define resilience as the ability of households to recover from a shock and bounce back to their pre-shock levels of production, this finding of excess mitigation might be labelled "resilience-plus," as it seems to imply that once convinced that the technologies generate resilience, farmers further intensify their investments. We return to this issue in Section 4.2 below.

Finally, the seed treatment variable (S_{ist}) 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 (forthcoming) discussed in Section 2.1 above, but well-

[33] 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.

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 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 yield effect (the point estimate drops from 77 kg/ha to a statistically insignificant 33 kg/ha). The estimated contemporaneous 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 happened during the growing season. We thus adapt the regression model 1 and estimate the following ANCOVA ITT specification:

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

The resource allocation outcome variable r_{ist} will either be total (not per-hectare) expenditures on maize inputs (measured in \$US PPP; see footnote 26) 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 regression equation 2.[34] Consistent with the impact of lagged shocks on yields discussed in Section 4.1, Table 4 and Figure 5 show that lagged drought and severe, covariate yield shocks dampen the allocation of inputs to maize, especially in the endline period.[35] Mitigation effects, which can only be measured at endline, show that both the DT seed and the insurance treatment exhibit what we earlier called excess mitigation.[36] Midline drought shocks are estimated to reduce input expenditures by \$38, whereas the DT treatment following a midline yield shocks boosts expenditures by more than double that amount (\$90). A similar pattern is revealed with yield shocks. Midline yield shocks reduce endline expenditures by an estimated \$54, whereas the investment treatment following that shock boosts spending by \$132. Because the measure is total expenditures on

[34]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.

[35]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.

[36]The mitigation effects of the treatment are defined analogously to those describe in footnote 32. 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: $\rho_2 + \lambda_0 + \lambda_t + \rho_0 + \rho_t$

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_{ist}				
S_{ist}	23.9***	7.3	-0.21*	0.12
$S_{ist} \times E_{ist}$	-11.7	11.0	0.34**	0.17
$S_{ist} \times d_{is(t-1)} \times E_{ist}$	78.2***	18.9	-0.07	0.17
Mitigation Impacts of Insurance Treatment, I_{ist}				
I_{ist}	1.6	6.9	0.55***	0.16
$I_{ist} \times E_{ist}$	-28.1	18.6	-0.62***	0.20
$I_{ist} \times z_{is(t-1)} \times E_{ist}$	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	

***, ** & * indicate statistical significance at the 1%, 5% & 10% level, respectively
Other controls: Household Head Age and Education, Predicted Poverty Prob. & and Intercropping Indicator
Standard errors clustered at the village levels.

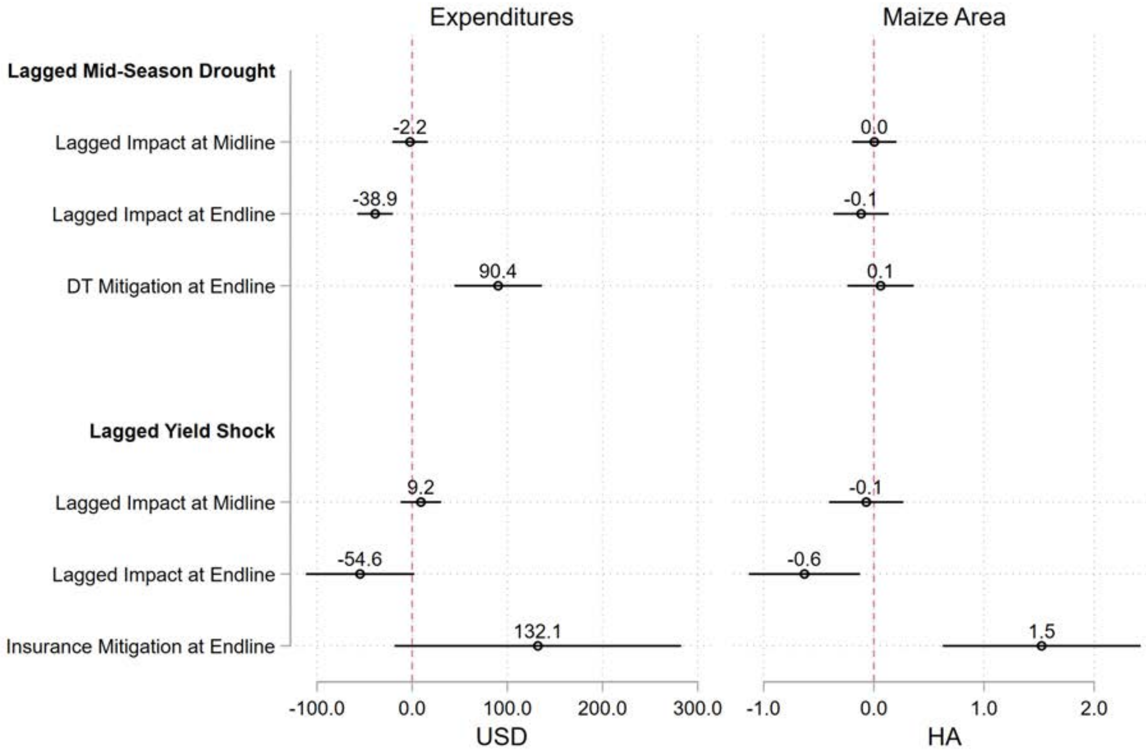


Figure 5: Shocks and Resource Allocation (ANCOVA Estimates)

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, those farmers who did not experience midline shocks, are estimated to back away from the novel risk management technologies and substantially reduce their expenditures. In contrast, as already discussed, households that experienced shocks in the midline substantially boosted their expenditures on seeds and fertilizers, exhibiting excess mitigation (or resilience-plus).

These results suggest a learning effect in which those farmers who had the opportunity to witness the two risk reduction technologies in action subsequently deepened their investment in them. Those farmers who did not witness the benefits of the technologies appear to have begun to walk away from using them. Returning to the descriptive statistics in Table 2 above, we see that compliance dropped by 5 percentage points for the DT treatment in endline, whereas it dropped 6 percentage points for those individuals in the combined seed-insurance treatment. The findings here are reminiscent of the work of Cai et al. (2020), who emphasize that without direct experiential learning, farmers tend to walk away from technologies that offer benefits only in the presence of shocks.

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 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 excess 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 walk away from the area expansion, whereas those who did experience shocks continue with expanded maize area.

While it is tempting to interpret these findings as pure learning effects, it is possible that the experience of drought or yield shocks in midline made those risks more salient to study farmers. To test this salience explanation, we can modify 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.

4.3 Food Insecurity

To test the ultimate 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.[37] Because of the reference periods used in the survey (see Figure 3), 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 those 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 5 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. There is no excess mitigation as seen in the case of inputs and yields, which is consistent with the interpretation that excess mitigation for those outcomes reflected a learning effect that

[37] 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 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

Explanatory Variables	ANCOVA Coef	ANCOVA Std Err	DiD *Coef.*	DiD *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_{ist}				
$S_{ist} \times Post_{ist}$	-1.81	1.74	2.19	2.66
$S_{ist} \times E_{ist}$	-0.39	2.16	0.17	2.11
$S_{ist} \times d_{is(t-1)} \times E_{ist}$	1.98	1.57	0.80	1.59
Mitigation Impacts of Insurance Treatment, I_{ist}				
$I_{ist} \times Post$	-0.13	1.71	-2.69	2.65
$I_{ist} \times E_{ist}$	1.45	2.13	1.33	2.13
$I_{ist} \times z_{is(t-1)} \times E_{ist}$	-7.10**	3.77	-6.95***	2.71
Control for Baseline Differences				
S_{ist}			-4.04**	1.67
I_{ist}			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	-16.85***	1.94
Cluster fixed effects	Included			
Other controls	Included			
Number of Observations	5568		8542	

***, ** & * indicate statistical significance at the 1%, 5% & 10% level, respectively
Other controls: Household Head Age and Education, Predicted Poverty Prob. & and Intercropping Indicator
Standard errors clustered at the village levels.

induced further investment.

5 Conclusion: From Resilience to Resilience-plus

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 main 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 also provide hope that thoughtfully-designed and appropriate risk management tools can reduce the risk burden in synergistic ways. Specifically, our results suggest that drought-tolerant maize seeds and drought-tolerant maize seed bundled with fail-safe index insurance effectively mitigated both the immediate and longer term consequences of the shocks they were designed to offset.[38] Strikingly, after farmers experienced the benefits of these technologies in the wake of what could have been a painful welfare shock, they subsequently 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 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

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

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.

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 stress tolerance and index insurance provide a compelling logic for bundling the two, and the results of this analysis provide evidence of the synergies associated with such a bundle. But we hasten to note that the specific bundle we tested in this study is much more a proof-of-concept than an optimized bundle. With better data, further experimentation and more evidence, there are many ways this or other genetic-financial bundles could be enhanced to more fully leverage these complementarities. In continued collaboration with private sector partners, such breakthroughs could usher in 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. In such cases, 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.

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Appendix 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	

***, ** & * indicate statistical significance at the 1%, 5% & 10% level, respectively
Other controls: Household Head Age and Education, Predicted Poverty Prob. 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, $d_{is(t-1)}$	-3.357	13.10
$d_{is(t-1)} \times$ Endline, E_{ist}	-35.71*	16.05
Lagged Yield Shock, $z_{is(t-1)}$	18.97	12.24
$z_{is(t-1)} \times E_{ist}$	-73.77	39.41
Risk Salience Effects		
$S_{ist} \times d_{is(t-1)}$	0.583	13.66
$I_{ist} \times z_{is(t-1)}$	-29.73*	11.71
Mitigation Impacts of DT Seed Treatment, S_{ist}		
S_{ist}	23.94*	12.00
$S_{ist} \times E_{ist}$	-12.16	15.54
$S_{ist} \times d_{is(t-1)} \times E_{ist}$	78.14***	22.50
Mitigation Impacts of Insurance Treatment, I_{ist}		
I_{ist}	12.05	10.09
$I_{ist} \times E_{ist}$	-39.07	20.76
$I_{ist} \times z_{is(t-1)} \times E_{ist}$	176.6*	81.68
Intercepts & Control Variables		
Baseline Dependent Variable	0.423**	0.138
E_{ist}	22.53	11.46
Cluster fixed effects	Included	
Other controls	Included	
Number of Observations	5568	

***, ** & * indicate statistical significance at the 1%, 5% & 10% levels
Other controls: Household Head Age and Education, Predicted Poverty Prob. & Intercropping Indicator.
Standard errors clustered at the village levels.

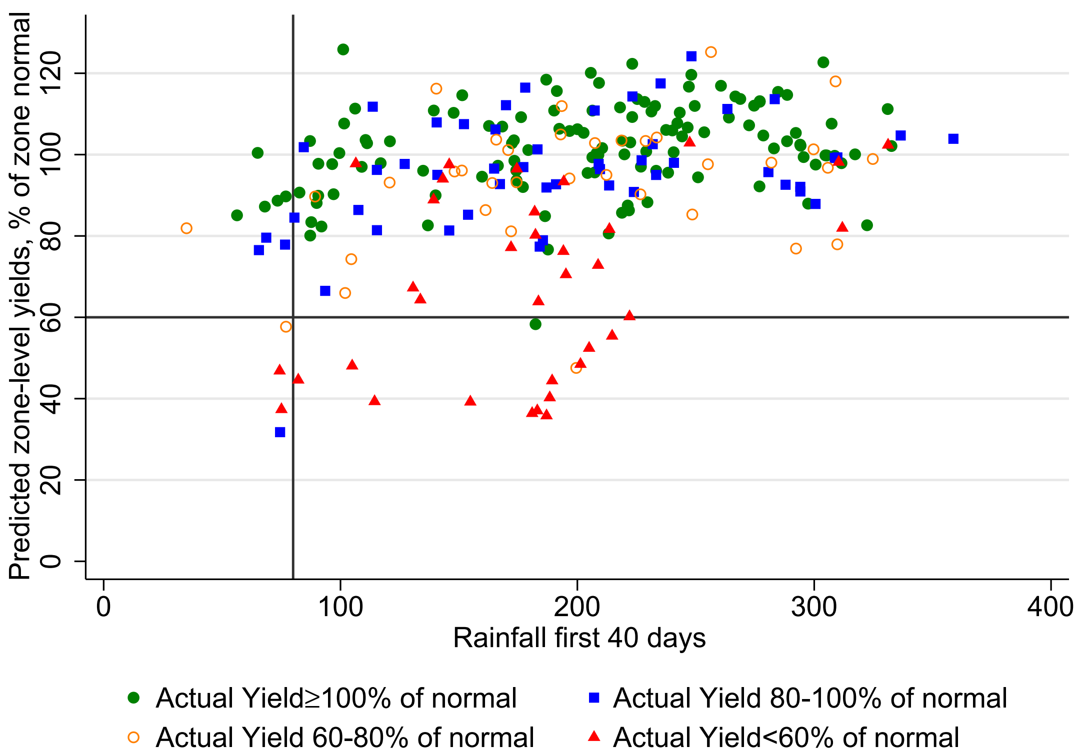

Figure A1: Tanzania