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Improved on-farm storage reduces seasonal food insecurity of smallholder farmer households – Evidence from a randomized control trial in Tanzania

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ABSTRACT

Ending hunger is a key goal of the 2030 Agenda for Sustainable Development, adopted in 2015. This goal notwithstanding, the prevalence of severe food insecurity of the world's population has increased. It is highest in Sub-Saharan Africa, where the seasonality of harvests leads to fluctuations in food insecurity, particularly in the lean season, the time before the harvest is brought in. We posit that addressing seasonal food insecurity requires not only increased food production, as is commonly argued, but also consideration of post-harvest losses during storage. Here we present the results of a randomized control trial on the effects of improved on-farm storage on seasonal food insecurity. Our intervention provided farming households from two districts in Tanzania with hermetic storage bags that can help reduce storage losses. Seasonal food insecurity was measured via multiple rounds of SMS-based surveys. The results show that the intervention reduced the proportion of severely food insecure households by 38% on average in the lean season, and by 20% in the full seasonal cycle. These findings demonstrate that a simple and inexpensive technology could contribute strongly to reducing seasonal food insecurity and improving smallholder farmers' year-round access to food.

1. Introduction

Ending hunger and ensuring access to food all year round is a key objective of the 2030 Agenda for Sustainable Development (Transforming our world: the 2030 Agenda for Sustainable Development, 2015). Yet, in the three years since the adoption of the Agenda in 2015, the prevalence of severe food insecurity has increased from 8.4 to 10.2% of the world's population (FAO, 2018). The prevalence of food insecurity is highest in Sub-Saharan Africa, with 29.8% of the population affected by severe food insecurity (FAO, 2018). The Food and Agriculture Organization of the United Nations warns that without increased efforts, the Sustainable Development Goal (SDG) of ending hunger will be missed by far.

In Sub-Saharan Africa, about 70–80% of farms are less than two hectares in size (Lowder et al., 2016). These small-scale farming households depend on food and income from their annual or semi-annual harvests. It is well established that the seasonality of harvests leads to fluctuations in food insecurity. Food insecurity and malnutrition have been shown to increase in the lean season, the time shortly before a new harvest is brought in (e.g. Christian and Dillon, 2018; Abizari et al., 2017; Hirvonen et al., 2016; Kaminski et al., 2016; Becquey et al., 2012; Savy et al., 2006). Much less is known about the specific mechanisms leading to fluctuations in food insecurity and options for mitigating this problem.

One prominent string of research argues that seasonal changes in food consumption are a consequence of credit and liquidity constraints, which compel households to sell their harvest early. As prices often increase after harvest and peak in the lean season, many households lack the resources to buy similar quantities later, explaining lower lean season consumption. A range of empirical studies have shown that credit and liquidity constraints indeed cause households to sell early (e.g. Kadjo et al., 2018; Burke et al., 2019; Fink et al., 2018; Dillon, 2017; Stephens and Barrett, 2011; Basu and Wong, 2015). However, studies assessing the effects of access to credits or loans on consumption or food security in the lean season do not find statistically significant effects (e.g. Burke et al., 2019; Fink et al., 2018; Basu and Wong, 2015).

We posit that addressing seasonal food insecurity requires consideration of post-harvest losses during storage. Independent of liquidity and credit constraints, households would only store their harvest until the lean season if expected price increases outweigh the

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expected quantities lost during storage. Yet, post-harvest losses during storage are substantial in Sub-Saharan Africa. A meta-analysis of measurements based on grain samples estimates maize post-harvest losses of 25.6% on average (Affognon et al., 2015). These post-harvest losses mainly occur during storage when insect infestation and mold damage the harvested produce (Affognon et al., 2015). Reducing storage losses would not only make an extended duration of storage more profitable for households, but also increase the quantity available for consumption, especially in the lean season. Hence, we argue that limiting post-harvest losses during storage could contribute to mitigating seasonal food insecurity.

To assess whether and how much reducing post-harvest losses could help reduce seasonal food insecurity, we randomly allocated a simple and inexpensive technology for improved storage to smallholder farming households in Tanzania, clustered at farmer group level, and tracked their food security during one seasonal cycle. The intervention consisted of hermetic storage bags, which have been shown to effectively reduce post-harvest losses in stored produce, mainly grains, even in extended periods of storage (e.g. Abass et al., 2018; Murdock et al., 2012; de Groote et al., 2013; Baoua et al., 2013; Chigoverah and Mvumi, 2016; Likhayo et al., 2016). Hermetic storage limits atmospheric oxygen, which causes desiccation of insects and other pests that damage stored grains (Murdock et al., 2012). In our field experiment we did not manipulate credit or liquidity constraints, as we focus on the effects of improved storage given the normal credit and liquidity situation in our sample.

Our research contributes to filling an important knowledge gap. Prior research has shown that improved storage conditions can increase storage quantity and storage duration. For example, an experimental study from Uganda shows that providing smallholder farmers with one hermetic storage bag extends storage duration by 3 weeks (Omotilewa et al., 2018), and an experimental study from Kenya finds that providing community saving clubs with hermetic storage bags increases the quantity stored by the clubs (Aggarwal et al., 2018). Yet, these studies do not offer an assessment of the de facto effects of improved storage on seasonal food security (Sheahan and Barrett, 2017), which strongly depend on how storage technologies are used and how their utilisation affects smallholder farmers' consumption and marketing behaviour. Partial exceptions are observational studies from Kenya (Gitonga et al., 2013) and Central America (Bokusheva et al., 2012) where households using hermetic metal silos benefit from an additional 5–6 weeks of adequate food provision over the year, and from Ethiopia (Tesfaye and Tirivayi, 2018) where households using improved on-farm storage (mainly airtight drums) report reduced food insecurity. A further notable exception is an experimental study implemented in another regional context (Indonesia) which finds no changes in staple food consumption, including in the lean season, following the provision of improved (non-hermetic) storage technologies (Basu and Wong, 2015). Here we present the results of the first experimental study that assesses the impacts of improved on-farm storage on seasonal food insecurity in a Sub-Saharan African country.

2. Methods

To estimate the effects of improved on-farm storage on household food insecurity, we randomly allocated hermetic storage bags and training in their use to some households (treatment group), but not others (control group). The hermetic bags were provided as a loss-reducing storage alternative to the commonly used polypropylene bags. The experiment was implemented as a matched-pair, cluster randomized control trial in two districts of Tanzania (Kilosa and Kondoa). Households in treatment clusters received five hermetic storage bags per household, with a capacity to store about 100 kg of maize in each bag. No intervention was conducted for farmer groups assigned to the control group during the duration of this study. We measured severe food insecurity with quarterly rounds of the reduced Coping Strategies Index (rCSI) over the course of fifteen months (c.f. Maxwell et al., 2014; Maxwell et al., 2008), using SMS-based mobile phone surveys. We estimate the intent-to-treat (ITT) effect as the weighted average of within-pair mean differences between treatment and control groups (Imai et al., 2009).

2.1. Experimental design

The experiment was implemented in two districts of Tanzania, selected due to their agro-ecological and market access differences. Kondoa is relatively remote, while Kilosa is close to Dar es Salaam and the major transit routes (road/sea). Yet, both districts bring in one maize harvest per year, and maize is the staple food in both. Fig. 1 shows a map of the study areas.

We used a matched-pair, cluster randomization design. Key to this experimental design is that clusters of individuals are matched in pairs prior to the randomization. Pair-wise matching is based on the similarity of observable pre-treatment covariates, which considerably reduces the variance of the treatment effect estimator, as proved in Imai et al. (2009). The authors show that from the perspective of efficiency, power, bias and robustness the approach is superior to other approaches, and advocate that pairing should be done whenever feasible.

Clustering was done at the level of farmer groups (organizations). An initial list of 70 farmer groups (35 in Kilosa district, 35 in Kondoa district) was proposed by non-governmental organization Helvetas Swiss Intercooperation (hereinafter called Helvetas)[1], the intervention partner. Prior to the random allocation, 67 farmer groups were visited by enumerators from Sustainable Agriculture Tanzania, an independent non-governmental organization, and informed about the research and offered to participate. Data collection and interventions were separated, and participants were assured that individual data would not be shared with intervention partners. On average, 93% of farmers approached in farmer groups visits gave their consent to participate.[2] All members of the visited farmer groups were eligible to participate. For three farmer groups, all located in Kondoa district, attempts to schedule a visit were not successful. Additionally, two farmer groups in Kilosa had overlapping members (i.e., farmers participating in both groups). These groups were removed from the sample prior to pair-wise matching and random allocation.

We subsequently paired clusters according to three baseline variables, namely median distance to market (walking time in minutes, from the pre-baseline survey), soil type, and a regional dummy (district). These variables were expected to strongly correlate with future outcomes studied, namely food security (c.f. Bruhn and McKenzie, 2009). The latter two variables were necessary matches in each pair, while median distance to market was used to allocate clusters in these strata through an "optimal greedy" algorithm using the R package "blockTools" (Moore and Schnakenberg; see also Balance Table A.1). After assignment of the experimental clusters to matched pairs, we ran an automated random allocation, using a random number seed, to assign the clusters in each matched pair to treatment and control conditions, respectively.

The intervention for treatment groups consisted of providing five hermetic storage bags, of the brand "Purdue Improved Crop Storage (PICS)", with the capacity to store approximately 100 kg of maize, per household in each treatment group, and three standardized training

[1] Helvetas is an independent Swiss development organization (www.helvetas.org). In Tanzania, Helvetas has been active since the 1970s. The interventions for our study were implemented by the team of the "Grain Postharvest Loss Prevention" project, which is carried out by Helvetas as a mandate from the Swiss Agency for Development and Cooperation.

[2] In total, 1023 farmers consented to participate, out of which 671 farmers subsequently participated in at least one of the surveys rounds. See Section 2.4 for details.

Fig. 1. Map of Study Areas in Tanzania. *Notes:* Figure shows the two study districts in Tanzania. Upper shape shows the administrative district boundaries for Kondoa, and lower shape shows the district boundaries of Kilosa. Source of geographic data: https://www.openstreetmap.org.

sessions on improved on-farm storage and the use of hermetic storage technologies. The interventions were carried out by Helvetas between July and October 2017, i.e. shortly before and after the harvest was brought in. The training sessions were held at the usual meeting place of each of the treatment farmer groups. The hermetic storage bags were provided after the conclusion of the last training session (September-October 2017) in the respective group. Among treatment farmers, 99.4% received the hermetic storage bags as confirmed by individual receipts - three farmers allocated to treatment could not be found and could hence not be provided hermetic storage bags. Though we lack data on the extent to which hermetic storage bags were subsequently used by farmers, insights from own field visits and visit made by Helvetas, suggest that the hermetic storage bags were actively used. In fact, we are not aware of an instance where a treatment farming household chose to store in traditional storage bags instead of the provided hermetic storage bags. The control group farmers did not participate in the intervention, yet they were also not prevented from purchasing hermetic storage bags on the market.

2.2. Measurement

We follow the definition of the Food and Agriculture Organization of the United Nations (2010) that "food insecurity exists when people do not have adequate physical, social or economic access to food" (p.8).[3] We measured food insecurity through the reduced Coping Strategies Index (rCSI) (Maxwell et al., 2008; Maxwell et al., 2014). The rCSI is a 5-item questionnaire that assesses the magnitude of measures taken by households to deal with stresses from food insecurity (Maxwell et al., 2008; see Table A.2 for questionnaire). We chose the rCSI due to its ability to capture short-term changes in food insecurity, which is critical to assessing seasonal fluctuations in food insecurity (Maxwell et al., 2014). The rCSI items include information on eating less expensive or less preferred food, reducing number of meals per day, limiting portion size, restricting consumption by adults in the households, and borrowing food and money from friends and relatives (Maxwell et al., 2008). For each item, respondents indicate the frequency in days over the past 30 days. Standard weights are used according to the severity of these coping strategies (Vaitla et al., 2017, see Table A.2 for details). Thresholds proposed in the literature are used to classify rCSI values into food (in)security categories (Vaitla et al., 2017): a) Food secure or mildly food insecure (rCSI values 0–4), b) Moderately food insecure (5–10), and c) Severely food insecure (> =11). We apply the threshold for severe food insecurity in our analysis. Our results are robust to using alternative thresholds as proposed by Maxwell et al. (2014). Table A.3 presents the respective robustness checks. We rescale the 30-day recall window used in our survey, compared to their 7-days recall window, and use the lower bounds for the thresholds to not underestimate food insecurity. Data for the rCSI was collected on a quarterly basis.

To measure self-reported post-harvest losses (PHL), we adopt the same questions and approach used in Kaminski and Christiaensen (2014) to facilitate comparison with their measurements from 2010 in Tanzania, Malawi and Uganda as part of the World Bank's Living Standard Measurement Survey's (LSMS) agricultural module. The two questions used are (1) "Was any portion of the production lost post-harvest to rotting, insects, rodents, etc?", and if yes, (2) "Out of 10 units of maize, how many were lost?". We restrict our questions to maize as the crop of interest. We used the original questions asked in Swahili, the

[3] This definition builds on the most commonly used definition of food security as adopted at the World Food Summit (1996) which is that "food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life" (Para. 1).

language in our study regions. In contrast to what is specified in Kaminski and Christiaensen, their Swahili version of the question did not include "theft" as one type of losses. Clearly, these post-harvest loss estimates need to be viewed with some caution as the approach is yet to be validated further, e.g. by contrasting self-reported values with actual grain samples, which has not been done so far. However, because our interest mainly lies in comparing differences in self-reported PHL between the experimental conditions, the self-reported PHL are suitable for our purpose. The PHL survey was conducted in October 2018 (Oct Y2).

2.3. Survey methods

All data, including the baseline, were collected through SMS-based mobile phone surveys, an efficient method for collecting data at high frequency, which is essential for variables with seasonal fluctuations and limited recall periods, where information can be remembered with sufficient precision by study participants. This approach also allowed us to collect data within a relatively short time period: in our case, SMS surveys were open for completion for only 5 days, limiting the extent to which short-term fluctuations (e.g. in food insecurity) might lead to inconsistent measurements. Measuring the rCSI, our main outcome variable, via SMS-based mobile phone surveys, has been extensively tested, especially by the United Nations World Food Programme (c.f. Mock et al., 2016; Morrow et al., 2016).

Relative to traditional face-to-face interviews, the cost savings of SMS-based surveys are extremely high, particularly when collecting multiple rounds of panel data in a large and geographically dispersed sample. The phone numbers of survey participants were collected during recruitment of farmer groups. As an incentive for participation and responding to the SMS surveys, respondents received a phone credit (airtime) of 1 USD after completing a survey. Both treatment and control group participants received equal airtime payouts after survey completion. Furthermore, prior research also indicates that response bias, e.g. due to social desirability relating to sensitive questions, is reduced in self-administered surveys, such as SMS-based surveys, where no personal interaction with interviewers exists (c.f. Krumpal, 2013, for an overview).

2.4. Missingness and attrition

Our choice of data collection via SMS-based surveys enables frequent measurement of our main outcome variable (severe food insecurity). Yet, our mode of data collection might result in a higher degree of missing data for a given measurement round relative to what would be expected in traditional face-to-face surveys. If missingness in outcome data is systematically related to potential outcomes, inference may be biased (Gerber and Green, 2012).

We consider these concerns as follows: When outcome data is missing for a whole cluster, the matched-pair design allows us to exclude both, the cluster with the missing data, and the corresponding cluster in the same pair. This procedure precludes the risk of bias regardless of the missing data mechanism (Imai et al., 2009). In this study, we exclude one cluster in Kondoa, where participants ceased to respond to the survey after the initial recruitment. Our full sample therefore consists of 31 matched pairs, i.e. 62 clusters, overall.

However, for missing unit-level (household) data within clusters, list-wise deletion requires the restrictive assumption that data is "missing completely at random" (Blackwell et al., 2017a). Instead, we adopt a more conservative assumption that data is "missing at random" (MAR), i.e. the missing values may depend on observed values in the data but not on unobservables (Blackwell et al., 2017a), and use multiple imputation techniques for missing values. 671 households participated in at least one of the survey rounds and multiple imputation is restricted to this panel. Table A.4 presents response rates for each survey round by experimental group. The average survey response rate was 61% for the control group and 66% for the treatment group. We generate 50 imputations for each of the missing values in the data and rerun all models with these 50 datasets (see Section 2.5). The multiple imputation is implemented with the R-package Amelia II, according to Blackwell et al. (2017a, 2017b). This approach to addressing the problem of missing outcome data in a field experiment is also used, for example, by King et al. (2009). In our analysis, results based on multiple imputation provide more conservative treatment effect estimates compared to list-wise deletion (c.f. Table A.5 and A.6, for comparison).

2.5. Quantities of interest

To analyse treatment effects for the full sample, we calculate the intent-to-treat (ITT) effect for all outcome variables of interest. The ITT is the total effect of the treatment on the outcomes of interest, regardless of experimental compliance (Gerber and Green, 2012), and offers a conservative estimation of the average effect of an intervention to improve on-farm storage. At the same time, the ITT is also the most realistic quantity when it comes to gauging the potential impacts of efforts to promote improved on-farm storage, such as in development programmes and policies where experimental compliance, in most cases, cannot be assured and may not even be desirable.

Given our experimental design, our main specification follows Imai et al. (2009), who derive a point estimator for the ITT as a weighted average of within-pair mean differences between treatment and control groups:

$$\hat{\psi}(w_k) \equiv \frac{1}{\sum_{k=1}^{m} w_k} \sum_{k=1}^{m} w_k \left\{ Z_k \left(\frac{\sum_{i=1}^{n_{1k}} Y_{i1k}}{n_{1k}} - \frac{\sum_{i=1}^{n_{2k}} Y_{i2k}}{n_{2k}} \right) + (1 - Z_k) \left(\frac{\sum_{i=1}^{n_{2k}} Y_{i2k}}{n_{2k}} - \frac{\sum_{i=1}^{n_{1k}} Y_{i1k}}{n_{1k}} \right) \right\}, \tag{1}$$

where the index for pairs is denoted by k, the index for clusters within each pair, and for units within each cluster is denoted by j and i, respectively. The variable Z_k identifies whether the first (Z_k=1) or second cluster (Z_k=0) in each of the m pairs was randomly assigned to treatment. As suggested by Imai et al. (2009), we use arithmetic weights, such that the weight $(w_k) = n_{1k} + n_{2k}$, which corresponds to the sum of the n observations of the two clusters in each pair indexed by k. The variance estimator is given by:

$$\hat{\sigma}(w_k) \equiv \frac{m}{(m-1)n^2} \sum_{k=1}^{m} \left[w_k \left\{ Z_k \left(\frac{\sum_{i=1}^{n_{1k}} Y_{i1k}}{n_{1k}} - \frac{\sum_{i=1}^{n_{2k}} Y_{i2k}}{n_{2k}} \right) + (1 - Z_k) \left(\frac{\sum_{i=1}^{n_{2k}} Y_{i2k}}{n_{2k}} - \frac{\sum_{i=1}^{n_{1k}} Y_{i1k}}{n_{1k}} \right) \right\} - \frac{n\hat{\psi}(w_k)}{m} \right]^2 \tag{2}$$

The estimator is approximately unbiased and does not hinge on modelling assumptions or assumptions about asymptotic properties. Imai et al. (2009) document that their approach is more powerful than other approaches considered. It, however, reflects a simple difference in means and does not control for baseline differences.

Therefore, to account for the observed, albeit statistically insignificant, baseline differences in the prevalence of severe food insecurity (see Table 1), we estimate an Analysis of Covariance (ANCOVA) model.[4] Our choice of using an ANCOVA model, rather than a traditional difference-in-difference estimation reflects the low empirical autocorrelation of the food security measurements between baseline and follow-up rounds. Autocorrelations in our data range between 0.22 and 0.39, which is typical for outcomes of interest in development economics (c.f. McKenzie, 2012). ANCOVA models provide the least biased estimator when baseline differences have little predictive power (i.e., low autocorrelation), as discussed in Frison and Pocock (1992), and further emphasized in McKenzie (2012).

[4] We thank an anonymous referee for suggesting this.

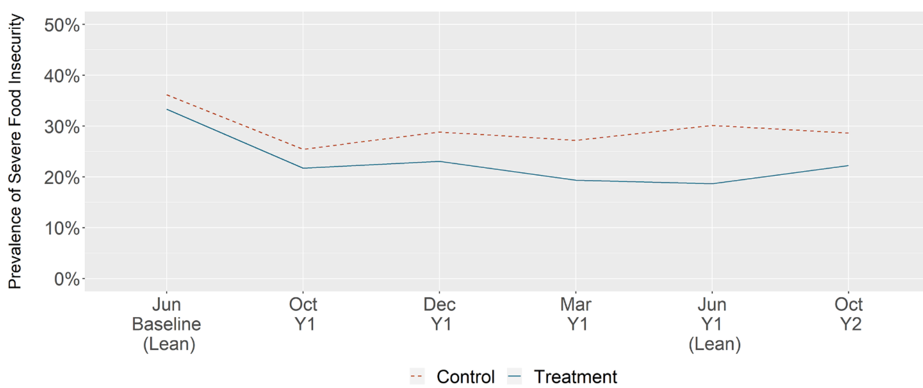

Fig. 2. Comparison of prevalence of severe food insecurity in treatment and control for different seasonal measurements. *Notes:* The horizontal axis indicates measurement points within our observation period. The vertical axis represents the prevalence of severe food insecurity expressed as the percentage of severely food insecure households. Lines based on point estimates according to cluster-level assignment to control (red, dashed lines) or treatment (blue, solid lines). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Effects of improved on-farm storage on the prevalence of severe food insecurity. The dependent variable is the prevalence of severe food insecurity expressed as the percentage of severely food insecure households. Prevalence of severe food insecurity based on threshold (> =11) proposed in Vaitla et al. (2017). ITT = Intent-to-treat. Negative ITT values correspond to favourable outcomes. P-values based on one-tailed *t* test. Sample sizes for pairs (m) and total number of observations (n) (m/n): 31/671.

	(1) Differences in Means			(2) ANCOVA	
	Control Group	ITT	p-value	ITT	p-value
Jun BL (Lean)	36.2	−2.8	0.26	–	–
Oct Y1	25.4	−3.7	0.20	−2.3	0.28
Dec Y1	28.9	−5.8	0.08	−3.9	0.16
Mar Y1	27.2	−7.8	0.03	−7.3	0.04
Jun Y1 (Lean)	30.1	−11.5	0.01	−9.6	0.02
Oct Y2	28.6	−6.4	0.10	−5.4	0.11
Full Season	53.5	−10.9	0.02	–	–

The ANCOVA model is estimated via a least squares regression of the following equation:

$$Y_i = \delta + \gamma TREAT_i + \theta Y_{i,PRE} + \varepsilon_i \quad (3)$$

where Y_i is the outcome of interest for individual i, $Y_{i,PRE}$ is the mean for unit i in the baseline (pre-treatment) survey round, $TREAT_i$ is a dummy variable which takes on one if unit i is assigned to treatment and zero if assigned to control, and δ captures the mean for the control group. The treatment effect (ITT) is then given by γ. We refrain from pooling multiple post-treatment survey rounds in the model, given that a focus of our analysis is on the seasonality of the treatment effect.

3. Results

3.1. Seasonal changes in severe food insecurity and treatment effects

The results show that the experimental treatment reduces the prevalence of severe food insecurity, and that the intent-to-treat (ITT) effect varies with seasonality. For each seasonal measurement, the prevalence of severe food insecurity is calculated as the proportion of households that are severely food insecure at that time.

In the control group, prevalence of severe food insecurity increases relatively steadily after the year's first harvest (Oct Y1), and peaks in the lean season (June Y1), before decreasing again as the year's second harvest has been brought in (Oct Y2, see Fig. 2). The prevalence of severe food insecurity is highest in the lean season when an estimated 30.1% of households in the control group are severely food insecure (June Y1, Table 1). This figure is similar to the estimate of 29.2% for Eastern Africa, reported by the Food and Agriculture Organization of the United Nations, albeit for 2017 and measured only through a 12-month recall period (FAO, 2018).[5] In stark contrast to the control group, in the treatment group severe food insecurity remains stable and slightly decreases after harvest.

Fig. 3 illustrates the seasonal changes in the effects of improved on-farm storage on the prevalence of severe food insecurity. The treatment effect increases after the implementation of the experimental intervention (Oct Y1) and is highest in the lean season (Jun Y1). In the lean season, and in the survey round preceding the lean season measurement (Mar Y1), the treatment led to a statistically significant reduction of the prevalence of severe food insecurity.

3.2. Effects on severe food insecurity in the lean season

Our results show that the experimental intervention reduced the prevalence of severe food insecurity in the lean season. Lean season food insecurity is measured for June (Y1), before the new harvest was brought in. Specifically, the treatment reduced by 38.2% the proportion of severely food insecure households, on average, in the lean season (see Table 1). The effect is statistically significant at the 5% level, with a statistical power[6] of 0.947. As our hypotheses are one-sided (e.g., we test whether improved on-farm storage reduces seasonal food insecurity of smallholder households), we calculate p-values from one-tailed t tests.

The results for the lean season hold up when accounting for differences in the prevalence of severe food insecurity at baseline. Because our baseline survey was conducted prior to random assignment to treatment or control, it is independent of assignment to experimental conditions. The results for the ANCOVA estimations show that the magnitude of the treatment effects remains robust and only changes slightly. While the difference in means ITT for the lean season has shown an 11.5 percentage points reduction in the prevalence of severe food insecurity, the ANCOVA estimation shows an ITT effect of a 9.6 percentage points reduction, which is statistically significant at the 5% level. These results enhance our confidence that the observed ITT effects are very unlikely to be due to pre-existing differences at baseline.

These results remain robust, and statistically significant to the following modifications. Our primary concern relates to the definition of severe food insecurity, where the literature has proposed two different

[5] The Food and Agriculture Organization of the United Nations only reports regionally aggregated values for its Prevalence of Severe Food Insecurity in most cases, including Tanzania.

[6] The approximate power function derived in Imai et al. (2009), indicates that, given the variances in our sample for the lean season measurement, the design allows to identify a treatment effect of 8.75 percentage points with a power of 0.8.

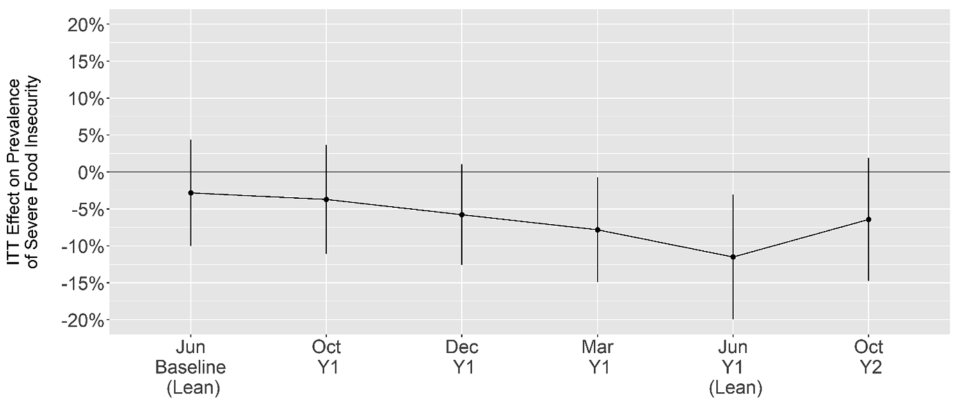

Fig. 3. Effect of cluster-level assignment of improved on-farm storage on the prevalence of severe food security for different seasonal measurements. *Notes:* The horizontal axis indicates measurement points within our observation period. The vertical axis represents, in percentage points, the Intent-to-Treat (ITT) effect on the prevalence of severe food insecurity. Lines based on point estimates according to cluster-level assignment to control or treatment. Vertical bars are 90% confidence intervals, calculated from clustered standard errors.

Table 2
Effects of improved on-farm storage on post-harvest losses. The dependent variable are post-harvest losses (PHL), according to farmer self-assessments. Values are expressed as percentages. The variable "Household incurred PHL" is a binary variable capturing whether farmers had (non-zero) post-harvest losses, and "Household proportion of PHL" captures the percentage of losses incurred by all households. P-values based on one-tailed *t* test. Sample sizes for pairs (m) and total number of observations (n) (m/n): 31/671.

	Control Group	ITT	p-value
Household incurred PHL (binary)	73.7	−11.1	0.01
Household proportion of PHL	30.9	−5.1	0.07

thresholds (see Section 2.2). In our first robustness check, we therefore re-estimate our model with an alternative threshold for severe food insecurity. Compared to the threshold used in our main specification, the value proposed in Maxwell et al. (2014) is higher, which leads to fewer households being categorized as food insecure in each seasonal measurement (see Table A.3). Specifically, 18.4% of the control group are classified as severely food insecure in the lean season. The experimental intervention reduced the proportion of severely food insecure households in the lean season by 7.1 percentage points, which translates into a reduction of 38.6% in the proportion of severely food insecure households in the lean season and compares well to the estimate of the main specification (38.2%). Second, we re-estimate the model based on a panel with complete observations for the outcomes of interest across all survey rounds. The results from this reduced panel, presented in Table A.5, show a similar prevalence of severe food insecurity in the control group in the lean season (31.7%) as in the main specification (30.1%). The estimated ITT effect, however, is slightly higher, indicating a 17.9 percentage points reduction in severe food insecurity. Such an upward bias could be expected without imputation of missing data.

3.3. Food insecurity in the full seasonal cycle

Our results demonstrate that the treatment effects observed for the specific seasonal measurements, peaking in the lean season, also translate into a reduction of the prevalence of severe food insecurity in the full seasonal cycle. We estimate the prevalence for the full seasonal cycle as the percentage of households where at least one out of four seasonal measurements (Oct Y1 until Jun Y1) had values classified as severely food insecure.

In our control group sample, the prevalence of severe food insecurity in the full seasonal cycle is 53.5%, which means that around half of the study population are severely food insecure at least at one point of the full season (see Table 1). The figure is higher than the prevalence of severe food insecurity in the lean season (30.1%). The difference implies that 23% of study households were either not observed during the lean season or not severely food insecure at that time in the lean season, but were observed and food insecure in at least one of the remaining three seasonal measurements.

For the full seasonal cycle, our results show that the intervention reduced by 20.4% the proportion of severely food insecure households, on average. The ITT is statistically significant at the 5% level. Again, these effects are qualitatively and quantitatively robust to the alternative specification of the severe food insecurity threshold. The robustness check suggests that the intervention reduced the proportion of severely food insecure households by 20.0% (see Table A.3). A slightly higher treatment effect is observed for the specification without imputation of missing values where we estimate a reduction of the proportion of severely food insecure households by 29.7% (see Table A.5). In summary, our results imply that the experimental treatment reduced the prevalence of food insecurity in the observation season.

3.4. Effects on post-harvest losses

Our expectation was that improved on-farm storage would lead to reduced post-harvest losses, and hence would enable households to better smooth their food consumption, and, by extension, food security throughout the agricultural season. Our results show that the treatment did effectively reduce post-harvest losses.

We use a farmer self-assessment of post-harvest losses incurred during the seasonal cycle, and follow the methodology used in Kaminski and Christiaensen (2014), which are part of the World Bank's Living Standard Measurement Survey's (LSMS) agricultural module. In our study sample, the majority of control group households (73.7%) incurred (non-zero) post-harvest losses. The proportion of the total maize production that is lost post-harvest is 30.9% for control group households, on average. Our results show that the intervention reduced the probability of incurring post-harvest losses by 11.1 percentage points and reduced the proportion of post-harvest losses by 5.1 percentage points, on average (see Table 2). The effects are statistically significant at the 5% level and 10% level, respectively.

The level of losses incurred are similar to the estimates by Affognon et al. (2015), who report maize post-harvest losses of 25.6%, on average, in Sub-Saharan Africa. Yet, they are well above the estimates of Kaminski and Christiaensen (2014) who estimate post-harvest losses of between 1.9% and 3.8% for a nationally representative household in Tanzania. While the latter study uses the same survey items as we use here, the former is a meta-analysis of loss estimates based on grain samples.

Our results remain robust when only complete observations for the post-harvest loss survey round (Oct Y2) are included in the estimation model (see Table A.6). The robustness check shows that the intervention reduced the probability of incurring post-harvest losses by 12.7 percentage points and the proportion of post-harvest losses by 4.5 percentage points, on average.

4. Discussion and conclusion

Current efforts to attain the 2030 Agenda for Sustainable Development goal of ending hunger prioritize increases in agricultural production, whereas post-harvest losses have received much less attention (Kitinoja et al., 2011). Our results suggest that improved on-farm storage substantially reduces the proportion of seasonally food insecure smallholder households. Such positive impacts on food security have rarely been documented in prior research on agricultural production interventions. Positive food security effects have thus far been documented for the provision of improved seeds (mainly orange-fleshed sweet potatoes) as shown in a meta-analysis for Sub-Saharan Africa (Stewart et al., 2015). Our results thus highlight the need for greater consideration of improved on-farm storage as a means for reducing severe food insecurity. Our findings further suggest that seasonal food insecurity problems require more attention, both in research and on the ground. While this is often challenging for researchers due to the high costs of multiple rounds of data collection, the approach used in this paper – SMS-based mobile phone surveys – turned out to be very cost-efficient.

Our results further suggest that promoting the adoption of improved on-farm storage can provide substantial food security benefits for smallholder farmers. Our design, however, estimates joint effects of the provision of the improved on-farm storage technology and training in improved on-farm storage. Disentangling the effects of the technology component from the knowledge and awareness component (training) would be beneficial to further inform policies and programmes that aim to promote the adoption of improved on-farm storage. Specifically, the conditions under which knowledge and awareness creation leads to subsequent adoption of hermetic storage bags as a low-cost storage technology[7], is an avenue for further research.

Prior research has produced contradictory results regarding levels of post-harvest losses, especially when comparing farmer self-reported information with losses measured based on grain samples (c.f. Affognon et al., 2015; Kaminski and Christiaensen, 2014). This divergence in findings led Christiaensen and Demery (2017) to add a cautionary note about the gains from better post-harvest handling, such as improved on-farm storage. Clearly, measurement of post-harvest losses, including the self-reported measurements used in our study, come with limitations. An important concern relates to the extent that farmers actually provide realistic self-assessments on proportions of post-harvest losses. A particular concern in this regard is that higher awareness and better knowledge about post-harvest losses, which is the aim of the trainings provided as part of the experimental intervention in this study, may influence perceptions and therefore bias reported proportions of post-harvest losses. Such considerations certainly merit further research. These limitations notwithstanding, our results, which adopt the methodology suggested in Kaminski and Christiaensen (2014), indicate that post-harvest losses in our study population are substantial, and much higher than estimates for the national maize harvest in Tanzania, based on nationally representative surveys. While some part of this difference can certainly be attributed to sample selection, it also raises questions about the external validity of our results. While generalizability is, of course, a common issue with all location-specific field experiments in the natural and social sciences, it will be important to use similar study designs to examine the effects of improved on-farm storage on food security in other areas of Tanzania as well as other countries in Sub-Saharan Africa and elsewhere. It would also be very interesting to expand the focus of such research to analyse whether food security outcomes depend on farm and household characteristics. Such detailed sub-group analysis would be feasible given sufficient sample size. Additionally, future research could extend the outcomes analysed to include poverty levels as well as nutritional and health outcomes.

These limitations notwithstanding, our findings show that a simple and inexpensive intervention to improve on-farm storage could contribute strongly to reducing seasonal food insecurity and improving smallholder farmers' year-round access to food. We hence hope that our study, which is the first RCT in a Sub-Saharan African country to look into the effects of improved on-farm storage on seasonal food security, paves the way for more research in this area. Such research can contribute in important ways to the larger debate on how to achieve the 2030 Agenda goal of ending hunger, and how much should be invested into reducing post-harvest losses, in addition to measures focusing on increasing food production.

CRediT authorship contribution statement

Michael Brander: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing, Visualization, Funding acquisition. **Thomas Bernauer:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Supervision. **Matthias Huss:** Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition.

[7] In most Sub-Saharan African countries, hermetic storage bags can be purchased for around 2–2.5 US Dollars per bag.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

See Tables A.1–A.6.

Table A.1
Balance of baseline characteristics between experimental groups. Table shows a comparison of baseline characteristics in experimental groups in the full study sample. Study districts (Kilosa and Kondoa) and the variable indicating median distance to market (measured as the time it takes respondents to walk to their market) were used for pair-wise matching. Baseline values and a test on the differences in means of the prevalence of food insecurity are reported in Table 1.

	Number of Households	Number of Groups	Mean Group Size	Percentage of Participants in Kilosa District	Percentage of Male Participants	Median Distance to Market
Control	321	31	10.35	51.71	55.33	68.25
Treatment	350	31	11.29	49.14	43.11	62.98

Table A.2
Items for the reduced Coping Strategies Index (rCSI) and respective weights as implemented via SMS-based mobile phone surveys. Question items and weights according to Vaitla et al. (2017).

#	Category	Question	Item Weight
1	Introduction	For the next 5 questions reply only with the number of days your household took action because there was not enough food or money to buy food. Reply 1 to continue	
2	Less Expensive Food	In the past 30 days, how many days did your household rely on less preferred or less expensive food due to lack of food/money? Reply number of days 0–30	1
3	Borrow and Get Help	In the past 30 days, how many days did your household borrow food or rely on help from a friend or relative due to lack of food/money? Reply number of days 0–30	2
4	Reduce Number of Meals	In the past 30 days, how many days did your household reduce the number of meals eaten in a day due to lack of food/money? Reply number of days 0–30	1
5	Limit Portion Size	In the past 30 days, how many days did your household limit portion sizes at mealtime due to lack of food/money? Reply number of days 0–30	1
6	Restrict Consumption	In the past 30 days, how many days did your household restrict consumption by adults so children could eat due to lack of food/money? Reply number of days 0–30	3

Table A.3
Robustness check for the effects of improved on-farm storage on the prevalence of severe food insecurity (alternative food insecurity threshold). The dependent variable is the prevalence of severe food insecurity expressed as the percentage of severely food insecure households. Prevalence of severe food insecurity based on alternative threshold (> 18) proposed in Maxwell et al. (2014). ITT = Intent-to-treat. Negative ITT values correspond to favourable outcomes. P-values based on one-tailed t test. Sample sizes for pairs (m) and total number of observations (n) (m/n): 31/671.

	(1) Differences in Means			(2) ANCOVA	
	Control Group	ITT	p-value	ITT	p-value
Jun BL (Lean)	21.3	−2.3	0.27	–	–
Oct Y1	14.2	−1.9	0.28	−0.9	0.39
Dec Y1	16.7	−3.2	0.19	−1.8	0.30
Mar Y1	15.8	−5.8	0.04	−4.6	0.07
Jun Y1 (Lean)	18.4	−7.1	0.02	−5.6	0.04
Oct Y2	16.3	−1.2	0.39	0.0	0.50
Full Season	36.5	−7.3	0.07	–	–

Table A.4
Response rates to the SMS surveys. Table shows survey completion rates for all survey rounds in the full sample. Completion rate is expressed as the percentage of participants that completed each round of SMS-based mobile phone surveys. Number of participants shows the total number of participants by experimental group and study districts to have participated in at least one of the survey rounds. In October Y2, two separate SMS survey rounds were conducted: reduced Coping Strategies Index (rCSI), and post-harvest losses (PHL).

	Full Time Period		Baseline and Seasonal Survey Rounds						
	Number of Participants	Mean Completion Rate	Jun BL (Lean)	Oct Y1	Dec Y1	Mar Y1	Jun Y1 (Lean)	Oct Y2 (rCSI)	Oct Y2 (PHL)
Control	321	61.33	60.75	61.37	56.07	61.37	51.40	68.85	69.47
Treatment	350	66.04	60.00	70.00	63.43	71.14	55.43	69.14	73.14

Table A.5
Effects of improved on-farm storage on the prevalence of severe food insecurity (panel restricted to complete observations). The dependent variable is the prevalence of severe food insecurity expressed as the percentage of severely food insecure households. Prevalence is based on the main threshold for severe food insecurity used in this study (> =11, see Section 2.2). Data is confined to households that completed all survey rounds in the seasonal cycle (Oct Y1 – Jun Y2). ITT = Intent-to-treat. Negative ITT values correspond to favourable outcomes. P-values based on one-tailed *t* test. Sample sizes for pairs (m) and total number of observations (n) (m/n): 25/215.

	(1) Differences in Means			(2) ANCOVA	
	Control Group	ITT	p-value	ITT	p-value
Jun BL (Lean)	32.7	4.0	0.30	–	–
Oct Y1	23.3	−3.0	0.35	−3.1	0.29
Dec Y1	27.8	−5.2	0.21	−4.8	0.19
Mar Y1	24.3	−5.8	0.17	−5.9	0.15
Jun Y1 (Lean)	31.7	−17.9	0.02	−13.6	0.01
Oct Y2	24.7	−5.5	0.24	−3.0	0.31
Full Season	42.4	−12.6	0.05	–	–

Table A.6
Effects of improved on-farm storage on post-harvest losses (panel restricted to complete observations). The dependent variable are post-harvest losses (PHL), according to farmer self-assessments. Values are expressed as percentages. Data is confined to households that completed the post-harvest losses survey round (Oct Y2). The variable “Household incurred PHL” is a binary variable capturing whether farmers had (non-zero) post-harvest losses, and “Household proportion of PHL” captures the percentage of losses incurred by all households. Sample sizes for pairs (m) and total number of observations (n) (m/n): 31/479.

	Control Group	ITT	p-value
Household incurred PHL (binary)	76.3	−12.7	0.00
Household proportion of PHL	31.3	−4.5	0.09

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