Received: 6 January 2022 | Accepted: 13 January 2023

DOI: 10.1111/ajae.12376

ARTICLE

Incentive mechanisms to exploit intraseasonal price arbitrage opportunities for smallholder farmers: Experimental evidence from Malawi

Tabitha Nindi[1] | Jacob Ricker-Gilbert[2] | Jonathan Bauchet[3]

[1]Malawi University of Science and Technology, Mikolongwe, Malawi

[2]Department of Agricultural Economics, Purdue University, West Lafayette, Indiana, USA

[3]Department of Agricultural Economics, White Lodging-J.W. Marriott, Jr. School of Hospitality and Tourism Management, Purdue University, West Lafayette, Indiana, USA

Correspondence
Jacob Ricker-Gilbert, Department of Agricultural Economics, 403 West State Street, West Lafayette, IN 47907, USA.
Email: jrickerg@purdue.edu

Abstract

Seasonal commodity price fluctuations can potentially offer farmers arbitrage opportunities to increase their income. However, smallholder farmers in most of sub-Saharan Africa often do not exploit these opportunities to the fullest extent possible. To inform this issue, we conducted a randomized controlled trial among 1739 smallholder farmers in Malawi to estimate the impact of two key post-harvest constraints, lack of appropriate storage technology and commitment issues, on farmers' legume storage and sales decisions. The treated groups received (i) an improved storage technology in the form of two hermetic (airtight) bags, (ii) the same improved storage technology under the condition that farmers store collectively with members of their farmer club in their village, and/or (iii) the improved storage technology under the condition that farmers store collectively at a centralized association warehouse. We analyzed the impacts of these treatments on storage behavior and revenue from sales. Results indicated that addressing the technological and commitment constraints simultaneously had the largest average impacts. One year after the intervention, farmers offered hermetic bags and the village storage program (Treatment 2) stored 24% more legumes at harvest, stored 27% longer, received a 3% higher price for their legumes and ultimately made 12% more on average than farmers in the control group. Farmers in that treatment also improved some (but not all) outcomes compared to farmers in other treatment groups. These findings suggest that combining technology with collective action that is localized and flexible can lead to better post-harvest outcomes for smallholder farmers.

KEYWORDS
grain storage commitment devices, group storage, hermetic bags, Malawi

JEL CLASSIFICATION
C21, C93, D13, Q16, Q18

1 | INTRODUCTION

Agricultural commodities often exhibit large intraseasonal price fluctuations in the developing world. This is particularly true in sub-Saharan Africa (SSA) where peak lean season grain prices can increase by as much as 50%–100% from harvest (Burke et al., 2019; Gilbert et al., 2017; Kaminski & Christiaensen, 2014). Furthermore, although these price fluctuations offer smallholder farmers temporal arbitrage opportunities when they sell grain, most of them do not exploit these opportunities to the fullest extent possible. This reduces their income and undermines their food security. In fact, many farmers sell a substantial amount of their grain immediately after harvest at low prices, sometimes at the expense of buying it back at a higher price later in the year when their own stocks are depleted. This stylized fact, often called "selling low and buying high," has been documented in the empirical literature (Burke et al., 2019; Dillon, 2021; Stephens & Barrett, 2011).

Data from our study offer evidence of farmers engaging in selling-low and buying-high behavior. For example, about 62% of them had their largest legume sale during the harvest season and 72%

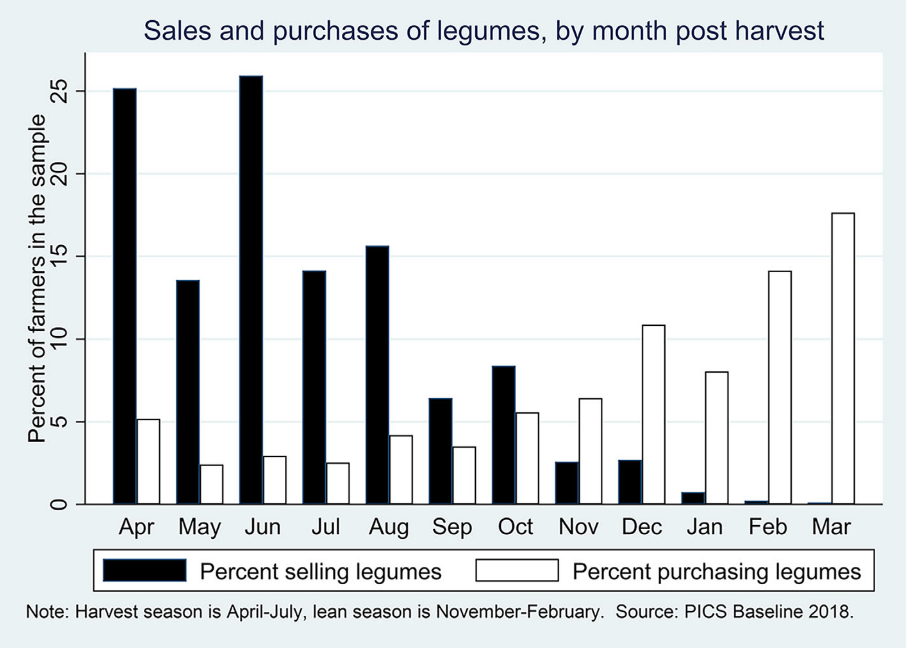

FIGURE 1 Baseline grain marketing trends

had their largest legume purchase during the lean season (6 or more months after harvest as seen in Figure 1). Furthermore, close to 46% of farmers in our sample sold legumes at harvest and purchased legumes in the lean season.

The existing literature has investigated this seemingly puzzling behavior. It has been found to relate to important constraints such as (i) lack of effective storage technologies (Aggarwal et al., 2018; Brander et al., 2021; Chegere, 2018; Kadjo et al., 2018; Omotilewa et al., 2018); (ii) harvest period cash and liquidity constraints that push farmers to liquidate their grain stocks in order to address urgent household expenses (Dillon, 2021; Kadjo et al., 2018; Sun et al., 2013); (iii) limited access to credit markets (Basu & Wong, 2015; Burke et al., 2019; Casaburi et al., 2014; Channa et al., 2022; Delavallade & Godlonton, 2023; Stephens & Barrett, 2011); (iv) limited access to output markets due to high transaction costs (Bernard et al., 2017); as well as (v) behavioral and social challenges including impatience, self-control, and social pressure to share, which limit farmers' commitment to store grain (Aggarwal et al., 2018; Ashraf et al., 2006; Baland et al., 2011; Basu, 2014; Brune et al., 2015; Delavallade & Godlonton, 2023).

The present study estimates the impacts of simultaneously addressing multiple constraints to smallholders' storage and sale behavior. It measured the effectiveness of three different treatments designed to relieve smallholder farmers' physical storage constraint and committment constraint at harvest. Specifically, we implemented a randomized controlled trial (RCT) with 1,739 smallholder farmers in central Malawi who grew two legume crops—groundnuts and soybeans—in the 2018/19 season. We measured the intent-to-treat (ITT) effects of being assigned to one of three treatments: (i) receiving an improved storage technology in the form of two hermetic (airtight) bags (T1: technology only); (ii) receiving the same improved storage technology, under the condition that farmers stored collectively with other members of their farmer club *in their village* (T2: technology + village storage program); and (iii) receiving the improved storage technology, under the condition that farmers stored collectively *at a centralized association warehouse outside their village* (T3: technology + warehouse storage program).

T1 provided only a technological solution to the storage problem. It consisted of hermetic storage bags, which cut off oxygen when closed, thereby killing insects and inhibiting mold growth that damage grain during storage. Empirical evidence suggested that crop damage by pests (i.e., weevils, large grain borer, or rodents) and molds significantly reduces grain market value (Kadjo et al., 2016). T2 and T3 addressed both technological and commitment constraints, while varying the location of storage (in terms of distance from home), the number of farmers involved in the group storage, and the legume deposit and withdrawal conditions to test the impact of different commitment devices. Storage contract terms were agreed upon between farmers in each club and were generally similar in T2 and T3. This included a reservation price increase when grain could be sold, which was expressed in percentage point price increases. On average grain were liquidated when there was a 50% price increase for clubs in both T2 and T3. Clubs also agreed on storage facilities themselves (in both treatment groups facilities were required to have a concrete floor and waterproof roof). The village storage program (T2) involved legume storage with other households who were members of the same farmer club (5–10 people within a farmer's village). Each club identified a storage location within their village and independently agreed on legume deposit and withdrawal terms and conditions. Conversely, the warehouse storage program (T3) required participants to store their legumes at a centralized warehouse run by the National Smallholder Farmers' Association of Malawi (NASFAM) that was located outside the village (further away from home) with multiple farmer clubs (10–15 clubs with 50 to 150 farmers). In that program, deposit and withdrawal conditions were agreed upon at a warehouse level that involved multiple clubs.

This study makes two main contributions to the literature on potential mechanisms to improve lean season income and smooth consumption for limited-resource farmers in the developing world. First, we investigate potential strategies to relieve two market failures preventing farmers from taking advantage of arbitrage opportunities with their crops with an RCT, as we compare the impact of providing a technological solution alone with the impact of providing the technology along with a commitment device. Essentially this is the comparison of outcomes in T1 versus T2, and in T1 versus T3. Brander et al. (2021), Chegere et al. (2021), and Omotilewa et al. (2018) only evaluated the impact of the technology solution (i.e., the effect of providing hermetic bags on farmers' storage behavior). Other studies have estimated the impact of an improved storage technology along with a loan collateralized with the value of stored grain (Basu & Wong, 2015; Channa et al., 2022). The closest study to ours is Aggarwal et al. (2018), who implemented an intervention with credit groups in Kenya that provided hermetic bags to people if they agreed to store maize with members of their group. This design allowed the authors to estimate the impact of a combined technology and commitment intervention. However, their design did not enable them to disentangle the net impact of relieving commitment constraints from the impact of the storage technology itself, which we test in the present study.

Separating out the net impact of commitment solutions is important because it allows us to test how self-control and social pressure may affect farmers' legume storage behavior once a quality and quantity preserving storage option is used. It is possible that when farmers store their legumes individually at home (as in T1), they are likely to be tempted to liquidate their legume stocks earlier due to impatience and limited self-control. In addition, when stocks are stored in plain sight, households may be pressured to sell them earlier than planned whenever their (extended) family has needs (Aggarwal et al., 2018; Delavallade & Godlonton, 2023). Both impatience and social pressure have been shown to be key constraints to cash savings (Anderson & Baland, 2002; Ashraf et al., 2006; Brune et al., 2015; Bryan et al., 2010; Dupas & Robinson, 2013; Thaler & Shefrin, 1981). Therefore, our work extends the evidence from cash savings to another important financial decision, relating to grain storage and sales. It notably adds to Aggarwal et al. (2018) by explicitly estimating and separating the causal impacts of the improved storage technology from those of commitment devices.

Our second contribution is to estimate and compare the impact of two types of commitment devices (village storage and warehouse storage) in order to identify which is a relatively more effective storage commitment device for smallholder farmers. This is essentially the comparison of T2 versus T3. This comparison is important because encouraging collective action is one potential way to address commitment constraints, build resiliency, and increase income and food security across the year for smallholder farmers. However, to date it is not clear which type of group commitment devices work best. The commitment devices implemented in this study build upon common grain storage programs for smallholder farmers in developing countries. For example, T2 (village storage) mirrored village grain banks, whereas T3 (warehouse storage) was similar to a warehouse receipt system. Village grain banks are farmer groups that help farmers to store seed together with a goal of ensuring increased access to improved seeds within their villages (Munthali & Okori, 2018). Warehouse receipt system programs are designed to facilitate commodity trade by enabling aggregation of known commodity quality and quantities from farmers. Though several papers have estimated the impact of savings through village grain banks type systems (Aggarwal et al., 2018) or warehouse receipt systems programs (Casaburi et al., 2014; Delavallade & Godlonton, 2023; Le Cotty et al., 2019), to our knowledge ours is the first to directly compare the effectiveness of these two types of commitment devices.[1]

Our results indicated that T2 (technology + village storage) had the largest impact on the outcomes of interest over the year following the intervention. Over the year after harvest, households in that treatment group stored 61 kg more legumes at harvest, stored 2.7 weeks longer, increased revenue from legume sales by MK 27,789, and obtained a MK 9 higher selling price on average, compared to the control group. People in T2 also stored more legumes at harvest on average than people in T1 (technology only) or T3 (technology + warehouse storage) and obtained a higher average legume sales price than people in T1 (technology only). We also measured impacts 4 and 8 months after the intervention, but we view these results as exploratory, complementing our main results

[1]A third, and relatively minor, contribution is that our study focused on storage of the legume crops, soybean and groundnuts. Most of the previous smallholder based empirical studies that attempt to alleviate post-harvest constraints focused on maize storage (Aggarwal et al., 2018; Burke et al., 2019; Channa et al., 2022; Stephens & Barrett, 2011). Exceptions to this are Delavallade and Godlonton (2023), whose intervention allowed storage of up to nine different crops (participants stored mostly maize and sorghum), and Casaburi et al. (2014), whose intervention focused on palm oil. Legumes are a relevant crop to study these issues because they are relatively higher value, often experience more seasonal price variation, and are more susceptible to insect pests in storage than is maize.

based on the annual outcomes, because they were less robust to multiple hypothesis testing, and they could be affected by possible bias from attrition.

Overall, these findings indicated that addressing both storage and commitment constraints simultaneously, specifically by requiring group storage within farmers' villages, was the most promising avenue to helping farmers take advantage of arbitrage opportunity arising from increases in legume prices over time. Our results also suggested that this specific combination of interventions generated better outcomes for participants than simply providing storage technology alone or encouraging people to engage in larger, more formal storage and sales arrangements, although the evidence about these nuanced differences is less precise.

The paper proceeds as follows. Section 2 provides background information and describes our experimental design and treatment groups. Section 3 contains details of the methodology and tests of the validity of our design. Results are described in Section 4. Section 5 discusses results and concludes.

2 | SETTING AND EXPERIMENTAL DESIGN

2.1 | Background on legume price seasonality and post-harvest losses in Malawi

Legumes including soybeans, common beans, groundnuts, pigeon peas, and cowpeas are an important source of inexpensive proteins relative to animal proteins for most households in SSA. In addition, selling legumes is an important source of income for many smallholders. Legume production, particularly of groundnut, soybean, pigeon pea, and cowpea, is increasing in Malawi. Shah et al. (2021) documented that the total cultivated area of groundnuts, soybeans, and pigeon peas increased by about 56% from the 2009/10 season to the 2018/2019 season, and legume sales increased by 46% in the same period. In the sample of smallholder farmers who participated in the intervention analyzed in the present study, the value of the legumes harvested (at the average sales price observed) represented about 57% of the average total household yearly income at baseline. Although governments in most of SSA intervene in the maize market to stabilize maize prices, for example in Malawi through the Control of Goods Act, in contrast, there is generally limited government interference in legume markets.

In this study, we focus on legumes, specifically groundnuts and soybeans, because their prices typically exhibit relatively larger seasonal price variations and fetch higher prices compared to maize. This is in line with empirical evidence from some recent studies in SSA that find limited price seasonality in maize during certain seasons (Abass et al., 2014; Burke et al., 2019; Cardell & Michelson, 2022; Channa et al., 2022). The Ministry of Agriculture's monthly price data for Malawi from 1989 to 2017 also showed larger intraseasonal variations in average prices for legumes relative to maize between harvest and lean season (Appendix 1). For example, the differences in average seasonal prices for soybeans and groundnuts were between 15 and 35 percent higher between harvest and lean season than for maize. Furthermore, Appendix 1 shows that maize prices did not increase on average between harvest and lean season in 7 out of the 29 years between 1989 and 2017 (note: prices failed to increase between harvest and lean seasons when the lines were below zero in Appendix 1). Similarly, groundnut prices did not increase in only 4 years, and soybean prices did not increase in 7 years. These findings are consistent with recent evidence from Cardell and Michelson (2022) who found that across 30 countries in SSA over 20 years maize prices did not rise between harvest and lean season nearly 16% of the time on average. In total, this information suggests that legume crops are relatively more viable as a stored commodity to exploit price arbitrage opportunities compared to maize in Malawi.

One key constraint that inhibits smallholders from storing crops at harvest for sale in the lean season is post-harvest losses (PHL). There are wide variations in estimates of households' PHL in SSA. For example, the reported PHL for maize ranges from 1.4 to 18% (Gustavsson et al., 2011;

Hodges et al., 2014; Kaminski & Christiaensen, 2014; Sheahan & Barrett, 2017). To our knowledge, very few studies have estimated PHL for specific legume crops in SSA. Mutungi and Affognon (2013) showed that about 4.2%–9.1% of beans and 10% of groundnuts were lost during storage in Malawi, and 7.7% of beans were lost in Kenya. Additionally, Ambler et al. (2018) reported that conditional on experiencing a loss, smallholders in Malawi lost 8% of their soybean harvest and 12% of their groundnut harvest during the post-harvest period. The authors also found that PHL was just 5% for maize. The relatively high levels of legume PHL compared to maize is another reason for our study evaluating storage interventions for legume crops.

2.2 | Sampling strategy

We utilized a multilevel sampling approach to select legume farmers in Malawi to participate in the study. Malawi is divided into 18 livelihood zones, which are locations that share common livelihood activities. The Kasungu-Lilongwe livelihood zone is considered to exhibit relatively higher potential for crop production compared to other zones. We purposely selected two districts from this zone, Lilongwe and Mchinji, because these districts are major producers of legumes in Malawi (Appendix 2). We chose this region because it is more likely to have farmers who produce legume surplus that could potentially be sold and/or stored at harvest for sale later in the year.

Like many countries in SSA, Malawi has an active network of smallholder farmer organizations. We worked with members of the National Smallholder Farmers' Association of Malawi (NASFAM), a farmer-based organization with membership throughout the country. NASFAM has 43 Farmer Associations across Malawi. In each association, NASFAM is organized in Group Action Centers (GACs), which include several farmer clubs. On average, associations count 21 GACs each, and GACs count 15 farmer clubs each. A club is made of about 10 farmers who reside within the same village. Some villages can include more than one club, and some clubs can include members in more than one village; such clubs and villages were excluded from our sample so that in our data, one village = one club. Villages that participated in our study were located six kilometers apart on average (range 1–8 km). Although villages whose inhabitants fell within the same GAC were very similar, villages were sufficiently far apart to limit possible treatment contamination across treatment and control groups.

To constitute our sample, we randomly selected 3 out of 15 NASFAM associations operating in the Lilongwe and Mchinji districts. In each of these associations, we randomly selected 12 GACs. Then, within each of the selected GACs, we randomly selected 12 clubs (among clubs that only include members living in one village). Because legumes were the focus crop in our study, we excluded farmers that did not plant legumes in the 2017/2018 cropping season, which was the year before the intervention started. In total, 377 farmer clubs (i.e., village level) were randomly selected to take part in the study, comprising a total of 1739 legume farmers (Appendix 3 shows a CONSORT diagram).

All farmers in the selected clubs were informed about the intervention through lead farmers in their villages. We randomly selected five farmers per treated club and 10 farmers per control club regardless of club size or number of farmers that showed up on the survey day in that club. Using lead farmers to inform other farmers could potentially limit the external validity of our study. However, we have no reason to expect, nor empirical indication from fieldwork, that any systematic group of farmers were unable to attend that meeting. We oversampled the control group *ex ante* to deal with potential attrition that could have been higher among that group. As such, it is likely that the probability of a farmer being sampled varied across clubs. In some situations, we were unable to recruit the targeted 5 (10) farmers per club for the treatment (control) group due to low farmer turn-up on scheduled survey days.

2.3 | Experimental design

Our intervention included three treatments, described below. Treatment assignment was random, made at the club level, and stratified by GAC. In each of the GACs, we randomly selected three clubs to be in each of the four treatment groups in the intervention, so 12 clubs per GAC were sampled. Randomizing at the club level was equivalent to randomizing at the village level, as there was one club per village in the intervention. This reduced possible spillover bias. Of the 377 clubs and 1739 farmers included in the study sample, 103 clubs (540 farmers) were assigned to the control group, 85 clubs (387 farmers) were assigned to the technology-only treatment (T1), 89 clubs (389 farmers) were assigned to the technology + village storage treatment (T2), and 100 clubs (423 farmers) were assigned to the technology + warehouse storage treatment (T3).[2] Power calculations indicated that a sample including 75 clubs per experimental arm and five households per club would provide a minimum detectable effect of 0.33 standard deviations in outcome comparisons between two arms of the experiment. This effect size is considered between small and medium (Duflo et al., 2008). Additional details are provided in Appendix 4, and intracluster correlation coefficients in Appendix 5.

2.4 | The physical storage technology (Treatment 1)

In Treatment 1 (T1: technology intervention), households were trained about the hermetic storage technology and given two 100-kilogram (kg) bags for free. The hermetic bags were Purdue Improved Crop Storage (PICS) bags. PICS bags are three-layer airtight storage bags that effectively protect grain pests and molds without the use of chemicals, simply by hermetically sealing their content. PICS bags have proved to be effective at storing many types of cereal grains including maize, rice, and sorghum as well as grain legumes, such as cowpeas, soybeans, and groundnuts (Baributsa et al., 2017; Sudini et al., 2015; Williams et al., 2014). The treatment was designed to help smallholder farmers overcome the storage technology constraint they face from insects and mold.[3]

We chose to provide only two 100-kg bags to treated farmers. This was little enough to reduce sharing of bags but significant enough to allow farmers to effectively store a substantial share of the average harvest for legumes, which was 520 kg at baseline. The training included in this treatment informed smallholder farmers about the benefits of using hermetic bags, as well as the prospects it presented for exploiting seasonal price arbitrage opportunities through storage.

2.5 | The village storage program (Treatment 2)

In Treatment 2 (T2: technology + village group storage arrangement), households received the same training and two 100-kg PICS bags provided in T1. Additionally, they agreed to store 200 kg of their legumes in PICS bags with fellow club members within their villages and only received the PICS bags if they agreed to the village storage component of the treatment. This treatment was designed to help farmers overcome the storage technology constraint as well as the behavioral commitment challenge associated with individual storage of legumes at home. These include social pressure to share, impatience, and limited self-control problems (Aggarwal et al., 2018; Ashraf et al., 2006; Baland et al., 2011; Brune et al., 2015).

The group storage arrangement allowed farmers to separate and deposit the 200 kg of their legumes stored in the PICS bags into a club-managed stock that was stored collectively away from home. Each club selected a stock keeper who was responsible for the club's stocks. That person was chosen based on trust and his or her storage ability (i.e., enough and secure space to store all members' legumes). The clubs agreed to liquidate the legumes when prices rose. Each club independently

[2]The allocation of clubs to control and treatment groups ended up somewhat unequal because we randomized clubs based on a pre-existing list, but some clubs were not active in reality. Given time constraints with the harvest coming, we could not replace these clubs.

[3]PICS bags need to be sealed after they are filled to become hermetic and eliminate insects and mold damage. People can open the bags for a short period of time to scoop grain out as needed, as long as they re-seal it afterwards. However, at the beginning of storage the bag should remain closed for about 30 days to kill insects and mold. As such, use of the PICS bags entails a form of commitment for entomological reasons.

agreed on storage length, a reservation price, and procedures for early legume withdrawal. On average, clubs agreed to sell when the price increased by 50% from the harvest price. The rationale behind the village storage intervention was that farmers may have been influenced to store longer through this arrangement than they would have on their own. In addition, the quantity of legumes deposited into the group stocks by an individual farmer was likely to be influenced by his or her peers in the group depending on the groups' anticipated gains of storage. Given self-control and other problems that may influence farmers to liquidate stocks early, we designed this storage intervention to test if group storage arrangements implemented locally within the village with a relatively small number of other farmers would induce people to store more legumes at harvest compared to those who only received the hermetic bags (T1) and those who receive the hermetic bags, but were instructed to store legumes in larger warehouses further from home with more farmers (T3).

2.6 | The warehouse storage program (Treatment 3)

In Treatment 3 (T3: technology + warehouse group storage arrangement), farmers received the same training and the same two 100-kg PICS bags given to households in T1, as well as an instruction to participate in a group storage arrangement with 200 kg of their legumes stored in the PICS bags. The group storage arrangements differed from those in T2 in three ways. First, farmers in T3 received some information on financial management. We provided farmers information about the benefits of storing legumes (a form of savings) and strategically marketing their products to exploit better prices.[4] Second, storage was centralized in NASFAM warehouses at the GAC level rather than within the farmers' villages.[5] Unlike the village storage program, this meant that more than one club stored in each centralized warehouse (i.e., between 5 to 10 farmers stored together per club for T2, whereas between 10 to 15 clubs stored together per warehouse in T3, with 5–10 farmers per club). Third, clubs using the same warehouse were required to synchronize their legume deposit and withdrawal conditions, which were more stringent than the village storage program's in T2.

The warehouse storage locations used in this treatment arm had the disadvantage of being much further away from the villages than the storage locations in T2 (e.g., 10 to 35 kilometers away in T3, versus 1 to 5 kilometers away in T2) and required smallholders to store with a larger group of people from a wider geographic region, with whom they may have had fewer social connections. However, the benefit of storing legumes at a larger warehouse with more people in T3 was that this treatment helped farmers assemble their legumes for easy off taking by big traders and processors. As such, it could have potentially facilitated more trading opportunities at higher prices for participants. This larger collectivization in T3 could have potentially increased farmers' bargaining power and ability to obtain higher prices for their legumes compared to the more localized village collectivization that occurred in T2.

2.7 | Control group

The control group included farmers that did not receive any treatment but resided in the same area as treated farmers and were also members of NASFAM clubs. Farmers in the control group were included in all follow-up data collection efforts throughout the intervention timeframe. The farmers in this group were asked whether they purchased PICS bags on their own before the baseline and whether they stored their legumes in groups. Only 14 households in the control group reported having bought PICS bags at baseline, with the number of bags bought per household ranging from 1 to 10 bags.

[4]This intervention was initially supposed to include a loan product from a bank, where the legumes stored in the warehouses were intended to be collateral for the loan that had a maximum repayment period of up to 3 months. However, the bank backed out at the last minute so farmers in this group only received the financial training. Fortunately, the bank pulled out before any farmer in T3 was promised or offered a loan.
[5]The GACs were made up of multiple villages ranging between 5 and 15 villages depending on village sizes.

3 | ESTIMATION STRATEGY

The study used data collected in four waves over a 12-month timeframe. A representation of the timeline of the study is presented in Figure 2. The baseline data used in this intervention were collected in April–May 2018. The questionnaire collected detailed data on agricultural production, legume storage and sales behavior, assets, consumption, expenditures, and credit and savings use. The survey included data on quantities of legumes stored at the previous harvest (i.e., from the 2016/17 season), weeks stored before largest sale, average selling and purchasing prices, and households' sales revenue.

This was followed by the implementation of the intervention: training and hermetic bags distribution took place just before the 2018 harvest (April–May). After implementing the intervention, data on key outcomes were collected four and 8 months later through two follow-up surveys. These surveys occurred at the end of August (covering the period from May to August, period 1), then at the end of December (September to December, period 2). Respondents were asked about outcomes including legume inventories, net quantity of legumes sold, and net value of sales during those time periods. Last, a final follow-up survey was conducted 1 year after the baseline, in April 2019. It asked questions about the outcomes in the third period after harvest (January to April) and captured the same detailed information as the baseline survey.

3.1 | Summary statistics

Table 1 presents baseline summary statistics. About 71% of the farmers in our sample reported that soybeans were their major legume in the baseline year, in terms of quantity harvested. Groundnut

Time	Season, Period	Activities
April-May 2018	2017/18, Harvest	**Baseline Study** • 1,739 farmers recruited in the study • 377 clubs; 274 treated + 103 control • Detailed survey (Demographics, agricultural production, storage and marketing activities, assets, consumption, expenditures, credit & saving use) **Treatment Assignment** • 103 clubs in control group • 85 clubs hermetic bags only (T1) • 89 clubs hermetic bags + village storage (T2) • 100 clubs hermetic bags + warehouse storage (T3)
August 2018	2017/18, Post-harvest	**Follow up survey round 1 (1st post-harvest period)** • Basic survey on outcomes of interest only between May and August
December 2018	2018/19, Planting	**Follow up survey round 2 (2nd post-harvest period)** • Basic survey on outcomes of interest only between September and December
April 2019	2018/19, Harvest	**Follow-up survey round 3 (3rd post-harvest survey: endline)** • Detailed survey including outcomes interest between January and April

FIGURE 2 Study timeline

TABLE 1 Summary statistics at baseline.

Variable	Count	Mean	Std. dev.	Median	Min.	Max.
Panel A: Outcome variables (harvest from 2016/17 season)						
Legume stored at harvest (kg)	1739	276	271	185	0	1135
Weeks stored before largest sale	1739	11	6	8	2	32
Yearly sales revenue from legumes (MK)	1739	234,018	133,408	213,500	27,808	920,548
Legume inventory at end of harvest period (kg)	1739	189	350	0	0	1095
Net legumes sales during harvest period (kg)	1739	393	214	350	0	629
Net legume sales value during harvest period (MK)	1739	112,934	61,918	106,750	−3	191,866
Panel B: Household variables						
Legume harvest from 2016/17 season (kg)	1739	520	390	0	0	1770
Legume post-harvest loss (% of 2017 harvest)	1739	6.7	11.5	443	0	50
Household used PICS bag(s) for crop storage (%)	1739	0.8	9			
Total household yearly income (MK)	1739	280,798	392,456	152,000	0	2,400,000
Household size	1739	5	2	5	1	10
Household head's age (years)	1739	41	13	41	20	68
Household head is female (%)	1739	14	35			
Survey respondent is female (%)	1733	46	50			
Landholding (acres)	1739	3.5	1.9	3	0.5	11.8
Loans outstanding (MK)	1739	9640	33,914	0	0	1,050,000
Household head has no education (%)	1739	13	34			
Number of students in household	1739	2.2	1.7	2	0.0	7.0
Years of NASFAM experience	1739	4	3	3	0	25
Total household cash savings (MK)	1739	6086	17,832	0	0	120,000
Distance to closest market (km)	1739	12	11	9	0	45
Fertilizer expenditure in previous year (MK)	1739	38,108	38,585	30,000	0	211,000
Major legume is soybeans (%)	1739	71	45			
Household purchased PICS bag(s) (%)	1739	0.06	0.06			
Household uses storage chemicals (%)	1739	5	22			
Household owns a bicycle (%)	1739	59	49			

Note: US\$1 = MK750. PICS bags are a type of grain hermetic storage bag that were used in the intervention. Actellic is the most common storage chemical used in Malawi. Medians, minimums, and maximums for binary variables were omitted for clarity. Variables in this table are based on farmers' reported data for the baseline year and/or baseline period; because the baseline survey was conducted in 2018 before the harvest from the 2017/18 season, harvest data apply to the 2016/17 season. Total household income was measured as the sum of income from 11 sources (e.g., sale of crops, sale of livestock, daily labor, household enterprise, wage, pension).

was the major legume for about 28% of the sample, and 1% grew other legume crops as their main legume, including pigeon peas and common beans. On average, farmers stored 276 kg of their major legume at harvest at baseline, and the average number of weeks farmers stored their legumes before the largest sale was 10 weeks. Farmers had an average net sales revenue of about MK 112,934 (US $1 ≈ MK 750) from sales of their major legume, with an average total sales revenue of about MK 234,017. The average reported post-harvest loss in the previous season was about 6.7% of the major legume stored. The typical intervention participant was male (86%), middle-aged (41 years on average), and living in a household of five members. Most participants were small-scale farmers,

TABLE 2 Randomization balance check.

Dependent variable: =1 if the household was assigned to …	T1	T2	T3
Legume storage at harvest in baseline year (100 kg)	0.0668*	0.0321	0.0421
	(0.0379)	(0.0372)	(0.0404)
Weeks legume stored until largest sale in baseline year	0.0150	0.0215*	0.0224*
	(0.0136)	(0.0130)	(0.0134)
Total legume sales revenue in baseline year (10,000 MK)	0.0160	0.0207*	0.0148
	(0.0109)	(0.0109)	(0.0105)
Baseline major legume inventory (100 kg)	0.0043	0.0074	−0.0065
	(0.0232)	(0.0214)	(0.0233)
Baseline net legume sales (100 kg)	−0.4496	−0.3879	0.6117
	(0.4231)	(0.3908)	(0.4050)
Baseline net value of legume sales (10,000 MK)	0.0852	0.0747	−0.2631*
	(0.1444)	(0.1348)	(0.1396)
Baseline legume post-harvest loss (% of inventory)	−0.0029	−0.0085	−0.0074
	(0.0064)	(0.0070)	(0.0063)
Baseline legume harvest (100 kg)	0.0098	0.0093	0.0104
	(0.0312)	(0.0295)	(0.0317)
=1 if used PICS bags at baseline	1.0480	−0.7092	0.3611
	(0.9298)	(1.2364)	(0.8250)
Baseline total income from all sources in (10,000 MK)	−0.0018	−0.0003	−0.0027
	(0.0025)	(0.0024)	(0.0025)
Household size	−0.1401	−0.0706	−0.0471
	(0.0645)	(0.0687)	(0.0719)
Age of household head	0.0021	−0.0017	−0.0038
	(0.0063)	(0.0065)	(0.0064)
=1 if household head is female	−0.1007	−0.0446	−0.0761
	(0.2356)	(0.2022)	(0.2247)
Landholding (acres)	0.0018	−0.0935	−0.0218
	(0.0565)	(0.0574)	(0.0529)
Loans outstanding in baseline year (10,000 MK)	−0.0467	0.0237	0.0281
	(0.0579)	(0.0278)	(0.0336)
=1 if household head has no education	−0.1542	0.2906	0.0241
	(0.2153)	(0.2123)	(0.2142)
Number of school goers in household	−0.0216	−0.0067	−0.0053
	(0.0699)	(0.0760)	(0.0716)
Years of NASFAM experience	0.0088	0.0356	0.0372
	(0.0329)	(0.0313)	(0.0312)
Baseline cash savings (10,000 MK)	0.0093	0.0360	0.0090
	(0.0522)	(0.0530)	(0.0507)
Distance to the closest market (km)	−0.0036	0.0035	0.0003
	(0.0086)	(0.0086)	(0.0077)
Amount spent on fertilizer (10,000 MK)	0.0283	0.0252	0.0269
	(0.0238)	(0.0266)	(0.0270)

(Continues)

TABLE 2 (Continued)

Dependent variable: =1 if the household was assigned to …	T1	T2	T3
=1 if harvested soybean in baseline year	0.2103	0.1470	0.3706*
	(0.1914)	(0.1947)	(0.1872)
=1 if used actellic in baseline year	0.1986	0.0898	0.0794
	(0.3260)	(0.3417)	(0.3527)
=1 if household owns a bicycle	0.2595	−0.0554	0.1563
	(0.1658)	(0.1671)	(0.1671)
Constant	1.0585	0.3056	0.4228
	(1.0469)	(1.1001)	(1.0996)
Observations		1739	
χ^2-test that coefficients in table are jointly equal to zero	$\chi^2 = 88; p = 0.095$		

Note: Standard errors clustered at the club level in parentheses. Coefficients are from a multinomial logit model; the control group is the base group, coefficients in the table compare each treatment group to the control group. All variables were measured at baseline. The regression includes a set of dummy variables controlling for group action centers (GACs). PICS bags are a type of grain hermetic storage bag.
$^*p < 0.1$.

cultivating 3.5 acres on average. Fertilizer use was low (MK 38,000 spent on fertilizer the previous year, on average), and households lived 12 km on average from the nearest market. The average length of time that households had been members of NASFAM was 4 years, with a maximum of 25 years.

3.2 | Test of randomization balance

Table 2 presents results from the test of balance in the randomization across treatment and control groups at baseline. We implemented a multinomial logit regression, comparing demographic and agricultural characteristics of households at baseline in each treatment group with the control group. Six of the 25 variables tested in Table 2 showed statistically significant differences at the 10% level or below. These were (i) quantity of legume stored at harvest, (ii) number of weeks that legumes were stored before the largest sale, (iii) total legume sales revenue, (iv) net value of legume sales, (v) household size, and (vi) a dummy indicating whether a household harvested soybeans. Because the randomization was done at the club level, it is not unexpected to identify imbalances in household-level characteristics. The chi-squared test that all coefficients were jointly equal to zero was not statistically significant ($\chi^2 = 88$; $p = 0.095$), suggesting that imbalance was not a source of bias in our estimates. Furthermore, in Appendices 6 and 7, we present coefficients from our main regressions (in Tables 3 and 4 respectively) with the six variables that were not balanced at baseline included as controls. These results were similar in magnitude and statistical significance to the main results where they were not included.

3.3 | Main econometric specifications

The main outcomes of interest in this study were measured 1 year after the intervention. They were (i) households' quantity of legumes stored at harvest, (ii) number of weeks stored before the largest legume sale, (iii) total sales revenue from legumes, (iv) average sale price of legumes. The 4-month period analysis considered the following outcomes: (a) quantity of legumes in storage at the end of the period, (b) net legume sales quantities in the period, and (c) net value of legume sales in the period, (d) average sale price of legumes in the period. Legume inventories represented the household's total legume inventory in a given period including legumes stored at home plus with the group. The net sales quantity was the difference between quantity sold and quantity purchased in a given period. Net value of sales was the value of legume sold minus the value of legumes purchased in every period.[6]

We estimated intent-to-treat effects on the outcomes discussed above that were measured yearly and in each period. We used an analysis of covariance (ANCOVA) specification to estimate intention to treat (ITT) effects on outcomes measured yearly (McKenzie, 2012).[7,8] The regression is specified as follows:

$$y_{ij(t=1)} = \alpha_0 + \alpha_1 T1_j + \alpha_2 T2_j + \alpha_3 T3_j + \alpha_4 y_{ij(t=0)} + \alpha_5 \mathbf{G}_j + \varepsilon_{ij}. \tag{1}$$

In Equation (1) above, i indexes farmers, j indexes clubs, and t indexes survey waves ($t = 0$ is the baseline survey, $t = 1$ is the third follow-up survey conducted 1 year after the baseline); y_{ij} is the observed outcome variable; $T1_j$, $T2_j$, and $T3_j$ are binary variables equal to one if a household lived in a village/club assigned to Treatment 1, Treatment 2, and Treatment 3, respectively, and equal to zero if not; $y_{ij(t=0)}$ is the value of the outcome at baseline; and $\mathbf{G}_j$ denotes a vector of dummy variables controlling for the NASFAM GAC of which the farmer is a member (the randomization was stratified by GAC). Finally, ε_{ij} is the idiosyncratic error term. Coefficient estimates $\widehat{\alpha}_1$ to $\widehat{\alpha}_3$ capture the annual effects (ITT) of each treatment with respect to the control group. We also ran F-tests post-estimation to compare differences among the treatments themselves ($\widehat{\alpha}_1 = \widehat{\alpha}_2 = \widehat{\alpha}_3$). We clustered standard errors at the club level to match the level of the randomization (Abadie et al., 2017).

Treatment effects by post-harvest period were estimated with data collected 4 and 8 months after harvest with the following regression:

$$y_{ijw} = \beta_1 + \sum_{X=1}^{3} \beta_{2,X} TX_j * \mathrm{W1}_{ijw} + \sum_{X=1}^{3} \beta_{3,\mathrm{X}} TX_{\mathrm{j}} * \mathrm{W2}_{ijw} + \beta_4 \mathrm{W2}_{ijw} + \beta_5 \mathrm{y}_{ij(\mathrm{w}-1)} + \beta_6 \mathbf{G}_{\mathrm{j}} + \mu_{ijw} \tag{2}$$

Equation (2) is estimated using three waves of data, from the baseline and the two follow-up surveys. They were conducted to cover the 4-month periods of May to August 2018, and September to December 2018.[9] Subscripts i and j, and T and A are the same as in Equation (1). The subscript w represents the survey waves: $w = 0$ at baseline, $w = 1$ in the first follow-up survey conducted 4 months after the baseline (period 1), and $w = 2$ in the second follow-up survey conducted 4 months after that (period 2). Because we include the lagged value of the outcome on the right-hand side of Equation (2), $W0_{ijw}$ is not included. The letter X represents Treatments 1 to 3, and W is a binary variable equal to one if the observation is from wave w and zero otherwise. For example, $W1_{ijw}$ is equal to one if the observation is from the second wave of surveys (the first follow-up, which captured data from the May to August 2018 period; $w = 1$) and zero if the observation is from the baseline or the second follow-up survey ($w = 0$ or $w = 2$).[10] Finally, $y_{ij(w-1)}$ is the lagged (by one

[6]It would have been time consuming and noisy to do a full income and consumption module as part of this survey, so we chose to focus on measurable outcomes on which we felt we would be able to pick up an effect. Other previously published studies in this literature look at the same or very similar outcomes related to storage and sales decisions across the post-harvest season (Aggarwal et al., 2018; Burke et al., 2019; Channa et al., 2022).

[7]According to McKenzie (2012), ANCOVA is more precise than a difference-in-differences specification when autocorrelations in outcomes are low. Autocorrelation coefficients for our main annual outcomes were low, ranging from −0.016 to 0.122.

[8]We also estimated local average treatment effects (LATE) of the three treatments, because compliance was high (60%–70%) but not perfect. For example, some households stored maize rather than legumes in the PICS bags. We used a two-stage least square specification in which actual participation in the intervention was instrumented with the random assignment (first stage estimates are shown in Appendix 24). Results were similar to our main results (Appendix 25).

[9]We did not include data from the third post-harvest survey in Equation (2) because they applied to the new harvest.

[10]The variable $W1_{ijw}$ is equal to one when $w = 1$ and zero otherwise, and $W2_{ijw}$ is equal to one when $w = 2$ and zero otherwise. The variable $W0_{ijw}$ alone does not appear because it is the omitted variable in the set of variables controlling for wave effects ($W1_{ijw}$ and $W2_{ijw}$).

wave) value of the outcome variable. All other letters are as in Equation (1), and μ_{ijw} is the idiosyncratic error term. As in Equation (1), standard errors were clustered at the club level. Coefficient estimates $\widehat{\beta}_{2,X}$ indicate the ITT effects of each treatment in Wave 2 and $\widehat{\beta}_{3,X}$ capture the ITT effect of the treatments in Wave 3, while controlling for previous quarter effects. The comparison group in this specification is the control group in the same period.

To estimate possible heterogeneity in treatment effects, we modified Equation (1) to add a binary variable indicating a dimension of heterogeneity and interacted each of the treatment binary variables with that variable. The three dimensions of heterogeneity we tested are (i) access to credit, (ii) access to legume markets, and (iii) education of the household head. We define these variables and report results in the Study Results section.

3.4 | Testing for potential attrition bias

As we conducted three follow-up surveys every 4 months after the baseline, some households could not be interviewed in some follow-up surveys. In some cases, households that were not found in one wave could be found in a later wave. In these cases, data for the former were filled in on a recall basis at the time of the follow-up survey. Unless otherwise indicated, all analyses conducted in this article included data collected from recall. In other cases, households dropped out of the sample entirely and were never found again (traditional attrition). Thus, there were two potential sources of bias from households not being found for a particular survey. The subsections below discuss how we addressed these separate issues in our analysis.

3.5 | Recall

Overall, 11% of households were not found in one survey wave were but found in a later wave; the percentage ranged from 9% to 14% in the treatment and control groups. We tested whether obtaining data from recall created bias in our estimates of treatment outcomes; the primary concern is whether households for whom we use recall data are systematically related to the treatment assignment. We ran two analyses to test this. First, we regressed a dummy variable indicating whether a household ever provided data on a recall basis on the three treatment indicators and whether a particular data point came from recall on the three treatment indicators (Appendix 8). Coefficients indicated that recall rates were not statistically significantly different in any of the three treatment groups and the control group, nor were they significantly different between the three treatment groups themselves (*F*-tests shown in the last line of Appendix 8 were not statistically significant).

Second, we ran our treatment effects model for the 4-month follow-up analyses with a dummy variable for whether the data from the period were from recall. Results, shown in Appendix 9, indicated that the estimates of treatment effects remained virtually unchanged from the main estimates in Table 4. In sum, findings in Appendices 8 and 9 indicate that recall data did not bias our results.

3.6 | (Traditional) attrition

Attrition refers to households that were surveyed in the baseline but could not be found in later survey waves (data for one or more subsequent survey waves were missing and could not be filled in by recall). 7% of the households (127 households) attrited in the first follow up, 15% (236 households) attrited in the second follow-up survey, and 24% (416 households) attrited in the third and last follow-up survey (Appendix 10 shows details by treatment group).

To determine the possibility that attrition biased our estimates of treatment effects, we conducted four analyses. First, we tested for differential attrition by treatment assignment across the three survey waves by regressing a dummy variable indicating that a household was not found in each follow-up survey wave on a set of dummy variables for the three treatment groups and a set of dummy variables for the NASFAM associations. It indicated that attrition was not associated with the treatment assignment for our main results that focused on the annual outcomes (Appendix 11, Column 1). There was differential attrition, however, in the first two follow-up survey waves that occurred 4 and 8 months after harvest (Appendix 11, Columns 2 and 3).

The second analysis was a test of selective attrition. We regressed all outcome variables, measured at baseline, on a binary variable indicating that a household attrited and a set of binary variables for the NASFAM associations. We analyzed attrition between baseline and the 1-year follow-up for the three outcomes measured annually, and between baseline and follow-ups 1 and 2 for the four outcomes measured in each period. The results, shown in Appendix 12, indicated that households that attrited in the last survey wave stored 47 fewer kg of legumes at harvest at baseline (17% of the mean storage quantity at baseline), on average, than households that did not attrit in that wave ($p = 0.006$). This finding indicates that attrition may have caused our results to be less externally valid for people who stored legumes at harvest, but it did not impact the validity of our treatment effects estimates (Özler, 2017). Two other coefficients, out of 12 in the table, were statistically significant at the 10% level.

Third, because the test above indicated that our main estimates (yearly outcomes) were affected by selective attrition, we implemented the attrition tests developed by Ghanem et al. (2021). This regression-based approach tests whether differences in the mean of outcomes were internally valid for the subsample of respondents who did not attrit (IV-R) and the entire study sample (IV-P). The results of this analysis paint a nuanced picture, which generally concurred with the previous two tests: (i) our analyses of quantities stored at harvest (annual outcome) could have been impacted by attrition since the IV-P test was statistically significant ($p = 0.049$; Appendix 13); (ii) analyses of three other annual outcomes did not suffer from attrition bias (p-values of both IV-R and IV-P tests were all >0.050); (iii) analyses of two of the four impacts 4 months after harvest could have suffered from attrition bias (p-values for both IV-R and IV-P tests were <0.001; Appendix 14); and (iv) our measures of all impacts 8 months after harvest were internally valid, despite differential attrition (p-values of both IV-R and IV-P tests were >0.090; Appendix 15).

Fourth, to estimate the impact of attrition on our results, we calculated Lee bounds for our estimates of impacts (Lee, 2009). Results from the Lee bounds calculation on the annual outcomes in Appendix 16 indicated that the village storage treatment (T2) had a positive impact. Both lower and upper Lee bounds were positive and statistically significant across outcomes. The lower bounds of the measured impacts of the technology only treatment (T1) and the warehouse storage treatment (T3) were generally not statistically significant, but nearly all the upper bounds were positive and statistically significant. Lee bound for the 4-month (Period 1) impacts suggested that all three treatments had a statistically significant impact on weeks before longest sale, sales revenue, and average selling price but not on quantity stored at harvest (Appendix 17). However, Lee bound results for the 8-month Period 2 impacts suggested that none of the treatment effects were statistically significant, as the lower bounds were negative or not statistically different from zero (Appendix 18).

In summary, analyses of potential attrition bias indicated that our main impact estimates, for yearly outcomes, were not biased by attrition nor the use of recall to capture some data points that were missing in particular survey waves. Estimates of period impacts (4-month and 8-month) could potentially be affected by attrition bias, but the period impact analyses were exploratory and informative in nature.

3.7 | Multiple hypothesis testing

Considering that we have multiple outcome variables and multiple specifications, we corrected standard errors in our main analyses to account for multiple hypotheses testing using Anderson' sharpened q-values (Anderson., 2008). Appendices 19 and 20 present the adjusted sharpened q-values for analyses presented in Tables 3 and 4, respectively. They showed that nearly all of our findings were robust to the adjustment for multiple hypotheses testing; the key exception is that coefficients indicating the yearly impacts of T2 and T3 on storage amount at harvest lost their statistical significance at the 5% level; p values increased to 0.117. Some of the tests that the impacts of various treatments were equal to each other also lost their statistical significance. These results do not affect our main findings about Treatment 2.

4 | STUDY RESULTS

4.1 | Impacts on Farmers' storage behavior

Table 3 presents the estimates of how the interventions affected the annually measured outcomes that were modeled in Equation 1. These were the main outcomes of interest in our study. Coefficient estimates indicated that the hermetic bag + village group storage intervention (T2) had the largest impacts on storage and sales: Households in this treatment group stored 61 kg more at harvest ($p = 0.001$), stored 2.7 weeks longer ($p = 0.005$), earned MK 27,789 more in legume sales ($p = 0.027$), and received a price that was MK 9.4 higher per kg ($p < 0.001$) than households in the control group, on average.

Offering hermetic bags only (T1) and the ability to store in a warehouse outside farmers' village (T3) had impacts on some outcomes relative to the control group but not on others. Specifically, households in T1 did not store statistically significantly more legumes at harvest and did not receive

TABLE 3 Treatment effects on annual outcomes for legumes.

Variable Dependent variable:	(1) Storage at harvest (kg)	(2) Weeks stored until largest sale	(3) Sales revenue (MK)	(4) Average selling price (MK)
=1 for PICS only (T1)	23	1.8**	33,703**	2.4
	(19)	(0.9)	(14,138)	(1.9)
=1 for PICS + village store (T2)	61***	2.7***	27,789**	9.4***
	(19)	(0.9)	(12,533)	(2.2)
=1 for PICS + warehouse store (T3)	27	1.5*	30,331**	9.1***
	(17)	(0.9)	(14,589)	(2.8)
Lagged value of the dep. variable	0.084***	−0.022	0.013	1.1***
	(0.021)	(0.046)	(0.039)	(0.1)
Constant	265***	9.0***	204,717***	−71.6***
	(29)	(2.1)	(31,272)	(22.7)
Observations	1323	1323	1323	1323
R-squared	0.073	0.063	0.052	0.251
Mean in control group at baseline	259	9.9	230,135	286.4
Estimates of impacts:				
Treatment 2 – Treatment 1	38**	0.9	−5913	7.0***
Treatment 3 – Treatment 1	5	−0.3	−3372	6.6**
Treatment 3 – Treatment 2	−33*	−1.1	2541	−0.4

Note: Standard errors clustered at the farmer club level in parentheses. US$1 = MK750. All regressions include a set of dummy variables controlling for group action centers (GACs). PICS bags are a type of grain hermetic storage bag that were used in the intervention.
***$p < 0.01$.**$p < 0.0$.*$p < 0.1$.

a higher average sales price for their legumes, but on average they waited 1.8 weeks longer to make their largest legume sale ($p = 0.046$) and earned MK 33,703 more in legume sales ($p = 0.018$) than households in the control group. Households offered hermetic bags and the ability to store in a warehouse outside their village (T3) stored 1.5 weeks longer ($p = 0.099$), earned MK 30,331 more revenue ($p = 0.038$), and received a price that was MK 9.1 higher per kg ($p = 0.001$) than households in the control group, on average.

Comparisons of coefficients among treatment groups confirmed that the hermetic bag + village storage program (T2) was the most effective treatment overall, although it did not always improve all outcomes compared to all other treatment groups. The clearest difference was that households in the T2 group stored more legumes at harvest than households in either T1 or T3, on average: 38 kg more than households in T1 ($p = 0.046$) and 33 kg more than households in T3 ($p = 0.053$). Households in T2 also received about MK 7.0 more per kg of legumes than did those in T1 on average ($p = 0.002$), but they did not receive an amount that was higher than those in T3. Households in T3 also received a premium on their legumes sales price that was MK 6.6 more per kg than did those in T1 on average ($p = 0.020$). The fact that participants in T2 and T3 received a price premium for their legumes (compared to the control group and to the T1 group) could have been due to enhanced marketing opportunities created by cooperative action and aggregation. Beyond this, the three treatments did not differ from each other in terms of their average impacts on weeks stored or sales revenue over the year following the intervention.

4.2 | Impacts on farmers' storage behavior by four-month time period

The effects of the treatments in each 4-month period post intervention, as presented in Equation 2, are shown in Table 4. We treated these results as exploratory, complementing our main results based on the annual outcomes (shown in Table 3). The 4-month time period results were less robust to multiple hypothesis testing, and there were some questions about possible bias from attrition, as explained earlier. However, we believe that the results in this subsection provided some useful insights into the storage and marketing behavior of intervention participants within the year that they were followed. The results are shown in Table 4; Panel A shows the impacts 4months after harvest (Period 1, between May and August 2018), and Panel B shows the impacts 8 months after harvest (Period 2, between September and December 2018). In both panels, the comparison group was the control group in each period.

The results in Table 4 indicated that treatments impacted all outcomes in Period 1, but each treatment had specific impacts. The evidence points to the hermetic bags + village storage program (T2) having had the largest impacts, both compared to the control group and compared to other treatment groups. Households in T2 had 59 kg more legume in inventory at the end of the first 4-month period ($p = 0.007$), sold 37 more kg of legumes ($p < 0.001$), earned nearly MK 11,000 more from legume sales ($p < 0.001$), and received a MK 17.7 higher sales price for legumes ($p < 0.001$) on average, compared to control households. Impacts were similar for households in T3, albeit smaller in magnitude for all outcomes: 57 kg more legume in inventory at the end of the first 4-month period ($p = 0.019$), 28 more kg of legumes sold ($p < 0.001$), MK 8229 more earned from legume sales ($p < 0.001$), and MK 15.9 higher sales price for legumes received ($p < 0.001$) on average, compared to control households. Household in T1 on average experienced higher sales (22 kg, $p < 0.001$), higher value of sales (MK 6200, $p < 0.001$), and a higher selling price (MK 11, $p = 0.005$) but did not have statistically significantly more kg of legumes in storage at the end of Period 1 (8 kg, $p = 0.683$) compared to control households.

Comparing the outcomes among treatment groups to each other revealed that in Period 1, Treatment 2 (hermetic bags + village storage) created the largest impact. Legume storage at the end of the period, net amount sold, net value of legume sales and average price received in Period 1 were all statistically significantly higher among households in the T2 group than among households in T1.

TABLE 4 Treatment effects on outcomes for legumes by 4-month time period.

Variable Dependent variable:	(1) Storage at end of period (kg)	(2) Net sales in period (kg)	(3) Net value of sales in period (MK)	(4) Average selling price in period (MK)
Panel A. Period 1: May–Aug, 2018				
=1 for PICS only (T1)	8	22***	6194***	11.1***
	(19)	(4)	(1308)	(3.9)
=1 for PICS + village store (T2)	59***	37***	10,991***	17.7***
	(22)	(4)	(1229)	(4.1)
=1 for PICS + warehouse store (T3)	57**	28***	8229***	15.9***
	(24)	(4)	(1278)	(4.1)
Panel B. Period 2: Sept–Dec, 2018				
=1 for PICS only (T1)	−0.03	15	6153	4.5
	(12)	(11)	(3785)	(4.1)
=1 for PICS + village store (T2)	29**	25**	8925**	11.4***
	(12)	(12)	(4073)	(4.2)
=1 for PICS + warehouse store (T3)	10	11	5373	8.2**
	(11)	(12)	(3909)	(4.1)
Lagged value of the dep. variable	0.021	0.002	0.006	0.2***
	(0.019)	(0.006)	(0.006)	(0.0)
Constant	114***	38***	14,403***	235.8***
	(26)	(12)	(4722)	(8.7)
Observations	3081	3081	3081	3081
R-squared	0.044	0.128	0.121	0.121
Mean in control group at baseline	196	411	117,895	286.4
Period 1 impacts:				
Treatment 2 – Treatment 1	51***	15***	4796***	6.7*
Treatment 3 – Treatment 1	49**	6	2035	4.9
Treatment 3 – Treatment 2	−2	−9***	−2761**	−1.8
Period 2 impacts:				
Treatment 2 – Treatment 1	29**	10	2771	6.9*
Treatment 3 – Treatment 1	10	−4	−780	3.7
Treatment 3 – Treatment 2	−19	−14	−3552	−3.2

Note: Standard errors clustered at the club level in parentheses. US$1 = MK750. Lagged values of the dependent variable are lagged by one quarter. All regressions include a dummy variable equal to 1 for the third follow-up survey and 0 for the second follow-up survey, and a set of dummy variables controlling for group action centers (GACs). PICS bags are a type of grain hermetic storage bag that were used in the intervention.

***$p < 0.01$.**$p < 0.05$.*$p < 0.1$.

Households in T2 also sold significantly more legumes, in both quantity and value, than those in T3, although kg stored at the end of Period 1 and average sales price received were similar in T2 and T3. Households in T3 exhibited similar outcomes as households in T1 at the end of the first period, except for a higher quantity of legumes in storage at the end of the period.

In total, results from the first 4-month period indicated that all three treatments helped households take advantage of short-term arbitrage relative to the control group. Further, when comparing among treatments, combining a technical solution and a commitment device in the form of village storage was generally the most effective intervention overall. That treatment generated average returns that were statistically higher than the technical solution only treatment in all four measured outcomes. It also generated a higher average return than the technical solution + warehouse storage treatment in two out of four measured outcomes.

Eight months after harvest at the end of Period 2, by 31 December 2018, only households in T2 experienced better outcomes from the intervention than households in the control group on average. These households had 29 kg more legumes in storage ($p = 0.021$), sold 25 kg more ($p = 0.047$), earned nearly MK 9000 more in legume sales ($p = 0.029$) and sold for about MK 11 more per kg ($p = 0.007$) on average than did households in the control group. However, these results should be taken with caution for a combination of two reasons. First, households in T1 and T3 groups did not fare statistically significantly better than households in the control group. Second, households in T2 did not fare statistically better than households in T1 and T3 (with the exception of T2 having higher legume inventory than T1 on average in period 2). In total, these results provided some additional suggestive evidence of the benefits of the combination of hermetic storage bags and a flexible village-based commitment device after 8 months of storage.

4.3 | Heterogeneity in treatment effects

As suggested by previous literature, access to credit markets could influence farmers' demand to store and hold legumes for sale later in the year by solving credit constraints, which are known to be binding (Aggarwal et al., 2018; Basu & Wong, 2015; Burke et al., 2019; Channa et al., 2022; Delavallade & Godlonton, 2023; Stephens & Barrett, 2011). Access to output markets likely play a similar role. In addition, the education level of the household head is also an important factor in households' decisions and likely affects decisions to store and sell legumes.

That being said, we found no evidence of heterogeneity in our estimates of treatment impacts. The analyses did not reveal any consistent heterogeneity in the impacts of the three treatments, by any of three dimensions of heterogeneity we tested: (i) credit access, defined as the household self-reporting having the ability to borrow money in the baseline year if it needed to; (ii) market access, defined as the household living within 5 km of the closest market; and (iii) household head education, defined as a binary variable equal to one if the head had any formal education (Appendices 21–23).

4.4 | Limitations

This section discusses three main limitations of the present study. First, we focused on the impacts of the intervention on immediate outcomes: legume storage, timing of sales, net sales revenue, and output prices received. We did not estimate the impact of our intervention on total household income or consumption, as that would have been noisy and time consuming. We also did not estimate whether inducing households to store legumes prompted them to store less or more of other crops like maize.[11] Investigating the impacts of a storage intervention on these outcomes could be a topic of future research.

We also did not investigate whether the storage intervention in this study produced any general equilibrium effects on the market price for legumes in central Malawi. In a recent paper, Burke et al. (2019) found general equilibrium effects, in the form of lower maize prices, in an isolated region of Kenya after respondents were offered a loan to borrow against their maize at harvest. However, in our context such price effects seem unlikely because the legume market in central Malawi is well

[11] Appendix 26 shows the impact of the treatments on maize post-harvest decisions, using the same outcomes and periods of analysis that we focused on in the main analyses. In these analyses, only one coefficient was statistically significant at the 5% level: households assigned to T3 (PICS bags + warehouse storage) reported having stored 48 fewer kg of maize at harvest, on average. Given that we did not find any impact on any other outcome for maize, we concluded that the intervention had no real impact on maize storage and sale decisions.

integrated into the national and regional markets for legumes, and the sample size of our study was small.

Finally, we should note that we did not investigate gender differentiated impacts of our intervention. Most of the respondents in the intervention were men, because they were mainly responsible for most of the legume marketing activities. However, women are heavily involved in cultivation of legumes and other crops in Malawi. We could not be certain exactly whose legumes were stored in hermetic bags and marketed as part of the intervention. But it seemed likely that it would have been the man's legumes if men and women cultivated and stored separately, or the household's combined legumes if they cultivated together and stored legumes together. Further investigation of the gender issues associated with legume storage interventions could be an area for future research.

4.5 | Simple benefit-effectiveness calculation of the intervention

The main results from our analysis in Table 3 suggested that the three treatment groups increased overall net sales revenue 1 year after the intervention compared to the control group. However, it is important to compare the gains in revenue from the treatments to the cost of implementing them, in order to understand the individual cost effectiveness of each treatment relative to the control group and the treatments relative cost effectiveness compared to each other. According to results in Table 3, each of the three treatment groups increased net sales revenue by MK 28,000-MK 34,000. Because regression coefficients were not statistically different from each other, we consider an average impact of the intervention of about MK 31,000 (≈ US $41.33). Assuming no training costs (i.e., farmers already knew how to use hermetic bags), the cost of PICS bags was MK 2000 per bag (≈ US $2.67).

For farmers in T1, who received two hermetic bags and could store at home, the returns to the treatment were therefore roughly MK 27,000 (≈ US $26.00), or almost 10% of farmers' average total yearly income (MK 280,798). In T2, farmers' costs were likely marginally higher than that of farmers in treatment 1, as the former had to transport their legumes to be collectively stored somewhere in the village with other farmers. We do not have data on those costs. Farmers in T3, who were required to store in NASFAM warehouses outside of their village, experienced significantly higher transport costs than those in T1 or T2, driving their overall cost effectiveness down. They also did not gain significantly higher revenue from selling their maize than did farmers in the other treatment groups. As such, T3 was less cost effective than T2, which was likely less cost effective than T1. However, it should be noted that all three treatments generated positive returns compared to the control group. This was due to increase quantities of legumes stored at harvest and slightly higher prices obtained by farmers in T2 and T3.

5 | DISCUSSION AND CONCLUSION

The key research question addressed in this study was: To what extent does the combination of treatments that can solve two grain storage constraints—storage technology constraint and commitment constraint—incentivize smallholder farmers to store more legumes at harvest so that they can take advantage of potential intraseasonal price arbitrage opportunities? To answer this question, we implemented a randomized controlled trial among smallholder farmers in Central Malawi to help them store legume crops after harvest. In it, one treatment group received only an improved storage technology, in the form of two hermetic (airtight) bags (T1: technology only). The second treatment group received the same improved storage technology under the condition that farmers store collectively with members of their farmer club in their village (T2: hermetic bags + village storage program), which addresses both the technological and commitment constraints. The third treatment group received the improved storage technology under the condition that farmers stored collectively at a centralized association warehouse (T3: hermetic bags + warehouse storage program); this intervention also tackles technology and commitment but induces a higher level of commitment by involving more farmers and farmer clubs in the group storage of legumes.

Our results suggested that solving technical storage constraints alone through the technology only treatment (T1) was not sufficient to cause farmers to store more at harvest, although it helped them store longer (18% longer), and it allowed them to earn a higher revenue from legume sales over the year (15% more) than the control group averages. Previous studies of this issue have found positive impacts of hermetic storage bags on food availability (Aggarwal et al., 2018; Brander et al., 2021) but inconclusive impacts of providing *only* bags on length of maize storage and revenue from sales (Omotilewa et al., 2019).

We also found the intervention that addressed the two constraints of storage technology and commitment through offering hermetic bags with a village storage program (T2) was the most effective approach to helping farmers take advantage of price arbitrage opportunities over the year following the intervention. The commitment device created by the village storage program appeared to have helped farmers overcome self-control and peer pressure issues. Smallholder farmers in T2 increased the amount of legumes that they stored at harvest by 24%, stored 27% longer, had revenue from legume sales 12% higher, and sold legumes at a 3.3% higher price than the mean of the control group at baseline 1 year after the intervention. These impacts are meaningful and informative about smallholder farmers' behavior, although the increased length of storage may not be long enough in an absolute sense to bring about consequential intertemporal arbitrage opportunities. These results are consistent with Aggarwal et al. (2018), who measured the impact of a combination of providing hermetic bags and the requirement that farmers store their maize in groups in the village. Our article advanced their work by explicitly estimating the marginal impacts of the commitment device over the technology-only solution of hermetic bags. We showed that a combined approach that included improved storage technology along with behavioral solutions was needed to help reduce storage constraints and partially overcome the "selling low and buying high" problem that many smallholders face.

We also found limited evidence that the type of commitment device offered farmers mattered. Unlike farmers in T2, farmers in the warehouse storage treatment (T3) did not consistently experience improved outcomes over the year (results from Table 3). Although households in T3 earned more from legume sales, stored longer, and sold legumes at a higher price than households in the control group on average, they did not store more at harvest than did the control group. They also did not earn higher revenue or sell at a higher price than households in T2. This could have been due to increased uncertainty around storing with a larger group of farmers at a centralized location outside the village.

These findings were in line with literature suggesting that social interventions like group storage tend to be more effective within smaller groups with closer social ties, where the trust and peer effects tend to be stronger than they are in larger groups (Dahl et al., 2014; Gonzalez-Mulé et al., 2014; Kandel & Lazear, 1992). Larger-scale storage programs, like warehouse receipt systems where farmers store in more centralized locations with more people, can potentially facilitate commodity trade by eliminating quality information asymmetry and reducing transaction costs for the buyers. They can also be used as commitment devices allowing farmers to separate and store portions of their harvest for sell later when prices rise. Though these systems likely have a place in a portfolio of grain management options, our findings suggest that in the context of our study, smaller scale, more localized grain storage schemes may be relatively more effective at relieving smallholder farmer's and commitment constraints.

Our findings provide evidence that governments, development agencies, and NGOs who seek to help farmers benefit from intraseasonal price arbitrage opportunities should combine technical and behavioral solutions that address multiple constraints simultaneously. This entails designing and promoting innovations that provide protection against self-control issues and leverage existing social mechanisms to help smallholder farmers make better decisions after harvest.

FUNDING INFORMATION

Nindi is a research fellow at Malawi University of Science and Technology; Ricker-Gilbert is professor in the Department of Agricultural Economics at Purdue University; Bauchet is associate professor in at Purdue University. We are grateful for comments and suggestions from Mrunal Shah, Nina Jovanovic, Yurani Arias-Granada, Qingyin Cai, and seminar participants at the 2019 African Association of Agricultural Economists Triannual conference. We also thank three anonymous reviewers and Editor Mark Bellemare for their comments that made this article much better. All remaining errors are our own. This research was supported by the United States Agency for International Development's Office of Foreign Disaster Assistance (USAID) under the project "Increasing Malawian Smallholder Farmers' Access to Improved Storage Technology and Credit" Agreement Number AID-OFDA-G-17-00250 at Purdue University. The CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS) and the Global Alliance on Agricultural Green Gases (GRA) provided supplemental funding through their CLIFF-GRADS research fellowship program. This work is registered at the AEA Trial Registry RCT (DOI: 10.1257/rct.8076-1.0). Human subject research was approved by Purdue University Institutional Review Board (protocol number 1802020251 approved on 04/24/2018).

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SUPPORTING INFORMATION

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How to cite this article: Nindi, Tabitha, Jacob Ricker-Gilbert, and Jonathan Bauchet. 2024. “Incentive Mechanisms to Exploit Intraseasonal Price Arbitrage Opportunities for Smallholder Farmers: Experimental Evidence from Malawi.” *American Journal of Agricultural Economics* 106(1): 330–353. https://doi.org/10.1111/ajae.12376