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Improved storage mitigates vulnerability to food-supply shocks in smallholder agriculture during the COVID-19 pandemic

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ABSTRACT

Millions of smallholder farmers in low-income countries are highly vulnerable to food-supply shocks, and reducing this vulnerability remains challenging in view of climatic changes. Restrictions to limit the spread of the COVID-19 pandemic produced a severe supply-side shock in rural areas of Sub-Saharan Africa, including through frictions in agricultural markets. We use a large-scale field experiment to examine the effects of improved on-farm storage on household food security during COVID-19 restrictions. Based on text message survey data we find that the prevalence of food insecurity increased in control group households during COVID-19 restrictions (coinciding with the agricultural lean season). In treatment households, equipped with an improved on-farm storage technology and training in its use, food insecurity was lower during COVID-19 restrictions. This underscores the benefits of improved on-farm storage for mitigating vulnerability to food-supply shocks. These insights are relevant for the larger, long-term question of climate change adaptation, and also regarding trade-offs between public health protection and food security.

1. Introduction

When COVID-19 started spreading globally in early 2020, many countries responded with severe restrictions to protect public health (Weible et al., 2020). Such restrictions are likely to have adverse food security effects particularly in low-income countries. In Sub-Saharan Africa (SSA), which had the highest prevalence of food insecurity even before COVID-19 (FAO et al., 2020), COVID-19 related restrictions are expected to aggravate already high levels of food insecurity (Barrett, 2020; Food Security Information Network, 2020), though empirical evidence on such effects remains scarce.

COVID-19 restrictions are paramount to a severe, unfamiliar (to farmers), and completely unexpected shock in the food supply system. Prior to COVID-19, farmers in large parts of SSA, except for areas previously affected by the Ebola virus disease, were unfamiliar with policy interventions that aim to curb the spread of an infectious disease. Movement restrictions, for example, disrupt local agricultural markets and labor supply for agricultural production and processing, and school closures cause school feeding programmes to cease (Food Security Information Network, 2020). In addition to poor urban households, which have received the most attention in this context, smallholder farming households are, presumably, also highly vulnerable to sudden food supply shocks (Frelat et al., 2015; IPCC, 2014). Smallholder farmers are the backbone of food production in SSA (Torero, 2020). Although smallholder farms are usually less than 2 ha in size, they account for the largest share of food production (Frelat et al., 2015) and are thus critical to food security in SSA (Herrero et al., 2010).

Smallholders' food stocks could, potentially, mitigate various types of food supply shocks, such as those emanating from a bad harvest, or COVID-19 restrictions. However, high storage losses make holding food stocks over extended periods of time unattractive. Losses gradually increase with time and are estimated at 25.6% of the maize production in the region on average, in the absence of suitable storage technologies (Affognon et al., 2015, c.f. also African Postharvest Losses Information System (APHLIS), 2020, for detailed data across regions, crops, and years).

Reducing storage losses could allow smallholders to store their harvest longer, which would increase quantities available for consumption

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by households and communities. Higher stock levels may help farmers to prepare for expected, periodic scarcities, such as the agricultural lean season, and also contribute to mitigating (unpredictable) supply shocks. In the lean season, which is the time shortly before a new harvest is brought in, food insecurity often increases as smallholder's own food stocks are depleted, and rising food prices limit access to food on markets (Kaminski et al., 2016). Improved on-farm storage has been shown to reduce lean season food insecurity among smallholder farmers in Tanzania (Brander et al., 2020), yet little is known about its potential to limit the adverse food security effects of a severe aggregate food security shock.

To assess the potential of a simple and cheap technology to this end, hermetic storage bags, we build on a large field experiment (randomized control trial) in Kakamega county, Western Kenya, which we initiated in September 2019. The study region is typical for many rural areas in SSA, which are characterized by smallholder farming and where the rural population is vulnerable to climate change related shocks to staple food production (maize). The experimental intervention consisted of low-cost hermetic storage bags that minimize storage losses (Likhayo et al., 2016; Ndegwa et al., 2016), as compared to polypropylene bags used by the vast majority of smallholder farmers. For example, evidence from on-farm trials in Kenya shows that maize stored in common polypropylene bags without chemical protectants was associated with losses of around 2.6–2.8% after 3 months of storage, 10–15% after 6 months of storage, and 30% after 9 months of storage (Likhayo et al., 2016). In contrast, maize stored in hermetic storage bags incurred losses of only 0.5–1.8% after 9 months of storage (Ndegwa et al., 2016). Hermetic storage limits atmospheric oxygen, thus causing desiccation of insects and other pests that damage stored grains (Murdock et al., 2012) and restricts fungal growth (Williams et al., 2014), when appropriately used. However, adoption rates of this technology are still very low, including in our study region (Channa et al., 2019).

The COVID-19 crisis and the ensuing lockdown in Kenya beginning in mid-March 2020 came completely unexpected, both to the farmers in our experiment and the research team. It thus created conditions for a quasi-experiment, where we can examine food-security outcomes not only in response to a randomly allocated treatment condition (hermetic storage bags), but also assess how the treatment performs (relative to control) under conditions of a severe food security shock. Specifically, we collected monthly data on household food insecurity for a full harvest cycle covering the time between the main harvest preceding and succeeding the start of COVID-19 restrictions.

2. COVID-19 restrictions in Kenya

In Kenya, the first set of COVID-19 restrictions were imposed on 16 March 2020 (Coronavirus, 2020). In a first stage, these restrictions included measures to limit or prohibit social events, international travel, and the closing of schools. These restrictions were quickly followed by a "dusk-to-dawn curfew" (7 pm to 5 am), which was effective from 25 March, and the cessation of movement in and out of metropolitan areas (including Nairobi and Mombasa) as of 8 April. These tight lockdown measures were gradually eased after 6 July 2020. Until this date, only a few selective measures had been relaxed (e.g. on 6 June, curfew hours were adjusted to 9pm-4am) and some variation existed in terms of the counties affected by a cessation of movement order.

For smallholder farming households in Kakamega county, the imposed restrictions had tangible effects on daily life. Farmers pointed out in focus group discussions that agricultural markets were severely distorted, inhibiting farmers from selling surplus stocks and limiting their ability to purchase food on the markets. Although agricultural markets were, in principle, allowed to operate, market stalls were obliged to ensure social distancing and hygiene standards, and many market participants were unable to meet those requirements (e.g. if masks or hand sanitizer were unavailable or social distancing simply not feasible). This in turn prompted authorities to close many market stalls. Additionally, movement restrictions, in particular the nightly curfew, had effects on agricultural trading routes for market participants who were unable to return home by the time of the curfew. Furthermore, conditional on the type of schools their children were supposed to attend, some families reported that the closing of schools implied that children missed out on school meals. Finally, several farmers also mentioned that they were anxious to go to the markets, especially at the beginning of COVID-19 restrictions, and decided to stay home. Taken together, COVID-19 restrictions had strong effects on the daily lives of smallholder farmers, which plausibly affected their household's food security situation.

3. Methods

To analyze the effects of an improved on-farm storage intervention on smallholder farming household's food security during COVID-19 restrictions, we build on a matched-pair, cluster randomized control trial (RCT).

3.1. Setting

Our RCT is undertaken with a representative sample of farmer groups in Kakamega county, Western Kenya. The study region is typical for many areas in SSA, characterized by smallholder farming with high agricultural production potential, yet prevailing food insecurity and poverty. In Kakamega, maize is the staple food and the predominant sales crop. Geographically, all of Kakamega's 12 sub-counties and 59 out of 60 wards are covered by our study. Our sample of farmer groups was randomly selected from a census list of farmer groups in Kakamega, which we established in collaboration with local authorities. Supplementary Fig. 1 provides a map of the study region and farmer group locations. The study was approved by the ETH Zurich Ethics Commission (EK, 2018-N-51) and *icipe's* Science Committee (no approval number used). The study design is registered in the American Economic Association (AEA) RCT Registry (Huss et al., 2020).

3.2. Experimental design

We used a matched-pair, cluster-randomization design, as suggested by Imai et al. (2009), who show that from the perspective of efficiency, power, bias, and robustness, pairing should be done whenever feasible. Baseline variables were used for pair-wise matching; specifically, food security, the fraction of female participants in clusters, cluster size, mean maize yield and mean market distance (Bruhn and McKenzie, 2009). To minimize spillover effects from treatment to control groups, random allocation was done at the level of spatial clusters of farmer groups, applying a 5 km geographic radius. Spatial clustering resulted in 62 experimental clusters, consisting of a total of 285 farmer groups (5′444 smallholder households). 3′220 smallholder households participated in surveys during the observation period for this analysis. Supplementary Table 1 presents the sample characteristics. The table shows that treatment and control group baseline characteristics do not substantially differ in the sample used in this study, i.e. the measurement rounds before and after COVID-19 restrictions (Panel A). Likewise, when comparing the sample used here with a sample of participants who were originally recruited but did not respond to the survey rounds before and after COVID-19 restrictions (Panel B), we do not find substantial differences in baseline characteristics. A notable exception from these findings are female-headed households, which participated to a slightly lesser extent in the survey rounds before and after COVID-19 restrictions (see also Discussion section).

3.3. Improved on-farm storage intervention

The intervention for treatment clusters consisted of five hermetic storage bags per household, with a capacity of 100kg of maize per bag, and a standardized training session on their use. The hermetic bags were sourced in a competitive process according to the procurement rules of ETH Zurich. The bag selected was of the brand "AgroZ". The training session was developed by the authors, based on materials provided by the UN World Food Programme. The interventions were implemented from 3 to 15 September 2019 by *icipe*.

3.4. Measurement

The RCT as a whole focuses on a variety of outcomes presumably affected by the experimental intervention, primarily food security and associated health outcomes (Huss et al., 2020). The analysis in this paper focuses on self-assessed food security. We measured self-assessed food security via the reduced Coping Strategies Index (rCSI) (Maxwell et al., 2008, 2014). The rCSI, a 5-item questionnaire, assesses the magnitude of measures taken by households to deal with food insecurity problems and tracks short-term fluctuations in food insecurity (Vaitla et al., 2017) (see Supplementary Table 2 for details). We applied standard thresholds (Vaitla et al., 2017) to classify rCSI values into food (in)security categories, using the threshold for food insecurity ($\geq$5). Supplementary Table 3 shows the results of a robustness check applying an alternative threshold value for food security (Maxwell et al., 2014). As we used a 30-day recall period in our surveys, whereas the threshold values are provided for 7-day recall windows, we rescaled our rCSI values accordingly. The choice of a 30-day recall period reflects the frequency of our data collection (monthly) and the benefits of an uninterrupted and continuous measurement of household food security in the observation period. While we acknowledge that a longer recall period comes with a potential disadvantage in terms of the reliability of our measurement at a specific point in time, our choice also reduces the extent to which short-term changes (e.g. daily) could bias our analysis.

3.5. Survey methods

Data was collected through SMS-based mobile phone surveys, an efficient and effective method to collect data at high frequency in our study area. Supplementary Table 4 shows the dates of all survey rounds. Of specific interest are the survey rounds just before and after the start of COVID-19 restrictions in Kenya. The survey round measuring food insecurity before COVID-19 restrictions was sent out on 14 March 2020 at 1pm (Eastern African Time) and was open for completion until 18 March at 3am. The follow-up survey, conducted after COVID-19 restrictions, was sent out on 11 April 2020 at 1pm and was open for completion until 16 April at 3am. Respondents received a phone credit (airtime), valued at 20 Kenyan Shilling, upon completion of a survey. All survey participants received equal airtime incentives, irrespective of experimental assignment or answers.

To facilitate the interpretation of the empirical results presented in this paper, the research team organized a series of focus group discussions with five different farmer groups in October 2020. The focus of these discussions was to explore the extent to which COVID-19 restrictions affected farmer's lives, what kind of expectations farmers had at different stages of the pandemic, and the kind of coping strategies farmers engaged in to mitigate adverse effects.

3.6. Statistical analysis

The intent-to-treat (ITT) effect, i.e., the total effect of the treatment on outcomes of interest, irrespective of experimental compliance (Gerber and Green, 2012), was estimated as the weighted average of within-pair mean differences between treatment and control clusters (Imai et al., 2009). We use arithmetic weights $(w_k) = n_{1k} + n_{2k}$, which is the sum of the n observations in both clusters of each pair indexed by k, as suggested in Imai et al. (2009). To control for potential differences between experimental groups before COVID-19 restrictions were enacted, we further estimate the ITT effect based on household differences between our measurements immediately before and after COVID-19 restrictions (King et al., 2009).

4. Results

Our results show that the prevalence of food insecurity increased in control group households during COVID-19 restrictions and the contemporaneous agricultural lean season. In treatment households, equipped with an improved on-farm storage technology and training in its use, food insecurity was lower during COVID-19 restrictions.

4.1. Sharp increase in food insecurity following COVID-19 restrictions

In our control group households, the prevalence of food insecurity was relatively stable prior to the COVID-19 crisis (see Fig. 1), i.e. between the main maize harvest in 2019 (around October 2019) and the start of Kenyan COVID-19 restrictions (mid-March 2020). In the 30 days immediately before the implementation of COVID-19 restrictions, 40.8% of households were food insecure. However, within 30 days of COVID-19 restrictions, the prevalence of food insecurity increased significantly by 8 percentage points (or 19.6%) to 48.8%. This increase amounts to a sudden change in the prevalence of food insecurity as compared to prior months (see Fig. 1). The prevalence of food insecurity among control group households subsequently remained at elevated levels until July. The food security situation then improved as COVID-19 restrictions in Kenya were eased and the agricultural lean season ended with the new main harvest around September 2020. Taken together, our results suggest a strong food security shock to which smallholder households were exposed during the COVID-19 pandemic (see also the Discussion section). Equally interesting, however, are our findings for the treatment group.

4.2. On-farm storage mitigates food security shock during COVID-19 restrictions

In contrast to our control group households, the prevalence of food insecurity among treatment households increased only slightly in the 30 days immediately following COVID-19 restrictions. Among treatment households, 39.5% of households were food insecure in the 30 days before COVID-19 restrictions (see Table 1). Within 30 days of COVID-19 restrictions, this prevalence increased by 3.7 percentage points (or 9.4%) to 43.2%, which is significantly less relative to the control group. To examine whether the experimental intervention (improved storage) affected the change in the prevalence of food insecurity before and after COVID-19 restrictions, we additionally estimate the treatment effect based on household differences between the two measurement rounds (King et al., 2009). We find that the experimental intervention mitigated parts of the increase in food insecurity observed immediately following COVID restrictions (see Table 1).

In subsequent months, food insecurity remained lower relative to control, albeit not significantly so in all measurement rounds (see Fig. 2 and Supplementary Table 4). In treatment households the initial food security shock observed during the COVID-19 pandemic was strongly buffered, whereas the effect was smaller in the subsequent period of prolonged food security stress (see Fig. 3). This latter finding may be explained by farmers' expectations on the duration of the restriction (see the Discussion section for details).

To illustrate the substantive meaning of our results, we extrapolate our findings to all smallholder households in the county of our study (an estimated 1.62 million people, with 90% of households growing maize, the staple crop we focus on; Ministry of Agriculture, Livestock and Fisheries, 2017). Given that our sample was drawn from a census list of farmer groups in the county, it is reasonable to assume these households are very similar in nature to the households in our sample, which implies that approximately 595′000 people would have been food insecure in the 30 days before COVID-19 restrictions. The number of food-insecure

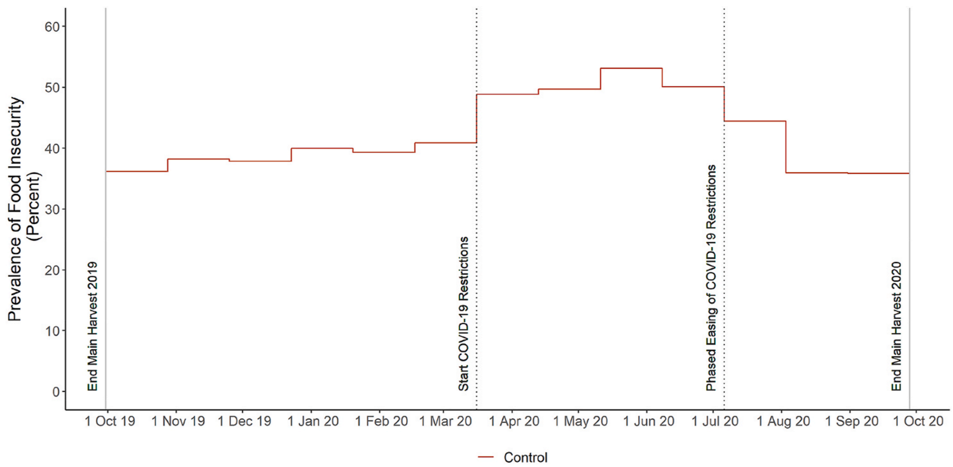

Fig. 1. Prevalence of food insecurity in control group households before and after COVID-19 restrictions.

The figure shows the prevalence of household food insecurity, as measured by the reduced Coping Strategies Index (rCSI) with a 30-day recall period for each survey round. Prevalence is calculated based on the weighted mean of all observations per survey round in the control group (for weights used, refer to section 3.6). Lines show the prevalence of food insecurity, i.e., the percentage of food-insecure households for each 30-day period. The dotted vertical lines represent the start (16 March, 2020) and easing of COVID-19 restrictions in Kenya (6 July, 2020). The average number of observations per survey round (control group only) is 1′077 (total number of observations in control group is 14′007 observations; see Supplementary Table 4 for details on number of observations for each survey round).

Table 1

Effects of improved on-farm storage on the prevalence of food insecurity in the 30 days before and after the start of COVID-19 restrictions.

	Control	ITT	CI lo	CI up	*P* value	*m/n/n0/n1*
Pre COVID-19	40,83	−1,35	−5,25	2,76	0,508	36/2453/1061/1392
Post COVID-19	48,82	−5,59	−9,56	−1,87	0,005	36/2494/1081/1413
Difference-in-Difference	6,60	−3,74	−7,71	0,29	0,069	36/2279/979/1300

The table presents the effects of improved on-farm storage on the prevalence of food insecurity, which is expressed as the percentage of food-insecure households, as measured for the 30 days before and after the start of COVID-19 restrictions. Prevalence for food insecurity based on standard threshold (≥5) (Vaitla et al., 2017). ITT=Intent-to-treat. Negative ITT values correspond to favorable outcomes. CI show 95% bootstrapped confidence intervals, lower (lo) and upper (up). *P* values based on non-parametric two-tailed t tests. The bootstrap is based on 1000 replications. Sample sizes by number of pairs (m), total number of observations (n), and number of observations in control (n0) and treatment conditions (n1) are reported in the last column.

people would then have increased by an estimated 117′000 people if none of the households had received the five hermetic storage bags and training in their use. In contrast, the number of food-insecure people would have increased only by 54′000 people in the 30 days following COVID-19 restrictions if all households had access to hermetic storage.

5. Discussion

In this paper, we examined the effects of an improved on-farm storage technology (hermetic storage bags and training in their use) on smallholder household food security during the COVID-19 pandemic. The findings show that food insecurity suddenly increased after the implementation of COVID-19 restrictions, but that the experimental intervention significantly curbed this increase. The ITT we find is of comparable magnitude to the effects of direct cash transfers to smallholder farmers reported by (Banerjee et al., 2020). Their experiment was implemented in a neighbouring county of Western Kenya, where smallholders were provided with either 0.75 USD per day (for 2 years prior to the pandemic) or 500 USD as lump-sum payment. The authors find that cash transfer recipients were 4.9 to 10.8 percentage points less likely to report experiencing hunger during the COVID-19 pandemic (control mean: 68%), as measured via phone surveys between late April and late June 2020. These food security benefits are similar to what we have reported here, yet the costs of the cash transfer interventions are

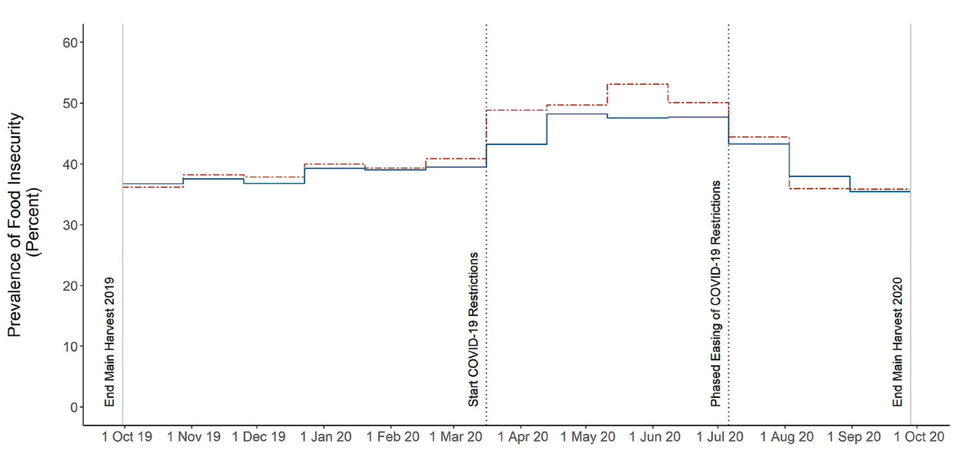

Fig. 2. Prevalence of food insecurity in treatment and control group households before and after COVID-19 restrictions.

The figure shows the prevalence of household food insecurity, as measured by the reduced Coping Strategies Index (rCSI) with a 30-day recall period for each survey round. Prevalence is calculated based on the weighted mean of all observations per survey round in the control group (for weights, refer to section 3.6). Lines show the prevalence of food insecurity, i.e., the percentage of food-insecure households for each 30-day period, for households randomly allocated to control (solid, red line) and treatment (dashed, blue line). The dotted vertical lines represent the start (16 March, 2020) and easing of COVID-19 restrictions in Kenya (6 July, 2020). The average number of observations per survey round (treatment and control group combined) is 2′474 (total number of observations is 32′168; see Supplementary Table 4 for details on number of observations for each survey round).

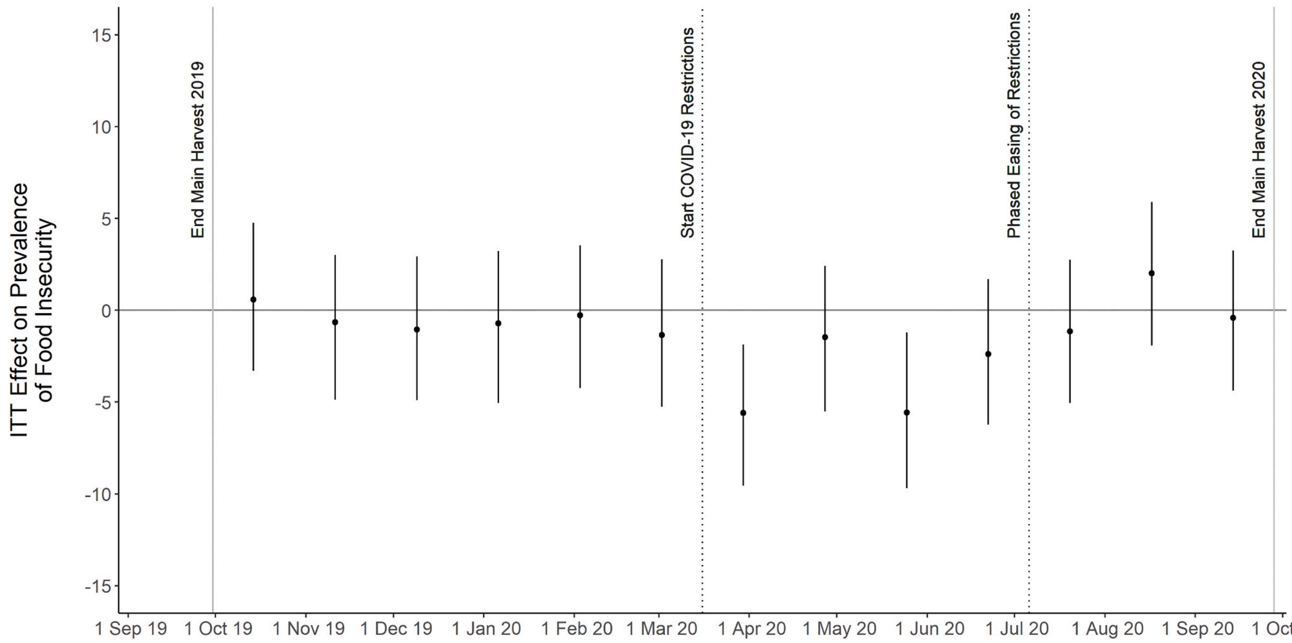

Fig. 3. Effect of cluster-level assignment to treatment and control on the prevalence of food insecurity.
The figure shows changes and intent-to-treat (ITT) effects on the prevalence of food insecurity. Points show the estimated ITT effects on the prevalence of food insecurity in each monthly survey round. Vertical bars are 95% bootstrapped confidence intervals. The dotted vertical lines represent the start (16 March, 2020) and easing of COVID-19 restrictions in Kenya (6 July, 2020). The average number of observations per survey round is 2′474 (total number of observations is 32′168 observations; see Supplementary Table 4 for details on number of observations for each survey round).

substantially higher compared to our intervention where the provision of hermetic storage bags and training in their use incurred costs of about 20 USD per household.

Our results further suggest that the intervention was more effective in buffering the food supply shocks that occurred early in the COVID-19 pandemic, whereas the subsequent food security stress was curtailed by a lesser extent. These results may reflect smallholder households' expectations on the duration of COVID-19 restrictions. At the outset, COVID-19 restrictions were announced to be in place for 30 days (Coronavirus: Kenya introduces tight restrictions, 2020). Our results are consistent with smallholder farmers initially expecting the COVID-19 restrictions to be lifted quickly. Subsequently, as restrictions were extended, farmers became more worried and anticipated that COVID-19 restrictions would remain for longer periods of time. Our results may hence reflect a situation where smallholder farmers, on average, used additional food stocks (enabled through improved on-farm storage) to safeguard against the first short-term shock, but had limited stocks left to fully buffer a prolonged period of COVID-19 restrictions and the gradually increasing lean season food stress. These interpretations are substantiated by farmers' statements in our focus group discussions. Interestingly, farmers also mentioned during the discussions that they had adapted their initial expectations afterwards. The perception of a substantial number of households was that if a second lockdown became necessary, potentially due to a second COVID-19 wave, it may be implemented for a significantly longer period. This consideration already prompted many families to adjust both their consumption and storage behavior regarding the recent harvest, as farmers indicated during the discussions.

Our study analyzes the effects of an experimental intervention during a period of increased food insecurity that coincided with COVID-19 restrictions. Hence we are unable to completely disentangle the relative contribution of COVID-19 restrictions to the observed increase in food insecurity from other factors, in particular the agricultural lean season, which are also likely to have affected household food insecurity at the same time. For several reasons, we are, however, confident that COVID-19 restrictions contributed, at least partially, to increased food insecurity. First, the prevalence of food insecurity in control group households increased suddenly in the 30 days immediately following COVID-19 restrictions. If these effects were due to the agricultural lean season, which is a predictable and familiar shock, we would expect a more gradual increase in food insecurity over time. Second, in our study area, the lean season typically begins later in the harvest year, namely in April or May (Burke et al., 2019), as farmers bring in another smaller (secondary) harvest around January or February. Third, no other major events (apart from the lean season) occurred during COVID-19 restrictions that could explain the sudden increase in food insecurity. While other areas in Kenya experienced severe problems with desert locust in the observation period (Roussi, 2020), our study area was not affected. With movement restrictions in place, and locust outbreaks primarily having affected pastoralist areas, spillover effects on food insecurity in our study region from affected areas elsewhere are unlikely. Taken together, we consider it likely that the observed increase in food insecurity in the first 30 days of COVID-19 restrictions was primarily due to this policy intervention. It is still possible that agricultural seasonality amplified food insecurity to some extent afterwards, as COVID-19 restrictions progressed. However, this does not undermine our main finding that treated households experienced a smaller increase in food insecurity under conditions where both treatment and control households experienced a food supply shock that appears to have been aggravated by COVID-19 restrictions at a time (lean season) where households often have a higher risk of food insecurity.

Our study uses SMS-based surveys, collected with a monthly frequency, over the duration of one full harvest cycle during which the COVID-19 restrictions occurred. SMS-based surveys allowed us to collect a continuous dataset uninterrupted by COVID-19 restrictions. However, given the self-assessed nature of our food security measure, there could be a concern that recipients strategically responded to the surveys in order to elicit support during the COVID-19 pandemic. If such bias were systematically different between experimental conditions, it would bias our ITT estimates. We consider the risk of a systematic response bias limited. Prior research has shown that response bias is reduced in self-administrated surveys (such as SMS-based surveys) as compared to face-to-face interviews due to the lack of personal interaction between respondents and interviewers (Krumpal, 2013). Furthermore, participants were informed that all data collection is kept separate from the team conducting the intervention, limiting incentives for strategic responses (e.g. households overreporting food insecurity to obtain more government or NGO support). Related to our measure of food insecurity, we consider that the literature has proposed two different thresholds to classify households in food insecurity categories (see Section 2.4), and hence re-estimate our model with the alternative threshold proposed in Maxwell (2014). We find that the substantive results remain very similar; the experimental treatment reduced (significantly) the prevalence of food-insecure households following COVID-19 restrictions (see Supplementary Table 3).

Another potential issue is whether our data collection mode (SMS-based surveys) may have affected the balance between treatment and control group characteristics (covariates). However, Supplementary Table 1 (Panel A) shows that baseline characteristics of the treatment group does not substantially differ from the characteristics of the control group in the sample used in this study, i.e. in the SMS-based survey rounds before and after COVID-19 restrictions. Furthermore, also when comparing the sample used here with a sample of participants who were originally recruited but did not respond in any survey round in our observation period, we find that baseline characteristics are remarkably similar (Supplementary Table 1, Panel B). The only notable exception is that female-headed households appeared less likely to participate in any of our survey rounds in our observation period, but that applies to both treatment and control group households alike, which limits the risk of bias in our treatment effect estimates. However, female-headed households have been shown to be on average more strongly affected by food insecurity (Kassie et al., 2014) and more vulnerable to sudden food system shocks (Kumar and Quisumbing, 2013), and the increase in food insecurity during COVID-19 restrictions estimated here may hence represent a lower bound.

Yet another discussion is merited by the fact that we look mainly at maize, a calorie-rich food. It would be interesting to also investigate to what extent households have access to more nutrient-dense foods as well, and whether such access differs between our treatment and control groups. COVID-19 related food security discussions have in fact paid considerable attention to nutrient-dense foods and their link with immune system functioning. However, in our specific case random allocation to treatment or control should lead to a very similar distribution of observable and non-observable confounding factors in treatment and control groups, including available food other than maize. It would be interesting, nevertheless, to investigate substitution processes between food types that different types of households may engage in as the availability of maize changes.

Finally, our work examined short-term impacts of an improved on-farm storage technology during the COVID-19 pandemic. We can, of course, not yet offer robust evidence on longer-term benefits of improved storage under conditions where farmers are confronted with arguably more common shocks, such as a bad harvest, or climatic changes that impact agricultural output over multiple years. However, evidence from a somewhat similar, but smaller-scale experiment in Tanzania suggests that improved on-farm storage is likely to reduce persistent food insecurity among smallholder farmers as well (Brander et al., 2020).

6. Conclusion

Both policy-makers and scientists have become increasingly interested in how food security in low-income countries could be improved not only through increasing agricultural production, but also through reducing post-harvest losses (Sheahan and Barrett, 2017). Low cost and easy to use technologies to that end are particularly interesting in low-income smallholder farming contexts (Godfray et al., 2010). Some such technologies exist, but adoption rates are still low (Channa et al., 2019), meaning that there is, presumably, a large unexploited potential for improving food security with a technology that is cheap, can be implemented even in the short run, and has no negative ecological implications (Affognon et al., 2015).

Our RCT in Kenya assesses the benefits of such a technology (hermetic storage bags) with regards to food security and also a range of associated health implications (see section 2 for details). The recent COVID-19 restrictions provide an opportunity for a first analysis of data from this research effort, both with respect to food security effects of a policy-induced shock and benefits of improved storage under such conditions. The findings show that smallholder household's food insecurity increased during COVID-19 restrictions, but that improved on-farm storage curbed these increases.

The main policy implication of our research is that greater efforts should be undertaken to promote the adoption and appropriate use of low-cost and easy to use technology for improved on-farm storage. Such action could help not only in attenuating the painful trade-offs between protecting public health and increased food security, as in the current COVID-19 crisis, but also in reducing the vulnerability of smallholder farmers to longer-term, climate change-induced or other types of shocks to the food system. Thus our work also contributes to the scarce, but growing literature that considers improved on-farm storage as an important climate change adaptation strategy, which is especially important as climatic changes may further increase post-harvest losses (Stathers et al., 2013; Lybbert and Sumner, 2012). Higher temperatures and more erratic precipitation can increase the risk of fungal growth (and associated foodborne pathogens, such as aflatoxin) and of insect infestation in stored produce (Fanzo et al., 2018; Stathers et al., 2013; Lybbert and Sumner, 2012). The resulting post-harvest losses and the risk of foodborne pathogens can, however, be mitigated by improved storage (Fanzo et al., 2018), which renders investing in improved on-farm storage solutions even more important (Stathers et al., 2013; Lybbert and Sumner, 2012).

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. Supplementary data

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Author contributions

M.H. and M.B. jointly conceived the project, acquired funding, developed the design and methods, collected, curated and analyzed the data, and contributed to writing of the paper; T.B. and U.E. contributed to the development of the study design, fundraising, and writing of the paper. M.K. contributed to the development of the study design, interpretation of the data, writing of the paper, and coordinated the fieldwork and field interventions.

Data and materials availability

Data and code are available from the authors. Further details on the study design, which also includes surveys on household health that are used for other research activities within the larger project, are available at the AEA RCT Registry (Huss et al., 2020).

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