The Effects of Risk Perceptions and Liquidity Constraints on the Storage Decisions of Maize and Legume Producers in Uganda

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[*] *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.*

Abstract

This study empirically investigates the effects of risk perceptions and liquidity constraints on the maize and legume storage decisions in Uganda. Maize is the most important staple food in Eastern and Southern Africa, and legume crops constitute the major source of protein for most of these consumers. While production is seasonal, consumption occurs year-round. As a result, postharvest storage decisions among smallholder farmers are important for food and income security. We use a randomized control trial implemented among more than 1000 farm households to study how perceptions of postharvest losses through improved storage technology, and cash saving at the beginning of harvest, influence storage decisions. We exogenously treated one group of farm households by providing them with improved storage technology. A control group continued to use traditional storage techniques. Preliminary investigation suggests that for maize, an expected loss of 1kg increased quantity stored by about 1kg. Households with cash on hand at the beginning of harvest increased storage by 60kgs. For legume crops, households store 2.5kg more when anticipating similar storage losses and 24kgs more when they possess cash savings at the beginning of harvest.

Keywords: food security, postharvest loss, RCT, liquidity constraint, Uganda

1 Introduction

This study empirically investigates the effects of risk perceptions and liquidity constraints on maize and legume storage decisions in Uganda. Maize is the most important staple food in Eastern and Southern Africa and legume crops, such as common and soya beans, constitute the major source of protein for most consumers (Larochelle and Alwang, 2014; Gitonga et al., 2013). The supply of these staples follows regular seasonal production cycles, but consumption demand is fairly constant across the year. Inventories of these crops can act as a buffer against market or supply uncertainties. Hence, it is important to understand postharvest grain management decisions among smallholder households in Uganda as contributors to overall food and income security.

Unlike most developed countries where farmers are assumed to store produce solely for price arbitrage, smallholder farm households in developing countries with limited market or credit access may store maize or legume for household food security, convenience yield, or price arbitrage purpose (Saha and Stroud, 1994; Renkow, 1990). Moreover, storage facilities and liquidity constraints at harvest period may influence households' storage decisions, determining whether or not they are income or food secure. Additionally, concerns about effective storage may lead households to selling their produce immediately after harvest. Others end up relinquishing potential increase in net income from price arbitrage. This phenomenon is referred to as 'sell low, buy high' puzzle by Stephens and Barrett (2011). It occurs when certain households typically forego inter-temporal price arbitrage opportunities through storage, sell their output at low prices at harvest or shortly after, only to end up repurchasing at higher prices later in the lean period. This sell high, buy low phenomenon has a negative impact on household's income and food access (Kadjo et al., 2013; Stephens and Barrett, 2011). In SSA, evidence suggests that seasonal fluctuations in grain prices between postharvest lows and subsequent pre-harvest peaks are between 50-100%. Most farmers have difficulty using storage to transfer grains between these periods due to lack of credit or savings, poor storage technology and need for urgent cash to meet immediate needs (Burke, 2014).

For purposes of this study we define risk perception as the ex ante expectation that a household holds regarding postharvest loss (PHL) during storage, as expressed when those storage decisions are made. We define liquidity as the amount of cash savings available at the beginning of harvest. We seek to answer three key questions. One, how does access to an improved storage technology that reduces a household's expectation of PHL affect the household's maize or legume storage decision? Two, how does access to cash savings at the time of harvest affect a farm household's decision to store maize or legume? And three, are the storage decisions for maize and legumes driven by common factors? More specifically, with reference to previous studies on this topic (e.g. Kadjo et al., 2013; Michler and Balagtas, 2013; Basu and Wong, 2015, 2012; Stephens and Barrett, 2011), we test the following hypotheses econometrically:

1) Access to an improved storage technology has no statistically significant effect on the quanties of maize or legumes stored at harvest.
2) Having cash savings or liquidity at harvest has no statistically significant effect on the quantities of maize or legumes stored at harvest.

To test these hypotheses we implemented a randomized control trial (RCT). We exogenously provided hermetic (air-tight) storage bags to households, with the understanding that these constituted an improved storage technology that could be used to reduce postharvest losses. We posit that receipt of the bags reduces a treated household's expectation of postharvest loss, thereby increasing the quantity of maize stored after harvest. Although we did not exogenously vary whether a household has cash saving at harvest or not, we have a reason to believe that adding this covariate may be informative. The conceptual framework motivating this set up is a two-period, consumption-saving model similar to Basu and Wong (2015). A farm household makes a decision on grain allocation to storage and consumption during harvest period to smoothing consumption through the postharvest period. As hypothesized above, the allocation decision may be subject to the influence of storage technology used (through postharvest loss) and lack of cash savings during harvest. We have assumed that production or quantity harvested is given at harvest, and that stored grain act as output in the postharvest period.

We make two contributions. First, we use an RCT to highlight an important and understudied subject, namely the impact of expected postharvest losses on ex ante storage decisions. Most previous work on storage has ignored expected losses and available storage technology in modelling a farmer's decision to sell or store grain at harvest (Stephens and Barrett, 2011; Park, 2006; Saha and Stroud, 1994). Although Kadjo et al., (2013) examined this subject, they did not use an experimental design to measure causal effects. Expected on-farm storage loss may be influencing smallholder farm household's storage decision. For instance, AGRA (2014) stated that the fear of storage losses among farmers is a motivation for selling crops earlier than intended. Our second contribution is to add to the body of empirical evidence regarding the determinants of storage decisions for two of the most important staples in Sub-Saharan Africa, maize and legumes.

Although the findings in this paper are preliminary because our study is still active, they provide some evidence that a household's expectation of storage losses and liquidity in the form of cash savings at harvest increases the quantity of maize and legume stored. The organization of this paper is as follows: section 2 describes background and previous literature, section 3 describes the experimental design in details while section 4 describes the methods—impact pathways and empirical framework. In section 5, we discuss some results, and section 6 concludes the study.

2 Background and literature review

There have been studies on smallholder farmers inventorying grains. Inter-seasonal price arbitrage and food security are common in the literature (Saha and Stroud, 1994; Renkow, 1990). Saha and Stroud (1994) and Ravallion (1987) have both argued that price arbitrage may not be a major determinant of storage for smallholder farm households in less developed countries where a vast majority of farm households meet their consumption requirements from their own production and on-farm inventory.

Renkow (1990) models on-farm storage decision under price risk, and argues that households store grains as contingency against supply shocks and convenience yield—where households meet food demand from their own stock. According to Saha and Stroud (1994), Renkow's model fails to consider risk aversion commonly attributed to developing countries farm households. Therefore, Saha and Stroud improved the model to generalize for risk aversion. They derived that contrary to commodity storage literature, positive stocks could be observed even when the expected future price is less than the summation of spot price and marginal storage cost.[1] Food security motive may dominate price arbitrage among risk-averse households. They argue that "…savings and storage are both forms of intertemporal income transfer, only storage can provide food security by shielding households from price risk." (pp. 527).

Recently, the typical approach in studying household grain management decisions have used a two-period (contrary to multi-period models earlier described) seasonal model in establishing optimal consumption, storage, or marketing decision at harvest (Basu and Wong, 2015; 2012; Kadjo et al., 2013). This approach restricts postharvest grain management practices to one cropping cycle. Typical smallholder farm households in SSA would exhaust their inventories before the next harvest period. Kadjo et al. extended the Stroud and Saha (1994) model to account for storage technology used by households. They find that expected loss has a negative impact on the volume of maize stored among farmers in Benin. Also, farmers with better physical and financial wealth during the harvest period smoothing grain use inter-temporally by storing more at harvest. The later finding suggests that liquidity constraint may indeed be inhibiting storage. Our paper examines similar hypotheses with different (bigger and wider geographic spread) dataset among maize and legume producers. And more importantly, we use an RCT where households are exogenously treated with improved storage technology. Stephens and Barrett (2011) developed a model of inter-temporal consumption smoothing through market participation and storage of grain staples. They find that if people have no other means of addressing temporary liquidity constraints, the optimal solution might be to convert non-cash wealth, grains, into cash.

[1] This argument is also supported by Ravallion (1987). For these studies, however, inter-temporal price is pretty flat in the study area (India) unlike evidence from SSA.

In other words, a liquidity-constrained household will store less grain irrespective of resource transfer mode used.

Lastly, in evaluating seasonal food storage and credit program among agricultural households in East Indonesia, Basu and Wong (2015; 2012) developed a stylized model of resource transfer in staple unit. Using an RCT, they examined how food credit and better food storage (technology) impact inter-temporal transfer of resources in staple units among households. They propound that, overall, the allocation to lean season weakly rises in response to credit access and better storage technology. Our economic framework is similar to Basu and Wong's model; but we test the two hypotheses above using a two-step equation (see Mason and Smale, 2013) where PHL is affected by the improved storage technology, and quantity of staple stored is affected by expectation of PHL.

3 Experimental design

We define the population of interest as the major maize and legume producing farm households in Uganda. It is important that we define this population to focus our sampling strategy. To have some form of national representation, we sampled households from the four agricultural production regions namely: Central without Kampala, Western, Northern, and Eastern. Kampala region which is mainly urban is not included in our sample. Our design covers both randomized sample selection and randomized control trial (RCT). We also discuss the study area.

3.1 Study area

To select the study area, first, we identified the major maize and legume producing districts across all four regions described above. This was done using data from previous years through the publicly available dataset from the World Bank's Living Standard Measurement Study—Integrated Surveys on Agriculture (LSMS-ISA). Once these districts were identified, we purposively selected two districts in each region based on their production. However, due to logistical problem—lack of accessibility in the field—in one of the districts in the Western region, we could only complete one-half of our sample size and had to select another district in the same region to complete the sample. Thus, in total, there are nine districts rather than eight as originally planned. The districts are Bukomansimbi and Mubende (Central); Kamwenge, Hoima, and

Kiryandongo (Western); Apac and Oyam (Northern); and Iganga and Sironko (Eastern). See Figure 1 for map of the study area.

3.2 Sample selection

In each of the purposively selected districts above, using production data provided by the district agricultural offices, we also purposively selected 3 major producing sub-counties with assistance from respective district agricultural/production officers (DAOs). This is necessary to ensure that we sample the right population representative of the maize and legume farm households. Failure to purposively select the sub-counties could adversely impact our sampled population and study, because our sample may fail to represent the population of interest. Afterwards, we randomly selected two parishes in each sub-county and followed that with another random selection of the villages or local council ones (LC1s).[2] That is, we used a multi-level stratified sampling approach to randomly select the LC1s. Thus, we have one LC1 per parish, two parishes per sub-county, and three sub-counties per district. In total, there are 48 LC1s (6 per district) in our sample.

The last level of randomization in our sample selection is at the household level. Within each selected LC1, the random selection of households was facilitated by the LC1 chairman who serves as the administrative head at that level. The chairman provided us a list of village (LC1) residents. From the list, we assigned each name a number—usually in order between 1 and 200 depending on the LC1 population—and randomly select 25 using a computer random number generator. In all, there are 1200 (25 per LC1 in 48 LC1s) randomly selected households in our sample. However, due to field vagaries and data clean-up, we are left with 1190 households. See Figure 2 for a schematic diagram of sample selection at household level.

3.3 Data

The data comes from a baseline survey and a post-intervention survey. We collected the first wave of data in a survey conducted between September and December, 2014 under the baseline survey for Purdue Improved Crop Storage-phase 3 (PICS3) project. The project is specifically aimed at mitigating postharvest loss through the use of hermetic PICS bags. Our data is the first of such

[2] Uganda has five layers of administrative unit. LC1 is the lowest administrative unit, and it sometimes comprises more than one village. However, LC1 and village are sometimes used interchangeably in this paper.

(data) tailored towards postharvest loss mitigation and its impact measurements in Uganda (US Department of State, 2013). The baseline survey instrument consists mainly of modules covering areas such as household characteristics, production, storage and postharvest grain management practices, and marketing among others.

With the exception of Sironko district, where there is only one major planting season because of high altitude, the remaining sampled districts have a bimodal agricultural season. Moreover, when our survey started in 2014, households have only concluded the first season in that year. Given that we were interested in storage practices over two seasons, we asked our questions about two consecutive seasons: the second agricultural season of 2013 (September, 2013—January, 2014); and first agricultural season of 2014 (March—August, 2014). Baseline data for both seasons are pooled for analysis in this paper.

3.4 Randomized control trial (RCT)

After completing the baseline survey, we randomly split the 48 LC1s into equal halves of 24. This was done because the villages in one-half will receive information and training on the use of hermetic storage technology; the remaining 24 villages will not. We refer to the treatment villages as *PICS* villages, and the control villages as *non-PICS* villages. This is one treatment. For the second treatment, within each *PICS* or treatment village, ten (10) households from the 25 that had been randomly selected initially were, again, randomly selected to exogenously receive one PICS hermetic bag each. That is, to be eligible for the second treatment, households must live within a *PICS* village. 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 treatment and control groups of households. Overall, there are 240 exogenously treated households in our sample.

In summary, there are three groups of households in our experimental sampling framework. First, there is a group of households in *non-PICS* villages. These households are the control group who neither got information about, nor access to, the technology. The second is a group households living within *PICS* villages but who were not treated with bags in the second treatment. Lastly, the third group is the treatment group of households who had received the second treatment and live within the *PICS* villages.

Generally, for internal validity, and to maximize the external validity of our randomized experiment, we have ensured that villages and also participating households are randomly selected, respectively; and that selection into treatment and control groups (for both treatments) are also randomly assigned (Angrist and Pischke, 2009; Duflo et al., 2007).

The treatment intervention was carried out in the summer of 2015. The *PICS* villages receive awareness demonstrations and trainings on effective use of the storage technology. These trainings were conducted by extension staff who had previously been trained within the districts. The demonstration activities were designed to coincide with harvest period when grains would be available. After the first treatment—demonstration activities, our enumerators set out to the *PICS* villages to give one PICS hermetic bag to each of the 10 households randomly chosen for the second treatment. The post-intervention survey will be conducted in the fall of 2016, about three cropping seasons after the treatment intervention.

4 Methods

As stated above, the production of staple food is seasonal but households need to smooth consumption year-round.[3] By (Basu and Wong, 2015; 2012; and Park, 2006), the household can store staples (maize and legume crops) during harvest to last through the postharvest period, or may elect to sell its produce at harvest, keep the earnings in cash form, and purchase staples and other goods as needed in the postharvest period. In effect, households are able to transfer resources across periods either by storing grain (non-cash transfer), or by selling grains immediately after harvest to use the cash later (cash transfer).[4] Basically, the household maximizes its utility by allocating its staple endowment (in staple units) between consumption in the harvest and lean periods. In other words, a household decides what quantity to use in harvest period and what quantity to store for lean period.

[3] Agricultural production from smallholder farmers in our sample is rain-fed, making production highly seasonal and rain-dependent.
[4] See Basu and Wong (2015) for more details on the inter-temporal transfer of assets in staple units across harvest and lean periods.

4.1 Impact pathways

In this study, we assume that postharvest storability of staple grains is a concern for farm households. The main goal of improved storage technology is to reduce infestation levels, leading to less damage to grains from insect pest (weevils and larger grain borers) attacks. Specifically, the PICS hermetic storage bags prevent or significantly lower gaseous exchange between the interior of the technology and the ambient environment. Since insect pests need oxygen for metabolism, depriving them of oxygen leads to inactivity, eventual desiccation, and death (Murdock and Baoua, 2014; Njoroge et al., 2014; Murdock et al., 2012).

As a result, the causal pathway is that the exogenous provision of PICS bags to treated households should lower their expectation of postharvest loss from on-farm storage, thereby leading to storage of more and quality grains for consumption or price arbitrage intent. Following the pathway above, we define the following equations:

$$ePHL_{iv} = f(PICSbag_i, PICSvillage_v, PICSbag_i * PICSvillage_v, \gamma_r, \varepsilon_{iv}) \quad (1)$$

$$Qty\ Stored_{iv} = g(ePHL_{iv}\ (.), \boldsymbol{X_i}, \sigma_{iv}) \quad (2)$$

In equation (1), the individual household's expectation of on-farm storage postharvest loss, $ePHL_{iv}$, is a function of technology used or the treatment status ($PICSbag_i$, within *PICSvillage v*), region fixed effect (γ_r), and the idiosyncratic error term. In equation (2), the quantity a household decides to allocate to storage at harvest is a function of their expectation of loss in storage; a vector ($\boldsymbol{X_{iv}}$) of household characteristics such as household size, technology experience, age of household head, and gender of household head; and individual-specific error term, σ_{iv}.

From the equations above, following Mason and Smale (2013), through chain rule, we can derive the marginal effect of the treatment (PICS hermetic technology) on the quantity a household decides to store. This is shown in equation (3).

$$\frac{\partial Qty\_Stored}{\partial technology} = \frac{\partial Qty\_Stored}{\partial ePHL\ (.)} * \frac{\partial ePHL\ (.)}{\partial technology} \quad (3)$$

From equation (3) above, the marginal effect of being treated with a PICS hermetic bag on the quantity of grain stored by households is the product of the marginal effects of the improved storage technology on expectation of storage loss; and that of expectation of storage loss on quantity stored. Each of these marginal effects is estimated separately and then multiplied as shown. We expect that the second term in the right hand side of the equation should be negative. That is, improved storage technology should reduce expectation of storage loss. Also, we expect that the first term in the product should be negative. This is because we would expect a rational household to dispose grain early rather than risk losing it in storage. That is, if a household expects to lose grains in storage, such household should end up reducing the quantity they would store. However, the effect of expected storage loss on quantity stored may be ambiguous as households may store more as buffer against expected losses. In general, if both terms are negative as expected, then the overall effect of improved storage technology on quantity stored should be positive. We test these empirically.

4.2 Empirical framework

The hypotheses of interest are to empirically test whether improved storage technology through ex-ante expectation of storage loss, and cash savings at harvest, affect household's storage decisions for maize and legume crops. We estimate the product terms in equation (3) from equations (1) & (2). The empirical equations are shown in equations (4 & 5) below. The parameters to be estimated are βs and αs in the respective equations.

$$ePHL_{iv} = \beta_0 + \beta_1 tech_i + \beta_2 PICS_v + \beta_3 tech_i * PICS_v + \gamma_r + \varepsilon_{iv} \quad (4)$$

$$Qty\ Stored_{iv} = \alpha_0 + \alpha_1 \boldsymbol{X_i} + \alpha_2 ePHL_{iv} + \alpha_3 Cash_{\boldsymbol{i}} + \sigma_{iv} \quad (5)$$

From equation (4) above, we expect that $(\beta_1 + \beta_3 * PICS)$ associated with storage technology use in *PICS* villages should be negative and significant because improved storage technology reduces infestation levels of postharvest pest attacks. That is, the expectation of postharvest storage loss should reduce among households using PICS hermetic storage technology. Furthermore, as discussed earlier, we expect that α_2 in equation (5), the parameter associated with expected storage loss at the beginning of storage shortly after harvest, should be negative.[5] Additionally, we assert that *ePHL* in equation (5) is exogenous because it is a function of randomly assigned storage technology.

On liquidity constraint, we expect that availability of cash savings during harvest period should alleviate such constraint for households and thus, households with access to cash savings at harvest

[5] To our knowledge, Kadjo et al., 2013 is the only study in SSA to have examined storage loss effects on household's storage decisions. Their finding supports this negative expectation.

should store more grain or for longer period than households who are liquidity constrained (Basu and Wong, 2015; Stephens and Barrett, 2011). That is, α_3 should be positive and significant. While we did not exogenously vary the cash savings variable in equation (5), this variable is pre-determined at the time the storage decision is made. For instance, the survey question used for this variable asks "…did you have some cash savings at the time you begin harvesting maize." Thus, we presume that the error term in equation (5) is orthogonal to the *Cash* variable in the model.

5 Results and discussion

Our study is still on-going and the post-intervention survey is yet to be conducted at this point. However, we discuss preliminary findings from the baseline data. First, we show some descriptive statistics from the experimental design group, and then show estimated results from equation (5) for both maize and legume crops using the baseline data. Generally, households either store or sell staples at or shortly after harvest. From the baseline data, 75% of households sell about 67% of total maize produced at or shortly after harvest in the first agricultural season of 2014. In the second season, less number of households (54%) sell less portion (41%) of production. This may suggest that households store more during the second cropping season of the year. See Figures 3 & 4. A similar pattern of selling/storage is also observed for legume crops in both seasons. On average, more households are selling more portion of legumes produced in the first season than the second. See Figures 5 & 6. Although the patterns are similar across maize and legume crops across seasons, the proportion of maize sold is higher than legumes. This suggests legumes may be produced more for consumption but maize as cash crop. If so, the use of hermetic technology may provide a price arbitrage opportunity that may be missing.

5.1 Descriptive statistics

Table 1 shows descriptive statistics across the treatment and control groups. For both maize and legume crops, the dependent variables show no significant difference (at 95% CL) across the two groups. This suggest the randomized distribution into treatment and control group is good enough. Similarly, household characteristics across the groups are no different. For instance, the average household size is 6.54 in the treated group and 6.34 in the control group. On production and postharvest grain management practices, the total quantity of maize produced is on average 892 and 927 kg in treatment and control groups, respectively. Similarly, there is no difference between productions for legume crops across the groups. Region fixed effects are also observed to be balanced across groups.

5.2 Baseline regressions

We are currently unable to estimate the parameters from equation (4) because the post-intervention data reflecting the outcome of our exogenous treatment is not yet available. However, we estimate equation (5) from the baseline data, with the understanding that parameter estimates may change with the post intervention data. The current identification strategy may not be fully causal, but we present estimations of equation (5) for both crops in tables 2 and 3. Column (1) shows a parsimonious estimate of equation (5) while column (2) adds household characteristics, production, and region fixed effects as covariates.

As shown in tables 2 and 3, contrary to expectation (and findings in Kadjo et al., 2013), parameters associated with expectation of storage loss are positive and statistically significant. We acknowledge these results are pre-intervention estimates from the baseline data, but they suggest that farm households in Uganda may be storing more maize (and legume crops) as a buffer in anticipation of losses. This impact is bigger in magnitude for legume crops than maize. Also, cash saving at the beginning of harvest has a positive and significant effect on quantity stored. For maize, having cash savings increased quantity stored by 60kgs whereas the same increases legume crop storage by about 24kgs.

Although they should be understood as preliminary, these results nevertheless provide some evidence that storage determinants for maize and legumes are similar. This is interesting given that maize may act as both a cash crop and a food crop for smallholder households, and that legumes are predominantly food crops. Expectation of storage losses have positive and significant effects on both maize and legume storage. Furthermore, for both maize and legumes, access to cash savings at the beginning of harvest increases the quantity of grain stored by a household. This later finding is similar to Stephens and Barrett’s (2011) findings from the maize market in Kenya that households with sufficient access to liquidity avoid selling at low prices immediately after harvest, with the implication that they must buy at higher market prices during the postharvest season.

6 Conclusions

Effective postharvest grain storage is important for smallholder farm households' food and income security. We implement an RCT to examine the causal effects of improved storage technology that reduces grain storage postharvest losses on households' storage decisions. We posit that the use of hermetic storage bags should lower expectation of postharvest losses from on-farm grain storage, which in turn would lead to storage of more quality grains. We also empirically test if liquidity at the beginning of harvest influences quantities of maize and legumes stored. Although our study is ongoing, in the interim, we find evidence to suggest that the expectation of postharvest loss and access to liquidity at harvest increases the quantity stored for both maize and legumes.

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Table1: Descriptive statistics of used variables

Variables	Treated (A)	Control (B)	Difference (B-A)
Dependent Variables (maize)			
Quantity stored (kg)	704.05	684.10	1121.35
Expected loss (kg)	16.68	29.47	12.79*
Legumes			
Quantity stored (kg)	160.00	172.41	12.41
Expected loss (kg)	4.68	4.29	-0.40
Household Characteristics			
Age of household head (years)	45.68	44.49	-1.19
Household size	6.54	6.34	-0.21
=1 if female-headed household	0.17	0.15	0.02
=1 if Polygamous	0.18	0.18	0.00
Production and PH practices			
Total quantity harvested-maize (kg)	892.00	927.81	35.63
Total quantity harvested-legumes (kg)	255.46	278.60	23.14
=1 if household use chemical protectant	0.10	0.13	0.03*
=1 if household has cash saving at harvest	0.50	0.47	-0.30
Region Effects			
=1 if REGION = 200, Eastern	0.25	0.25	0.00
=1 if REGION = 300, Northern	0.25	0.25	0.00
=1 if REGION = 400, 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

Table 2: Determinants of Maize Storage

Variables	(1) Parsimonious Qty stored from own-produced maize (kg)	(2) Full Qty stored from own-produced maize (kg)
Expected quantity loss (kg)	1.005***	0.972***
	(0.298)	(0.291)
=1 if cash saving at harvest	57.528**	60.164**
	(29.073)	(30.220)
Total quantity harvested (kg)	0.684***	0.692***
	(0.053)	(0.055)
Total off-farm revenue (UGX)		0.000
		(0.000)
Technology experience (years)		-6.512*
		(3.772)
Distance to nearest market (km)		0.062
		(0.736)
Household size		1.338
		(4.564)
=1 if female-headed household		45.014
		(27.372)
Age of household head		0.480
		(0.852)
=1 if polygamous household		57.867
		(39.941)
REGION = 200, Eastern		54.669
		(45.783)
REGION = 300, Northern		127.687***
		(37.921)
REGION = 400, Western		95.320**
		(45.015)
Season1 = 1 for 1st season 2014 and 0 otherwise		-16.262
		(24.789)
Constant	-23.770	-93.409
	(30.949)	(76.543)
Observations	2,133	2,125
R-squared	0.716	0.728

Table 3: Determinants of Legume Storage

Variables	(1) Parsimonious Qty stored from own-produced legume (kg)	(2) Full Qty stored from own-produced legume (kg)
Expected quantity loss (kg)	2.543***	2.492***
	(0.842)	(0.824)
=1 if cash saving at harvest	20.738**	24.348**
	(9.691)	(9.567)
Total quantity harvested (kg)	0.391***	0.386***
	(0.063)	(0.067)
Total off-farm revenue (UGX)		$-4.56e^{-6}$**
		(0.000)
Technology experience (years)		0.160
		(0.187)
Distance to nearest market (km)		-0.090
		(0.188)
Household size		4.038**
		(1.771)
=1 if female-headed household		-20.162*
		(11.971)
Age of household head		-0.081
		(0.107)
=1 if polygamous household		3.043
		(10.126)
REGION = 200, Eastern		-48.220***
		(14.926)
REGION = 300, Northern		-30.650**
		(15.253)
REGION = 400, Western		-31.417**
		(15.411)
Season1 = 1 for 1st season 2014 and 0 otherwise		-2.845
		(7.489)
Constant	41.115***	52.762***
	(12.014)	(17.613)
Observations	2,018	2,011
R-squared	0.426	0.443

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

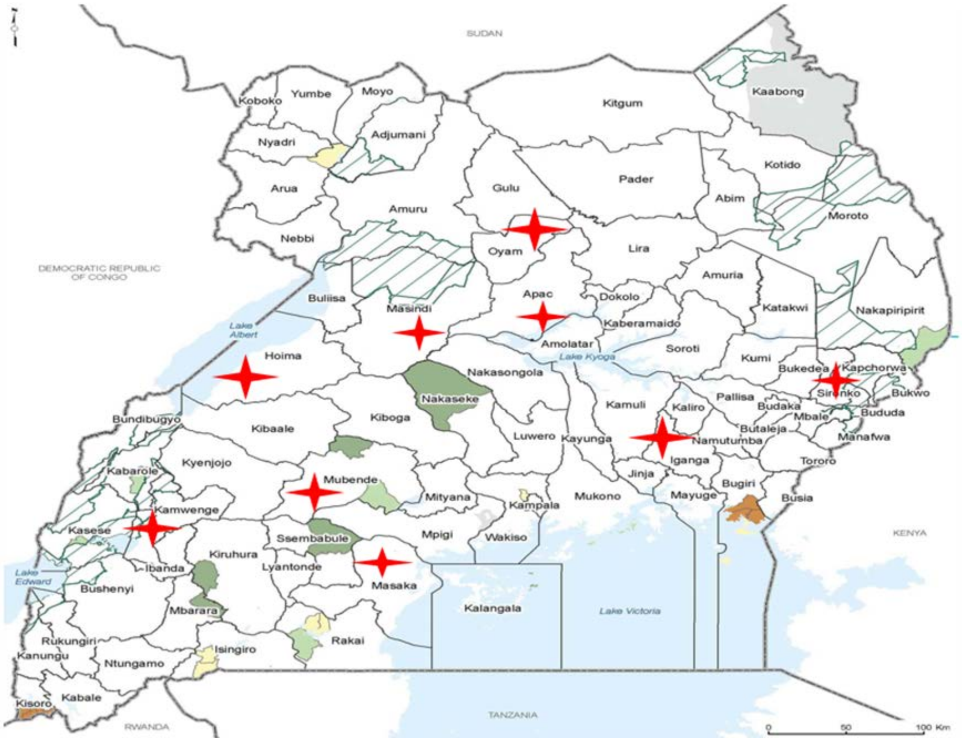

Figure 1: Map showing study area in stars

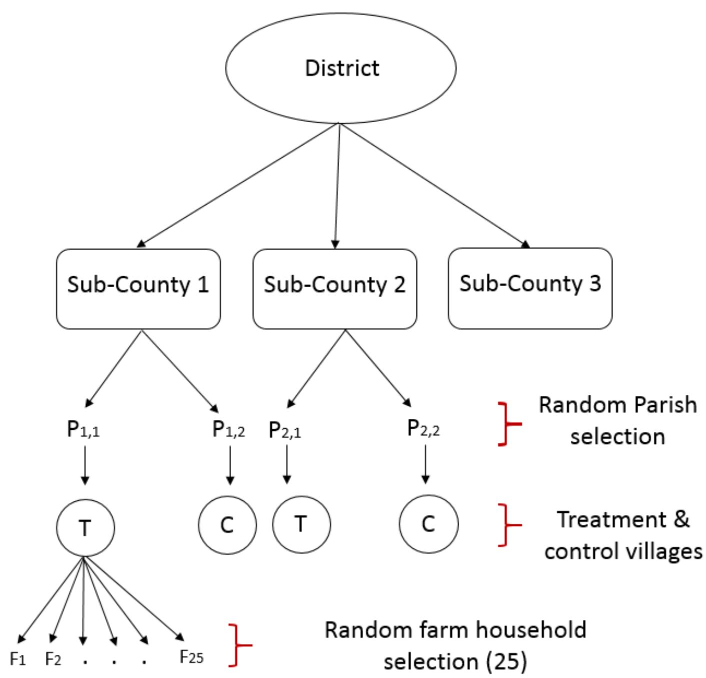

Figure 2: Randomized sample design for household level

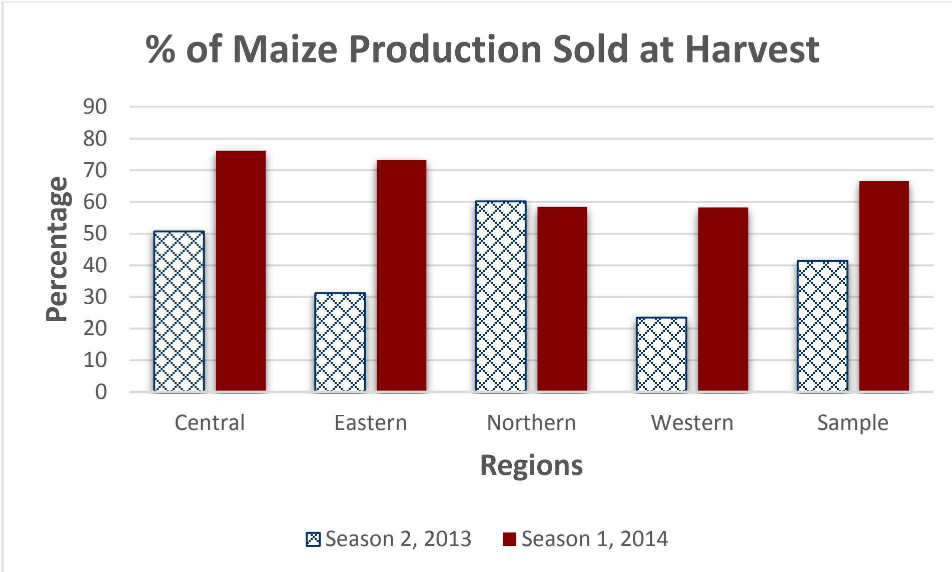

Figure 3: Percentage of maize production sold at harvest

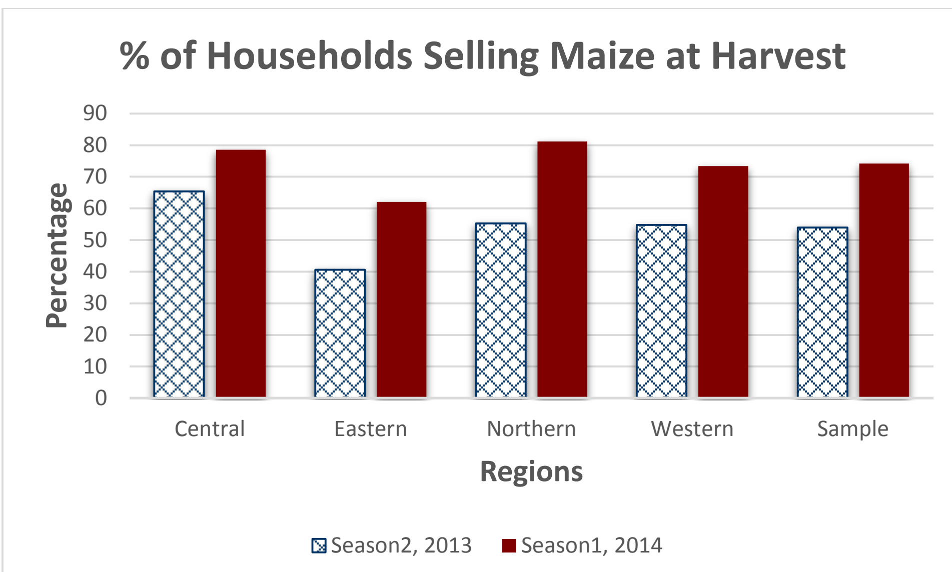

Figure 4: Percentage of households selling maize at harvest

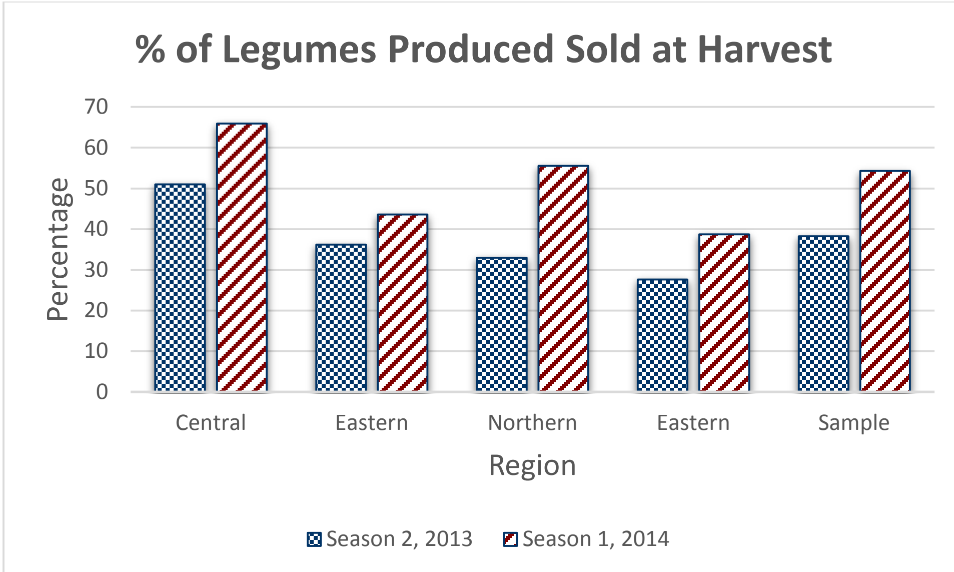

Figure 5: Percentage of legume produced sold at harvest

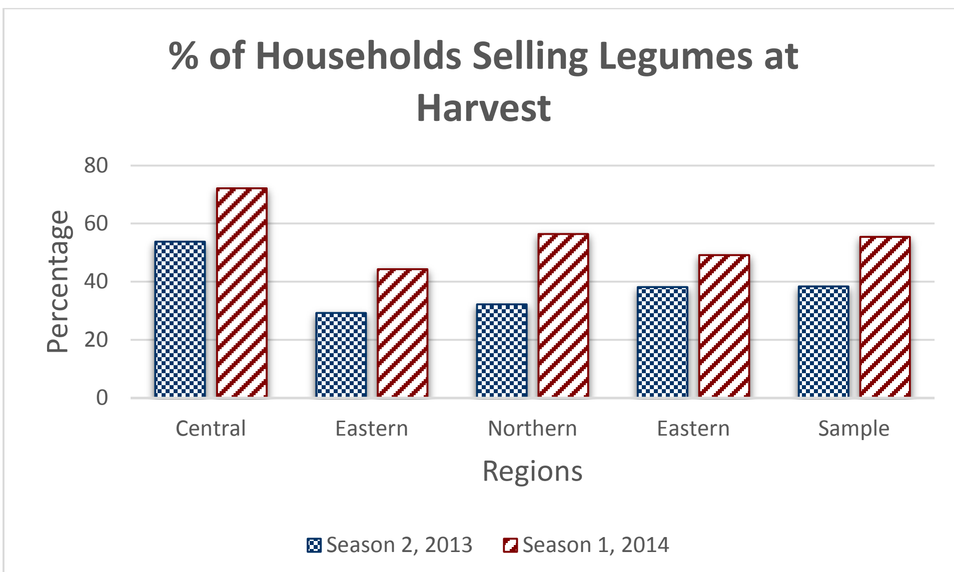

Figure 6: Percentage of households selling legume crops at harvest