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Abstract

Many poverty alleviation and development programs focus on increasing agricultural production and productivity through the use of improved seed varieties and chemical fertilizer; but ignore what happens in the postharvest season. However, increasing productivity without proper postharvest grain management practices will also increase quantity and quality losses. In this study, we use a randomized control trial implemented among 1190 farm households across the maize growing regions of Uganda to examine the impact of improved storage technology on household storage decisions at harvest, and on their input use. We exogenously treated one group of farm households providing them with hermetic storage bags. The control group continued to use traditional storage techniques. However, since the study is still on-going and post intervention data is not yet available, we used chemical protectant as a proxy for improved storage technology, and used panel estimation techniques to control for unobserved heterogeneity using our baseline data. Our results indicate that on average, protectant use increases maize storage by about 150 kilograms of maize at harvest with statistical significance. We also find that the use of storage protectant increases the length of storage for consumption by 3.7 weeks on average. Since the average length of hungry season per households' in our dataset is 9 weeks, these findings are important to household food security.

[*] *Corinne Alexander passed away in January 2016. She was an original member of the research team and leaves a valuable research legacy. She lives on in our memories*

1.0 Introduction

Many poverty alleviation or development programs have focused on increasing agricultural production and productivity through encouraging smallholder farm households to increase the use of improved seed varieties and chemical fertilizer. However, many programs do not consider what happens to the extra grain that is produced in the post-harvest season. For instance, maize is the most important staple food in Eastern and Southern Africa (Gitonga et al., 2013); and increasing its productivity has a positive impact on the welfare of poor households in sub-Saharan Africa (Bezu et al., 2014; Mason and Smale, 2013; Smale et al., 1995). However, the softer kernel high-yielding hybrid maize varieties commonly promoted in sub-Saharan Africa (SSA) offer less natural protection to storage insect attacks relative to the lower-yielding traditional varieties which store well (Golob, 2002).

Therefore, smallholder farm households face a rational decision of making a choice between the improved seed varieties to increase production, but with storability concerns vs. the low-yielding traditional seed varieties which are less susceptible to storage pest attacks. Previous studies have focused on the estimation of postharvest losses in SSA (Affognon et al., 2015; Kaminski and Christiaensen, 2014; Hodges et al., 2011), and retrospective studies of postharvest grain management practices or storage technologies to reduce such losses (Murdock and Baoua, 2014; De Groote et al., 2013; Gitonga et al., 2013; Bokusheva et al., 2012; Tefera et al., 2011). However, with a few exceptions (Langyintuo and Mungoma, 2008; Gyasi et al., 2003), issues relating to postharvest grain losses are largely ignored in studies that model the adoption of improved seed varieties among smallholder farm households. Thus, the relationships between postharvest grain management practices, storability concerns, and adoption of improved seed varieties in SSA remains poorly understood.

To our knowledge, sparse literature exists on the causal link between storage technology and improved inputs use among smallholder farmers in SSA. Ricker-Gilbert and Jones (2015) examined how storage chemical use—a form of storage technology—impacts the adoption of improved seed varieties in Malawi. They find that the use of chemical protectant is significantly associated with the probability of adopting improved seed varieties. They however suggested the use of a randomized control trial (RCT) as the ideal identification strategy to measure causal effects.

The objective of this study is therefore to use an RCT investigate the relationships above in two contexts: first, we investigate the primary role of exogenous change in storage technology on household's storage behavior (quantity of grain stored and length of storage); second, we examine if there are behavioral changes such as uptake of improved seed varieties, more fertilizer uses and reduced usage of storage chemicals associated with improved storage technology use. The exogenous change in storage technology comes from an RCT where we randomly selected a group of households to receive an improved storage technology in the form of a hermetic (airtight) triple-layer polyethylene bag called the Purdue Improved Crop Storage

(PICS) bag.[1] A control group continued to use traditional storage techniques. Our approach of using RCT is to eliminate omitted variables bias or unobserved heterogeneity associated with self-selection bias in observational studies. RCTs are usually referred to as the '*gold standard'* for impact evaluations and are typically free of selection bias because individuals are randomly assigned into treatment and control groups (Duflo, Glennerster, and Kremer, 2007).

With the first objective, we try to answer the question how the use of improved storage technology impact the quantity of grain stored and also the length of storage while holding other factors constant. According to AGRA (2014), fear of storage losses is partly reported as motivation for selling crops earlier than intended in SSA. We test the following null hypotheses:

1) The use of improved storage technology has no significant effect on grain storage decisions (quantity of grain stored).
2) The use of improved storage technology has no significant impact on the length of storage period (number of weeks).

With the second objective, we attempt to answer the question how the use of improved storage technology impact production-related behavioral changes such as improved seed variety adoption, fertilizer use; and storage chemical use among smallholder households. We further test the following null hypotheses:

3) The use of improved storage technology has no statistically significant impact on inputs such as improved seed and fertilizer.
4) The use of improved storage technology has no statistically significant impact on the total area of land planted to improved seed varieties.
5) The use of improved storage technology has no statistically significant impact on the share of cultivated area planted to improved seed.
6) The use of improved storage technology by smallholder households has no statistically significant impact on their storage chemical use.

The contribution of this research is two-fold: first, we estimate the relationship between storage technology use and improved input adoption, filling a policy research gap in developing countries in SSA. Our study will shed more light on the impact of improved storage technology on grain storage decisions and input use among smallholder households (Ricker-Gilbert and Jones, 2015; Gitonga et al., 2013). Second, to the best of our knowledge, this is the first study to use RCT to investigate the relationships between postharvest storage technology and input-use decisions in SSA.[2]

[1] For more on PICS technology, what it does and how it works, please see Baributsa et al., (2010).

[2] One other study (Ndegwa et al., 2015) has used RCT to investigate the effectiveness of hermetic storage bags and its economic viability in an on-farm trial in Kenya. Relative to this essay, the sampling in that study is limited in geographic focus and size; and the objectives are also different.

We posit that the storage technologies used by rural households may affect their adoption of improved inputs to increase grain productivity and production through many channels. Perceived storability concerns is one of such channels. Gyasi et al. (2003) in Ghana and Langyintuo and Mungoma (2008) in Zambia examined the role of perceived storability in improved maize variety adoption. These studies used a binary variable to capture storability concerns. Gyasi et al. find it not significant while Langyintuo and Mungoma find it negative and significant among well-endowed rural farmers. However, both of these studies did not account for postharvest storage technology or practices used by the households. Further evidence that storability concerns influences the adoption of hybrid maize varieties exists. Katengeza et al. (2012) and Derera et al. (2006) alluded that in addition to early maturity and high-yield, weevil-resistance, hard endosperm and good husk cover against storage pests are important traits productive farmers consider if they were to plant hybrid maize varieties. Based on these studies, assuming households' concerns about storability is removed through the use of hermetic storage bags, we empirically test if they adopt or use more of improved seed varieties.

Furthermore, another channel through which storage technology might affect improved input use and production is through increased income. Studies have previously shown that, on average, households who use hermetic storage technologies increased their income (Moussa et al., 2014; Gitonga et al., 2013; Bokusheva et al., 2012). Langyintuo and Mungoma (2008) find that well-endowed households are significantly more likely to adopt improved maize variety. Likewise, Katengeza et al. (2012) asserted that one of the most important challenges to a farmer's adoption is lack of cash income. Thus, linking these studies together suggests that there is an implicit connection between storage technology and improved input use; we intend to make the connection explicit.

Data for this study is a panel format comprising two waves: the first wave is from our baseline survey conducted between September and December of 2014 as part of the PICS—phase three (PICS3) project. The baseline survey was needed to understand, ex-ante, the production, storage practices, consumption and marketing behaviors of grain producing households in Uganda. After the baseline survey, the treatment intervention was implemented in July of 2015. The ex-post survey will be conducted between September and December of 2016; two years after the baseline survey or about three cropping cycles after the treatment intervention. Thus, we have household-level panel data generating horizontal and vertical variations in both treatment and control groups.

Although this study is set up as a randomized control trial; however, for this paper, the post-intervention data is yet unavailable. Therefore, we only address the first objective of our study. We estimate the impacts of improved storage technology on quantity of grain stored and length of storage, using storage chemical protectant as a proxy for hermetic storage technology. Moreover, our baseline data covers two cropping cycles including the 2nd agricultural season of 2013 (September 2013—January 2014) and the 1st agricultural season of 2014 (March—August 2014). Hence, in this paper, we refer to the baseline data as a pseudo-panel. Using observational data approach, we exploit the pseudo-panel nature of our cross-sectional baseline data. Whereas we try to control for potential confounders in using only the pseudo-panel baseline data, we are cautious not to claim causality with the results as currently presented until our experimental study is complete.

The rest of the article is organized as follows: section two describes storage losses and postharvest grain management practices in Uganda. In section three, we detail our experimental design and data collection. In section four we discuss the impact pathways for our treatment effects, followed by the treatment effects and empirical model in section five. Section six shows our results and discussion, and section seven concludes and offers policy recommendation.

2.0 Storage Losses and Postharvest Grain Management in Uganda

In Uganda, on-farm postharvest grain losses for maize are, on average, about 6% of quantity stored; but reach up to 100% in some cases (Kaminski and Christiaensen, 2014; anecdotal evidence). Moreover, 63% of the total postharvest grain losses by smallholder farm households are due to storage-related issues such as lack of storage, pest infestation, or poor quality storage technologies (World Bank, 2011). Storage-related losses are important to smallholder farm households because the production of maize is largely seasonal due to rain-fed agriculture, but consumption or demand is fairly constant year-round. The inventory of produced maize is essential for income and food security as it may act as a buffer against market or supply uncertainty in the postharvest season. Thus, losing part of stored grains adversely impacts households.

Currently, the predominant storage technologies used by households are single-layer woven polypropylene bags called “kaveras” (71%); heaped-in-house, where maize is left on the cob (11%); traditional and improved granaries (8%); and private off-farm facilities (2%). The use of hermetic (airtight) technology is less than 1% in our sample. (See Table1) However, there are current efforts to increase the use of hermetic improved storage technology—Purdue Improved Crop Storage (PICS) bags—to mitigate postharvest grain losses. Hence, the opportunity to investigate the impacts of using the PICS technology on households’ behavioral responses to maize quantity stored and duration of storage; and also, improved input and storage chemical use.

Unlike most developed countries, where farmers are assumed to store produce solely for price arbitrage, smallholder farm households in less developed countries with limited market or credit access may store maize or legume for household food security or price arbitrage purposes (Saha and Stroud , 1994; Renkow, 1990). In fact, in Uganda, only about 17% of the households stored maize to sell in the lean period with the remaining storing mainly for consumption and partly for seed. Urgent need for cash and concerns about storage losses, at harvest period, are the major reasons smallholder households sell their maize immediately after harvest. These households may repurchase maize at higher prices later in the lean period. They may also be relinquishing potential increase in net income from price arbitrage. The ‘sell low, buy high’ attitude affects household’s income and food access (Kadjo et al., 2013; Stephens and Barrett, 2011).

Table1: Distribution of rural farm households by storage technologies used

Storage Technology	Season 1, 2014 (%)	Season 2, 2013 (%)	Sample Average (%)
(Woven polypropylene bag	71.20	70.54	70.9
Heaped in House	10.65	10.69	10.8
Traditional granaries	6.54	7.34	6.9
Private off-farm store	1.75	1.86	1.8
Improved granaries	1.22	0.84	1.03
Open-air hanging	0.79	0.93	0.86
Hermetic (drum/silo/jerrycan)	0.78	0.65	0.72
Metal silo/drum	0.17	0.19	0.18
Hermetic (PICS Bag)	0.09	0.19	0.14
Community storage facility	0.09	0.09	0.09
Others	6.7	6.7	6.7
Total N =	**1146**	**1076**	**1111**

Source: Authors’ compilation

3.0 Experimental Design and Data Collection

The data for this paper comes from the baseline survey conducted between October and December of 2014. The survey tool includes modules on household demographic characteristics; production-related details such as total area of cultivated land, area cultivated per crop, input use levels, and crop yields; postharvest grain management practices such as storage technologies and techniques used, and quantities stored at harvest; marketing activities in both harvest and lean periods; assets and household well-being indicators like crop income, off-farm income; food and nutrition security questions; and social networks. Our baseline data covers two cropping cycles which includes the 2nd agricultural season of 2013 (September 2013—January 2014) and the 1st agricultural season of 2014 (March—August 2014). Although we conducted one survey, as earlier indicated, we have data over two cropping seasons and refer to the data as a pseudo-panel.

To select the study area, we first identified the major maize and legume producing districts across Uganda using data from previous years from the publicly available dataset from the World Bank’s Living Standard Measurement Study—Integrated Surveys on Agriculture (LSMS-ISA). Then, we purposively selected two districts in each of the four regions within Uganda to give the survey a semblance of national representation. Second, we use a multi-level stratified sampling approach to select representative households in the sample. That is, in each of the selected district, we also purposively selected three major producing sub-counties with the assistance from the district agricultural/production officers (DAOs). The purposive selection of the sub-counties is to ensure that we sample the right population representative of the maize and legumes producing households.

From there our sampling design includes three levels of randomization; we randomly selected two parishes in each sub-county and followed that with another random selection of the villages or local council ones (LC1s).[3] From there we randomly selected smallholder households to be interviewed. In total, there are 48 (6*8) LC1s in our sample and 1,200 (25 per LC1) randomly selected smallholder farm households from the selected LC1s.[4] The random selection of the households at the LC1 level was facilitated by the LC1 chairmen who provided lists of village residents. We assigned each name on the list a number and randomly chose 25 using a computer random number generator.

After the baseline data collection, we conducted two randomized treatments. For the first treatment we, randomly split the 48 LC1s into two equal groups of 24. Thus, within each sub-county, we randomly selected one LC1 into a treatment group, and another into a control group. The treatment and control LC1s are referred to as *PICS* and *non-PICS* villages, respectively. Between July and August of 2015, there were extension or demonstration activities within the *PICS* villages. These demonstrations were conducted by the NGO Conservation League USA (CLUSA), and participants were introduced to the PICS hermetic technology, and shown how to properly use it. The *non-PICS* villages receive no such demonstrations.

For the second treatment, after the demonstration or awareness activities had been completed, 10 households in the PICS demonstration villages, from the initial 25 that had been randomly surveyed in the baseline were randomly selected to receive one PICS hermetic bag each. The eligibility for the second treatment is conditional on households living within the *PICS* villages which had earlier received demonstration activities on how to effectively use the technology. The choice of a sub-sample of 10 is based on power calculations to be able to have a minimum detectable effect (MDE) in outcomes between the treated and control groups of households. Overall, there are 240 exogenously treated households in our sample. This group is compared against remaining households who did not receive the bag.[5]

To complete the study, we will conduct a post-intervention survey to collect a second wave of data between October and December of 2016. This is about three cropping seasons after the treatment intervention and two calendar years after the baseline survey.

4.0 Conceptual Framework: Impact Pathways

[3] LC1 is the lowest administrative unit in Uganda, and it sometimes comprises more than one village. However, we use LC1 and village interchangeably in this paper.

[4] See Appendix I for a schematic diagram of sampling design.

[5] We acknowledge the remaining 15 households in each *PICS* village may purchase the technology if they have access to it and are willing to pay for it. However, we control for this effect using an interaction term between the first and second treatments.

In this study, we make the following assumptions: 1) households believe that the improved maize varieties have higher yields than traditional varieties; and 2) that postharvest storability of the improved variety is a concern.[6] Given that an improved storage technology, PICS bag, is exogenously provided to households to overcome grain storability concerns, and that such households perceive they can now effectively store their grains in the postharvest season:[7] we posit that such households will store more of better quality grains for longer period; and adopt improved seed varieties and its complimentary input, fertilizer, leading to higher maize production.

The causal pathway is as follows: first, we expect the use of the storage technology to increase confidence in household's ability to store grains effectively; thereby increasing the quantity and proportion of grain stored for a longer period. Second, as a result of longer storage period, we expect households to either take advantage of inter-temporal price arbitrage or make less expenditure on food during the lean period. This will increase their net income and in turn, they could invest in improved inputs such as high-yielding seed varieties and fertilizer needed to boost productivity and production in the next cropping cycle (Langyintuo and Mungoma, 2008).

In general, concerning the hypotheses and expectation from the causal pathway described above, we expect the following relationships as presented in equations (1) through (7).

$$\frac{\partial quantity\_stored}{\partial technology} > 0 \tag{1}$$

$$\frac{\partial storage\_length}{\partial technology} > 0 \tag{2}$$

$$\frac{\partial improved\_seed}{\partial technology} > 0 \tag{3}$$

$$\frac{\partial fertilizer}{\partial technology} > 0 \tag{4}$$

$$\frac{\partial total\_area\_improved\_seed}{\partial technology} > 0 \tag{5}$$

$$\frac{\partial share\_area\_improved\_seed}{\partial technology} > 0 \tag{6}$$

$$\frac{\partial storage\_chemical}{\partial technology} < 0 \tag{7}$$

The first two equations (1) and (2) are associated with the first objective of this study—the impacts of using improved storage technology on storage decisions. The remaining five equations are associated with the second objective—impacts of using improved storage technology on production-related behavioral change.

[6] These are widely believed assumptions in SSA (Ntege-Nanyeenya et al., 1997; also, anecdotal evidence).
[7] Anecdotal evidence from previous farmers using the technology suggests they trust the bags to perform.

On quantity stored and length of storage in equations (1) and (2), we expect, on average, a positive differential in the causal relationship among users of the technology relative to non-users of the technology. On improved seed and fertilizer use in equations (3) and (4), on average, we also expect that households in the treatment group should use more. That is, there should be a positive differential in the causal relationships between the PICS storage technology use and improved grain varieties and fertilizer use among the treated. In addition, on the areas cultivated to improved seed hypotheses, we expect that both the total area and proportion of crop area cultivated under improved seed varieties should be higher among the treatment group. (See equations 5 and 6.) Lastly, on the storage chemical or protectant use, one of the major advantages of hermetic storage technologies is the protection it offers to grains without storage chemicals. Thus, we would expect that the households in the treatment groups should, on average, use less of storage chemicals as shown in equation (7).

5.0 Methods: Treatment Effects and Empirical Framework

Potentially, there are other observed or unobserved factors that could influence the causal pathway described above. If such factors are not controlled or accounted for, the impact of the storage technology on postharvest grain management decisions and production-related input use behaviors might be endogenous and biased. To establish causality, we adopt an ex-ante random selection of the households into treatment and control groups for clean impact assessment. If both groups share similar characteristics ex-ante, then the use of RCT creates a suitable counterfactual or potential outcome for the treatment group.

A counterfactual is the potential effect of a treatment on treated households in the absence of the treatment. For instance, how would farm households who got the technology have fared in its absence or vice versa? This cannot be measured for any individual since the two events (outcome with and without the technology) cannot be observed simultaneously. However, with an RCT, we can measure the average impacts of using the technology (treatment) on a group of households, and compare such impacts with an ex-ante similar group (control) who did not use the technology. With randomization, the control group is a valid counterfactual devoid of selection bias. (See Angrist and Pischke, 2009; Duflo et al., 2007.)

Therefore, let y_i, y_i^1 and y_i^0 represent the observed outcome, and potential outcomes if treated and untreated, respectively, for a given household i. Also, let $D_i = 1$ and $D_i = 0$ represent treatment and no treatment, respectively, E is the expectation symbol. Then, the average treatment effect is the difference in expectation of the potential outcome variables between treated group and the control group who did not receive the technology. By independence of randomized treatment, the ATE is related to the average observed outcomes conditional on being treated as shown in the first line of equation (8).

$$E[y_i|D_i = 1] - E[y_i|D_i = 0] = E\left[y_i^1\middle|D_i = 1\right] - E\left[y_i^0\middle|D_i = 0\right]$$

$$= E\left[y_i^1 - y_i^0 \middle| D_i = 1\right] + E\left[y_i^0 \middle| D_i = 1\right] - E\left[y_i^0 \middle| D_i = 0\right] \qquad (8)$$

The left hand side of equation (8) is the observed difference in outcome variables between the treated and control groups. The second line is derived by adding and subtracting the counterfactual expectation term, $E[y_i^0|D_i = 1]$, to the right hand side of the first line in the equation. The term, $E\left[y_i^1 - y_i^0 \middle| D_i = 1\right]$, is the average causal effect of using an improved storage technology for the households who got treated. The last two terms, $E[y^0|T = 1\,] - E[y^0|T = 0\,]$, represent the selection bias; it is the difference in the potential outcomes between the households who got the technology (had they not gotten it) and the control group households who did not receive the technology. This bias could be positive or negative, provided the last two terms do not sum up to zero. In much empirical work such as this study, the essential goal is to either find ways to correct for the bias or make sure it does not exist by design (Duflo et al., 2007). Randomly assigning households to control and treatment group eliminates the selection bias. It ensures that the outcomes of interest between the two groups differ in expectation only through the treatment. In fact, given the randomly assigned treatment of receiving a PICS bag, equation (8) simplifies further to

$$E[y_i^1 - y_i^0|D_i = 1] = E[y_i^1 - y_i^0].$$

Moreover, since the experimental study is still on-going, we use the ex-ante baseline survey data to try to elicit an experimental outcome. To achieve our first objective in the absence of the complete panel data from post-intervention survey, we make the usual conditional independence assumption and control for observable characteristics that may influence grain quantity stored and length of storage. The conditional independence assumption maintains that conditional on observed variables, selection bias in equation (8) disappears (Angrist and Pischke, 2009). We also attempt to correct for unobserved heterogeneity by using panel estimation techniques.

Ideal identification strategy

To investigate the causal impact from both objectives above, the ideal identification strategy is to estimate both the average treatment effects (ATE) and intent-to-treat (ITT). Recall, since the eligibility for exogenous treatment of receiving PICS bags requires that households live within the *PICS* (treatment) villages, it is possible that there will be spillover effects of the treatment on untreated households within the *PICS* villages. Consequently, the mean impacts of eligibility—living within a *PICS* village—on the outcome variables are estimated as ITT.

Let y_i be the observed dependent variables (quantity stored; length of storage; fertilizer use; improved seed use; share of maize land cultivated to improved variety; and storage chemical use), and P_i be a dummy variable for household (i) in either *PICS* or *non-PICS* villages, respectively. Further, let $\boldsymbol{X}_i$ be a vector of observed household factors, institutional and other characteristics affecting outcomes of interest such as age and sex of household head, family size, household non crop revenue, household distance to the nearest market, total quantity of maize harvested and region effects. The parameters to be estimated are β_o, $\boldsymbol{\beta_1}$, and β_2; and μ_i is the error term as shown in equation (9). Then, using the observed outcomes, the ITT estimation is β_2 in equation (10) below. In the ideal identification scenario, the inclusion of covariates, $\boldsymbol{X}_i$, in equation (9) is for efficiency.

$$y_{ij} = \beta_o + \boldsymbol{\beta_1 X}_i + \beta_2 P_i + \mu_i \tag{9}$$

$$ITT = E[y_i|\boldsymbol{X}_i, P_i = 1] - E[y_i|\boldsymbol{X}_i, P_i = 0] = \beta_2 \tag{10}$$

For the ATE, it is equivalent to the difference in expectation of the outcome variables between the treated and control groups. In addition to the variables described in equation (9) above, let D_i be a dummy variable equal to one if a household is randomly selected to receive the technology; and ε_i is the error term. The empirical equation (11) to be estimated includes the treatment variable, D_i, and an interaction term between eligibility, P_i, and the treatment variable. The ATE is estimated as shown in equation (12).

$$y_i = \beta_o + \boldsymbol{\beta_1 X_i} + \beta_2 P_i + \beta_3 P_i * D_i + \varepsilon_i \tag{11}$$

$$ATE = E[y_i|\boldsymbol{X}_i, D_i = 1] - E[y_i|\boldsymbol{X}_i, D_i = 0] = (\beta_2 + \beta_3) \tag{12}$$

Current Identification Strategy

Given the context and data currently available, we use observational data approach. First, using ordinary least square (OLS) estimator, we pooled the dataset from across the two seasons in our baseline survey and use protectant to proxy for improved storage technology. Thus, the tested covariate of interest is the use of protectant. Second, whereas we controlled for observed heterogeneity in the pooled OLS estimation, potentially, there could be individual unobserved heterogeneity influencing our outcome variables (quantity stored and length of storage). Therefore, we exploit the pseudo-panel nature of our data, as earlier described, to account for unobserved heterogeneity by using the fixed effects (FE) estimator and also the correlated random effects estimator (CRE) by Mundlak (1978).

For the pooled OLS regression, we make the conditional independence assumption to control for observed covariates that may influence quantity stored and length of storage. See equation (13). Let $\boldsymbol{X_i}$ be the observed covariates including total quantity harvested, livestock revenue to account for wealth, distance to market to account for market access, region effects, and also household characteristics; D_i is a dummy variable for protectant use; the parameters to be estimated are β_o, $\boldsymbol{\beta_1}$, and β_2; and θ_i is the individual specific error term.

$$y_i = \beta_o + \boldsymbol{\beta_1 X_i} + \beta_2 D_i + \theta_i \tag{13}$$

To account for unobserved heterogeneity as implied above, we use the longitudinal variations in time for each household to exploit the panel nature of the dataset as shown in equation (14). All parameters are the same as in equation (13) but with the addition of time dummy for cropping seasons (the panel identifier); and the unobserved effects captured in A_i.

$$y_{it} = \beta_o + \boldsymbol{\beta_1 X_{it}} + \beta_2 D_{it} + \beta_3 ag\_season_t + A_i + \theta_{it} \qquad (14)$$

The FE estimator demeans each covariate in equation (14) to remove the time-invariant individual heterogeneity, but the CRE estimator includes the means of the explanatory variables to achieve the same effect. It assumes $A_i$is random but correlate with $\boldsymbol{X_{it}}$. The key for both estimations is the assumption that the individual unobserved heterogeneity, A_i, appears without the time subscript (Wooldridge, 2010; Angrist and Pischke, 2009; Cameron and Trivedi, 2009).

6.0 Results and Discussion

Descriptive Statistics

In Table 2, we present the ex-ante means of the variables used in our estimations to show pre-treatment balance of baseline randomization. On average, the differential quantity stored per household in both treatment and control groups is 32 kilograms of maize. However, there is no statistical difference between the mean variable in both groups. The length of storage is about 15 weeks across both groups with no statistical difference. Rather surprisingly, households in the control group used more storage chemicals. There is a statistically weak 3 percentage point differential between the treatment and control groups. This could mean that more households in the control group consider postharvest pest attacks a problem. However, the variable *chemical protectant* will be replaced by the actual treatment of receiving PICS bag when our study is completed. Furthermore, the average households' distance to the nearest market between the two groups differ slightly with weak statistical significance. The suggests that some households in the control group leave further away from the market. Overall, the remaining variables are well balanced. Statistically, there are equal proportion of people with cash savings at the beginning of harvest in both groups; average age of household head is balanced; and household size is also balanced. Lastly, the control and treatment households are evenly distributed across the regions in our study area.

Storage

The factors determining maize storage at harvest are presented in Table 3 below. The key tested covariate of interest is whether the use of storage chemical protectant has an impact on quantity of maize stored at harvest. From the parsimonious estimate, controlling for maize output and household cash saving at the beginning of harvest in column (1) shows that, on average, protectant use has a positive marginal effect of 88 kilograms on quantity of maize stored at harvest. Also, cash saving at harvest has a positive marginal effect of about 65 kilograms of maize, on average. Controlling for total quantity of maize harvested, an additional kilogram of harvested maize leads 0.71 kilograms stored.

In column (2), we included more covariates to control for more factors that may influence household storage decisions. We discussed these covariates in the *current identification sub-section*. Although the precision declined (now significant at 10% confidence level), on average, the use of chemical protectant still shows a positive association of 81 kilograms with quantity stored. On the other hand, having cash savings at the beginning of harvest shows a significantly positive marginal effect of 69 kilograms on the quantity of maize stored, and additional UGX 100,000 made from livestock sales within the year increases storage by 2.1 kilograms, on average.[8] These results are consistent with storage commodity literature suggesting that liquidity at harvest enables households to store more grain during the harvest period. For example, Stephens and Barrett (2011) find that households with sufficient access to liquidity avoid selling low at harvest and buying high at postharvest in the maize market in Kenya; Basu and Wong (2015) also find similar outcome in their study with Indonesia farmers.

Furthermore, although imprecisely estimated, the other covariates in our pooled OLS estimation show a positive relationship with maize quantity stored. On average, additional km of road in distance to the nearest market has a marginal effect of 0.5 kilograms. This is expected because the discomfort associated with traveling more distance to buy grains should encourage households to store more from their own production. Also, household size and polygamous households show marginal effects of 1kilograms and 56 kilograms, respectively. These results are expected because more mouths to feed should increase storage allocation from own-produced maize. Also, polygamous households are likely to produce and store more to feed larger family members, and to keep everyone happy. On average, female-headed households store 38 kilograms more, ceteris paribus. This indicates that female-headed households may be more concerned about feeding their households (storage for consumption) rather than selling for cash at harvest.

In columns (3) and (4), we control for unobserved heterogeneity and present the results from FE and CRE estimators, respectively. In both cases, the use of storage protectant shows a positive association with quantity of maize stored at harvest. With the FE model, protectant use has a significant marginal effect of about 189 kilograms on quantity stored. The estimate from CRE shows a smaller significant marginal effect of 149 kilograms. By implication, when we account for the within-household variation over the two seasons, OLS estimator indicated a downward bias. The downward selection bias could mean that households who are less informed or less knowledgeable are more likely to use storage chemicals leading to attenuation bias on their maize quantities stored. In addition, relative to results from OLS estimates, the coefficient

[8] At the time of data collection in 2014, 1 USD is equivalent to about 2,800 UGX.

for cash savings are now negative but no longer significant. This suggests that the positive increase in storage from cash saving could be due to unobserved heterogeneity. Although imprecisely estimated, like the result from OLS estimator, a female-headed household, on average, stores 42 kilograms more than the male-headed ones at harvest. For the region effects, the base is the central without Kampala region. All the other regions produced more grains than the base region.

Overall, we consider the CRE estimated results as the most robust in this paper. This is because few households switched protectant use between the two cropping seasons examined. This may adversely impact the FE estimator but the CRE should be robust to this problem. We have attempted to control for observed heterogeneity and deal with unobserved heterogeneity using panel data methods; we acknowledge that the results presented here may not be fully causal. The findings from our RCT study when concluded, should however, show full causality.

Storage Period

The result of factors determining the length of storage period for maize consumption is presented in Table 4. The dependent variable is the expected length of storage for consumption. There is no significant difference between the expected and actual length of storage for consumption. Hence, we present results for just one of the two variables. In column (1), we show a parsimonious model estimates while column (2) controls for observed heterogeneity by adding additional covariates. These covariates include variables that control for stored maize, market access, household heterogeneity, and regional effects.

As observed in column (1), the use of storage chemical protectant marginally increases the length of storage by about 4.25 weeks, on average. In column (2) when more covariates are added to control for observed heterogeneity, the marginal effect of protectant use on storage length reduced to nearly 3.5 weeks, on average. In columns (3&4), we show results for FE and CRE estimators, respectively. When unobserved heterogeneity is accounted for using either of these estimators, the marginal effect is close to 4 weeks on average. This is a big impact. Relative to the length of lean period (hungry season) of households in our data—9 weeks on average, these marginal effects are close to half of the entire lean period.

In addition, on average, having cash savings as at the beginning of harvesting is positively associated with a longer storage period. The marginal increase is about a week, although this is no longer precisely estimated under the FE and CRE estimators. As expected, the sign of coefficients associated with a large family such as the number of household members; polygamous households; and age of household head are negative, albeit only the age of household head is significant. Furthermore, controlling for region effects shows that households in the eastern region would store for additional four weeks, on average. This is because Sironko district in the eastern region has only one cropping season, thus households are expected to store for longer period.

Table 2: Difference between treatment and control groups from the ex-ante randomization

Variables	Treated (A)	Control (B)	Difference (A-B)
Dependent Variables			
Quantity stored (kg)	638	606	-32
Length of storage (weeks)	14.9	14.8	-0.1
Explanatory Variables			
=1 if household use chemical protectant	0.09	0.12	0.03*
=1 if household has cash saving at harvest	0.49	0.46	-0.03
Total quantity harvested (kg)	892	928	36
Livestock revenue (1,000 UGX)[a]	259	261	-2
Distance to the nearest market (km)	2.34	3.40	1.06*
Household size	6.5	6.4	0.10
=1 if Polygamous	0.17	0.17	0.00
Age of household head (years)	45.7	44.5	-1.2
=1 if female-headed household	0.18	0.16	-0.02
=1 if REGION is Eastern	0.25	0.25	0.00
=1 if REGION is Northern	0.25	0.25	0.00
=1 if REGION is Western	0.25	0.25	0.00
=1 if 1st agricultural season	0.5	0.5	0.00

*** p<0.01, ** p<0.05, * p<0.1

[a] 1USD is approximately = 2800 UGX in 2014

Table 3: Determinants of Maize Storage

VARIABLES	(1) Parsimonious Qty stored (kg)	(2) Full OLS Qty stored (kg)	(3) FE Qty Stored (kg)	(4) CRE Qty stored (kg)
=1 if HH used protectant	88.991**	80.512*	189.558**	148.999*
	(42.132)	(43.692)	(87.477)	(90.094)
=1 if cash saving at harvest	64.726**	69.646**	-11.632	-6.608
	(29.605)	(29.949)	(40.577)	(39.262)
Total quantity harvested (kg)	0.710***	0.718***	0.634***	0.634***
	(0.047)	(0.050)	(0.087)	(0.087)
Livestock revenue		$2.1e^{-5}$*	-	$2.9e^{-5}$*
		(0.000)		(0.000)
Distance to nearest market (km)		0.538	-	0.551
		(0.750)		(0.681)
Household Size		1.048	-	-0.083
		(4.404)		(5.111)
=1 If household is polygamous		57.159	-	58.285
		(39.902)		(47.961)
Age of household head		0.011		0.032
		(0.769)	-	(0.974)
Female headed household		38.141		41.800
		(26.412)		(30.675)
=1 if REGION is Eastern		42.945	-	56.693
		(46.008)		(54.839)
=1 if REGION is Northern		109.740***		114.935**
		(37.642)	-	(45.932)
=1 if REGION is Western		91.149**		102.209*
		(45.817)		(52.301)
=1 if 1st season, 2014		-8.474	8.165	5.700
		(24.744)	(18.282)	(18.291)
Average covariates?				yes
Fixed Effects?			yes	
Constant	-46.003	-141.000**	45.965	-161.217*
	(28.163)	(70.702)	(79.444)	(84.660)
Observations	2,229	2,221	2,221	2,221
Number of household id			1179	1179
R-squared	0.703	0.714	0.564	0.716

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Determinants of Maize Storage Length for Consumption at Harvest Period

VARIABLES	(1) Pooled OLS Length (weeks)	(2) Pooled OLS Length (weeks)	(1) FE Length (weeks)	(2) CRE Length (weeks)
=1 if HH used protectant	4.25***	3.59***	3.74**	3.74**
	(0.652)	(0.627)	(1.705)	(1.711)
=1 if cash saving at harvest	1.39***	1.16***	0.62	0.64
	(0.410)	(0.393)	(0.762)	(0.762)
Qty stored at harvest (kg)	0.001***	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Distance to nearest market (km)		0.035**		0.035**
		(0.015)		(0.017)
Number of household members		0.025		0.032
		(0.068)		(0.084)
=1 If household is polygamous		-0.535		-0.553
		(0.528)		(0.701)
Age of household head		-0.027*		-0.026
		(0.015)		(0.018)
Female headed household		0.431		0.445
		(0.552)		(0.601)
=1 if REGION is Eastern		4.887***		4.884***
		(0.576)		(1.182)
=1 if REGION is Northern		-2.684***		-2.686***
		(0.553)		(0.940)
=1 if REGION is Western		0.707		0.700
		(0.493)		(0.958)
=1 if 1st season 2014		0.934**	1.002***	0.991***
		(0.385)	(0.358)	(0.363)
Average covariates?				yes
Fixed Effects?			yes	
Constant	13.24***	12.99***	13.130***	12.810***
	(0.287)	(0.866)	(0.469)	(1.108)
Observations	2,363	2,363	2,363	2,363
Number of household id			1,186	1,186
R-squared	0.047	0.123	0.045	0.123

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

7.0 Conclusion and Policy Recommendations

Many poverty alleviation or development programs focus on increasing agricultural production and productivity through the encouragement of smallholder farm households to increase their use of improved seed varieties and chemical fertilizer. However, many programs ignore what happens to the extra grain that is produced in the post-harvest season. Postharvest concerns may affect whether or not improved seeds are adopted. In this study, we have attempted to: one, determine if the use of improved storage technology influences smallholder households' storage decisions (quantities stored and length of storage); and two, determine ultimately, if improved storage technology has a causal effect on the adoption of improved inputs such as high-yielding seed varieties and fertilizer use.

Although this study intends to experimentally use exogenously given hermetic storage bags to understand this impact, we were only able address the first objective using the data currently available from our first round of survey. Using panel estimation techniques, we made efforts to control for unobserved heterogeneity and used covariates to control for observed confounders. We have shown that storage chemical protectant—as a proxy for improved storage technology—has a positive association with both the quantity of maize stored and the length of storage for consumption. This is a key finding that should interest policy makers and development partners interested in reducing food insecurity among smallholder farmers. Moreover, despite protectant use having positive impacts on storage decisions, we do not necessarily advocate for storage chemical use. Storage chemical protectants may have health hazards that have not been discussed here. There are other non-chemical improved storage technologies such as the PICS hermetic bags used in our on-going RCT.

Whereas this paper has shown that improved storage technology may facilitate more storage and extend storage length, we are cautious not to claim full causality with the current empirical approach. In the future, with the completion of our RCT imminent, and the post-intervention data available, we should be more confident on claiming causal effects from our findings. Thus, the next phase of this study will be to use the post-intervention data (after the exogenous intervention of giving PICS bags to randomly selected households) to achieve the second objective of the study—investigate causal relationships between improved postharvest storage technology and improved input use. Policy makers and their development partners might change approach if reducing postharvest loss through improved storage technology does lead to uptake of improved seed varieties and fertilizer.

8.0 References

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Appendix I

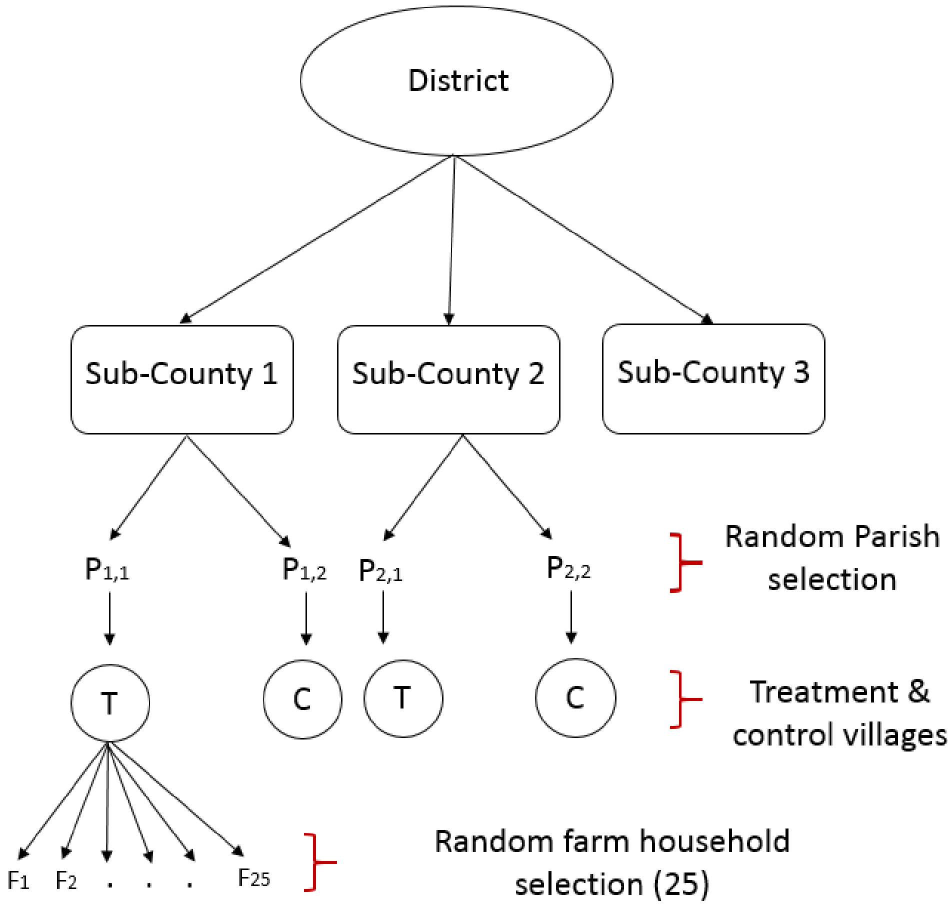

Figure 1: Randomized sampling design for household data collection