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Regular Article

Overcoming smallholder farmers' post-harvest constraints through harvest loans and storage technology: Insights from a randomized controlled trial in Tanzania

Hira Channa [a], Jacob Ricker-Gilbert [b,*], Shiferaw Feleke [c], Tahirou Abdoulaye [d]

[a] The World Bank, USA
[b] Department of Agricultural Economics, Purdue University, USA
[c] International Institute of Tropical Agriculture, Tanzania
[d] International Institute of Tropical Agriculture, Mali

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ABSTRACT

Maintaining staple grains throughout the year and managing liquidity are two major challenges that smallholder farmers face at harvest. We implemented a randomized controlled trial in Tanzania that was designed to address these post-harvest constraints. First, we offered treated farmers two hermetic (airtight) storage bags, which helped preserve grain quantity and quality. Second, we offered other treated farmers a loan at harvest, which reduced the liquidity constraints they faced. Repayment was due with interest six months from harvest when maize prices were traditionally higher. We did not find a significant impact of the storage intervention. However, those offered the loan stored 29 percent more and sold 50 percent more maize on average in the lean season compared to farmers in the control group. Nevertheless, an unexpected maize export ban in Tanzania likely attenuated the outcomes of both interventions. This highlighted the challenges surrounding agricultural financial products in the developing world.

1. Introduction

While improving staple crop production remains a major challenge in Sub-Saharan Africa (SSA), smallholder farm households growing maize and other grains face numerous challenges in the post-harvest season. First, maintaining the quantity and quality of stocks throughout the year is difficult because pests consume grain in storage, reducing the quantity available to households (Chegere et al., 2021; Omotilewa et al., 2018). Likewise, fungi that produce mold and aflatoxin infect poorly stored grain, reducing the quality of safe food available to households (Bauchet et al., 2021; Magnan et al., 2021). This undermines both food safety and food security of limited resource households throughout the year.

The second challenge deals with price seasonality and lack of credit because grain prices are usually lower at harvest than later in the season. Unfortunately, pressing liquidity demands mean that households are often unable to exploit the significant price seasonality in many grain markets in SSA (Abdoulaye and Sanders, 2006; Aggarwal et al., 2018; Dillon, 2021). As a result, they may end up in a situation called the "sell-low, buy-high" phenomenon where they sell their maize for low prices at harvest to pay off debts and meet expenses, only to buy back grains for consumption when prices are normally at their highest later in the year (Stephens and Barrett, 2011; Bergquist et al., 2019). In combination, pest damage and economic constraints create a situation that undermines food security and reduces income for smallholder farmers in SSA.

With these considerations in mind, the objective of the present article is to test the extent to which both the post-harvest quantity/quality constraint and the post-harvest liquidity constraint impact smallholder farmers' decision-making behavior related to maize inventories and maize sales. We conducted a randomized controlled trial (RCT) in the Mbeya region in the southern highlands of Tanzania during the 2017/18 harvest season to test the relative importance of each constraint for smallholder farmers.

* Corresponding author.
E-mail address: jrickerg@purdue.edu (J. Ricker-Gilbert).

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The first treatment dealt with the quantity and quality challenges faced by smallholder farmers. We provided randomly selected participants with a new storage technology, namely two hermetic (airtight) storage bags that each held up to 100 kg of shelled maize. The hermetic bags protected stored grain by killing insects and neutralizing mold growth. The bags can reduce PHL to nearly zero when used properly (Baributsa et al., 2014). As a result, hermetic bags are a potentially important technological innovation for smallholder farmers because in their absence farmers take other adaptation measures to mitigate PHL. These include applying chemical insecticides to kill insects that eat stored grain. Insecticides help to preserve quantity but reduce food quality by making grain less safe to eat. Use of storage insecticides on maize was widespread by smallholders in our study area, and Kaminski and Christiaensen (2014) found that 49% of smallholders in Tanzania applied storage protectants to their maize during the 2010/11 season.

Furthermore, while survey data often indicates that farmers report relatively low levels of post-harvest losses, there is little doubt that large losses can occur. For example, Kaminiski and Christiaensen found that average PHL in Tanzania was between only between 2.9 and 4.4% in the 2008/19 and 2010/11 seasons. However, those who experienced PHL actually lost between 19.7 and 23.1% of their maize harvest. Thus, the hermetic bag technology intervention had the potential to help smallholders in our study maintain grain quantity during storage by protecting them from average and extreme losses, while also preserving quality by eliminating the need for storage chemical insecticides.

The second intervention addressed farmers' liquidity constraints at harvest by offering them access to a loan product that was new to them. Randomly selected farmers were offered a loan of $36.00 in cash at harvest, which was equivalent in value to two 100 kg bags of shelled maize on the market during that time. Recipients collateralized the loan with 200 kg of maize stored in two hermetic bags, and loan repayment was due six months later at 12% interest (24% annual rate), when maize prices were expected to be much higher.[1]

The credit product we offered allowed households to borrow against their maize stock and take advantage of intra-seasonal price variation. Past studies have investigated the extent to which intra-seasonal price risk is a reason why households do not store to take advantage of intra-seasonal arbitrage opportunities (Saha and Stroud, 1994). Though both the recent and longer-run historic seasonal maize price data for the Mbeya region suggested a consistent price rise of greater than 40% in the six months following harvest (see Figs. 1–3), large intra-seasonal price increases do not necessarily happen every year (Chapoto and Jayne 2009; Cardell and Michelson, 2020). Regardless, the fact that the loan value was collateralized by maize stored in hermetic bags reduced the downside price risk that farmers faced, and reduced risk for the NGO who offered the loan. Furthermore, respondents were able to repay their loan in installments, and they could also repay their loan earlier than six months or hold their grain longer and repay the loan later than the six month timeframe.

This article builds upon the limited previous experimental research that has tried to understand and test interventions that could alleviate smallholder farmers' post-harvest constraints and help them benefit from intra-seasonal grain price arbitrage opportunities. One set of studies investigated how access to credit at harvest relieves liquidity constraints. For example, Bergquist et al. (2019) implemented an RCT in Kenya where recipients were offered a loan at harvest similar to the one in the present study. The authors found that providing credit immediately after harvest increased farmers' profits from maize sales on average. Delavallade and Godlonton (2020) evaluated a harvest credit and community warehouse storage program in Burkina Faso. They found that participants in the program stored longer and obtained a higher sales price for their crops and thus received higher revenue on average. However, both the Bergquist, Burke and Miguel, and the Delavallade and Godlonton interventions collateralized stored grain using traditional technologies that offered no protection from insects and mold. As such, they did not address the quantity/quality constraint.

Previous research that investigated the impact of improved storage technology on relieving the quantity/quality constraint has found that it plays a critical role in affecting smallholders' decisions at harvest. For example, Aggarwal et al. (2018) implemented an RCT in Kenya that provided farmers the option of storing their maize collectively with members of their village savings group in hermetic bags. The authors found that households who accepted this treatment stored maize longer, sold 23% more maize on average, and were able to obtain higher prices than the control group by waiting until later in the year to sell. Nindi, Ricker-Gilbert, and Bauchet (2021) also combined hermetic bags and group storage as part of an RCT in Malawi and found positive benefits to the length of time and quantity of legumes stored after harvest. Another recent RCT in Uganda found that farmers who were randomly offered hermetic bags stored significantly more maize for a longer period of time (Omotilewa et al., 2018), while an RCT in Tanzania found that households who were randomly offered hermetic bags had a 38% lower prevalence of food insecurity in the lean season (Brander et al., 2021). Another study found that those offered hermetic bags stored maize longer, lost less, stored better quality maize, and obtained a higher price for maize that they sold (Chegere et al., 2021). Though these studies addressed storage quantity, and quality constraints using hermetic bags, none of them tested the effect of credit on reducing liquidity constraints faced by smallholders in the post-harvest season.

By evaluating both a storage intervention and a credit intervention, our study builds on the previous literature cited above, which focused on reducing either the quantity/quality or the liquidity constraint at harvest individually but not in combination. We also compliment previous literature that sought to understand factors that affect seasonal variation in household consumption, welfare and investment. For example, offering credit to households in the lean season has been found to induce smallholders to work more on their own farm and increase agricultural investment and output (Fink et al., 2020). In addition, offering households access to formal savings accounts has been found to promote productive investments and income (Brune et al., 2016; Flory 2018). In this regard, our study is perhaps the closest in terms of design to Basu and Wong (2015), where the authors introduced a new storage technology and a food credit program during the lean season in Indonesia. They found that the food credit intervention increased income and minimized seasonal gaps in consumption. Our study compliments Basu and Wong because they offered participants an in-kind loan for food in the lean season that was repaid at harvest, while we offered participants credit at harvest to be paid back with grain sales in the lean season. The credit loan offered by Basu and Wong during the lean season was meant to help reduce seasonal declines in consumption, while the loan at harvest in our intervention was designed to help smallholder farmers take advantage of expected seasonal price increases to increase income. In addition, we tested whether access to improved storage technology to reduce quantity and quality loss or access to credit at harvest to reduce liquidity constraints is more important for household income. In doing so, we offer important insights into smallholder behavior and evidence about whether it is more effective to target post-harvest interventions towards technological or financial innovations.

Our results indicated that there was a great deal of interest in the loan product as well as the storage intervention. Eighty percent of the farmers to whom we offered the loan product accepted it. This was higher than the 60–65% uptake that Bergquist et al. (2019) found for a comparable loan product in Kenya. Theirs was already much higher than uptake of micro-credit products in general, which Karlan et al. (2010)

[1] Our intervention does not have a full factorial design because we could not incorporate a separate credit intervention without using maize stored in hermetic bags as collateral. The NGO that offered the loan did not see that option as a viable financial product, because they were concerned about farmers not maintaining the quantity and quality of the collateralized maize without storing it in hermetic bags.

found to range between 2 and 55%.

While we did not find statistically significant impacts of the storage intervention on its own, our credit intervention allowed farmers to store 29% more maize until later in the year and resulted in a 50% increase in the overall quantity of net maize sales throughout the year. Evidence suggested that this increase was driven by sales in the later part of the year when prices were traditionally higher. We also found that the subsample of participants who were already net sellers of maize before our intervention benefited more from our treatment as compared to those who were net buyers or autarkic during the baseline year.

It is worth noting that the maize price pattern during our intervention year affected our results. Maize prices did not rise in the lean season, in contrast to the previous years' price patterns, because the government of Tanzania imposed an export ban on the crop. The government intervention introduced additional maize supply on the domestic market, which depressed maize prices. This likely attenuated the outcomes in our intervention related to maize sales and storage. The ban highlights the challenges surrounding agricultural financial products in the developing world. However, we conducted a simple simulation exercise using maize price data from Mbeya, Tanzania, between 1993 and 2017. The simulation suggested that in an average year, there was a 72% probability that treated farmers would have obtained a positive return on investment from the loan product we offered to them.

2. Setting and project design

2.1. Maize price seasonality in Tanzania

Maize is the main cereal consumed by most Tanzanians, providing an estimated 60% of their calorie requirements. Most of the maize produced is used for home consumption, and the remainder is primarily sold in local markets. While yields have been growing and currently stand at an average of 1.4 metric tons/hectare, production growth has primarily been driven by increases in land shares allocated to maize or by bringing fallow land into production (Wilson and Lewis, 2015). Mbeya region, where our research is conducted, is a surplus producing region responsible for 11% of maize production in Tanzania (Wilson and Lewis, 2015).

Using maize price data from the Mbeya region in Tanzania, we found that for the last 17 years, average maize prices in the planting season (December–January) were nearly 35% higher than they were at harvest time (June). This seasonality was particularly sharp for the two years prior to our intervention (2015/16 and 2016/17) when the prices were nearly 80% higher in the lean season (Fig. 1). Additionally, we found that seasonality in maize prices was higher over time than for other crops like beans and rice and that seasonality in the Mbeya region was higher than it was in other regions of Tanzania (Figs. 2 and 3).

Various factors have been found to affect maize price seasonality in Tanzania. Baffes et al. (2019) found that regional prices (for example, the retail price of maize in Nairobi, Kenya) drove nearly a third of the price variation in Tanzania. The remaining price variation was attributed to domestic factors such as production shocks, maize harvest cycles, and government policies such as export bans. Gilbert, Christiaensen, and Kaminski (2017) used pricing data for various food commodities across seven countries in Africa and found significant price seasonality, especially for maize (around 33% on average), which was almost three times larger than an international reference price. In a related study, Kaminski et al. (2016) showed that price seasonality has been very much present in recent years in Tanzania, and additionally that seasonality has had a significant impact on household consumption.

2.2. Maize trade between Tanzania and its neighbors

Tanzania is primarily self-sufficient in maize production as evaluated by the level of domestic production against domestic consumption (FEWS NET, 2019). Imports and exports constitute a relatively small proportion of overall maize consumption in the country, with imports and exports forming 1% and 3% of total domestic consumption respectively (FAOSTAT, Food and Agriculture Organization of the United Nations, 2021). In most seasons, Tanzania is a surplus maize producer, exporting maize to other countries in Eastern and Southern Africa. Maize exports from Tanzania are an important source of food for neighboring maize deficit markets in Eastern and Southern Africa, particularly during years of drought. (Tridge, 2021).[2]

Tanzania is a member of the East Africa Community (EAC's) common market, along with Kenya, Uganda, Burundi, and Rwanda. Which sets a 50% common external tariff (CET) designed to protect domestic producers from imports outside the bloc. Countries in the EAC also charge a 50% tariff to an importing country outside the bloc.[3] When countries outside the EAC import maize from Tanzania, they generally charge a similar 50% or higher Tariff on Tanzanian maize (Tridge, 2021).

The first policy instrument used by the Tanzanian government to regulate the maize market is the National Food Reserve Agency (NFRA). It purchases maize during the primary harvest season, stores it in government warehouses, and sells it during the lean season. The NFRA's purchase price for maize is generally higher than prevailing market prices, providing a boon for farmers who produce enough maize to sell to NRFA (see Mason et al. 2015 for an example of this in Zambia). Maize sales by the NFRA begin around August or September each marketing year, but the most significant sales occur during the lean season between October and February.

Export bans are the second policy instrument that Tanzania has often used to reduce maize trade. While the export ban may help keep some maize in the country, benefiting urban consumers, maize farmers in surplus regions are adversely affected because the ban reduces their access to higher prices on international markets (Makombe and Kropp, 2016). Baffes et al. (2019) found that an export ban in Tanzania reduced maize prices by 3.1%, and Diao and Kennedy (2016) used a computable general equilibrium model to show that producer prices for maize fell significantly following a ban, hurting rural maize sellers while benefiting urban maize consumers. Export bans also have been found to encourage bribery and illegal trade through bush 'panya' routes across Tanzania's highly-permeable borders (Wilson and Lewis, 2015).

2.3. Storage technology intervention

The technology intervention used in this study was to provide treated farmers with two hermetic (airtight) storage bags that each held 100 kg of shelled maize. The brand of hermetic bag offered in the intervention was the Purdue Improved Crop Storage (PICS) hermetic bag developed at Purdue University. The PICS bag is a three-layer hermetic bag that consists of an outside layer of woven polypropylene and two inner layers of polyethylene. The bag is effective for virtually any dried grain, and when grain is placed in a PICS bags and it is closed and tied properly, the airtight environment that is created kills insect pests through suffocation. This greatly reduces losses during storage (Baributsa et al., 2014). There is also evidence suggesting that the airtight seal helps contain the spread of aflatoxin in stored grain, unlike with standard single-layer woven bags used by most farmers in SSA (Bauchet et al. 2021). Thus, the PICS bag protects the quantity and quality of stored grain across the post-harvest season.

A disadvantage of the PICS bag is its high cost relative to the single-layer woven bag. One PICS bag, which holds 100 kg of shelled maize,

[2] When Tanzania has a poor production year it imports maize from South Africa, Zambia, Zimbabwe, Bulgaria, United Arab Emirates, Argentina, and United States (Tridge, 2021).

[3] While EAC countries have to normally charge the 50% CET on imports from outside the bloc, they can also import maize from outside the bloc duty-free if there is a pressing need.

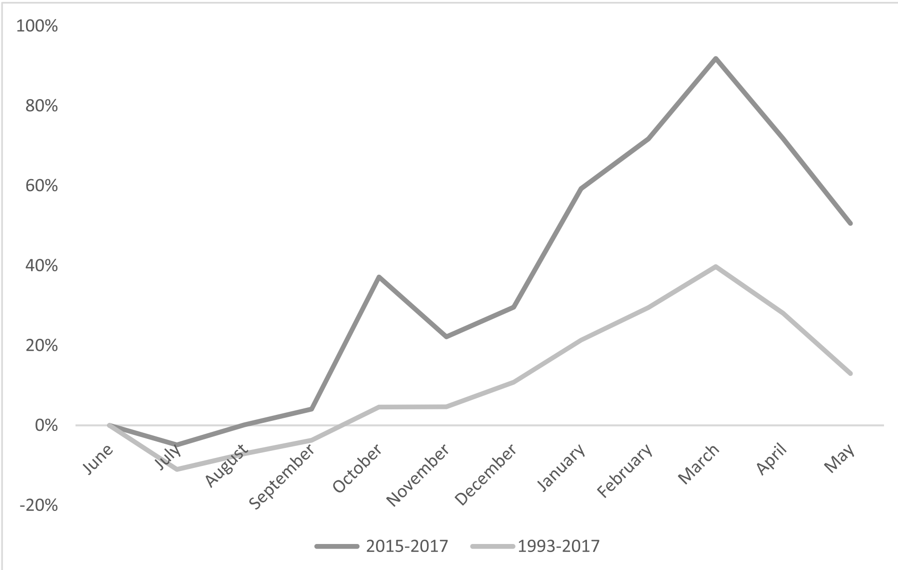

Fig. 1. Maize price change from harvest in Mbeya, Tanzania. Notes: (1) Graph made by authors based on city level maize price data provided by the Ministry of Industry (Tanzania). The graph was calculated by averaging prices for each month across the different years. The y axis represented how much higher the average price in that month was compared to the average price in at harvest in June. (2) The Mbeya region has been primarily a unimodal maize production area. June has generally been when the harvest began, and when maize prices have been the lowest. (3) The grey line represented the price rise from June on average for the years 1993–2017 while the black line showed the price rise for 2015– 2017, which were the two years prior to the intervention.

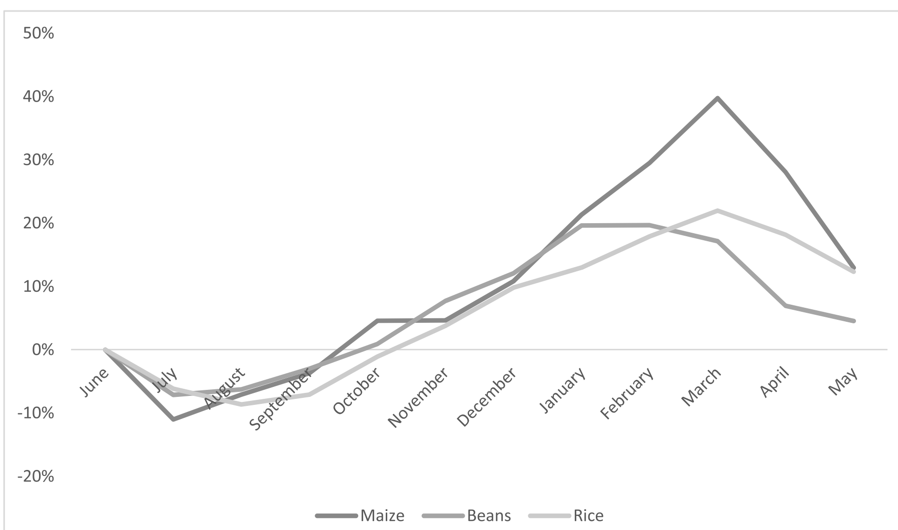

Fig. 2. Price behavior of maize, compared to bean and rice in Mbeya, Tanzania (1993–2017). Notes: (1) Graph made by authors based on city level price data provided by the Ministry of Industry (Tanzania). The graph was calculated by averaging prices for each month across the different years. The y axis represented how much higher the average price in that month was compared to the average price in at harvest in June.

cost roughly $2.30,[4] while one single layer woven bag with the same capacity costs only $0.70 in Tanzania during 2017/18. However, unlike single-layer woven bags, the PICS bag can be reused for multiple years.[5] Additionally, the PICS bag does not require the application of storage chemicals to kill insects. This reduces operating costs and mitigates the potential adverse health effects associated with those chemicals.

2.4. Loan intervention

We worked with an NGO partner called Phiretajo to design and implement an intervention that potentially reduces smallholders' liquidity constraints at harvest. Phiretajo is a local NGO based in the Mbeya region that registers and trains village credit clubs called Village Savings Cooperative Banks (VICOBA). The term VICOBA (kikundi in Swahili) refers to a group of individuals (typically between 15 and 30 people) who come together to save and invest money. The group meets every week or every other week, and each member buys "shares" in the VICOBA, which is a form of saving for the group members. Since members have almost no access to loans through formal banks, the

[4] USD 1 = TSh 2200 around the time of this intervention.

[5] In Niger for example, a survey of 121 farmers using PICS bags for cowpea storage, found that up to 79% of farmers found that the bag was effective for storage even after 3 years of use (Baributsa et al., 2014).

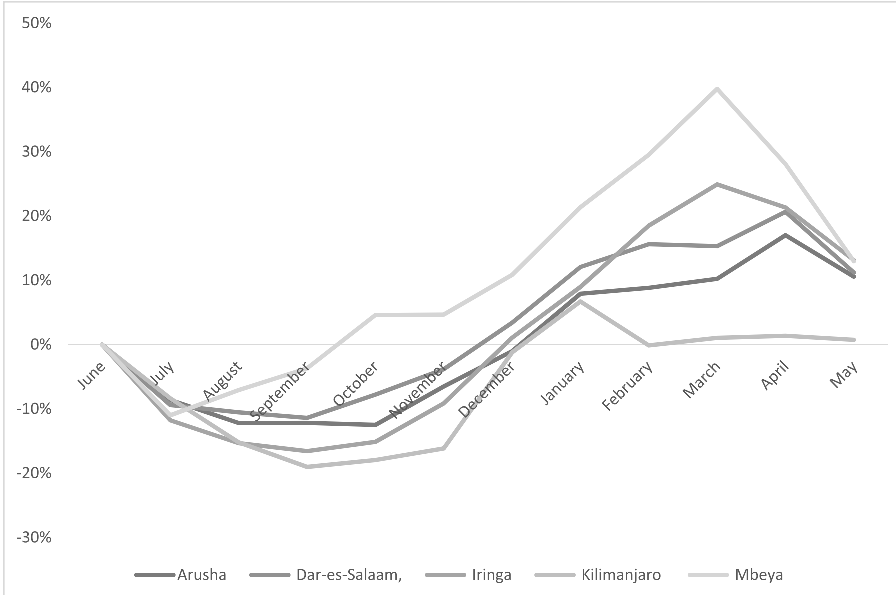

Fig. 3. Price behavior of maize in Mbeya, Tanzania compared to other regions (1993–2017). Notes: (1) Graph made by authors based on city level price data provided by the Ministry of Industry (Tanzania). The graph was calculated by averaging prices for each month across the different years. The y axis represented how much higher the average price in that month was compared to the average price in at harvest in June.

VICOBA lends to members who make a case for needing the money for business reasons. The number of "shares" purchased by the member affects how much he or she can borrow from the VICOBA. Essentially the more shares a member has purchased from the VICOBA, the more money he or she can borrow from it.

The members of each VICOBA elect a chairperson, secretary, and accountant. To be officially registered, a VICOBA must pay a sum of Tanzanian Shillings (TSh) 300,000 (US $137.00) in total to Phiretajo and the district government. Phiretajo assists the VICOBAs in their region with registration, trains them so that the VICOBAs function more effectively, and helps them open bank accounts. VICOBA membership is almost always exclusive, so a member can only belong to one group.[6]

The loan product offered to VICOBA members as part of the intervention was approximately worth the value at harvest of the grain in two PICS bags of maize. Each PICS bag holds 100 kg of shelled maize, so 200 kg were valued at about TSh 80,000 (US $36.00) at the time of harvest in June 2017. The money for the loan belonged to Phiretajo and was given to farmers in cash at harvest. Recipients had the choice of either purchasing additional maize or using maize from their own harvest to store as collateral for the loan that was held in the PICS bags.[7]

The maize was stored in a central location in each village, either a government office or the home of one of the group leaders. The expectation was that the farmers would sell their maize in six months to pay back the loan to Phiretajo with 12% interest. The 12% interest rate was higher than the 10% internal lending rate of the credit group but much lower than the 20–25% interest rate, which would be the cheapest outside option for farmers (e.g.: a group loan from a formal Bank). However, only 2% of our sample indicated that they had access to any formal sources of credit besides the VICOBA, and for 78% of the sample, the VICOBA was their main credit source.

A key distinguishing factor of our loan intervention was that it utilized PICS bags to store the maize, and therefore incorporated the storage intervention into the loan. The main reason for this was that Phiretajo officials (whose money was at risk with the loan) believed that the storage losses would be too high if farmers used traditional technology, and therefore repayment would be lower. However, we do not consider combining the PICS bags with the loan as a cumulative intervention because the hermetic bags used for collateral were tied to the credit intervention and could not have been used for any other purpose.

2.5. Intervention implementation

The activities associated with our intervention were conducted in collaboration with Purdue University, the International Institute of Tropical Agriculture (IITA), and the NGO Phiretajo. The paragraphs below describe the randomization, which is also summarized in Fig. 4, while the timeline of the activities is summarized in Fig. 5. From April 24-May 31, 2017 a team of 10 enumerators and two supervisors along with three trainers visited the randomly selected VICOBAS in seven districts from the Mbeya region.[8] We visited 132 VICOBAs during this time as shown in Fig. 4.[9] Each VICOBA group was randomly selected into one of three groups:

1. Control Group: This group did not receive any training, bags, or loans. Ten randomly selected individuals from this group were selected and surveyed. These groups received training on hermetic storage at the endline survey (Group 1).
2. Storage Group: The entire group received training on the use of PICS bags. Subsequently, ten individuals within the group were

[6] In our intervention there were only three people who were members of multiple VICOBAS. To deal with this, we randomly selected them into either one of the two groups.

[7] The loan agreement was signed with between each individual farmer and Phiretajo. However, the repayment was guaranteed by other members of the group. We provided an example of a sample loan agreement that was signed by participants in the credit treatment in Appendix B1.

[8] A map of the region was provided in Appendix B2.

[9] It should be noted that occasionally, the VICOBA groups become aware of the treatment status of neighboring VICOBAs. However, this was not a serious concern because our treatment interventions were explicitly defined as the offer of two free bags or the offer of the two free bags plus the loan product to randomly selected individuals in the treatment VICOBAs.

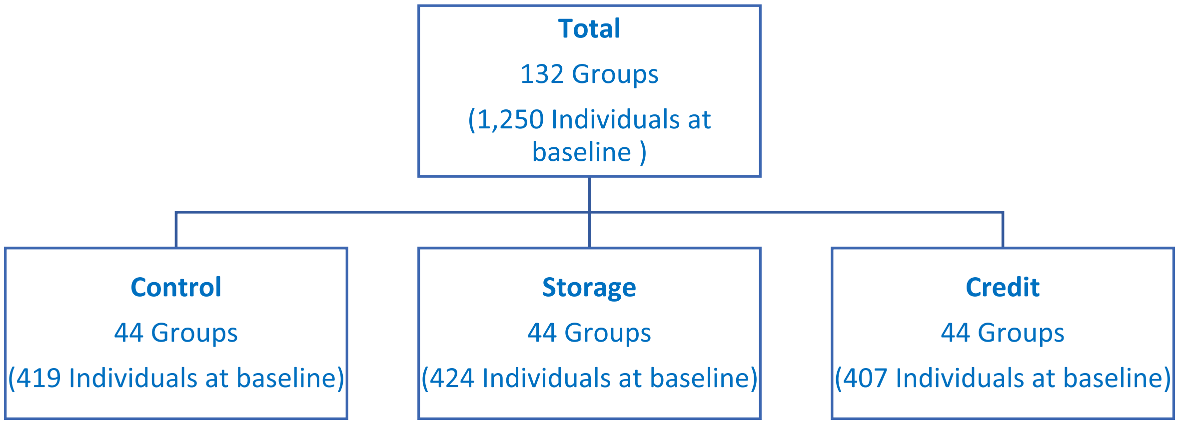

Fig. 4. Design of Randomized Controlled Trial. Notes: We were able to interview 1, 238 respondent out of the 1, 250 at endline. The eventual distribution of respondents by treatment group was as follows: Control = 417 individuals; Storage = 420 individuals; Credit = 401 individuals.

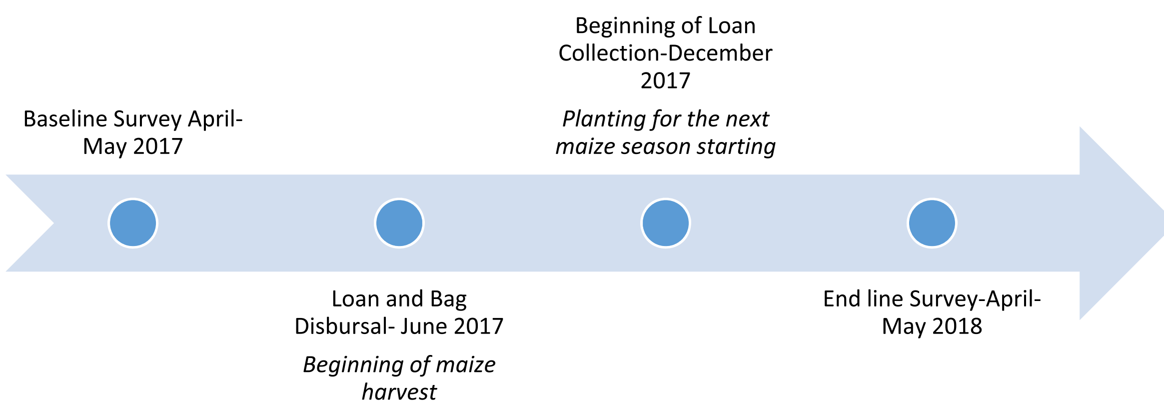

Fig. 5. Timeline of Activities.Notes: This figure provided the timeline of the main activities of the intervention analyzed in this study.

randomly selected in an open lottery to receive two free bags that held 100 kg of shelled maize each. (Group 2).

3. Credit Group: The entire group received training on the use of PICS bags and an introduction to the loan product. Subsequently, ten individuals within the group were randomly selected in an open lottery and were offered a loan at the time of harvest worth approximately TSh 80,000 (US $36.00). The loan was collateralized with grain stored in two PICS bags, and the value of the loan was equivalent to roughly 200 kg of shelled maize at harvest. If the respondents accepted the loan offer, then the PICS bags were given for free (Group 3).

The participants who received only the two PICS bags in the storage group, or the PICS bags and the loan in the credit group, constituted the treated individuals in the intervention. The training for the storage and credit groups involved a demonstration on how the bag should be used, followed by a video that explained the economic and health benefits of using the PICS bags.

The control group (Group 1) was told that ten individuals would be randomly selected for a simple survey on maize production, consumption, and sales along with other household demographic questions. They did not receive any information about the bags or the loan at the time of the baseline survey or during the intervention, but they were trained on the PICS bags during the endline survey in May–June 2018.

For the storage group (Group 2), the ten individuals who received the PICS bags were encouraged to store maize in them, but no restrictions were placed on the use of the bags. For the credit group (Group 3), members were told that individuals would receive two bags and be offered a loan of TSh 80,000 (US $36.00) at the time of harvest, to be paid back in 6 months at an interest rate of 12%. In addition, they were told that the collateral for the loan would be two 100-kg bags of maize stored in the PICS bags. The two bags of maize had to be stored at a central location, which would be either a village office or the home of one of the group leaders, or a senior member as agreed upon by the group. People in Group 3 had to accept both the loan and the PICS bags and could not choose one or the other.

The storage training took between 30 and 45 min to complete. The training on the PICS technology was led by experienced extension professionals who had been trained earlier on a larger Gates Foundation project on hermetic storage. One employee from the credit NGO Phiretajo attended the meetings with the groups in the credit treatment to introduce the loan product. The credit training took an extra 20–30 min to administer. The enumerators only administered surveys and did not train participants.

For transparency, the randomization within the VICOBA groups occurred by open lottery following the training. Slips of paper were distributed in a bowl with numbers from one to the total number of members present. Those who got slips with the numbers from 1 to 10 would receive the bags or the bags and the loan. All groups that participated in the intervention (including the control) received a collective gift of stationery worth TSh 20,000 (US $11.00) per group.[10] Additionally, all the participants who took part in the survey received a journal (for recording maize sales and purchases) which they were asked to fill before or after their weekly meetings for the next year.[11]

In total, we ended up with a sample of 1250 participants from 132 VICOBA groups. Even though we targeted 10 participants per group for the intervention, we had fewer than 10 individuals from some of the 132 VICOBA groups. This was because the size of the VICOBA groups that we worked with varied quite substantially, and not all individuals who were part of the VICOBAs decided to participate in the meeting when the intervention was introduced. The number of people who attended the intervention meeting ranged from 6 to 40. As a result, we ended up with 419 individuals in the control group, 424 in the storage group, and 407 in the credit group in the baseline survey.[12] In order to ensure there was no bias from being selected from groups of different sizes, we weighted our descriptive and regression analyses by the inverse probability of being selected to participate in the intervention. This put relatively more weight on observations that had a lower probability of being randomly selected for treatment. Ultimately, adding the inverse probability weights had little impact on our results.

The endline survey was held after a full calendar year, in May 2018. We were able to re-interview 1238 out of the 1250 people originally interviewed during the baseline survey for an attrition rate of less than 1%. Of the 1238 people who were resampled, 417 were in the control group, 420 were in the storage group and 401 were in the credit group. Attrition was very low because we conducted phone interviews if respondents were not available for interviews in their homes or meeting space after two visits by the team. Of the total interviews conducted for the end-line, 21% were conducted over the phone.[13]

3. Initial baseline statistics

Table 1 provided the means and standard deviations for 12 key variables by control and treatment groups. In our case, since we had multiple treatment groups, this greatly increased the number of t-tests that we would need to do to check for balance, increasing the probability of a positive significance by chance (Type 1 error). Instead, we utilized a statistic recommended by Imbens and Rubin (2015) as a method for checking balance which reflects the size of the difference. This is referred to as the normalized difference of the mean of the treatment group μ_1 compared to the control group μ_o using the following equation:

$$t = \left(\mu_1 - \mu_0\right) \Big/ \left(\sqrt{(\sigma_1^2 + \sigma_0^2)} \Big/ 2\right) \tag{1}$$

where σ_1 is the treatment group standard deviation, and σ_0 is the control group standard deviation. We found that the t-statistic was smaller than 0.25 for all our variables, implying that the differences between groups was small. As an additional check we also provided F-statistics for joint orthogonality for each variable across all the four groups of respondents (control and three treatment groups). These regressions included district fixed effects with standard errors clustered at the VICOBA level. Using this F-test we found that all variables were balanced.

The baseline data provided in Table 1 first presents summaries of all variables related to maize production, consumption, and trading. We then looked at input use, including storage chemical use, fertilizer use, land cultivated, and maize seed expenditure. The last two variables showed the Progress out of Poverty Index (PPI), which we describe later, and the money borrowed by the household from the VICOBA. All these variables were based on information for the year April 2016–March 2017, the year prior to the intervention.

Table 1 showed that farmers in our sample harvested 1559 kg of maize on average at baseline. Average maize inventory was 639 kg in January of 2017, around the time the next planting season began, and when maize prices have traditionally risen in the region. Self-reported maize losses during storage in the table were almost negligible in our sample (averaging 12 kg per household). This average was driven by a few observations with higher losses, and 90% of the sample reported zero losses. As a percentage of maize harvested, these losses were much lower than the loss estimates ranging from 1.4 to 5.9% provided by Kaminski and Christiaensen (2014), which they calculated using household survey data from Malawi, Uganda and Tanzania. Generally, farmers in our sample took precautionary measures to reduce losses, including applying storage chemicals and selling early because of the risk of storage losses. This was demonstrated by the fact that 56% of our sample used storage chemicals in the baseline year, and average storage chemical expenditure among users was TSh 7259 (US $3.00).[14]

The simple poverty scorecard index was developed from a series of 10 questions using Tanzania's Household Budget Survey data. The score in our table showed that for our sample, the average household's likelihood of being below the poverty line was 31%, when using the US $1.90/day poverty line.[15]

4. Empirical model

This section explains how we estimated the impact of our intervention on the two main outcomes in our study. The outcomes are:

i) Maize inventory held by the household six months after harvest in kilograms (kgs). This corresponded to the beginning of January 2018, and was relevant as an outcome variable since prices had historically peaked in January in Mbeya, Tanzania. The variable included the quantity of maize that treated had stored in the PICS

[10] The decision to give gifts as a group and not to individuals was made by our partner Phiretajo.

[11] This was intended to provide supplemental high frequency data on maize sales, purchases and consumption, but a very small proportion of the respondents actually filled out the journal.

[12] Our sample size was powered to pick up an MDE of 0.3 which implied a treatment effect of 170 kg of maize inventory. This was smaller than the expected 200 kg impact of our treatment effect, so it offered some added statistical power in the event of lower take-up of the intervention. See appendix B3 for further explanation of the power calculations used in this study.

[13] We regressed being interviewed on the phone in the end line survey on the treatment indicators using a linear probability model. Treatment assignment was not correlated with being interviewed on the phone at the endline, suggesting that phone interviews were balanced across groups (Results are presented in Table A1).

[14] Data collected from nearby markets suggests that one application of storage chemicals cost farmers TSh 374/100 kg bag (17 cents/bag) on average.

[15] Further details related to the scorecard can be found at http://www.simplepovertyscorecard.com/TZA_2011_ENG.pdf.

Table 1
Descriptive statistics and balance test.

Variables	(1) Control	(2) Storage	(3) Credit	(4) Total	(5) (1)–(2)	(6) (1)–(3)	(7) (2)–(3)	(8) F-test
Maize harvested in June 2016 (kg)	1536 [134]	1379 [129]	1600 [158]	1504 [80]	0.1	−0.038	−0.134	1.23
Total maize consumed by household between April 2016–March 2017 (kg)	419 [17]	392 [16]	393 [15]	401 [9.24]	0.118	0.112	−0.005	1.29
Net maize sales by household between April 2016–March 2017 (TSh)	304,000 [50,839]	289,000 [53,679]	410,000 [67,095]	333,000 [33,104]	0.022	−0.137	−0.153	1.56
Proportion of households who were net sellers based on net maize sales between April 2016–March 2017	0.51 [0.50]	0.47 [0.04]	0.54 [0.04]	0.51 (0.02)	−0.016	0.04	0.056	1.83
Proportion of autarkic households based on net maize sales between April 2016–March 2017	0.30 [0.46]	0.31 [0.46]	0.28 [0.45]	0.30 [0.46]	−0.09	0.039	0.129	0.40
Amount spent on storage chemicals between April 2016–March 2017 (TSh)	7580 [605]	6742 [709]	6521 [738]	6953 [394]	0.084	0.105	0.023	1.09
Fertilizer expense of household between April 2016–March 2017 (TSh)	147,000 [19,490]	123,000 [15,487]	130,000 [19,932]	133,000 [10,611]	0.127	0.082	−0.036	0.37
Total cost of maize seed purchased between April 2016–March 2017 (TSh)	3030 [665]	1792 [460]	2771 [630]	2526 [341]	0.119	0.022	−0.098	1.63
Maize inventory beginning of January 2017(kg)	628 [54]	625 [54]	625 [63]	626 [33]	0.005	0.004	−0.001	0.02
Num. of hermetic bags owned before intervention (No)	0.34 [0.11]	0.17 [0.09]	0.13 [0.05]	0.22 [0.04]	0.135	0.179	0.045	1.51
Maize losses reported by farmers due to insect damage (kg)	10.02 [1.41]	13.54 [1.82]	12.59 [2.01]	12.02 [1.02]	−0.13	−0.09	−0.03	1.26
Progress out of Poverty Index score of the household based on data collected during baseline survey	48 [1]	48 [1]	49 [1]	48 [12.96]	−0.043	−0.098	−0.052	1.01
Money borrowed from the VICOBA between April 2016–March 2017 (TSh)	234,000 [48,752]	224,000 [54,446]	237,000 [68,238]	232,000 [32,913]	0.018	−0.004	−0.021	0.13

Notes: (1) The table above shows the summary statistics by treatment categories from column 1–3. Mean and standard errors shown.
(2) Imbens and Rubin suggested an alternate normalized difference statistic comparing each treatment category with the others. Shown here from column 4–6.
$(\hat{\Delta}_{ct} = \frac{(\widehat{X_t} - \widehat{X_C})}{\sqrt{(S_c^2 + S_t^2)/2}})$.
(3)Results from an F-test for joint orthogonality for each of the variables. Standard errors clustered at the VICOBA level and fixed effects for district dummies were included in all estimation regressions for F tests. Exchange rate at the time of the baseline survey was 1 USD = 2200 TSh. (4) ***, **, and * indicate significance at the 1, 5, and 10 percent critical level respectively. (5)This data was winsorized at the 1st and 99th percentile.

bags that were given to those in the treated groups, in addition to other maize that was stored.

ii) Net maize sales, in terms of monetary value. This was the net maize revenue in TSh for the year, calculated as total maize sales minus total maize purchases. We adjusted the balance for the credit group by subtracting the amount of interest (9600 TSh ≈ US $4.00) on the loan from the value of households in the credit group's net maize sales.
iii) Net maize sales in quantity (kg) throughout the intervention year. We calculated this in terms of quantity (kg) by subtracting maize purchases from maize sales by the household across the year.
iv)
   A Maize purchases during the harvest period, from June–September 2017, measured in both kg and value.
   B Maize sales during the lean period, from January–March 2018, measured in both kg and value.

We estimated the following model to measure how our intervention affected the dependent variables of interest, y, for individual i in VICOBA group j as follows:

$$y_{i,j} = \alpha + \beta_1 storage_j + \beta_2 credit_j + \gamma D_d + e_{i,j} \tag{2}$$

where *storage* and *credit* are both indicator variables equal to one if the individual received the storage or credit treatment. The coefficient estimates on $\widehat{\beta}_1$ and $\widehat{\beta}_2$ measured the Intention-to-Treat (IIT) estimates of the interventions. They were identified by the difference between the control and treatment groups during the intervention year. A vector of district level dummies was denoted by D_d with γ as a parameter vector to estimate. Standard errors were clustered at the VICOBA level. This specification was noted as *POST* in the results tables.

Additionally, we used an Analysis of Covariance (ANCOVA) specification that utilized the baseline data that we collected. This specification was the same as the one shown in equation (2), except that it had the previous period's outcome variable as a control.[16] ANCOVA is often more precise than a difference-in-difference specification in a setting like ours where we had a single baseline and follow-up survey (McKenzie, 2012).

Equation (2) did not allow the treatment dummy to vary across quarters of the year. However, for net maize sales, we might expect the treatment effect to have varied considerably across the quarters. For example, for the treated group, sales could have fallen in the quarter following harvest but increased later in the year, when prices should have risen. The specification to examine quarterly effects of our interventions was estimated as follows:

[16] Calculations shown by McKenzie (2012) indicated that if the correlation is between 0.25 and 0.5 then there can be increased power by using ANCOVA instead of difference-in-differences or just a "POST" method. The POST method was equivalent to the OLS method in our paper. The correlation between the baseline outcome and the intervention year outcome was 0.45 and 0.40 for net sales through the year (TSh), and maize inventory in the beginning of January 2018 respectively. This justified our use of ANCOVA.

$$y_{i,q,j} = \alpha + \sum_{q=1}^{q=4} \beta_{1,q} Q_q {*}storage_j + \sum_{q=1}^{q=4} \beta_{2,q} Q_q {*}credit_j + \delta y\_b_{i,q,j} + \partial Q_q + \gamma D_d + \varepsilon_{i,t} \tag{3}$$

where the outcome variables were calculated as described above, except that the calculation was done per quarter, instead of for the entire year. Therefore, the treatment values varied by each quarter in the model estimated in equation (3). For example, the credit intervention had a treatment vector $\beta_{q,2}$, which consisted of four different values, one for each quarter (e.g. interactions between the treatment and quarter dummies). We also used the ANCOVA specification here, so $y\_b_{i,q,j}$ denotes the baseline value of the outcome variable. The quarter level dummies was denoted by Q_q, while the error term was denoted by ε. Standard errors were again clustered at the VICOBA level.

We also conducted exploratory heterogeneity analysis by interacting the treatment variables with dummy variables reflecting household characteristics during the baseline year. We specified this model as follows:

$$y_{i,j} = \alpha + \beta_1 X_{i,j} + \sum_{X=0}^{X=1} \beta_{2,x} X_{i,j} {*}storage_j + \sum_{X=0}^{X=1} \beta_{3,x} X_{i,j} {*}credit_j + \delta y\_b_{i,j} + \gamma D_d + \mu_{i,t} \tag{4}$$

We identified three household characteristics, denoted by X, that might have affected how our intervention changed the outcomes of interest. First, we tested if being "storage constrained" at baseline would have had an impact on the treatment effect. Intuitively we might expect that those who were not constrained would have already optimized their storage decisions and thus were less likely to benefit from our storage intervention. To proxy this, we used baseline storage chemical expenditure by the household as an indicator of storage constraints. While hermetic bags ensure better quality maize that is safer to eat, they are a substitute for storage chemicals that also kill insects in storage. Therefore, we treated those who were spending more money than the 75th percentile on storage chemicals in our sample at baseline as being less storage constrained then those who were using less than the 75th percentile. Thus, we treated the latter group as being "storage constrained" in our analysis.

Second, we analyzed the heterogeneity in credit constraints across our sample. Since we were working with credit groups, everyone in our sample had access to credit through the group, and this was the main source of credit for 78% of our sample. However, as mentioned earlier the amount that an individual could borrow from the credit group was linked to her contributions to the group in the form of "shares" purchased. Therefore, we treated those who had contributed more to the group than the 75th percentile in that group at baseline as being less credit constrained then those who were contributing less than the 75th percentile. As such, the latter group was considered "credit constrained" in our analysis.

Third, 51% of the people in our sample were net sellers of maize during the baseline year, meaning that they sold more maize across the year than they purchased. Generally, being a net seller of maize is a rough proxy for wealth and food security. For that reason, we tested if the net sellers at baseline in our treatment groups responded differently to the interventions than those who were net buyers or autarkic during the baseline year.

If we take the example of the net seller dummy in the specification shown in equation (4), β_1 would estimate the treatment effect for those who received the storage intervention but were not net sellers of maize (e.g. net maize buyers or autarkic), while β_2 reflected the treatment effect for those who received the storage intervention and were net sellers of maize. The coefficients in the heterogeneity analysis were compared with people in the control group who faced similar constraints (e.g. people in the storage group who were net sellers are compared to people in the control group who were net sellers).[17] The error term in equation (4) was denoted by ε. All other variables were the same as in previous equations.

5. Results

5.1. Intervention take-up

All of the respondents except for one in the storage treatment verbally accepted the free hermetic storage bags that were offered as part of the storage intervention. Unfortunately, two groups who were selected did not receive the bags because of miscommunication with our implementing partners. In total, 95% (403) of the respondents who were selected received the bags and thus complied with the storage intervention. Of the total respondents offered the loan, 81% (330/407) accepted and received it. This high take-up could likely have been explained by the fact that most farmers recognized the intertemporal arbitrage opportunity that the loan offered, as well as the fact that the VICOBA credit groups had an existing relationship with the lending partner Phiretajo.

Farmers' recognition of the potential opportunity offered by the loan could be seen in Fig. 6. The figure presented what people in the credit group said when asked about what they did with the money from the loan at harvest. The most common use of the loan was to buy more maize to store (35%). This again suggested that respondents saw a business opportunity through arbitrage with the loan. Agricultural inputs were purchased with the loan by 24% of the respondents, while 15% used it to pay for household expenses. The latter use is what we might have expected from people who were credit-constrained. Overall, since these people were members of a credit group, they likely were less credit-constrained *ex ante* than the general population of smallholders in Tanzania. This may help explain why only 15% of recipients used the loan to pay for household expenses. Finally, 27% of respondents in the credit group used the loan money for other reasons, such as business investments and home repairs.

5.2. Primary effects of the intervention

Table 2 presented the results for the models estimated in equation (2). The results showed the impact of our intervention on maize inventory in January 2018 (the lean season) that occurred 6 months after harvest, and net maize sales between April 2017 and March 2018 in terms of quantity (kg) and value (TSh). We presented two specifications for each of these outcomes. The first specification presented the POST estimates. Following equation (2), this was an OLS estimation of the outcome variable for the intervention year regressed on the treatment dummies. We then presented results from the ANCOVA specification, with baseline values of the dependent variables. In our discussion, we focused primarily on the results of the ANCOVA specification.

We started by examining the impact of our intervention on maize inventory held by the household in the beginning of January 2018, using the ANCOVA specification in Column 1 of Table 2. We found that the credit treatment increased the amount of maize stored by 223 kg on average ($p = 0.021$), which was 29% more than the control group's average inventory. The coefficient associated with the storage treatment suggested that those who received two PICS bags had 137 kg more maize in storage in January 2018 on average than the control group did, but

[17] We ran three separate regressions for each of the characteristics against which we were examining heterogeneity, i) storage chemical use, ii) shares brought from the VICOBA and iii) net seller of maize. The results presented in Table 4 of the results were combined for simplicity. The full regression output for each of the three characteristics were shown in Appendix A-6, A-7 and A-8 respectively.

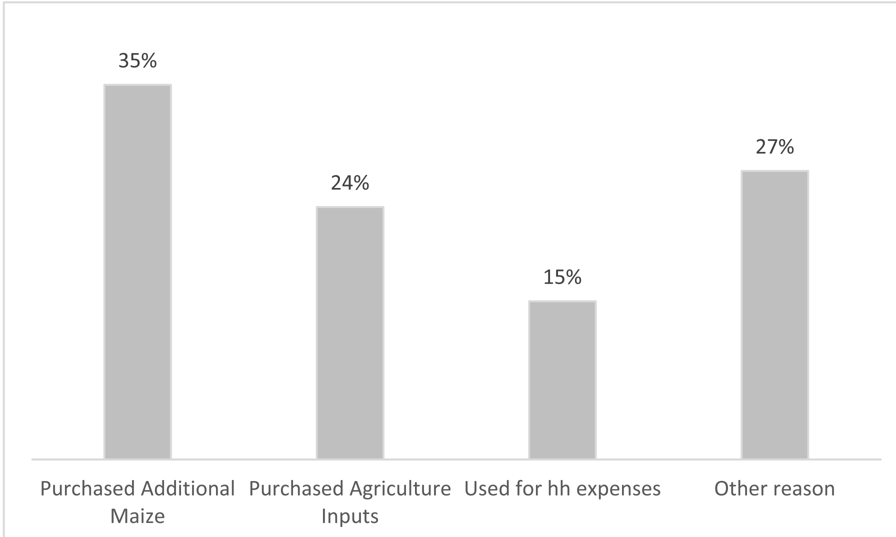

Fig. 6. Loan Utilization. Notes: This figure was generated based on responses in the survey when we asked those who took up the loan what they did with the money. In the case that the loan was utilized for multiple purposes, the major use has been presented here. Other reason included investments in non-agricultural business and home repairs.

Table 2
Main outcomes post-intervention.

Variables	(1) Maize inventory in January 2018 (kg)		(2) Quantity of net maize sales during April 2017–March 2018 (kg)		(3) Value of net maize sales during April 2017–March 2018 (TSh)	
	POST	ANCOVA	POST	ANCOVA	POST	ANCOVA
Group 2: Storage	142 (105)	137 (104)	123 (123)	129 (97)	12,398 (36,005)	15,302 (28,235)
Group 3: Credit	247* (127)	223** (95)	327** (162)	233* (118)	59,913 (44,362)	36,510 (35,164)
Maize inventory beginning of Jan–March 2017		0.54*** (0.00)				
Net maize sales during April 2016–March 2017 (kg)				0.439*** (0.0723)		
Net maize sales during April 2016–March 2017 (Tsh)						0.243*** (0.0249)
Control mean and standard deviation	753 (1018)		478 (1231)		168,422 (364,090)	
Observations	1238	1238	1238	1238	1238	1238
R-squared	0.090	0.222	0.122	0.274	0.143	0.322
Storage = Credit	0.403	0.401	0.175	0.332	0.227	0.487

Notes: (1) The table above provided results from regression specification shown in Equation (2). It presented Intention to Treat Estimates from a cross-sectional post-intervention (POST) analysis and an ANCOVA regression on the treatment dummies.
(2) POST was a regression of the post-intervention variable on the treatment dummies. ANCOVA estimation included the baseline year's value of the outcome variables.
(3) The outcome variables respectively were: (1) maize Inventory in Jan 2018 (kg). (2) quantity of net maize sales in kg through the year. (3) value of net maize sales in TSh through the year (maize sales-maize purchases-interest rate paid by credit group).
(4) Standard errors were clustered at VICOBA Level.
(5) District Fixed Effects and constant included in all specifications.
(6) Observations have also been probability weighted by the likelihood of them being selected for any treatment, or for being surveyed.
(7) ***, **, and * indicate significance at the 1, 5, and 10 percent critical level respectively.
(8) We also calculated sharpened q values to control for multiple hypothesis testing and our outcomes remain significant at the 10% level. Results presented in Appendix Table A3.

the estimate was not significant at the 10% level ($p = 0.189$).

Column 2 in Table 2 indicated that net maize sales (kg) increased by 233 kg ($p = 0.05$) on average for people in the credit group, which was a 50% increase in net maize sold compared to the control group in the intervention year. This finding may be somewhat mechanical because the loan conditions meant that recipients were supposed to store 200 kg of maize as collateral. However, it suggested that the credit intervention was needed to alleviate constraints and it caused farmers to store

Table 3
Quarter level analysis.

Variables	(1) Quantity of net maize sales during April 2017–March 2018 (kg)	(2) Value of net maize sales during April 2017–March 2018 (TSh)
	ANCOVA	ANCOVA
Group 2: Storage group in quarter 1, before and during harvest (April–June 2017)	−52 (34)	−19,938 (13,002)
Group 2: Storage group in quarter 2, during and right after harvest (July–Sept 2017)	20 (49)	8722 (19,303)
Group 2: Storage group in quarter 3, one quarter after harvest (October–December 2017)	77 (63)	27,636 (21,590)
Group 2: Storage group in quarter 4, two quarters after harvest (January–March 2018)	28 (39)	13,290 (13,478)
Group 3: Credit group in quarter 1, before and during harvest (April–June 2017)	−51 (31)	−16,356 (12,223)
Group 3: Credit group in quarter 2, during and right after harvest (July–Sept 2017)	5 (48)	8190 (18,353)
Group 3: Credit group in quarter 3, one quarter after harvest (October–December 2017)	128* (69)	38,195* (21,378)
Group 3: Credit group in quarter 4, two quarters after harvest (January–March 2018)	91* (47)	30,759* (17,007)
Net Maize Sales in quarter of baseline year (kg)	0.222*** (0.00)	
Net maize sales in quarter of baseline year (TSh)		0.000859 (0.00)
R-squared	0.092	0.052
Group 2:Storage = Group 3: Credit in April–June 2017	0.985	0.707
Group 2:Storage = Group 3: Credit in July–September 2017	0.755	0.978
Group 2:Storage = Group 3: Credit in October–December 2017	0.442	0.639
Group 2:Storage = Group 3: Credit in January–March 2018	0.181	0.279
Control group mean sales in quarter 1, before and during harvest (April–June 2017)	74 (393)	26,690 (156,958)
Control group mean sales in quarter 2, during and right after harvest (July–Sept 2017)	158 (606)	58,029 (218,129)
Control group mean sales in quarter 3, one quarter after harvest (October–December 2017)	198 (680)	60,958 (210,804)
Control group mean sales in quarter 4, two quarters after harvest (January–March 2018)	83 (390)	25,139 (1280,77)

Notes: (1) The table above provided results from regression specification shown in Equation (3). It presented Intention to Treat Estimates from a an ANCOVA regression on the treatment dummies interacted with the quarter level dummies. Constant included in all models.
(2) ANCOVA estimation included the baseline year's value of the outcome variables.
(3) The outcome variables were: (1) quantity of net maize sales in kg through the year (maize sales - maize purchases - interest rate paid by credit group); (2) value of net maize sales in TSh through the year.
(4) Standard errors were clustered at VICOBA Level and district Fixed Effects and constant included.
(5) Observations have also been probability weighted by the likelihood of them being selected for any treatment or for being surveyed.
(6) ***, **, and * indicate significance at the 1, 5, and 10 percent critical level respectively.
(7) All treatment effects estimated in reference to control group (Group 1).
(8) Number of observations = 4952 in all columns.
(9) Harvest in the Mbeya region ranged from late May to early July. Maize prices were at their highest between December and February.

quantitatively more maize into the lean season, as it was intended to do. If people were not credit constrained, they could have refused the intervention or sold the collateralized maize earlier in the season to pay back the loan. It is also worth noting that in comparison, the storage treatment did not incentivize this behavior by itself without the addition of the harvest loan that was offered to people in the credit treatment.

We next looked at net maize sales in terms of value in column 3.[18] We found no statistically significant impact on net maize sales in terms of value for any of the interventions in any specifications in Table 2. The coefficient for the storage treatment was positive but not significant (at the 10% level) for net maize sales, either in terms of quantity in column 2 or value in column 3.[19]

We also estimated the impact of the treatments on total maize purchased at harvest, from June–September 2017, and total sales during the lean season, from January–March 2018. This enabled us to understand more about the extent to which the credit and/or storage treatment encouraged people to buy "low" at harvest and/or sell "high" in the lean season. These results were shown in Appendix table A5. The results of these separate analyses were consistent with those in Table 2. They showed that the credit treatment did not have a statistically significant effect on maize purchases at harvest, but had a statistically significant effect on maize sales during the lean season. On average, people in the credit treatment sold 87 kg more maize than the control group at that time of year. This suggested that there was a movement of sales into the lean season caused by the credit intervention.

For all the outcomes discussed above, we could not reject the null that the coefficients estimates for the impact of the storage and the credit treatments were not different from each other. It should be noted that our experiment was powered to pick up differences between the control group and the treatment groups, and not to pick up differences between the treatment groups themselves. As such, this might have suggested that there was an impact of the storage intervention in comparison to the control group because we could not reject the null that they were equivalent to the credit intervention. However, the impact estimates of the storage intervention were smaller and noisier compared to those of the credit group.

We extended the analysis of net maize sales in Table 3 by allowing the treatment effect to vary across the quarters. We did this by disaggregating the sales data quarter wise, following equation (3) that we presented earlier. While the results were noisy, the coefficients suggested that the credit treatment resulted in a transfer of sales into later in the marketing year. Column 1 indicated that net maize sales in terms of quantity for the credit group were higher by 128 kg (p value = 0.066) on average one quarter after harvest between October and December 2017 compared to the control group. This represented a 65% increase in sales. The credit group also sold 91 kg (p value = 0.055) more maize on

[18] To calculate the value of net maize sales (TSh), we used VICOBA level price values instead of individual prices. As a robustness check we also provided the results using individual level prices. The results, provided in Table A2, were qualitatively the same as in column 3 of Table 2.

[19] We also calculated sharpened q values for our results in Table 2. These were presented in Appendix table A3. Results for the credit intervention remained significant at the 10% level. As an additional robustness check we also regressed each treatment separately. The results using an ANCOVA specification, provided in Table A4, did not change significantly from when we regressed the treatments together.

Table 4
Heterogeneity effects.

Treatment	Household Characteristics	(1) Maize inventory in January 2018 (kg)	(2) Quantity of net maize sales during April 2017–March 2018 (kg)	(3) Value of net maize sales during April 2017–March 2018 (TSh)
Storage	Not storage constrained	12.41 (259.0)	−232.8 (324.8)	−142,475 (107,736)
	Storage constrained	167.5* (97.03)	216.1** (94.09)	48,412 (41,429)
	Not credit constrained	265.4 (174.1)	21.98 (196.7)	19,283 (89,449)
	Credit constrained	106.0 (123.0)	155.8 (103.8)	10,001 (46,166)
	Net buyers of maize or autarkic	−78.58 (66.69)	−50.29 (99.13)	−23,650 (38,228)
	Net sellers of maize	359.6** (181.1)	301.1* (174.5)	45,302 (74,305)
Credit	Not storage constrained	126.8 (229.5)	182.1 (318.1)	−72,627 (108,873)
	Storage constrained	245.2** (96.42)	243.8** (108.6)	69,813 (49,163)
	Not credit constrained	320.0 (224.1)	457.9 (277.7)	93,929 (109,918)
	Credit constrained	201.4** (94.19)	181.1 (112.9)	30,450 (50,563)
	Net buyers of maize or autarkic	−36.48 (72.90)	−13.14 (103.8)	−9891 (36,411)
	Net sellers of maize	427.1*** (160.7)	442.4** (179.6)	86,885 (80,826)

Notes: (1) The table above provided results from regression specification shown in Equation (4). We ran separate regressions for each characteristic, but the results presented here were combined for simplicity. The full regression output for each of the three characteristics have been shown in Appendix A-6, A-7 and A-8 respectively.
(2) The outcome variables respective were: (1) maize inventory in Jan 2018 (kg). (2) quantity of net maize sales in kg through the year (maize sales-maize purchases-interest rate paid by credit group). (3) value of net maize sales in TSh through the year.
(3) ***, **, and * indicate significance at the 1, 5, and 10 percent critical level respectively.
(4) All treatment effects estimated in reference to control group that faced the same constraint (Group 1).
(5) Number of observations = 1238 in all columns.

average between January and March 2018, two quarters after harvest, compared to the control group. This represented a 110% increase in sales. Column 2 indicated that the credit group also sold TSh 38,195 (p value = 0.076) more maize on average between October and December 2017, than the control group, which represented a 63% increase in value of sales. In addition, the credit group sold TSh 30,759 (p value = 0.073) more maize on average between January and March 2018, compared to the control group. This represented a 122% increase in the value of sales over the control group.

3.3. *Exploring treatment heterogeneity*

We also estimated possible sources of heterogeneity in our treatment effects to test if there were sub-populations for whom the treatments were below or above the average for the entire sample. This analysis was also exploratory and served to provide descriptive insights into the nature of the treatment effects.

We considered storage and credit constraints and household status as a net seller of maize as sources of heterogeneity in the analysis. The results discussed in this section are presented in Table 4. The coefficients compared sub-samples of the treatment groups to the sub-sample of the control group who faced the same constraints. These results followed equation (4), We also calculated sharpened q values to control for multiple hypothesis testing, and our outcomes remained significant at the 10% level. The full regression tables are presented in Appendix tables A6-A8.

From the coefficients presented in Table 4, we found that those who were storage constrained, as defined by storage chemical expenditure below the 75th percentile of the sample, were more responsive to the storage and credit treatments. They had 168 kg more maize (p value = 0.087) in storage in January 2018 on average, and sold 216 kg (p-value = 0.023) more maize on average than those in the control group who were also storage constrained. We also found that those who were storage constrained and received the credit treatment had 245 kg (p-value = 0.012) more maize on average in storage in the lean season and sold 244 kg (p-value = 0.026) more maize on average than the sub-sample in the control group who were storage constrained. It is interesting to note that the credit intervention benefited those who were storage constrained at baseline. This might have been because the credit intervention included two bags of maize stored as collateral in the PICS bags. This meant that the treated households increased maize inventory into the lean season without increasing storage chemical expenditure, because the PICS bags were a direct substitute for the chemicals.

Second, we found that people who were credit constrained, defined as those who held below the 75th percentile in shares of their VICOBA group and received the credit treatment, had 201 kg more maize (p-value = 0.034) on average in storage in January 2018 compared to the control group who was credit constrained. This suggested that the credit intervention caused those who were facing larger credit constraints to increase their maize stocks in the lean season compared to those households in the control group who faced smaller credit constraints. We did not find an impact on the value of net maize sales for credit constrained households compared to the credit constrained control group. We also did not find an impact from the storage intervention on credit constrained households.

In order to further understand the impact of the credit treatment on harvest season purchases and lean season sales of maize, we interacted the treatment variables with the credit constrained variable to see how the outcomes of interest were affected. Results in Appendix table A9 indicated that those who were credit constrained and received the credit intervention did not buy significantly more maize at harvest than did credit constrained households in the control group. However, they sold 75 kg more maize in the lean season on average than did those in the control group who were credit constrained. This suggested that the intervention may have helped some of the less well-off participants in terms of credit access, indicating that the harvest loan was progressive in that dimension.

Third, we found that those who were net sellers of maize in the baseline year appeared to have benefited from our storage and our credit intervention. Net sellers who received our storage intervention had 360 kg more maize in inventory in the lean season (p value = 0.049) on average as compared to net sellers in the control group, and they sold 301 kg more maize (p value = 0.087) on average. Similarly, net sellers in our credit intervention had 427 kg (p value = 0.009) more maize on average in the lean season compared to net sellers in the control group. Net sellers in the credit intervention also sold 442 kg more maize (p value = 0.015) on average than net sellers in the control group.

In appendix table A10 we interacted the treatment intervention indicators with the net seller dummy to see the impact on net purchases of maize at harvest and net sales of maize in the lean season. Results from the table showed that on average net sellers who received the credit intervention sold 170 kg more maize during the lean season on average than did the control group participants who were net sellers. This suggested that those who were more inclined to sell maize *ex ante* benefited from the credit intervention that enabled them to sell maize later in the year.

The heterogeneity analysis of credit constrained and net sellers in the

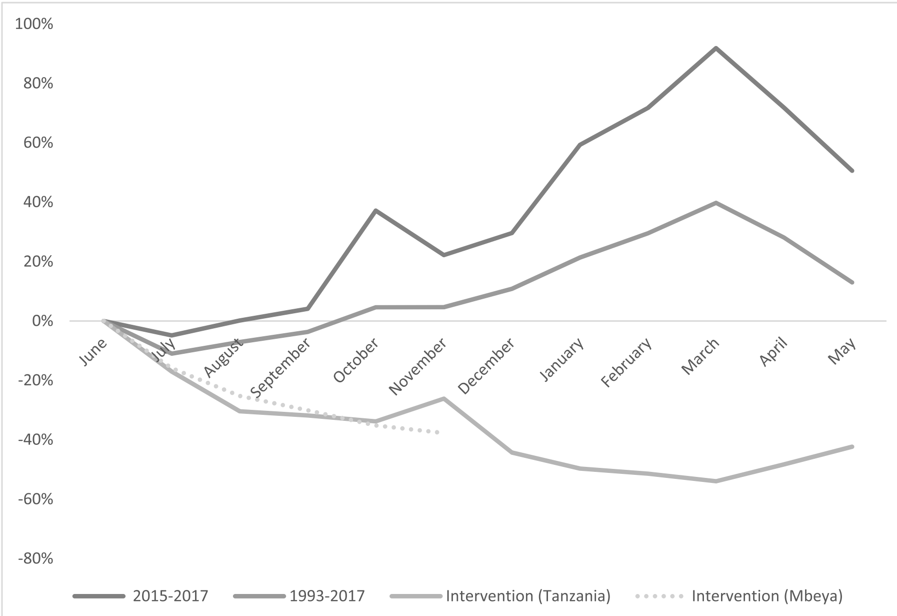

Fig. 7. Price behavior for last 24 years, compared to intervention year. Notes: (1) We have two series of data reflecting the price pattern in the intervention year, from June 2017–June 2018. The dotted line reflected the same data source used for the other price graphs in the paper provided to us by the Minister of Industries, Tanzania. However, this data is incomplete and was only available to us only through November 2018. (2) The other series showing price data from the intervention year was taken from the USDA GAINS Report on Tanzania, from June 2017–June 2018. These data were representative for all of Tanzania and not the Mbeya region.

sample suggested that there were some mixed results in terms of how progressive the credit intervention that provided a loan at harvest was for households in our sample. The credit constrained households benefited from the loan more than the non-credit constrained did. However, those who were net sellers benefited more from the credit intervention than did net-buyers and autarkic households. Though the heterogeneity analysis was exploratory in nature, a possible area of future research would be to use the results from this work and other storage interventions (e.g. Aggarwal et al., 2018; Bergquist et al., 2019; Omotilewa et al., 2018) to further explore such sources of heterogeneity.[20]

5.4. Impact of maize price pattern on outcomes

As discussed earlier, the estimated magnitude of our intervention's impact was likely attenuated because maize prices did not rise in Tanzania during December 2017–February 2018, as had been observed in previous years (Fig. 7). Maize prices across the prior 17 years had risen by an average of 40% in the months of December–February following the harvest in June. However, in our intervention year maize prices did not rise much and were close to where they had been in the previous June.

Anecdotal evidence suggested that a maize export ban put in place by the Tanzanian government around harvest time in June 2017 combined with a bumper harvest in neighboring Zambia could have contributed to the limited price increase during the year of our intervention.

Furthermore, our communications with Tanzanian government officials and a review of news reports suggested that the stated reason behind the placement of the export ban was to prevent a maize shortage in the country (Kamndaya, 2017). The Tanzanian government's reasoning for this was the 80% price differential between harvest in June 2016 and the following lean season that started in January 2017. The perception among government officials was that uncontrolled exports to Kenya were responsible for this price rise.

The lack of maize price increase across the 2017/18 season affected the loan repayment rates associated with the credit intervention. Loan repayment was 85% overall, which was lower than expected. However, the proportion of respondents who repaid at least part of their loan was higher at 90%.[21]

As the unexpected events during the year of our intervention likely attenuated the impacts of the credit intervention, we conducted a simple simulation in Appendix table A12 using the wholesale maize prices in Mbeya, Tanzania from 1993-2017.[22] The results presented in Appendix A12 showed the simulated range of returns on the loan. We found that 72% of the simulated results estimated that profits from the loan would be greater than zero. Furthermore, the simulated results suggested that overall the probability of a greater than 20% return on the loan was 36%, while the probability of a greater than 20% loss from the loan was just 4%.

6. Conclusions

This article provided insights from an RCT, which offered a storage or a credit intervention to smallholder farmers who were members of a savings/credit group in Southern Tanzania at harvest. The storage

[20] In addition to this analysis we also used a machine learning (ML) method developed by Chernozhukov et al. (2018) to test for heterogeneity. ML methods allow for the analysis of heterogenous treatment effects along many dimensions while avoiding the issues of overfitting and multiple hypothesis testing. However, our tests for overall heterogeneity using the Best Linear Predictor (BLP) and Group Average Treatment Effects (GATES) showed no evidence that the key covariates described heterogeneity for any of the two treatment on the key outcomes (maize inventory in Jan 2018, and net maize sales in quantity and value). Results from the ML methods were reported in Appendix Table A11.

[21] Because of the unusual situation with regards to the prices at the time of loan repayment, many groups requested extension when repayment was supposed to begin. Our partner Pheretajo was familiar with these groups and agreed upon extensions in repayment dates without an increase in interest payments. In order to avoid repeat visits (because groups also requested being able to return the loan piecemeal), Pheretajo also began to utilize mobile money for repayments. Transaction costs were borne by the group members who used mobile money to repay the loan.

[22] We calculated the mean and standard deviation of the wholesale maize prices in Mbeya between 1993 and 2017. We then generated 200 random values from a normal distribution parametrized with this mean and standard deviation. We then calculated the profit that a farmer would have made at the price point if they invested in the loan product utilized in our intervention.

intervention provided randomly selected farmers with a new storage technology, two hermetic (airtight) storage bags that each held up to 100 kg of shelled maize. The credit intervention offered randomly selected farmers a loan at harvest equivalent to 200 kg of maize ≈ US $36.00 that was to be paid back six months later at 12% interest. The loan was collateralized with maize stored in hermetic bags to preserve their quantity and quality. The unique contribution of our article was that it was the first to offer causal estimates on the impact of an intervention that potentially reduced both the storage and credit constraints that many smallholder farmers face at harvest. By experimentally testing whether access to improved storage technology to reduce quantity and quality losses or access to credit at harvest to reduce liquidity constraints is more important for household income, we offer important insights into smallholder behavior. Our results also offer information about whether it is more effective to target post-harvest interventions towards technological or financial innovations.

The loan product offered in our intervention was well-received by participants. The take-up rate for the loan was about 81%, which was significantly higher than other micro-credit products offered in previous studies (Bergquist et al., 2019; Karlan et al. 2010). In addition, the most popular use of the money from the loan at harvest was to purchase more maize for storage and sale later in the year (more than 1/3 of participants gave this response). This suggests that at harvest many participants believed *ex ante* that there was a meaningful arbitrage opportunity from storing maize until later in the year.

Our results indicated that the storage intervention on its own did not have a significant average effect on maize inventory in the lean season or net maize sales across the year. Conversely, the credit intervention allowed farmers to store 29% more maize in the lean season and increased the quantity of maize they sold (adjusted for maize purchases) by 50% compared to the control group. When we allowed treatment effects to vary across quarters of the year, we found evidence that the credit intervention allowed recipients to transfer sales later into the year. These farmers were able to increase net maize sales over the year by increasing total maize sales during the lean season. These results were consistent with those found in Bergquist et al. (2019) who offered a similar loan product in Kenya, but without the storage technology intervention. Our findings also complimented other studies that offered loans to smallholders in the lean season that they could be repay at harvest. Those studies found that the credit led to more on-farm labor and higher agricultural output (Fink et al., 2020), along with increased incomes and reductions in seasonal consumption gaps (Basu and Wong 2015). Future research might consider randomizing the offer of credit to smallholders at different times of the year to see when it has the largest effect on income and consumption.

We also found evidence of heterogeneity in our treatment effect estimates. Those who were storage constrained at baseline benefited from the intervention in terms of storing and selling more maize later in the year when they received the storage or the credit intervention. Also, those who were credit constrained sold more maize across the season in response to the credit intervention. However, people who were already net sellers of maize at baseline (e.g.: they sold more maize than they purchased) benefited more from our treatment compared to those in the control group who were net sellers of maize, and those in the treatment groups who were not net sellers of maize. This finding is interesting and highlights another one of the challenges associated with micro-credit. Namely, that people who can make the greatest use of the loan tend to be those people who are better-off, to begin with.

It is likely that our findings were attenuated because maize prices did not increase significantly in the marketing season following our intervention. This seems to have been due in large part to i) a maize export ban put in place by the Tanzanian government shortly after harvest in June 2017 and ii) a bumper harvest in neighboring Zambia. This experience highlighted the high uncertainty associated with agricultural credit products, the returns on which are affected by many uncontrollable factors. However, our simulations suggested that in the average year in Mbeya, Tanzania between 1993 and 2017 the intra-seasonal price variation between harvest and lean periods would have enabled the average person who received the loan at harvest to earn a positive return 72% of the time.

The main take-away for our NGO partner, who offered farmers credit, was that storing the collateralized maize for the loan in hermetic bags lowered their risk. This was because maize stored in hermetic bags was much less likely to suffer damage from insects and mold compared to maize stored in traditional woven bags. Therefore, in the event of a loan default, the lender knew it would have good quality maize to repossess. Despite the uncertainty caused by lower maize prices during our intervention marketing year, which led to a repayment rate of about 85%, the NGO independently scaled up the credit product to 200 credit groups in the next season. They offered credit collateralized with 200 kg of common beans stored in hermetic bags. The NGO chose to switch the loan collateral from maize to beans because of beans higher value and because the Tanzanian government traditionally has been less likely to intervene in the bean market than in the maize market.

The export ban during the intervention year highlighted some of the key challenges to expanding the offering of agricultural financial products and its broader implications on the persistence of price seasonality in this region and other neighboring areas. That being said, the high take-up of the storage technology and the loan by participants, the scaling-up of the intervention by our NGO partner the following year, and our finding that those who received the loan increased maize inventory in the lean season and increased maize sales throughout the year suggested that these constraints are a significant obstacle for smallholder farmers. Overall, our interventions seem to have enabled them to better manage the significant post-harvest challenges that they face.

Author contribution

- *Channa*: conceptualization, data curation, formal analysis, investigation, methodology, project administration, validation, writing original draft.
- *Ricker-Gilbert:* conceptualization, data curation, investigation, methodology, project administration, funding acquisition, validation, review and editing.
- *Feleke:* project administration, methodology, review and editing.
- *Abdoulaye:* conceptualization, funding acquisition, review and editing.

Data statement

The authors will make the data and code used in this article available upon request, and will post it on the journal website if and when the manuscript is accepted for publication.

Declaration of competing interest

We the authors declare that we have no conflicts of interest related to the publication of this manuscript.

Data availability

Data will be made available on request.

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Appendix

Table A1
Probabity of being interviewed by phone at the endline survey

VARIABLES	Phone Interview
Storage	0.0313 (0.0420)
Credit	−0.00809 (0.0437)
Constant	0.151*** (0.0400)
Observations	1238
R-squared	0.018

Notes: (1) We regressed the dummy of being interviewed by phone on treatment assignment. Constant included in models but coefficients not shown.
(2) Robust standard errors in parentheses.
(3) Standard errors clustered at VICOBA Level and district Fixed Effects and constant included.
(4) Observations have also been probability weighted by the likelihood of them being selected for any treatment, or for being surveyed.
(5) ***, **, and * indicate significance at the 1, 5, and 10 percent critical level respectively.
(6) All treatment effects estimated in reference to control group (Group 1).
(7) Number of observations = 1238 in all columns.

Table A2
Net Maize sales with individual prices

VARIABLES	Value of net maize sales during April 2017–March 2018 (TSh)	
	POST	ANCOVA
Group 2: Storage	17,811 (52,999)	11,782 (44,270)
Group 3: Credit	84,796 (66,297)	42,339 (51,918)
Maize inventory beginning of Jan–March 2017		
Net maize sales during April 2016–March 2017 (TSh)		0.289*** (0.0457)
Net maize sales during April 2016–March 2017 (kg)		
Control mean and standard deviation	198,739 (501,732)	
Observations	1238	1238
R-squared	0.131	0.298
Storage = Credit	0.239	0.470

Notes: The table above provided results from regression specification shown in Equation (2) and used the same specification used for the results presented in Table 2. However, the value of net maize sales was calculated using individual reported prices instead of the standardized prices at the VICOBA level used in earlier tables. The results did not change significantly.

Table A3
Unadjusted P values from Table 2, compared to sharpened q values

Variables	Storage		Credit	
	Unadjusted p values	Sharpened q values	Unadjusted p values	Sharpened q values
Maize inventory in January 2018 (kg)	0.189	0.396	0.021	0.068
Net maize sales during April 2017–March 2018 (TSh)	0.791	0.396	0.416	0.161
Net maize sales during April 2017–March 2018 (kg)	0.186	0.396	0.051	0.068

Notes: (1) This table presented the False Discovery Rate adjusted p values shown by Anderson (2008).
(2) We treated each intervention (storage and credit) as a family.

Table A4
ANCOVA Analysis of key outcomes, separately for each treatment variable

VARIABLES	(1) Maize inventory in January 2018 (kg)		(2) Quantity of net maize sales during April 2017–March 2018 (kg)		(3) Value of net maize sales during April 2017–March 2018 (TSh)	
	Storage	Credit	Storage	Credit	Storage	Credit
Group 2: Storage	129.6 (98.42)		145.5 (103.8)		15,819 (28,084)	
Group 3: Credit		217.3* (114.8)		206.5** (91.07)		36,131 (35,168)
Net maize sales during April 2016–March 2017 (TSh)	0.221*** (0.0331)	0.252*** (0.0346)				
Maize inventory beginning of Jan–March 2017			0.383*** (0.0595)	0.618*** (0.132)		
Net maize sales during April 2016–March 2017 (kg)					0.354*** (0.0662)	0.494*** (0.0918)
Control mean and standard deviation	478 (1231)		753 (1018)		168,422 (364,090)	
Observations	837	818	837	818	837	818
R-squared	0.277	0.316	0.148	0.249	0.200	0.298

Notes: The table above provided results from regression specification shown in Equation (2) and used the same specification as the results presented in Table 2. However, the difference in this specification is that each treatment was regressed against the outcome separately. The results did not change.

Table A5
Maize purchases at harvest and maize sales in lean season

	(1) Maize purchases in June 2017–Sept 2017 (kg)	(2) Maize purchases in June 2017–Sept 2017 (Value)	(3) Maize sales in Jan 2018–Mar 2018(kg)	(4) Maize sales in Jan 2018–Mar 2018(Value)
Group 2: Storage	1.631 (2.392)	663 (1088)	22.68 (39.43)	8193 (12,151)
Group 3: Credit	0.962 (2.489)	503 (1158)	86.79* (45.99)	27,226* (14,169)
Maize purchases in June 2016–Sept 2016 (kg)	0.0392 (0.0262)			
Maize sales in Jan 2017–Mar 2017 (kg)			0.291*** (0.0942)	
Logged maize purchases in June 2016–Sept 2016 (Value)		0.0400 (0.0249)		
Logged maize sales in Jan 2017–Mar 2017 (Value)				0.0946*** (0.0322)
Constant		5032** (1938)		−1072 (12,078)
Observations		1238		1238
R-squared		0.073		0.092

Notes (1) The table presents ANCOVA estimates.
(2) The dependent variables were total maize purchases and sales as opposed to the net sales presented in earlier tables.
(3) The outcome variables were: (1) Maize purchases in June 2017–Sept 2017 in quantity (kg) and value (Tsh). (2) Maize sales from January 2018–March in quantity (kg) and value (Tsh).
(4) Standard errors clustered at VICOBA Level and district Fixed Effects and constant included.
(5) Observations have also been probability weighted by the likelihood of them being selected for any treatment or for being surveyed.
(6) ***, **, and * indicate significance at the 1, 5, and 10 percent critical level respectively.
(7) Number of observations = 1238 in all columns.

Table A6
Hetrogeneity in treatment effect (Storage chemical expenditure).

	(1) Maize inventory in January 2018 (kg)	(2) Quantity of net maize sales during April 2017–March 2018 (kg)	(3) Value of net maize sales during April 2017–March 2018 (TSh)
Group 2: Storage * If household was not a low user of storage chemicals (below 75th percentile) = 0	12.41 (259.0)	−232.8 (324.8)	−142,475 (107,736)
Group 2: Storage * If household was low user of storage chemicals (below 75th percentile) = 1	167.5* (97.03)	216.1** (94.09)	48,412 (41,429)
Group 3: Credit * If household was not a low user of storage chemicals (below 75th percentile) = 0	126.8 (229.5)	182.1 (318.1)	−72,627 (108,873)
Group 3: Credit * If household was low user of storage chemicals (below 75th percentile) = 1	245.2** (96.42)	243.8** (108.6)	69,813 (49,163)
If household was low user of storage chemicals (below 75th percentile) = 1	−236.6 (182.9)	−626.5*** (221.4)	−232,649*** (76,262)
Maize inventory beginning of Jan–March 2017	0.528*** (0.0962)		
Quantity of net maize sales during April 2016–March 2017 (kg)		0.424*** (0.0747)	
Value of net maize sales during April 2016–March 2017 (TSh)			0.281*** (0.0459)
Constant	391.7** (196.0)	447.0** (223.2)	197,224** (83,579)
Observations	1238	1238	1238
R-squared	0.225	0.293	0.308

Notes: (1) The table presented ANCOVA estimates.
(2) The treatment variables were interacted with a dummy variable signifying storage constraint respectively. The dummy = 1 if storage chemical expenditure was below the 75th percentile.
(3) The outcome variables respective were: (1) maize inventory in Jan 2018 (kg). (2) quantity of net maize sales in kg through the year (maize sales-maize purchases-interest rate paid by credit group). (3) value of net maize sales in TSh through the year.
(4) Standard errors clustered at VICOBA Level and district Fixed Effects and constant included.
(5) Observations have also been probability weighted by the likelihood of them being selected for any treatment, or for being surveyed.
(6) ***, **, and * indicate significance at the 1, 5, and 10 percent critical level respectively.
(7) All treatment effects estimated in reference to control group that faced the same constraint (Group 1).
(8) Number of observations = 1238 in all columns.

Table A7
Hetrogeneity in treatment effect (credit constrained based on shares purchased from the VICOBA)

	(1) Maize inventory in January 2018 (kg)	(2) Quantity of net maize sales during April 2017–March 2018 (kg)	(3) Value of net maize sales during April 2017–March 2018 (TSh)
Group 2: Storage * If household was not a low contributor to VICOBA in form of shares (below 75th percentile) = 0	265.4 (174.1)	21.98 (196.7)	19,283 (89,449)
Group 2: Storage * If household was a low contributor to VICOBA in form of shares (below 75th percentile) = 1	106.0 (123.0)	155.8 (103.8)	10,001 (46,166)
Group 3: Credit * If household was not a low contributor to VICOBA in form of shares (below 75th percentile) = 0	320.0 (224.1)	457.9 (277.7)	93,929 (109,918)
Group 3: Credit * If household was a low contributor to VICOBA in form of shares (below 75th percentile) = 1	201.4** (94.19)	181.1 (112.9)	30,450 (50,563)
If household was a low contributor to VICOBA in form of shares (below 75th percentile) = 1	−65.02 (128.5)	−71.19 (170.2)	−6657 (76,405)
Maize inventory beginning of Jan–March 2017	0.532*** (0.0913)		
Quantity of net maize sales during April 2016–March 2017 (kg)		0.435*** (0.0699)	
Value of net maize sales during April 2016–March 2017 (TSh)			0.287*** (0.0454)
Constant	248.0* (148.3)	−8.429 (174.3)	12,857 (78,931)
Observations	1238	1238	1238
R-squared	0.225	0.293	0.308

Notes: (1) The table presents ANCOVA estimates. (2) The treatment variables were interacted with a dummy variable signifying credit constraint respectively. The dummy = 1 if shares bought from VICOBA were below the 75th percentile in that VICOBA.
(3) The outcome variables respective were: (1) maize inventory in Jan 2018 (kg). (2) quantity of net maize sales in kg through the year (maize sales-maize purchases-interest rate paid by credit group). (3) value of net maize sales in TSh through the year.
(4) Standard errors clustered at VICOBA Level and district Fixed Effects and constant included.
(5) Observations have also been probability weighted by the likelihood of them being selected for any treatment, or for being surveyed.
(6) ***, **, and * indicate significance at the 1, 5, and 10 percent critical level respectively.
(7) All treatment effects estimated in reference to control group that faced the same constraint (Group 1).
(8) Number of observations = 1238 in all columns.

Table A8
Hetrogeneity in treatment effect (Net sellers of maize)

	(1) Maize inventory in January 2018 (kg)	(2) Quantity of net maize sales during April 2017–March 2018 (kg)	(3) Value of net maize sales during April 2017–March 2018 (TSh)
Group 2: Storage * If household was not a net seller of maize for the year 2016–2017 = 0	−78.58 (66.69)	−50.29 (99.13)	−23,650 (38,228)
Group 2: Storage * If household was a net seller of maize for the year 2016–2017 = 1	359.6** (181.1)	301.1* (174.5)	45,302 (74,305)
Group 3: Credit * If household was not a net seller of maize for the year 2016–2017 = 0	−36.48 (72.90)	−13.14 (103.8)	−9891 (36,411)
Group 3: Credit * If household was a net seller of maize for the year 2016–2017 = 1	427.1*** (160.7)	442.4** (179.6)	86,885 (80,826)
If household was a net seller of maize for the year 2016–2017 = 1	−15.62 (112.2)	−234.1 (160.8)	−55,892 (57,570)
Maize inventory beginning of Jan–March 2017 (kg)	0.487*** (0.0991)		
Quantity of net maize sales during April 2016–March 2017 (kg)		0.432*** (0.0833)	
Value of net maize sales during April 2016–March 2017 (TSh)			0.288*** (0.0539)
Constant	303.8*** (75.47)	79.92 (95.55)	39,748 (35,237)
Observations	1238	1238	1238
R-squared	0.240	0.279	0.299

Notes: (1) The table presents ANCOVA estimates.
(2) The treatment variables were interacted with a dummy variable signifying that the household was a net seller of maize in the baseline year (Net seller of maize = 1).
(3) The outcome variables respective were: (1) maize inventory in Jan 2018 (kg). (2) quantity of net maize sales in kg through the year (maize sales-maize purchases-interest rate paid by credit group). (3) value of net maize sales in TSh through the year.
(4) Standard errors clustered at VICOBA Level and district Fixed Effects and constant included.
(5) Observations have also been probability weighted by the likelihood of them being selected for any treatment, or for being surveyed.
(6) ***, **, and * indicate significance at the 1, 5, and 10 percent critical level respectively.
(7) All treatment effects estimated in reference to control group that faced the same constraint (Group 1).
(8) Number of observations = 1238 in all columns.

Table A9
Maize purchases at harvest and maize sales in lean season interacted with credit constrained dummy

VARIABLES	(1) Maize purchases in June 2017–Sept 2017 (kg)	(2) Maize purchases in June 2017–Sept 2017 (Value)	(3) Maize sales in Jan 2018–Mar 2018 (kg)	(4) Maize sales in Jan 2018–Mar 2018(Value)
Storage # Not credit Constrained	−2.036 (5.082)	−1120 (2545)	5.827 (91.86)	8091 (30,107)
Storage # Credit constrained	2.547 (2.699)	1110 (1184)	27.14 (41.62)	8317 (12,588)
Credit # Not credit Constrained	0.762 (5.191)	246.0 (2655)	137.2 (120.9)	44,306 (35,950)
Credit # Credit constrained	1.033 (2.715)	579.5 (1189)	75.30* (39.36)	23,304* (12,332)
Credit constrained = 1	−2.455 (4.370)	−1512 (2102)	−45.81 (56.53)	−12,468 (15,904)
Amount of maize bought between June–September 2016(kg)	0.0388 (0.0265)			
Amount of maize sold between April–June 2017(kg)			0.288*** (0.0945)	
Logged maize purchases in June 2016–Sept 2016 (Value)		0.0396 (0.0252)		
Logged maize sales in Jan 2017–Mar 2017 (Value)				0.0933*** (0.0323)
Constant	15.57*** (5.108)	6254*** (2343)	44.83 (67.49)	9022 (19,349)
Observations	1238	1238	1238	1238
R-squared	0.067	0.074	0.107	0.096

Notes (1) The table presents ANCOVA estimates.
(2) The treatment variables were interacted with a dummy variable signifying credit constraint respectively. The dummy = 1 if shares bought from VICOBA were below the 75th percentile in that VICOBA.
(2) The dependent variables were total maize purchases and sales as opposed to the net sales presented in earlier tables.
(3) The outcome variables were: (1) Maize purchases in June 2017–Sept 2017 in quantity (kg) and value (Tsh). (2) Maize sales from January 2018–March in quantity (kg) and value (Tsh).
(4) Standard errors clustered at VICOBA Level and district Fixed Effects and constant included.
(5) Observations have also been probability weighted by the likelihood of them being selected for any treatment or for being surveyed.
(6) ***, **, and * indicate significance at the 1, 5, and 10 percent critical level respectively.
(7) Number of observations = 1238 in all columns.

Table A10
Maize purchases at harvest and maize sales in lean season interacted with net seller dummy variable

VARIABLES	(1) Maize purchases in June 2017–Sept 2017 (kg)	(2) Maize purchases in June 2017–Sept 2017 (Value)	(3) Maize sales in Jan 2018–Mar 2018 (kg)	(4) Maize sales in Jan 2018–Mar 2018 (Value)
Storage # Net Buyer or Autarkic	4.567 (4.326)	2114 (1990)	−42.83 (28.75)	−12,190 (8518)
Storage # Net seller	−1.500 (1.919)	−868.6 (956.0)	89.78 (69.11)	29,244 (21,293)
Credit t# Net Buyer or Autarkic	4.406 (5.113)	2207 (2431)	−18.15 (31.78)	−4021 (9421)
Credit # Net seller	−1.618 (1.560)	−783.8 (771.0)	170.0** (72.28)	51,851** (22,189)
Net seller of maize = 1	−1.362 (3.348)	−476.9 (1654)	−30.98 (43.21)	−7325 (12,428)
Amount of maize bought between June–September 2016 (kg)	0.0322 (0.0268)			
Amount of maize sold between April–June 2017 (kg)			0.267*** (0.0978)	
Maize Purchases in June 2016–Sept 2016 (Value)		0.0338 (0.0255)		
Maize Sales in Jan 2017–Mar 2017 (Value)				0.0853** (0.0336)
Constant	13.13** (6.086)	4759* (2496)	47.69 (32.00)	10,581 (9414)
Observations	1238	1238	1238	1238
R-squared	0.074	0.081	0.116	0.105

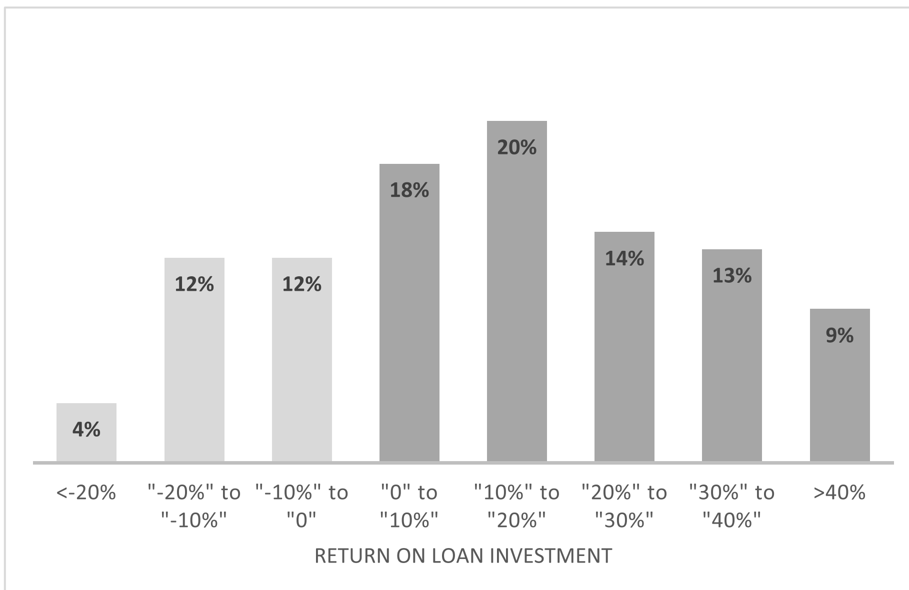
Notes (1) The table presents ANCOVA estimates.
(2) The treatment variables were interacted with a dummy variable signifying that the household was a net seller of maize in the baseline year (Net seller of maize = 1).
(3) The dependent variables were total maize purchases and sales as opposed to the net sales presented in earlier tables.
(4) The outcome variables were: (1) Maize purchases in June 2017–Sept 2017 in quantity (kg) and value (Tsh). (2) Maize sales from January 2018–March in quantity (kg) and value (Tsh).
(5) Standard errors clustered at VICOBA Level and district Fixed Effects and constant included.
(6) Observations have also been probability weighted by the likelihood of them being selected for any treatment or for being surveyed.
(7) ***, **, and * indicate significance at the 1, 5, and 10 percent critical level respectively.
(8) Number of observations = 1238 in all columns.

Table A11
Best linear prediction and group average treatment effects (GATES) heterogeneity detection

Treatment Variable	Best Linear Predictor		GATES		
	ATE	HET	Most Affected	Least Affected	Difference
Outcome Variable: Value of net maize sales during April 2017–March 2018 (TSh)					
Credit	49939.08	0.24	54242.84	43728.76	1700.08
	(-42805.32,143597.13)	(-0.36,0.85)	(-78232.88,184625.53)	(157660.53,0.89)	(-156922.1,172775.37)
	0.59	0.83	0.82	0.89	1
Storage	17881.33	0.41	70968.87	−34951.5	106185.2
	(-67904.07,104946.53)	(-0.14,1)	(-41523.97,186761.42)	(77181.16,1)	(-49006.23,260269.13)
	1	0.29	0.42	1	0.35
Outcome Variable: Maize inventory in January 2018 (kg)					
Credit	136.08	0.14	159.87	101.31	54.26
	(-62.33,333.45)	(-0.42,0.72)	(-164.48,485.25)	(312.36,0.73)	(-338,459.58)
	0.34	1	0.62	0.73	1
Storage	100.95	0	143.85	50.36	75.34
	(-82.27,283.8)	(-0.63,0.63)	(-144.74,431.6)	(271.29,1)	(-285.95,434.48)
	0.56	1	0.65	1	1
Outcome Variable: Maize sales during April 2017–March 2018 (kg)					
Credit	74.89	0.15	317.41	−177.05	681
	(-255.16,647.46)	(-0.08,0.35)	(-238,901.94)	(581.97,0.92)	(-503.15,1405.37)
	1	0.37	0.52	0.92	0.53
Storage	45.03	0.43	182.98	−80.76	281.95
	(-192.25,294.43)	(-0.19,0.93)	(-144.26,511.77)	(280.17,1)	(-229.74,769.78)
	1	0.3	0.52	1	0.53

Notes: 1) ATE referred to average treatment effect and HET to heterogeneity loading parameter. Most and least affected referred to ATE among most and least affected respectively. Difference referred to ATE of most affected minus ATE of least affected. 90% confidence intervals in parentheses, p-values in brackets.
2) We used three groups for the GATES analysis.
3) Results were presented using the Elastic Net method. Results from the Random Forest method and Neural Network were similar.

Appendix A12. Maize price simulations



Notes: In order to get a range of potential profit/loss values that farmers could have made we ran a simple simulation, by drawing 200 values from a normal distribution parametrized by the mean and standard deviation from the wholesale maize prices in Mbeya, Tanzania from 1993-2017. The graph above showed the range of returns on the loan. Returns below zero were marked in light grey and return above zero were marked in dark grey. As the graph above indicates, 72% of the returns simulated were greater than zero.

$$Return\ on\ investment\ (\%) = \frac{Revenue\ from\ selling - (Loan\ Amount + Interest\ Rate)}{Loan\ Amount + Interest\ Rate} * 100$$

Appendix B1. Loan Agreement sample in English

Phiretajo VICOBA Sustainable Development Agency
P.O.Box 1415 Mbeya - Tanzania Reg: 83017
Email:phiretajo@gmail.com Tel: +255 25 2504222

Photo of the borrower

PICS – CREDIT LOAN FORM FOR 2 BAGS OF MAIZE AND 2 PICS BAGS

Name of applicant _________________________________Mob tel no __________

Name of **VICOBA** group____________________ membership number_____

Number of sub group _____________

Domicile–sub village

neighbourhood____________________village___________________

Ward________________District ____________

This agreement has been made today… date..........month .... year 2017.

BETWEEN

PHIRETAJO VICOBA SUSTAINABLE DEVELOPMENT AGENCY, wa S.L.P 1415, Mbeya. **Wherein in this contract is known as MICROCREDIT / lenders as one party**

AND

___________________of P.O. Box___________________wherein in this contract is known as the **BORROWER** on the other party.

THE CONTRACT WITNESSES THE FOLLOWING TERMS AND CONDITIONS:

1. That the borrower is obliged to keep the maize in PICS bags and store under the VICOBA group observance and his/her village government/ward for the duration of the experiment.
2. That he/she will receive 2 PICS bags free of charge.
3. That the Vicoba member will receive a loan of Tsh 80000 in cash.

1. That the loan given to a VICOBA group member will be charged 15% interest rate for six months.
2. That the repayment of this loan will be made in one lump sum on the return date date..........month .... year 2017.
3. That seasonal price change from increased crop prices will belong to the concerned VICOBA group member (borrower).
4. That the VICOBA group member (borrower) will repay the loan and an interest rate of 15%.
5. That the VICOBA group member will store two bags of maize in PICS bag under the supervision of the village government up to the specified return date of date..........month .... year 2017 as a condition of receiving this loan
6. That the borrower must be a VICOBA group member who won the lottery through the PICS - CREDIT survey.
7. That the borrower on his own consent has decided / has agreed to borrow the loan of TZS 80,000.
8. That this loan is valid for six months (6) from the date of signing this contract.
9. That the borrower must obtain sponsorship from leaders of his/her VICOBA group and all its members, government sub village/village.
10. That the Borrower will to repay the loan within the period specified in this contract.
11. That the conditions set in this contract shall not be breached throughout the period of experiment.
12. That borrower with his sponsors confirm that they have read and fully understand the terms and conditions of this contract.

2: **Warranty of the SUB GROUP**

WE four members (4) of the Sub Group VICOBA number _______ acknowledge that we know well Mr/ Ms _________________________ who is a fellow group member and we are assertive of him/her the borrowing of two (2) bags of maize.
We pledge to monitor and ensure that the maize is safe for the duration of the experiment until the return date. date..........month .... year 2017.

NAME	POSITION	SIGNATURE/THUMB
1. ____________________________	____________________	___________________
2.____________________________	____________________	____________________
3.____________________________	____________________	____________________
4.___________________________	____________________	____________________

C: SUB GROUP DECISIONS FOR THE LOAN REQUEST;

____

____

. (*continued*).

Signature of the Sub Group Secretary________________________ Date _______________

D: WARRANTY OF THE BORROWERS FAMILY:
I____________________________________ the wife / husband /sibling of the loan beneficiary pledge to oversee security of the maize for the entire period of the loan and not otherwise.

NAME AND SIGNATURE OF THE FAMILY

NAME	RELATIONSHIP	SIGNATURE/THUMB	
1. __________________________	___________________	__________________	Photo of family trustee
2.__________________________	___________________	__________________	

VICOBA GROUP BOND (To be filled by the Secretary/Chairperson)

I……………………………………Chairperson of …………………………VICOBA group located, at …………..ward/division……………… neighbourhood/village………………meeting ………………… time ………………meeting location ……………… I affirm that the borrower is a live member of our VICOBA group and that he/she has the ability to abide to contract conditions. The VICOBA group affirms to supervise the 2 bags of maize that the borrower will store for all the period of the experiment. These 2 bags of maize will not be kept at the borrowers household and instead will be stored at the village government premises for security reasons and that VICOBA leadership will collaborate with the village government to make sure that the maize bags are safe during the period of the experiment.

Signature……………………………… Date…………………………

Chairperson

Signature .... Date ....

Secretary

E: VILLAGE GOVERNMENT CONFIRMATION;
Village government .... Ward ....District .... We recognize this VICOBA group.. and we know the borrower Mr/Ms..who has been awarded this loan to store 2 bags of maize that will be stored in PICS bags. This village government affirms to take care of the maize bags in collaboration with the group leadership during the period of the experiment to the end.

. (*continued*).

Full name of the Village Executive Office / Ward : ______________________________r
P.O. Box: ___________________________________
Tel Number : _________________________________
Signature__________________ Date__________________Stamp_______________________

Full Name of the Village Chairperson : ______________________________
P.O. Box: ___________________________________
Tel nummber : _________________________________
Signature__________________ Date__________________

F : FOR OFFICE USE

PVSDA COORDINATOR DECISION DISTRICT _________________

____

____

Name : ____________________________

Signature: ___________________________

Date : ________________________

BOND FORM FOR GROUP _____________ VICOBA

WE group members of VICOBA Group _________________________whose names are listed here below have agreed to sponsor our group member Mr/ Ms ___________________________who has been awarded this loan under the condition of storing two bags of maize in PICS bags. We affirm to take care of the maize during all the experimentation period to enable our researchers obtain good results.

Our names are listed here below with our signatures that we support the borrower.

S/N	NAME	MOB. TEL NUMBER	SIGNATURE
1			
2			
3			
4			
5			
6			
7			
8			
9			
10			
11			
12			
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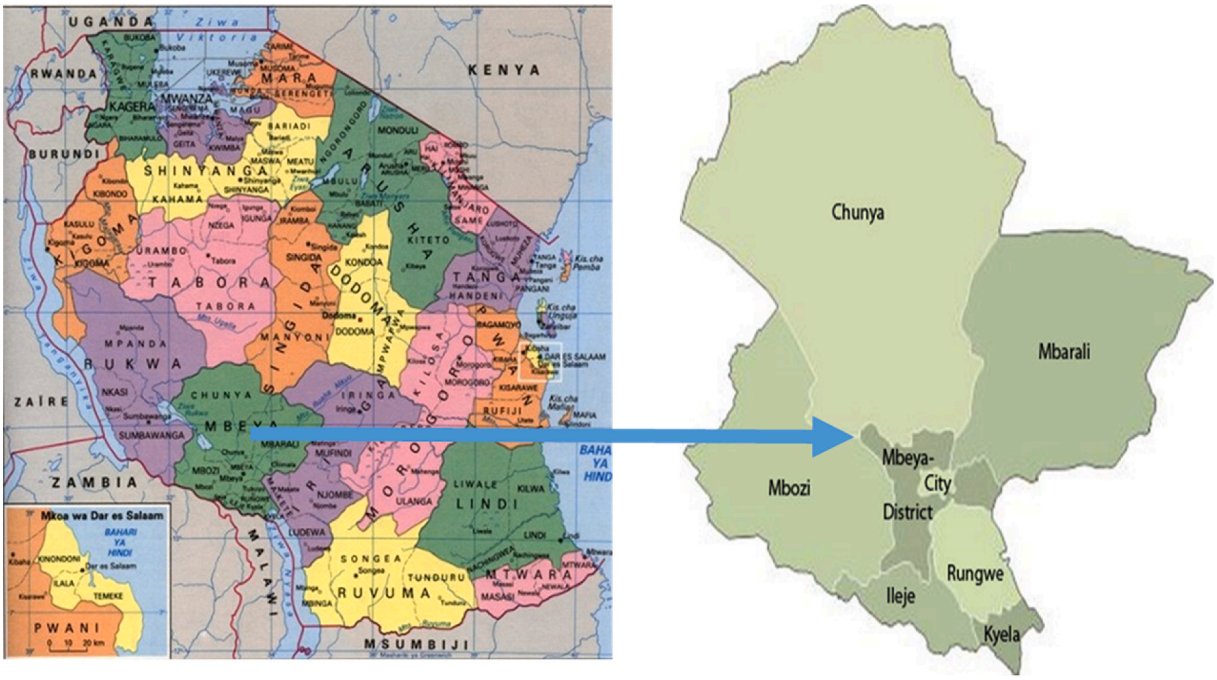
. (*continued*).

Appendix B2. Mbeya region where the experiment was conducted



Appendix B3. Power Calculations

We used data from the Living Standards Measurement Survey (LSMS) collected by the World Bank during the 2014/15 season in Tanzania to create power calculations for this study. Using this dataset, we found that the average amount of maize stored by households was 339 kg with a standard error of 549, and the average amount of maize harvested by households was 836 kg with a standard error of 986. Unfortunately, we did not have maize inventory specifically for the lean season since the LSMS survey was conducted throughout the year.

As mentioned, our storage intervention consisted of two hermetic bags that held 100 kg of shelled maize each; we, therefore, used 200 kg as the size of the treatment effect. The credit intervention also consisted of a loan worth two bags of maize, so we expected a similarly sized effect.

We used these effects and the Tanzania LSMS data to calculate sample sizes that were powered at the 80% level. For lack of a better value we used an intracluster correlation of 0.02 that was found within villages using the LSMS data as a proxy for group-level intra-cluster correlation.

These calculations assumed that a treatment effect of 200 kg would result in an MDE of 0.36. With a sample size of 400 individuals in 40 groups, we were powered to pick up an MDE of 0.30. This is considered a small to medium range for MDE when designing experiments (Duflo et al., 2007). Also, since the outcomes of interest: maize inventory, quantity of maize sales and value of maize sales were likely to be correlated across time, the use of a baseline survey and endline survey that measured the dependent variable at different points in time increased statistical power.

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