# TWO ESSAYS ON POST-HARVEST DRYING AND STORAGE PRACTICES FOR MAIZE IN SUB-SAHARAN AFRICA

by

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*To Mom and Dad, for always being loving and supportive, even after all of the grey hairs I have given you over the years.*

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# ABSTRACT

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This thesis consists of two essays that each discuss a major component of the post-harvest management of maize in sub-Saharan Africa: drying and storage. The first essay uses cross-country data about on-farm storage decisions between 2013 and 2015 to assess the severity of storage loss in the absence of improved storage technologies. We find that while losses are low, farmers report on average that they lose more than expected and sell earlier than originally intended at harvest. Additionally, we look for evidence that farmers use adaptation strategies for the purpose of mitigating storage loss and find that storage chemicals are effective at both reducing loss and increasing storage duration. The second essay introduces a third-party moisture testing service to traders in western Kenya to elicit willingness to pay for external quality verification using two moisture detection devices, a low-cost hygrometer and a commercial grade moisture meter. We find that while traders value the moisture meter service more, the hygrometer service is more profitable for potential service providers. Further, when offered a chance to purchase the hygrometer device at/around market price ($2.50), only 15% of traders accepted the offer, suggesting that a service provider model is a viable way to make moisture testing more widely accessible and standard practice in the future.

**Keywords:** Maize, storage loss, sub-Saharan Africa, farmers, farmer behavior, drying, Kenya, maize traders, moisture content, moisture testing service, experimental auction

# CHAPTER 1. A CROSS-COUNTRY ANALYSIS ON THE CURRENT STATE OF STORAGE LOSS AND PRACTICES IN SUB-SAHARAN AFRICA

## Abstract

There is emerging evidence from smallholder farmers' self-reported data to suggest that storage losses in SSA are lower on average than initially believed. However, little is known about farmers' perception of storage loss and the adaptation strategies they use to mitigate or avoid loss. This study uses unique cross-sectional data from five countries in SSA to provide an in-depth analysis of the current state of storage loss. In this paper, we compare farmers' storage loss expectations to actual outcomes and in addition, consider distribution across farmers as a key indicator of the severity of loss. Linear regressions are used to assess the effectiveness of three adaptation strategies that farmers may use to reduce loss: i) planting traditional maize varieties that are less susceptible to loss, ii) applying storage chemicals to kill insect and pests that create storage loss, and iii) selling earlier than intended to avoid accumulating loss. We find that losses are low and comparable to other estimates in current literature, but on average farmers report that they lose more than expected and sell earlier than they originally intend at harvest. Storage chemicals are effective at reducing loss and increasing storage duration, but there is little evidence to suggest that farm households plant traditional varieties or sell earlier to mitigate loss.

**Keywords:** Storage loss, maize, sub-Saharan Africa, farmers, farmer behavior

## 1.1 Introduction

Due to global initiatives such as the United Nations Sustainable Development Goals, post-harvest loss (PHL) has become a rising issue on the development agenda. In sub-Saharan Africa (SSA), most PHL occurs on-farm during harvesting, handling, or in storage, which translates to income loss, a concern for smallholder farmers already faced with food insecurity and constrained by lack of income liquidity and access to credit (Sheahan and Barrett, 2017). Much of the current literature focuses on storage loss, in particular of maize, because of its vital importance as a staple crop for millions in SSA, making up 20% of the plant-based food supply (Ng'ang'a et al., 2016) and 30% of land under cereal production (Affognon et al., 2015; Cairns et al., 2013). One of the main reasons for emphasizing storage loss is because commonly used traditional storage methods for maize, such as granaries, woven bags, or leaving it heaped in-house, leave the crop vulnerable to mold and pests, such as the maize weevil or larger grain borer.

However, we cannot conclusively say if farmers perceive storage loss in maize to be a problem. Estimates of storage loss in the current literature vary by source and household-reported estimates tend to be low, but this does not mean that storage loss is not a problem. Sheahan and Barrett suggest that low averages could be a result of the methodology or because farmers use loss-mediating technologies or early sales that deflate farmers' perception of loss (2017). Other studies suggest that average losses do not reflect distribution of losses (Kaminski and Christiaensen, 2014; Ambler et al., 2018). Household-reported losses also include only noticeable damaged grain, thereby these estimates cannot account for poor quality grain and associated food safety concerns such as unobservable aflatoxin contaminants (Tubbs et al., 2017). Because we do not know what factors drive these low estimates, little can be said of the extent that current storage practices contribute to food insecurity in SSA.

Kaminski and Christiaensen find that only a small number of surveyed farmers reported having any on-farm losses, but those that do typically report large losses (2014). Only 7% of respondents in Malawi and 22% in Uganda reported losses, which ranged from 21-27% total on-farm post-harvest loss on average. When averaged across the whole sample, these losses reduce to 1.4% in Malawi and 5.9% in Uganda. Ambler et al. report that only 26% of households in Malawi reported maize losses throughout the whole post-harvest period (2018). Additionally, they find that maize losses in storage are low (at 21%), relative to harvest, transport, and processing. This is still high compared to Kaminski and Christiaensen (2014), likely because Ambler et al. (2018) only include in their sample those households that experienced loss. Additionally, they include damaged maize as well (maize with 'very little damage,' 'some damage,' 'extensive damage,' and 'complete loss'), although this still does not account for unobservable quality damage.

Neither of these papers offer an explanation as to what causes the high losses in only these few households, but only marginal losses in others. Regardless of what the actual % storage loss is, we hypothesize that estimates may be low because farmers behave rationally and adopt strategies that help mitigate or minimize loss to the point where the marginal benefit of mitigating losses equals the marginal cost of doing so. However, the decision to use such strategies may not account for all indirect costs to health and livelihood. Therefore, using adaptation strategies may not be optimal, despite mitigating loss.

The present article uses self-reported survey data from smallholder farmers in Ethiopia, Ghana, Nigeria, Tanzania and Uganda to provide an in-depth, cross-country analysis of storage loss in SSA in the absence of hermetic storage. Our overall objective is to estimate the current state and perception of storage loss in SSA as reported by smallholder farmers. In this regard, we compare actual storage loss to farmers' expectations of loss at the time they put maize in storage.

Second, we analyze effectiveness of different adaptation strategies farmers may use to reduce losses in storage. In particular, we consider three main adaptation strategies: 1) planting lower-yielding, traditional maize varieties that store better than higher-yielding hybrids, 2) applying storage chemicals; and 3) selling maize stored earlier than intended (presumably at a lower price).

Considering the first adaptation strategy mentioned above, expected storage loss may incentivize farmers to avoid planting high-yielding dent varieties of maize, because their softer outer shell leaves the kernels more susceptible to mold and insect infestation (Ricker-Gilbert and Jones, 2015; Omotilewa et al., 2018).[1] Second, we consider the extent to which farmers apply storage chemicals on their maize to protect against molds or insects, which could have unintended health effects (Hayes, 1991). Third, maize farmers may sell their stored grains earlier in the season than they otherwise might, to avoid losing additional maize in storage, even if they lose the opportunity to sell maize at a higher price later in the season (Sheahan and Barrett, 2017). These adaptation strategies and their implications on health and livelihood are discussed further in the background section.

These strategies may be used in the absence of more efficient, but more expensive and less accessible, storage technology. Our data come from baseline surveys conducted as part of a project to introduce a hermetic storage technology, the Purdue Improved Crop Storage (PICS) bag, throughout SSA. At the time these surveys were conducted, hermetic storage was not commonly used for maize storage on-farm. Thus, this paper gives us an opportunity to report on the state of

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[1] Farmers may even avoid planting maize altogether and opt for crops less susceptible to loss in the field, such as sorghum and millet (Kaminski and Christiaensen, 2014). Planting maize instead of other crops that have a higher expected loss could also be an adaptation strategy. This adaptation strategy is not discussed in the scope of this paper, as we consider specifically maize storage and thus our data do not capture the decision to not plant or store maize.

storage loss at the beginning of the project and provides insights on storage issues in SSA in the absence of such technology.

We make three main contributions to current post-harvest loss literature. First, we use a cross-country approach to analyze the current state of storage loss across SSA, including farmers' use of several adaptation strategies. These findings create a baseline to reference for assessing adoption and impact of the PICS hermetic storage bag when the project concludes. Our approach also advances the current literature as the results are generalizable over a larger sample area than previous studies and allows us to assess variation in losses across a wider geographical scope.

Second, our study is unique in that we quantify and compare loss using different forms of measurement. We measure farmers' expectations of storage loss at the time they make their storage decision to what they actually observe during the storage period. Farmers' perceptions are an influential tool in the decision-making process, thus it is crucial that we understand how severe of a problem farmers perceive their own storage loss to be. In addition, we consider storage length as an alternative indicator of storage loss. If measurements are truly low, independent of any adaptation strategies, farmers may not notice small quantities of loss and therefore may under-report loss. By including both actual and intended storage length in our analysis, we can compare farmers' temporal losses to physical quantity loss and obtain more robust results. Lastly, we assess farmers' use and effectiveness of three adaptation strategies that may be driving the low average estimates of storage loss from the current literature.

We find that across our sample, storage loss exhibits a positive distribution, with most households reporting no or low loss and only few reporting high levels of loss. In general, expectations are correlated with, but do not perfectly match actual outcomes of storage loss or length (for sale). Expected and actual storage losses are positively correlated, however not at a one-to-one ratio. This could suggest that farmers update their expectations as they learn more about storage conditions or adopt practices to mitigate loss. Further, households sell maize earlier than intended, except in Nigeria where farmers store maize for longer than intended. Again, intended and actual storage length are positively correlated, but at a less-than-one ratio. Lastly, applying storage chemicals does significantly reduce losses and increase storage length, but there is little evidence to support that storing traditional varieties or selling earlier are used to reduce loss.

## 1.2 Background

### *1.2.1 Storage loss and technology in SSA*

The African Postharvest Losses Information System (APHLIS) measures postharvest losses along the value chain in SSA based on estimates from peer-reviewed literature and local and seasonal conditions. Thus, losses reported in APHLIS are averaged across numerous measurement strategies. They report that storage loss averaged 4.3% in Ethiopia, 5.0% in Tanzania, and 2.4% in Uganda (2011). In West Africa, APHLIS reports that on average, 5.2% in Ghana and 5.0% in Nigeria of maize was lost in storage in 2011.

At the time this study was conducted, use of hermetic storage technologies was very low and most households reported used traditional storage (see Table 1—9 in Appendix). In our sample, ninety percent of the total sample reported using traditional storage (excluding other storage). The most common traditional storage method used by farmers in our sample is the woven bag/single layer plastic bag (72%).[2] Other forms of traditional storage methods used by the farmers across

[2] 'Single layer plastic bag' is a broad term. Depending on the material, manufacturer, durability, etc., a single layer plastic bag could be traditional (similar to the woven bag) or improved. In our data, we consider the single layer plastic bag to be traditional based on anecdotal evidence from our study regions.

our sample include heaping the maize in-house, open-air hanging, and traditional granaries. These traditional methods of storing maize offer minimal protection against infestation by insects, pests, and molds.

We consider hermetic storage to be the most effective at controlling storage loss due to an airtight seal, as they deprive any insect or mold of the necessary oxygen to grow and/or reproduce. Three layer hermetic bags, such as the PICS and GrainPro bags, are more effective than the traditional woven or single-layer plastic bag at reducing losses incurred by larger pests, such as rats, but may not as effective as technologies with harder, impenetrable surfaces such as a silo or can. Other improved storage methods are more effective versions of traditional storage methods. For example, an improved granary may be covered by an iron roof rather than with less sturdy, more accessible materials like timber. In our sample, 2.8% use hermetic storage and 2.3% used other improved storage technologies. At the time this data were collected, hermetic storage was not widely adopted yet. Additionally, we see minimal use of other improved storage technologies as most farmers use traditional bags for storage.

### *1.2.2 Major causes of storage loss in SSA*

Understanding why storage loss occurs is key to analyzing what adaptation strategies farmers use, why they use them, and how successful they are. Most visible losses incurred during storage in SSA are caused by insects, followed by rodents. The most common sources of loss and damage to stored maize are the maize weevil (*Sitophilus zeamais*) and the larger grain borer (LGB) (*Prostephanus truncatus*) (De Groote et al., 2013; Ng'ang'a et al., 2016). As previously discussed, quality damage incurred by mold or moisture may not be observable to farmers and the severity of mold infestation may be under-reported. Thus, it seems that the majority of farmers would use adaptation strategies that specifically target visible insect and/or rodent infestation. This could include storing grain in an environment that is either inaccessible or unfit for insects to survive, removing the grain from storage altogether, or applying chemicals that make the grain uninhabitable for the insects.

### *1.2.3 Storage loss adaptation strategies*

***Planting local varieties***

Farmers may make planting decisions to avoid or mitigate storage loss post-harvest. Omotilewa et al. find evidence of this, as they report that farmers in Uganda are ten percentage points more likely to plant a higher-yielding maize variety if they store the maize in hermetic technology, thereby reducing the threat of loss (2018).[3] High-yielding dent maize varieties (softer outer shell) are more susceptible to insect infestation in traditional storage compared to the lower-yielding local flint varieties (harder outer shell), thus farmers who lack improved[4] storage may avoid the high-yielding varieties altogether in favor of varieties that are less risky in storage (Ricker-Gilbert and Jones, 2015; Sheahan and Barrett, 2017). In theory, this rationale makes sense, as farmers would pay more for higher-yielding seeds, but would lose some or all of the extra production in traditional storage. In this case, the risk of storage loss dis-incentivizes farmers from increasing their productivity, at the opportunity cost of foregoing the additional maize to sell or consume.

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[3]Our study uses the baseline data from Omotilewa et al., which lends further support that this strategy may be used by farmers in our sample (2018).

[4] Here, 'improved' refers to improved storage methods, including hermetic, that are more effective than traditional storage at preventing or reducing loss. What we classify as 'improved' in Table 1—9 is broad, context-specific and ultimately depends on the effectiveness of the material.

***Applying storage chemicals***

Throughout storage, farmers make the decision to apply or not apply storage chemicals, and may re-assess this decision multiple times during storage. Current literature suggests that this is a popular strategy to reduce pest and insect infestation (Kaminski and Christiaensen, 2014). Sheahan and Barrett summarize three major problems associated with storage chemical use (2017). First, given the reputation in SSA of unreliable quality in storage chemicals, the use of such chemicals may not be cost-effective at mitigating storage loss (Williamson et al., 2008; Williamson, 2003; 2011). In addition, both short-term (acute) and long-term (chronic) adverse health effects are well documented (Hayes, 1991). Lastly, because of genetic variability for resistance traits in insects, storage chemicals can only protect against most but not all individuals, thereby leaving the ones resistant to the chemicals. Over time, the reduced genetic variability leads to stronger resistance in the insect population (Boyer et al., 2012). Considering the limited confidence farmers in SSA seem to have in the effectiveness of storage chemicals, this is not an ideal adaptation strategy, but farmers may resort to chemical use in the absence of potentially more cost-effective and safer strategies, such as hermetic storage technologies.

***Selling earlier than intended***

Our last adaptation strategy is selling maize earlier than intended. Price spikes between the post-harvest and following pre-harvest lean season in grain markets are common and drastic in developing countries, with some prices rising by 50-100%. However, as a result of numerous possible financial or storage constraints, smallholder farmers tend to sell their grain early, thereby flooding the market and driving the price down to a seasonal low. As the market supply is depleted and smallholders buy back maize in the lean season, the price spikes to a seasonal high, until the market is flooded again after the next harvest. Economists refer to this as the “sell low-buy high” phenomenon, where the maize market is essentially a high-interest lender for rural smallholders. Much of the literature accredits this trend to credit constraint as the underlying cause; households sell early so as to have instant income to pay bills, purchase inputs for the next season, pay school fees, etc. (Stephens and Barrett, 2010; Burke et al., 2019). Yet the credit constraint problem ignores maize stored with the intention to sell later in the season or to consume at home throughout the lean season.

In addition to credit constraints, recent literature on post-harvest losses suggest that smallholders could be selling earlier due to the pressure of avoiding storage loss (Sheahan and Barrett, 2017). There remains little quantitative analysis on the decision to sell early so as to avoid further storage loss, but is frequently suggested as a possible explanation for the low levels of storage loss reported by farmers. However, this may be in tandem with the problem of credit constraint, and it is not known to what extent storage loss influences the decision to sell early. Yet because selling early mitigates further storage loss and provides instant income, farmers may be incentivized to sell their maize early for a combination of reasons, in addition to credit constraint often cited in the literature. Farmers in our study reported both actual and intended storage length of maize stored for sale, thereby allowing us to compare the two and determine if farmers actually sold earlier than intended.

## 1.3 Data and Methods

We used cross-sectional data aggregated from baseline surveys about on-farm storage practices during the most recent major and minor maize season, conducted as part of the baseline surveys for the PICS3 Project at Purdue University in Ethiopia (2014), Ghana (2014-2015), Nigeria (2013-

2014), Tanzania (2013-2014) and Uganda (2013-2014). In total, 3,683 households were randomly sampled; 294 in Ethiopia, 289 in Ghana, 1,646 in Nigeria, 289 in Tanzania, and 1,165 in Uganda. The surveys occurred across the maize growing zones in the different countries. Because the sample sizes differ between countries and do not accurately reflect relative population ratios, we weighted regression results based on the inverse of the probability of being selected into the study at the country level. The probability of selection was calculated as the number of survey participant households selected, divided by the total rural population of the respective country in the year surveyed. Rural population data come from the database provided by the World Development Indicators of the World Bank (2019).

Each respondent was asked to answer survey questions for the most recent major maize season and minor maize season. The surveys asked about household characteristics and assets; quantity of maize produced, stored, and lost; expected quantity of maize lost in storage; actual and intended storage length for sale and consumption; storage chemical use; major source of loss in storage; and storage technology used, among other important post-harvest storage indicators. Data were reported at the storage method level (e.g.: woven bag, granary, hermetic bag, etc.) for each household; thus, some households had more than one observation per season. Across all five countries, there were 184 households that reported two storage methods for either season; 6 households that reported three storage methods; and 1 that reported four storage methods. Because the number of observations per household per season differ across our sample, we use robust standard errors clustered at the household level.

Household storage loss is the amount of maize lost in storage, calculated as a percent of the total amount of maize stored in the respective season, reported at the storage method level within each household. We included households that reported no loss, as long as they stored maize.

Expected storage loss is calculated in the same manner and refers to the amount of maize the household expected to lose at the beginning of storage. Storage length refers to the number of weeks that maize was stored for sale before being completely depleted, reported for each storage method used by each household. Intended storage length refers to the length of time the household intended to store maize for at the beginning of storage. All survey responses were recorded at the end of storage as recall information. Thus, the values of farmers' expectations (expected loss and intended length) from the beginning of the agricultural season are reported at the end of the storage period.

Planting lower-yielding varieties that are less susceptible to loss in storage is reported as the share of total maize cultivated area used for local maize varieties. Households reported maize land and production in terms of local, open pollinated varieties (OPV), hybrids, or recycled hybrids. We consider OPV, hybrids, and recycled hybrids to be improved maize, and local to be traditional varieties.[5] The use of the other adaptation strategies (applying storage chemicals and selling earlier than intended) are reported as binary variables. We consider households to use storage chemicals as an adaptation strategy if they reported applying chemicals to any maize stored. Lastly, a household sold earlier than intended if his intended length of storage was greater than actual length of storage.

We used four groups of control variables: (1) year and season; (2) location; (3) household characteristics; and (4) farm characteristics. A full list of household and farm characteristics can be found in Table 1—8 in Appendix. Year and season variables distinguish between the

[5] This is an approximation for higher-yielding dent and lower-yielding flint varieties, as most higher-yielding hybrids and OPVs are dent varieties, while most lower-yielding local varieties are flint (Ricker-Gilbert and Jones, 2015).

agricultural season (major and minor) for which farmers reported data. The major season occurs during the long-rain season and typically has larger overall production; the minor season occurs during the short-rain season. As surveys were conducted during different years, we also wanted to control for any variation resulting from year-related shocks, such as drought, export bans, increased pest infestations, etc. Binary variables were used for years 2014 and 2015, with 2013 used as the reference year. Location controls include country binary variables, where Ghana is used as the reference category. This was decided based on the fact that Ghana has the median expected storage loss, and this does not affect the significance of any results. Additionally, two within-country geographical identifiers were included to account for variability in climate and market conditions within each country.

## 1.4 Hypotheses and Models

Our analysis is twofold. First, we offer supplementary descriptive statistics on the state of storage loss in SSA. We look at average storage losses and length, storage method, major reported sources of loss, and distribution of losses. This allows us to compare the basic characteristics of our data with results found in the current literature. As part of this analysis, we compare households' realized storage loss and length to their expectations. Determining whether households on average meet their loss target set at the start of the storage season, or under-/over-estimate will help inform the results from our main regression analysis. Second, we present linear models estimated by OLS that measure (1) the correlation strength between actual and expected storage loss and length and (2) whether the three adaptation strategies reduce actual storage loss.

### *1.4.1 Descriptive statistics*

Before analyzing use of the three adaptation strategies of interest, we first assess the state of storage loss in our sample. These results can help us compare if storage loss in our sample is consistent with the current literature. First, we consider the distribution of actual storage loss and length. Previous literature has reported that many farmers report zero or low losses and only a few report high losses (Kaminski and Christiaensen, 2014; Ambler et al., 2018). In this case, storage loss would exhibit a positively skewed distribution. Examining the distribution of losses across farmers is crucial, as a positively skewed distribution can deflate the average losses and could account for the small average losses we see in other studies. Therefore, we report both skewness (the scale and direction of asymmetry) and kurtosis (the sharpness of the peak) using STATA's distribution statistics, and test if skewness and kurtosis deviate from a normal distribution ("Descriptive Statistics Using the…"; D'Agostino et al., 1990). We present the following null hypothesis:

*$H_0$1: Actual storage loss exhibits a normal distribution*

We expect that our data exhibit a positive distribution, where only a small percentage of households report losses, but those who do report high levels of loss. In general, we anticipate finding results similar to the current literature that suggest on average, losses are low. If this is the case, then a positively skewed distribution would contribute to the low estimates. In addition, low levels of loss on average, with at least some households reporting high losses, would also indicate that households do employ some strategies to reduce losses.

In addition, we are interested in the difference in expected storage loss when households make the storage decision to their actual realized loss later in the season, and intended storage length to actual length. We use two-tailed, paired t-tests to test the following null hypotheses:

*$H_0$2: There is no difference between actual and expected storage loss*

*$H_0 3$: There is no difference in actual and intended length of storage in maize stored for sale*

Quantity of maize lost in storage (both actual and expected) are reported as a percentage of total quantity of maize stored. The actual and intended length of storage for maize are reported in weeks. We are interested in comparing expected and actual losses and length to see if expectations accurately predict real outcomes. If so, this could indicate that farmers employ adaptation strategies to meet a pre-set goal. Contrarily, it could also imply that respondents report only after the fact that they did not lose more than expected and the result could be a fault of collecting recall information. If not, it may suggest that losses are more stochastic and require that farmers re-assess their storage goals and practices on a continuous basis as more information about the environment, storage conditions, market prices, etc. become available.

### *1.4.2 Storage loss expectations and adaptation strategies*

Next, we assess what is driving the variation in actual losses and storage length. This section provides further explanation for the trends we see in the descriptive statistics, as well as explores the factors that reduce, or cause, storage loss. There likely is unobservable endogeneity in the following models, as the observed variables are outcomes of continuous decision-making processes. Because of this, it is important to note that we can only assume correlation with confidence, but cannot assume causation. We analyze (1) storage loss and (2) storage length, using the following linear regression models:

$$ActualLoss_{ij} = \beta_0 + \beta_1 ExpLoss_{ij} + \beta_2 Storage_{ij} + \beta_3 Variety_i + \beta_4 ChemApply_{ij} + \beta_5 SellEarly_{ij} + \beta_6 Sale_{ij} + \beta_7 Time_i + \beta_8 Location_{ij} + \beta_9 HH_{ij} + \beta_{10} Farm_{ij} + \omega_i + \varepsilon_{ij} \quad (1.1)$$

$$ActualLength_{ij} = \beta_0 + \beta_1 IntLength_{ij} + \beta_2 Storage_{ij} + \beta_3 Variety_i + \beta_4 ChemApply_{ij} + \beta_5 ExpLoss_{ij} + \beta_6 Time_i + \beta_7 Location_{ij} + \beta_8 HH_{ij} + \beta_9 Farm_{ij} + \omega_i + \varepsilon_{ij} \qquad (1.2)$$

Where $ActualLoss_{ij}$ is the actual storage loss (as a percent of total maize stored) and $ActualLength_{ij}$ the actual storage length for sale (weeks) for storage method $j$ of household $i$; $ExpLoss_{ij}$ is the expected storage loss (as a percent of total maize stored) and $IntLength_{ij}$ is the intended storage length for sale (weeks), for storage method $j$ of household $i$; $Storage_{ij}$ is a vector of two binary variables, the first indicating if the *j*th type of storage used by household $i$ was hermetic storage and the second indicating other improved storage according to Table 1—2; $Variety_{ij}$ is the share of total maize cultivated land planted with local maize for household *i*; $ChemApply_{ij}$ is equal to 1 if household *i* applied storage chemicals to stored maize $j$; $SellEarly_{ij}$ is equal to 1 if household *i* sold maize $j$ earlier than intended if maize was stored for sale; $Sale_{ij}$ is a binary variable equal to 1 if the *j*th maize stored by household $i$ was stored for sale[6]; $Time_i$, $Location_i$, $HH_i$ and $Farm_i$ are vectors containing the variables according to the year and season, location, household characteristics, and farm characteristics categories in Table 1—8 of Appendix; $\omega_i$ is the household-specific error term; and $\varepsilon_{ij}$ is an error term specific to household *i*'s use of storage method $j$.

$ExpLoss_{ij}$ is included in Equation (1.2) because we assume a correlation between storage loss and length; i.e., the longer maize is stored for, the more deterioration occurs. However, the direction of causality is not explicit, as more time in storage increases loss but increased loss could induce farmers to sell and decrease storage length. To address the problem of reverse causality,

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[6] Observations are recorded by storage method for each household $i$, therefore each observation could be stored for multiple purposes (sale, consumption, and/or seed). The variable *Sale* is included to distinguish between maize stored at least in part for sale, and maize not stored for sale.

we instead use expected loss, which is strongly correlated with actual loss (Table 1—6). Since the expected loss value comes from the initial time maize was placed in storage, we can be sure of the direction of causality. We do not use intended storage length in Equation (1.1), as this storage length only refers to maize stored for sale and would therefore reduce the number of usable observations. Including intended storage length in Equation (1.1) would ignore storage loss in maize stored only for consumption and/or seed and may give a biased analysis of storage loss in general. We do not include $SellEarly_{ij}$ in Equation (1.2), since this variable is derived from the relationship between actual and intended storage length, which are already included in the Equation.

Storage method is included in Equations (1.1) and (1.2) only to control for the effectiveness of storage material as discussed before. However, only 2.8% of observations were stored in hermetic technology and only 2.3% in other improved storage technology, while 89.8% use traditional means of storage (Table 1—9, Appendix). Given the small proportion of the sample using improved storage, compared to traditional, it is not likely that we will be able to deduce strong (or any) significant effects in the models. Thus, any insignificance is a result of weak statistical power and cannot adequately speak to the effectiveness of improved storage methods in reducing storage loss and increasing storage length.

First we examine the correlation between actual and expected losses. Coefficient $\widehat{\beta_1}$ in each model can tell us how strong of a predictor expected storage loss and intended storage length are of actual outcomes. If expected storage loss (length) does strongly predict actual loss (length), it could indicate that households set some pre-determined goal that and then adjust their storage practices to meet this goal. We present the following null hypotheses:

*$H_0$4:* *Expected storage loss has no effect on the amount of maize a farmer actually loses in storage*

*$H_0$5:* *Intended storage length has no effect on the length of time a farmer actually stores maize for before selling*

If $\widehat{\beta_1}$ is greater than 1, then a one percent increase in expected storage loss (one week increase in intended storage length) would result in a more than one percent increase in actual storage loss (more than one week increase in actual storage length). This means that households on average under-estimate losses (length). The opposite is true if $\widehat{\beta_1}$ is less than 1, and expected loss (length) is a perfect predictor of actual loss (length) if $\widehat{\beta_1}$ is equal to 1. We predict that there will be a significant correlation between actual and expected losses but expected losses do not perfectly predict actual outcomes. Whether expected loss (length) under- or over-estimates actual outcomes, we expect results to be consistent with what we find from the difference-in-means tests.

Next, coefficients $\widehat{\beta_3}$, $\widehat{\beta_4}$ and $\widehat{\beta_5}$ tell us how effective the three adaptation strategies are at reducing storage loss. If each of these strategies did significantly reduce losses in our sample, it could indicate that households used them for the explicit purpose of storage loss control. We hypothesize:

*$H_0$6a:* *Planting traditional maize varieties has no effect on storage loss*

*$H_0$6b:* *Planting traditional maize varieties has no effect on storage length for sale*

*$H_0$7a:* *Applying storage chemicals has no effect on storage loss*

*$H_0$7b:* *Applying storage chemicals has no effect on storage length for sale*

*$H_0$8a:* *Selling early has no effect on storage loss*

*$H_0$8b:* *Expected storage loss has no effect on storage length for sale*

Selling early is not included when considering storage length for sale, as the binary variable $SellEarly_{ij}$ is derived from the relationship between actual and intended storage length for sale and therefore excluded from Equation (1.2). However, we can look at the effect that expected storage loss has on storage length, which is related to this idea of selling earlier to avoid incurring additional losses. If these strategies are used as adaptations to storage loss, then we would expect that storing traditional varieties and applying storage chemicals reduce loss and increase storage length. Selling early would also reduce loss, and expecting higher losses would induce farmers to store for a shorter period of time.

## 1.5 Results

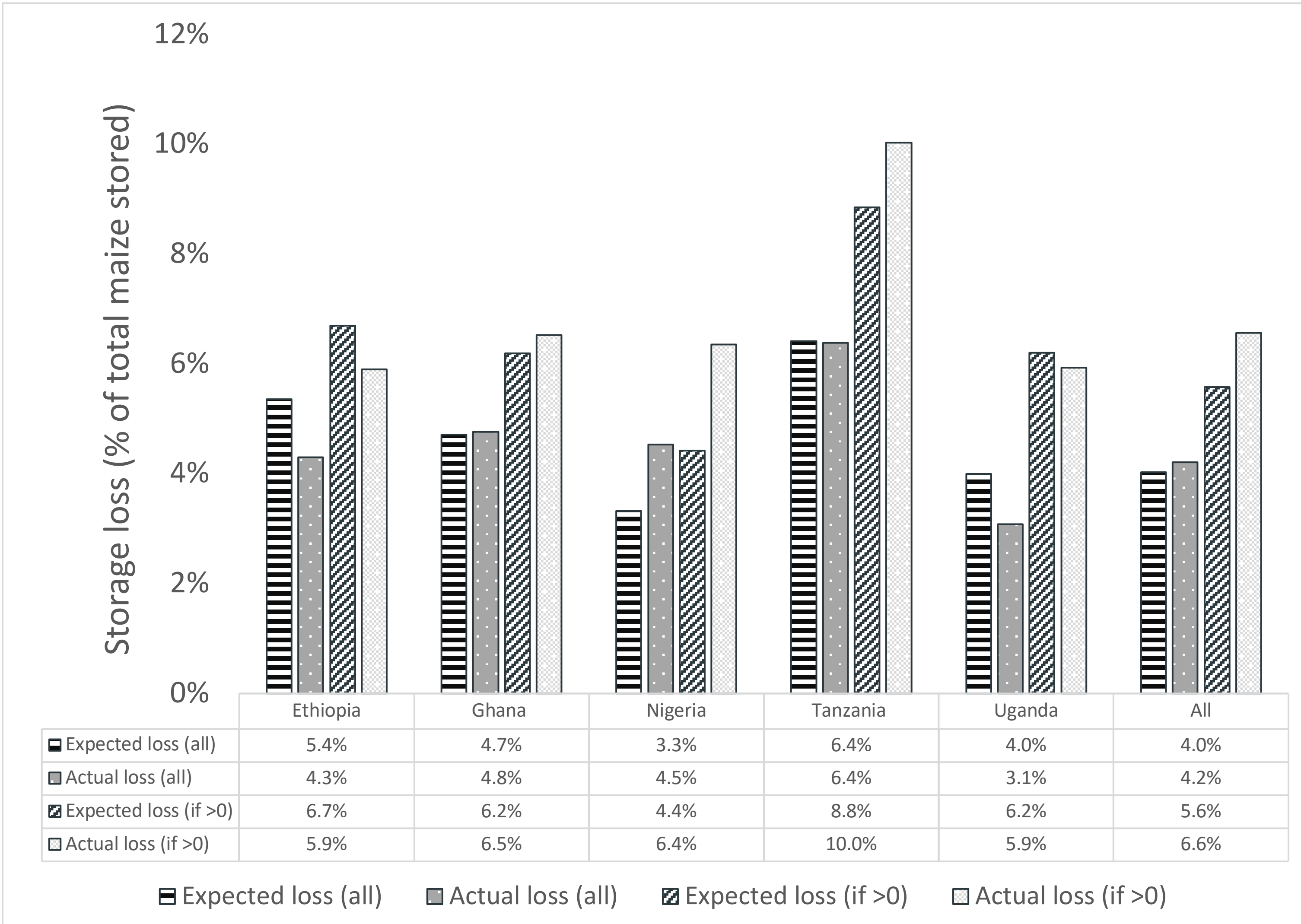
### *1.5.1 Descriptive statistics*

Aggregated across the full 3,683 households over two seasons, a total of about one million kilograms of maize were stored and 251,757 kilograms were lost in storage, equating to an overall loss of only 2.51%. Storage loss estimates in SSA vary in the literature, with self-reported data trending towards low estimates. Our data produces similarly low estimates to those of Kaminski and Christiaensen (2014). The households that did incur loss, lost on average 6.6%, compared to a 4.21% loss average when also considering those households that incurred no loss (Figure 1—1). However, 64% of our sample reported incurring some loss, compared to just 7-22% in their study (Figure 1—2). This 6.6% estimate is still low, suggesting that even when considering those who lost some maize in storage, losses are still concentrated at low levels. In other words, including households that reported no losses does not explain the relatively low estimates found across the current literature.

Table 1—1 shows that the proportion of the sample using storage chemicals varies by country. About three quarters of all households in Ethiopia reported using storage chemicals, while only 12% in Uganda did. Similarly, almost all households (98%) reported storing improved varieties in Ethiopia, but households in all other countries stored mostly traditional varieties (65% traditional and above). These results suggest higher levels of use in some inputs may encourage further input use, possibly more or better fertilizer, more labor, etc. Ethiopian maize yields are almost three times as high as yields in all other countries, which could suggest higher improved input use in general in Ethiopia. Here, the higher levels of loss-reducing input use and much higher yields may compensate for the added loss from storing mostly improved varieties and hybrids.

Despite differences in input use, selling earlier than intended is homogenous across countries. Overall, only 32% of households sold maize earlier than intended. Across countries, this rate ranges from 22% of households in Nigeria, to 46% in Uganda. Respondents reported that insects (66%) and rodents (23%) caused the greatest loss to maize in storage (Figure 1—3). This suggests that any adaptation strategies farmers employ would likely be targeted at insect and pest control. Improved storage, particularly hermetic storage, would be more effective at controlling insects than traditional storage methods. In the absence of such technology, or even as a complement to more effective storage methods, all three of our adaptation strategies can be used to reduce insect infestation.

In Figure 1—4, we present the distribution of losses for all observations that report positive losses (excluding observations that report no loss). Over 60% of households reported losses below 5%, and over 80% reported losses below 10% across all countries combined. This trend is also true for all countries individually, excluding Tanzania where less households lose between 5 and 10%. Very few households report losses above 20% in all countries. However, the few households that do report losses greater than 20%, lose a significant portion of their harvest. Nineteen households reported losing more than 60%, ten reported losing more than 80%, and six reported losing all of their stored maize. Skewness and kurtosis statistics are reported in Table 1—2. The positive skewness statistics indicate a positively skewed distribution, while the high and positive kurtosis statistics indicate that the distribution is steep. All statistics suggest that actual storage loss significantly deviates from a normal distribution. Therefore, we reject the null Hypothesis 1 and conclude that storage loss is positively skewed, so that most lose only a little (less than 5% loss) and just a few households lose a lot (more than 20% loss). This finding is in line with other studies such as Kaminski and Christiaensen (2014) and Ambler et al. (2018).




| | Ethiopia | Ghana | Nigeria | Tanzania | Uganda | All |
|---|---|---|---|---|---|---|
| Expected loss (all) | 5.4% | 4.7% | 3.3% | 6.4% | 4.0% | 4.0% |
| Actual loss (all) | 4.3% | 4.8% | 4.5% | 6.4% | 3.1% | 4.2% |
| Expected loss (if >0) | 6.7% | 6.2% | 4.4% | 8.8% | 6.2% | 5.6% |
| Actual loss (if >0) | 5.9% | 6.5% | 6.4% | 10.0% | 5.9% | 6.6% |

**Figure 1–1. Mean storage loss (expected and actual) by country**

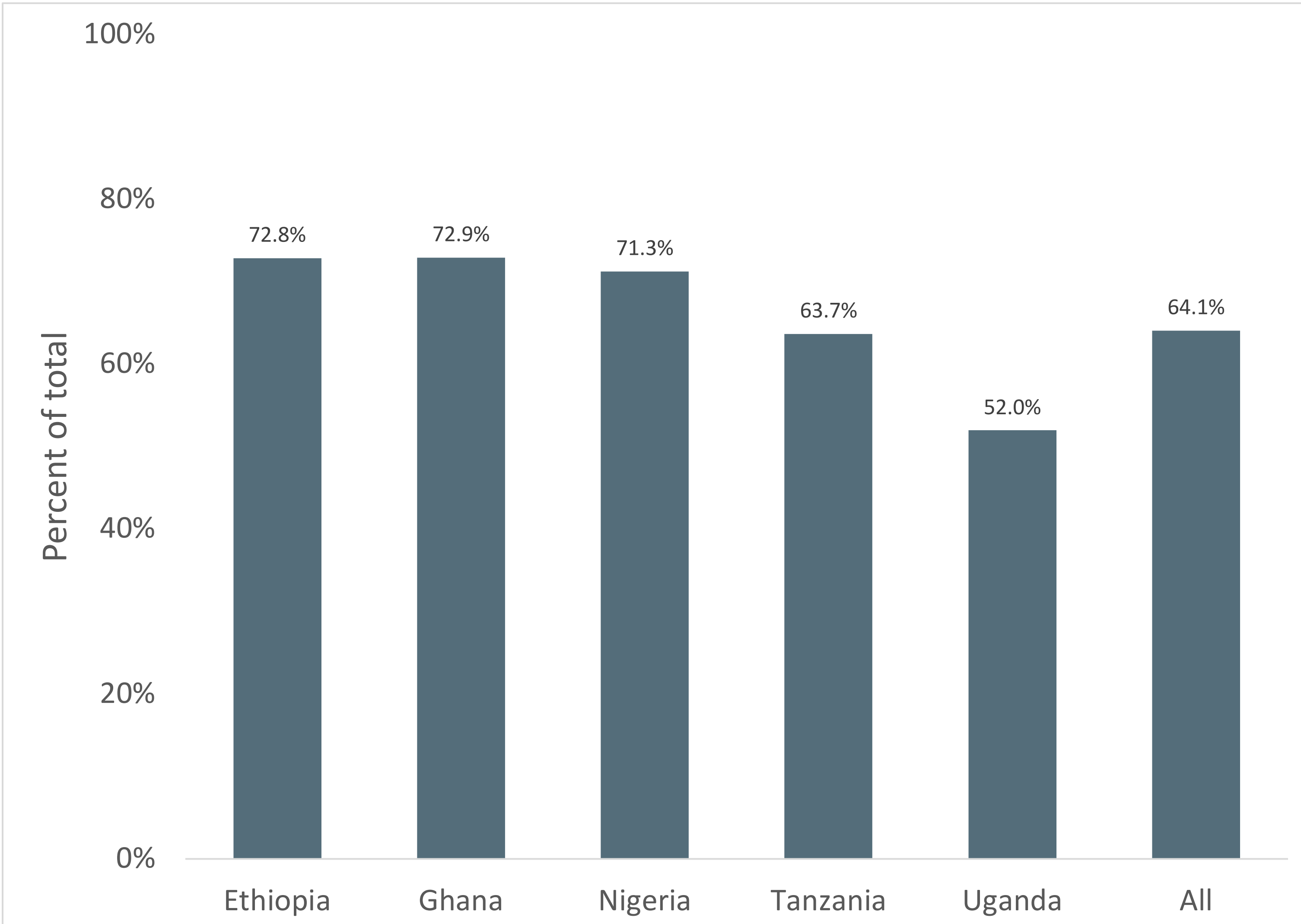



**Figure 1–2. Households reporting losses greater than zero**

**Table 1–1. Sample means of demographic characteristics**

| Variable | Ethiopia n=324 | Ghana n=384 | Nigeria n=2,922 | Tanzania n=597 | Uganda n=2,215 | All n=6,442 |
|---|---|---|---|---|---|---|
| Age of household head (years) | 42.27 | 51.05 | 44.98 | 44.05 | 44.63 | 45.00 |
| Gender of household head (=1 if Male) | 0.93 | 0.91 | 0.98 | 0.89 | 0.82 | 0.91 |
| Number of people in household | 7.45 | 9.61 | 9.10 | 6.75 | 6.41 | 7.91 |
| Education of household head (years) | 4.62 | 2.82 | 3.45 | 3.05 | 2.63 | 3.15 |
| Number of children under 10 in household | 2.00 | 2.75 | 3.48 | 2.39 | 2.31 | 2.86 |
| Farming experience of household head (years) | 21.66 | 22.55 | 19.65 | 13.03 | 20.81 | 19.71 |
| Total farmland (ha) | 0.66 | 1.68 | 3.98 | 1.82 | 2.06 | 2.81 |
| Total maize farmland (ha) | 0.29 | 1.02 | 1.43 | 0.79 | 0.81 | 1.08 |
| Total crops produced (kg) | 3,988 | 3,894 | 11,719 | 3,918 | 4,324 | 7,598 |
| Total maize produced (kg) | 2,752 | 2,333 | 3,609 | 2,892 | 1,292 | 2,627 |
| Total yield (kg/ha) | 7,831 | 2,688 | 4,147 | 2,366 | 2,619 | 3,555 |
| Total maize yield (kg/ha) | 9,461 | 2,885 | 3,685 | 3,184 | 2,395 | 3,438 |
| Total maize stored (kg) | 2,760 | 3,084 | 1,711 | 2,008 | 792 | 1,557 |
| Total maize stored for sale (kg) | 1,462 | 2,183 | 734 | 486 | 587 | 784 |
| Total maize stored for consumption (kg) | 908 | 380 | 854 | 1,440 | 187 | 654 |
| Total maize stored for seed (kg) | 356 | 444 | - | 22 | 14 | 51 |
| Stored maize for sale (=1 if yes) | 0.69 | 0.80 | 0.55 | 0.49 | 0.57 | 0.57 |
| Stored maize for consumption (=1 if yes) | 0.92 | 0.82 | 0.90 | 0.91 | 0.90 | 0.90 |
| Stored maize for seed (=1 if yes) | 0.25 | 0.42 | - | 0.62 | 0.70 | 0.34 |
| Distance of nearest market (km) | 4.68 | 11.91 | 5.36 | 4.48 | 3.31 | 4.93 |

**Table 1—1 continued**

| | | | | | | |
|---|---|---|---|---|---|---|
| Household applied storage chemicals (=1 if yes) | 0.74 | 0.41 | 0.52 | 0.50 | 0.12 | 0.38 |
| Household applied storage chemicals on maize stored for sale (=1 if yes) | 0.76 | 0.43 | 0.54 | 0.51 | 0.11 | 0.39 |
| *N=* | *224* | *306* | *1,603* | *290* | *1,263* | *3,686* |
| Household stored traditional variety of maize (=1 if yes) | 0.02 | 0.73 | 0.66 | 0.67 | 0.65 | 0.63 |
| Share of land cultivated using traditional varieties (% of maize land cultivated) | 1.6% | 69.0% | 65.9% | 68.7% | 65.4% | 63.0% |
| Share of land cultivated using traditional varieties (% of all land cultivated) | 0.4% | 44.3% | 31.6% | 28.4% | 21.6% | 27.0% |
| Household sold stored maize earlier than intended if stored for sale (=1 if yes) | 0.41 | 0.36 | 0.22 | 0.35 | 0.46 | 0.32 |
| *N=* | *228* | *316* | *1,818* | *298* | *1,186* | *3,846* |

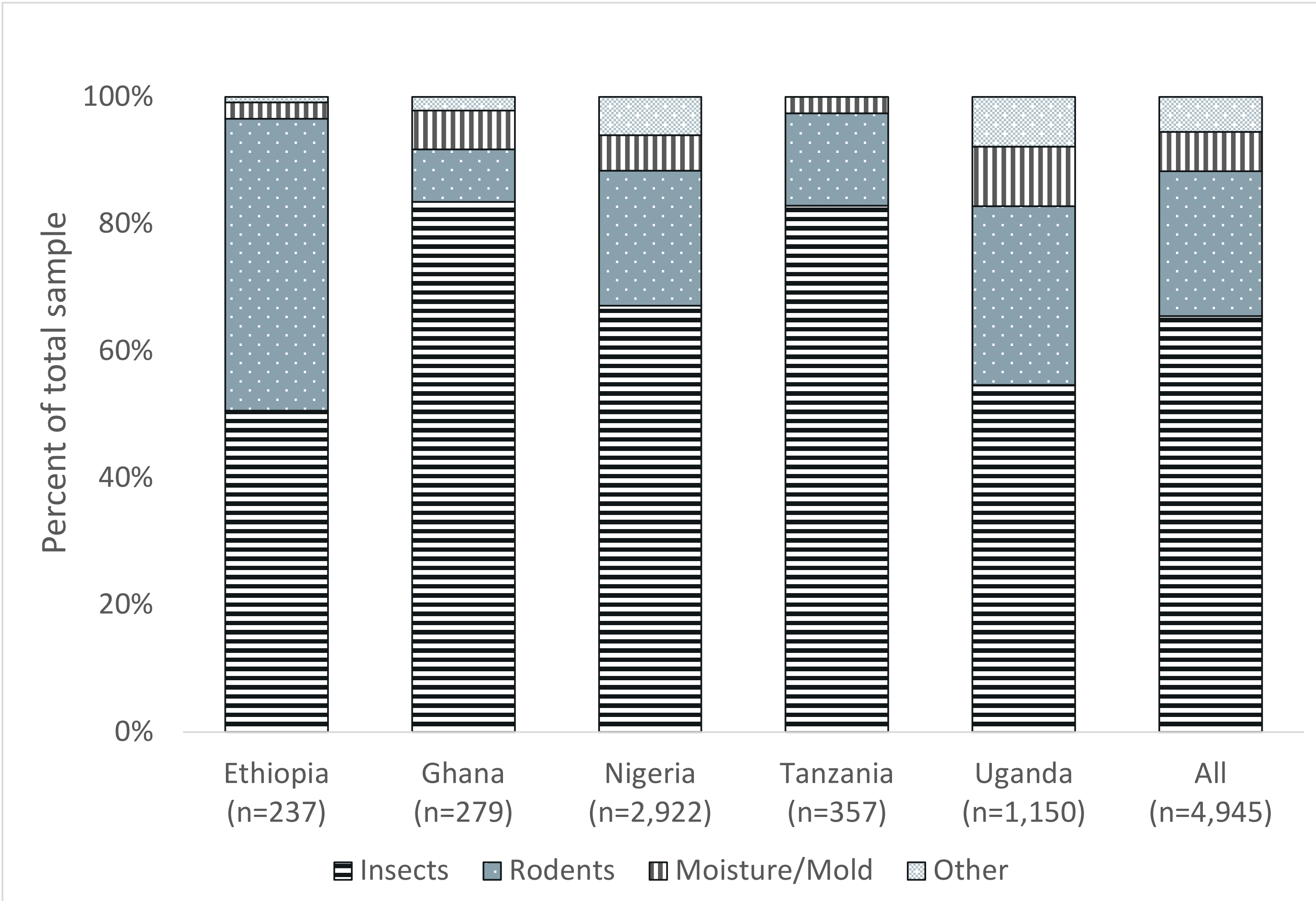
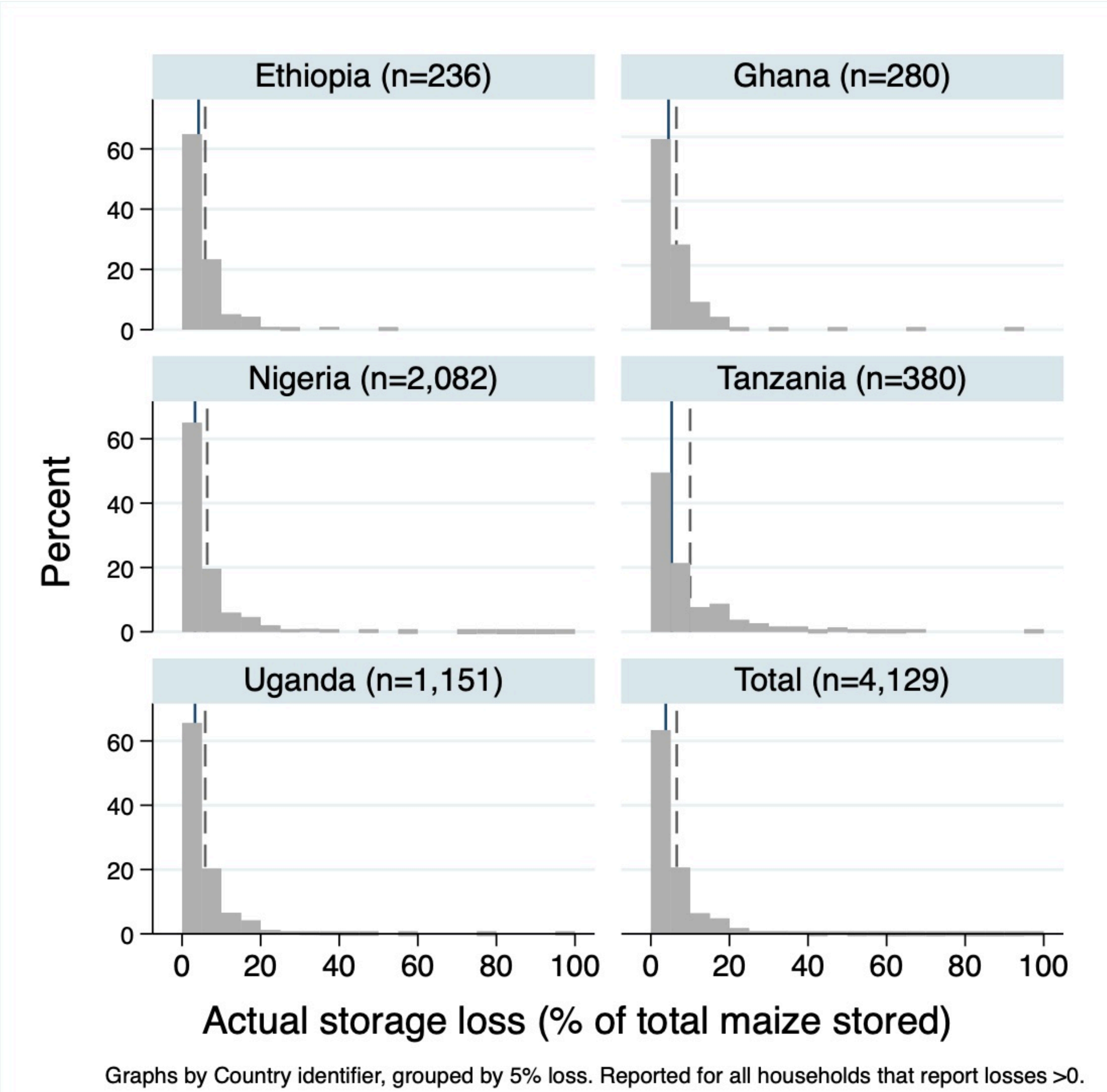



**Figure 1–3. Major source of loss reported**




Means are represented by the gray dashed lines and medians are represented by the blue solid lines. Means are reported in Table 1—4. Medians are as follows: Ethiopia (4.2); Ghana (4.5); Nigeria (3.3); Tanzania (5.3); Uganda (3.3); and All (3.8).

**Figure 1–4. Distribution of storage loss**

**Table 1–2. Testing Distribution of Storage Loss (for losses >0)**

| Country | N | Skewness | Kurtosis |
|---|---|---|---|
| Ethiopia*** | 236 | 3.229 | 18.321 |
| Ghana*** | 280 | 6.107 | 54.461 |
| Nigeria*** | 2,082 | 4.334 | 31.619 |
| Tanzania*** | 380 | 2.793 | 13.86 |
| Uganda*** | 1,151 | 5.432 | 49.932 |
| All*** | 4,129 | 4.419 | 32.858 |

Skewness and kurtosis are generated using STATA and tested as described by D'Agostino, Belanger, and D'Agostino (1990). ***p<0.01, **p<0.05, *p<0.1.

### *1.5.2 Are actual and expected losses the same?*

Tables 1—3 and 1—4, show the difference in expected and actual storage loss within each country and across all countries with a mean difference test. Table 1—3 considers all observations, even households that report zero loss, while Table 1—4 measures storage loss only if the household experienced a positive amount of loss, which accounts for about 64% of all observations (Figure 1—1). A graphical comparison of storage loss, both expected and actual, is presented in Figure 1—1.

We find that across all observations, households lose 0.17% more than expected. However, this finding varies by country. Farmers in Nigeria under-estimated how much loss they would incur; by 1.2%. This is surprising, as all other countries lose less than or what they expected to lose. Contrarily, Ugandan and Ethiopian farmers over-estimated losses by 0.9% and 1.1%, respectively. Even though expected and actual losses are significantly different in Ethiopia, Nigeria, Uganda, and overall on average, the differences are still small and would be difficult to quantify by sight. However negligible those differences were, they are significant, indicating that farmers did notice a difference between expected and actual losses.

Of those that reported positive losses, we found that losses were about 1% higher than expected (Table 1—4). This is a larger difference than what we find in Table 1—3, suggesting that a large enough proportion of the sample that did not lose in storage also expected to not lose any maize in storage, thereby weighing down the average difference reported in Table 1—3. However, this result appears to be driven by the relatively large Nigerian sample size, where we see a larger difference between expected and actual losses when considering only those that lost some maize in storage.

Along with Nigeria, the difference in expected and actual losses in Tanzania becomes significant in Table 1—4, which indicates that of those who lost maize in storage, households tended to under-estimate loss (i.e., they lost more than expected). In Ethiopia and Uganda, we see the opposite result. There is no difference in expected and actual losses in Table 1—4, contrary to Table 1—3, where loss was over-estimated (households lost less than expected on average). Ghana exhibits no difference in expected and actual storage loss, regardless if zero-loss observations are included. Based on results across all countries in Tables 1—3 and 1—4, we can reject the null Hypothesis 2 and conclude that on average, households lose more in storage than expected.

**Table 1–3. Difference in expected and actual storage loss (all observations) (% of total maize stored)**

| Country | Expected | Actual | Difference | t-value |
|---|---|---|---|---|
| Ethiopia***<br>(N=324) | 5.36%<br>(0.405) | 4.30%<br>(0.348) | 1.07%<br>(0.388) | 2.748 |
| Ghana<br>(N=384) | 4.71%<br>(0.375) | 4.76%<br>(0.386) | -0.05%<br>(0.252) | 0.184 |
| Nigeria***<br>(N=2,922) | 3.33%<br>(0.133) | 4.53%<br>(0.155) | -1.20%<br>(0.133) | 9.052 |
| Tanzania<br>(N=597) | 6.42%<br>(0.467) | 6.38%<br>(0.453) | 0.03%<br>(0.425) | 0.076 |
| Uganda***<br>(N=2,215) | 4.00%<br>(0.167) | 3.08%<br>(0.144) | 0.92%<br>(0.150) | 6.150 |
| *All**<br>*(N=6,442)* | *4.03%*<br>*(0.099)* | *4.21%*<br>*(0.101)* | *-0.17%*<br>*(0.093)* | *1.885* |

A positive difference denotes that expected storage loss was higher than actual.
Standard errors reported in parentheses. ***p<0.01, **p<0.05, *<0.1

**Table 1–4. Difference in expected and actual storage loss (only observations that lost maize in storage) (% of total maize stored)**

| Country | Expected | Actual | Difference | t-value |
|---|---|---|---|---|
| Ethiopia<br>(N=324) | 6.69%<br>(0.510) | 5.90%<br>(0.434) | 0.80%<br>(0.511) | 1.557 |
| Ghana<br>(N=384) | 6.20%<br>(0.475) | 6.53%<br>(0.490) | -0.33%<br>(0.329) | 1.011 |
| Nigeria***<br>(N=2,922) | 4.42%<br>(0.177) | 6.36%<br>(0.204) | -1.94%<br>(0.179) | 10.798 |
| Tanzania**<br>(N=597) | 8.85%<br>(0.608) | 10.03%<br>(0.641) | -1.18%<br>(0.557) | 2.118 |
| Uganda<br>(N=2,215) | 6.21%<br>(0.260) | 5.93%<br>(0.250) | 0.28%<br>(0.236) | 1.173 |
| *All****<br>*(N=6,442)* | *5.58%*<br>(0.137) | *6.56%*<br>(0.144) | *-0.99%*<br>(0.129) | *7.618* |

A positive difference denotes that expected storage loss was higher than actual.
Standard errors reported in parentheses. ***p<0.01, **p<0.05, *<0.1

Within each country, households on average did not store maize for the intended length (Table 1—5). Overall and in all countries except Nigeria, storage length was over-estimated (households sold earlier than intended) on average. However, according to Table 1—1, less than half of households (only 35-46%) across all countries except Nigeria actually sold earlier than intended. This indicates that in these countries, those who did sell earlier, sold much earlier, thereby outweighing the majority of those who did not. Households in Ethiopia sold on average three weeks earlier, which is a much more noticeable difference than losing 1% more than expected in maize weight. Depending on the inter-seasonal price fluctuations, three weeks may result in a significant and observable loss in potential income.

Contrarily, households in Nigeria stored longer than intended on average. Nigerian households also lost almost 2% more in storage than expected, which is consistent with the hypothesis that farmers sell earlier to avoid loss. However, these are unconditional means and do not take into consideration the reason for selling early. We reject the null Hypothesis 3 that intended and actual storage length is the same based on the statistical significance of all six paired t-tests in Table 1—5. Instead, we can conclude that on average, households store for less time than intended, but only in Nigeria households store longer than intended.

**Table 1–5. Difference in intended and actual storage length for sale (weeks)**

| Country | Intended | Actual | Difference | t-value |
|---|---|---|---|---|
| Ethiopia*** (N=228) | 25.98 (0.690) | 23.05 (0.706) | 2.93 (0.414) | 7.071 |
| Ghana*** (N=308) | 21.93 (0.650) | 19.54 (0.654) | 2.39 (0.410) | 5.837 |
| Nigeria*** (N=2,879) | 15.18 (0.242) | 16.19 (0.271) | -1.01 (0.211) | 4.795 |
| Tanzania** (N=320) | 24.42 (0.847) | 23.11 (0.891) | 1.31 (0.638) | 2.051 |
| Uganda*** (N=1,246) | 10.64 (0.197) | 8.27 (0.163) | 2.37 (0.163) | 14.522 |
| *All*** (N=5,015)* | *15.56 (0.177)* | *15.19 (0.191)* | *0.37 (0.141)* | *2.644* |

A positive difference denotes that expected storage length was higher than actual.
Standard errors reported in parentheses. ***p<0.01, **p<0.05, *<0.1

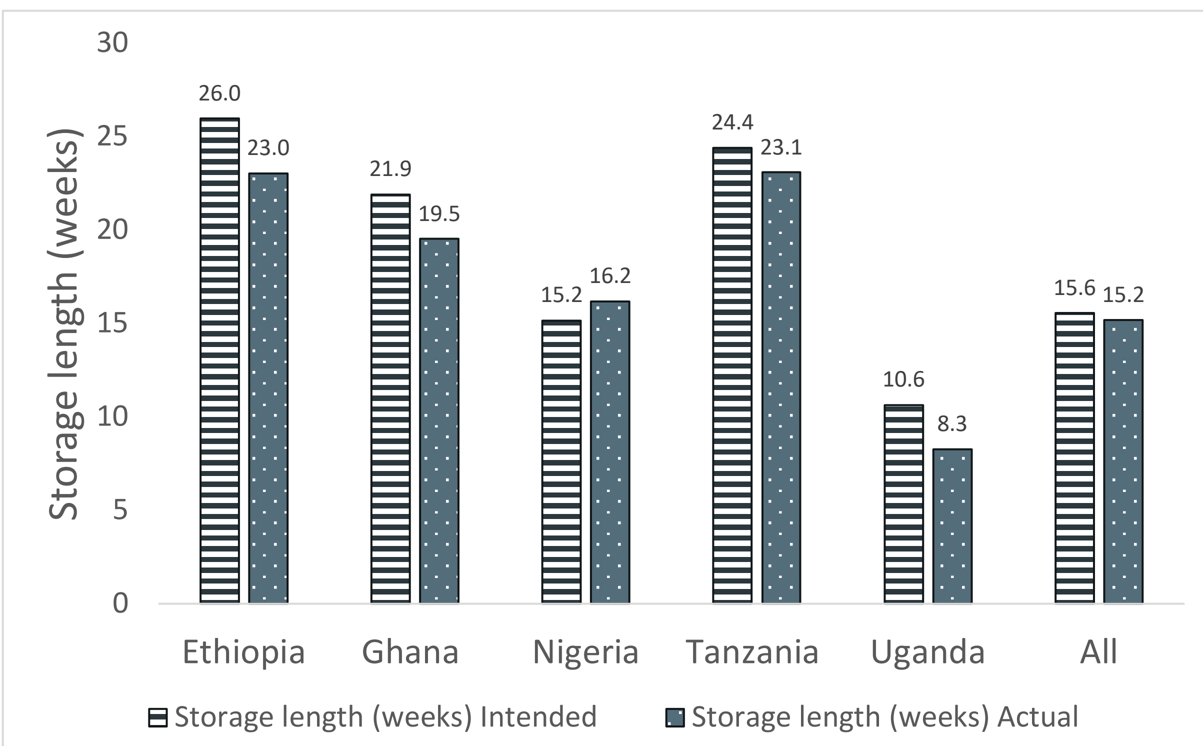



**Figure 1–5. Mean storage length**

*1.5.3 Do farmers use adaptation strategies to reduce storage loss?*

Equation (1.1) tests the effect of using adaptation strategies on storage loss. The constant term, $\widehat{\beta_0}$ is not statistically different than zero in the later specifications, suggesting that it is possible to obtain zero, or near zero, loss in storage. Before discussing these adaptation strategies, we first look more closely at the relationship between expected and actual loss, $\widehat{\beta_1}$. In Tables 1—3 and 1—4, we found evidence that suggests farmers on average over-estimate storage loss, although in small amounts. Results in Table 1—6 indicate that farmers' expectations are positively correlated with actual outcomes, however at a less-than-one ratio. This trend stays strong throughout all six model specifications. We can reject Hypothesis 4 that expected storage loss is not correlated with actual loss, as $\widehat{\beta_1}$ is statistically greater than zero. Additionally, the first model specification that includes only expected loss and storage method explains 31.9% of the variation in actual storage loss. All other variables included in the sixth specification adds only about 2% to the R-squared value, suggesting that most of the observable variation in actual storage loss is attributed to farmers' expectations and storage method, but the use of adaptation strategies only explain little.

To see if this ratio is truly less than one, we use an F-test which tests whether the coefficient on expected loss is equal to one. With a lowest F-value of 50.01, we conclude that this $\widehat{\beta_1}$ coefficient is statistically different than 1. Thus, we can confidently say that a one percent increase in expected storage loss is correlated with a less than one percent increase in actual storage loss, meaning that farmers over-estimate storage loss on average. This is contrary to the over-estimations in Tables 1—3 and 1—4, where actual loss is higher than expected. The results of the mean difference test may have been driven by the large sample share of Nigeria, as we see in Table 1—6 that after controlling for the country, the results remain robust. According to the results from Equation (1.1), storage loss should be over-estimated, but we see in practice that farmers actually under-estimate losses. Therefore, there must be some other driver behind the realized difference in expectation and outcomes than what we see in our model.

We see little evidence that planting traditional maize varieties actually reduces loss, compared to storing hybrids and OPVs. In addition, Table 1—6 shows that selling early does not reduce actual storage loss. Thus, the shorter than intended storage time in Table 1—5 is likely a result of some other constraint besides storage loss. The only adaptation strategy that does significantly reduce loss is applying storage chemicals, by about 1%. Outside of applying storage chemicals, it does not seem that farmers use the adaptation strategies for the purpose of mitigating storage loss. There are many other factors influencing farmers' decisions on which varieties to plant and store, and when to sell, such as input costs, availability of seeds and other inputs, financial liquidity, etc. This suggests that these other factors are stronger drivers in the decisions that farmers make, which may not be surprising when considering that small amounts of loss may be inconspicuous. Based on the results, we cannot reject Hypotheses 6a and 8a that storing traditional maize and selling early reduce storage loss. We do reject Hypothesis 7a, as applying storage chemicals does reduce loss. For a full list of results, see Table 1—10 in Appendix.

**Table 1–6. Effect of expected storage loss and adaptation strategy use on actual storage loss (% of total maize stored)**

N=6,442

| Variable | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Expected loss | 0.562*** | 0.561*** | 0.561*** | 0.561*** | 0.562*** | 0.559*** |
| (% of total) | (0.062) | (0.061) | (0.062) | (0.062) | (0.063) | (0.063) |
| Used hermetic storage | 0.892 | 0.718 | 0.824 | 0.920 | 0.991 | 0.958 |
| (=1 if yes) | (0.930) | (0.943) | (0.940) | (0.936) | (0.933) | (0.933) |
| Used other improved storage | -0.506 | -0.404 | -0.485 | -0.895** | -1.025** | -1.016** |
| (=1 if yes) | (0.432) | (0.437) | (0.436) | (0.447) | (0.453) | (0.452) |
| Share of land cultivated using traditional varieties | - | -0.002 | -0.002 | -0.005* | -0.003 | -0.004 |
| (% of maize land cultivated) | - | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) |
| Applied storage chemicals | - | -0.906*** | -0.700*** | -1.125*** | -1.080*** | -1.047*** |
| (=1 if yes) | - | (0.247) | (0.268) | (0.297) | (0.300) | (0.298) |
| Sold maize earlier than intended | - | -0.004 | 0.084 | 0.439 | 0.406 | 0.383 |
| (=1 if yes) | - | (0.313) | (0.314) | (0.310) | (0.313) | (0.313) |
| Year & season controls | no | no | yes | yes | yes | yes |
| Location controls | no | no | no | yes | yes | yes |
| Household characteristics | no | no | no | no | yes | yes |
| Asset Score | - | - | - | - | -0.026 | -0.005 |
| (1 point for each asset owned) | - | - | - | - | (0.076) | (0.076) |
| Farm characteristics | no | no | no | no | no | yes |
| $\beta_0$ | 2.470*** | 2.96*** | 3.904*** | 2.690* | 0.784 | 1.007 |
| | (0.320) | (0.429) | (0.521) | (1.378) | (1.541) | (1.515) |
| F-statistic: coefficient on expected loss is equal to 1 | 50.01*** | 50.94*** | 50.44*** | 49.28*** | 48.59*** | 49.04*** |
| $R^2$ | *0.3191* | *0.3219* | *0.3240* | *0.3361* | *0.3392* | *0.3408* |

### *1.5.4 Do farmers use adaptation strategies to increase storage length?*

Table 1—7 displays the results of Equation (1.2). As expected, there is a strong, significant relationship between intended and actual storage length. Previously, we saw that households on average over-estimated storage length in Table 1—5. This is consistent with results in Table 1—7, which show this positive correlation between intended and actual length occur at a less-than-one ratio. i.e., a one week increase in intended storage length leads to a less than one week increase in actual length. The significant and consistent coefficient $\widehat{\beta_1}$ throughout all six model specifications leads us to reject Hypothesis 5 that intended storage length has no effect on the length of time that farmers actually store their maize before selling.

Similar to what we did with storage loss, we use an F-test to see if intended and actual length exhibit at a one-to-one ratio, i.e., a one week increase in intended storage length leads to a one week increase in actual length. With a lowest F-statistic of 208.47, we can confidently conclude that coefficient $\widehat{\beta_1}$ is statistically less than one, indicating that farmers do over-estimate storage length at the start of the storage period. This is consistent with results from Table 1—5 and supports the hypothesis that farmers re-evaluate their optimal storage goals during storage once they receive more information about environmental conditions, effectiveness of adaptation strategies, market prices, etc.

For each additional percent of land planted with traditional maize, storage time (for sale) decreases by about 0.05 weeks, or just a few hours. Switching an additional 5% of maize land from improved to traditional varieties would not even decrease storage length by 2 days. Although a very small time difference, this effect is strongly significant throughout all six model specifications, and becomes slightly larger as we control for more of the variation in storage length. This is contrary to what we expected, as previous literature suggests traditional flint varieties are less susceptible to loss in traditional storage because of its hard outer shell (Ricker-Gilbert and Jones, 2015; Sheahan and Barrett, 2017; Omotilewa et al., 2018).

Most land cultivated for maize is planted with traditional varieties, thus this negative effect could be a result planting more traditional maize on the margin. On average, households cultivated 63% (or 0.60 hectares) of maize land with local maize, compared to a 36% share cultivated with improved varieties (0.46 ha on average). The benefit gained in storage length by planting one more percent of land with traditional instead of improved varieties may be outweighed by the loss of the additional yield gain from that one percent of land. With less maize to store, the maize would deplete quicker.

Alternatively and more likely, some unobserved factor could be correlated with both storage length and use of traditional varieties, such as cash liquidity. This could be possible, as storage length may be affected by planting and input decisions for the next season. If households use traditional varieties because they are cheaper than improved varieties and sell early because of financial constraints, it could explain this significant effect of $\widehat{\beta_3}$ in Equation (1.2). Owning more assets does increase storage length, but asset ownership is only an approximation of income and does not account for liquidity during the storage period. A more precise measure of income could provide more insight into some combined effect of liquidity constraints and planting local maize.

As predicted, storage chemicals increase storage length by almost two weeks. Based on the results in Table 1—7, we conclude that we can reject both Hypotheses 6b and 7b, as planting traditional varieties decreases storage length, while applying storage chemicals increases length. However, we cannot deduce to what degree unobserved factors such as income are affecting the decision to plant local maize. It does not seem that expected storage loss affects how long a household stores maize before selling. Expected loss here is a measure of the farmers' expectation at the beginning of storage, but it is possible that as expected loss changes over the storage period and converges to actual loss as new information is assessed, the correlation between expected loss and actual storage length becomes significant. However our data do not capture changing expectations over time. Therefore, we cannot reject Hypothesis 8b that expected loss (estimated at the beginning of storage) does not affect farmers' decision on when to sell maize. For a full list of results, see Table 1—11 in Appendix.

**Table 1–7. Effect of intended storage length and adaptation strategy use on actual storage length for maize sold (weeks)**

N=5,015

| Variable | 1 | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|---|
| Intended storage length for sale | 0.768*** | 0.725*** | 0.724*** | 0.716*** | 0.714*** | 0.713*** |
| (weeks) | (0.016) | (0.017) | (0.017) | (0.017) | (0.017) | (0.017) |
| Used hermetic storage | 0.083 | 0.318 | 0.875 | 0.942 | 0.976 | 1.016 |
| (=1 if yes) | (1.234) | (1.214) | (1.187) | (1.179) | (1.180) | (1.180) |
| Used other improved storage[7] | -0.824 | -0.284 | -0.816 | -1.320 | -1.388* | -1.392* |
| (=1 if yes) | (0.899) | (0.854) | (0.857) | (0.830) | (0.826) | (0.825) |
| Share of land cultivated using traditional varieties | - | -0.040*** | -0.045*** | -0.054*** | -0.053*** | -0.052*** |
| (% of maize land cultivated) | - | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Applied storage chemicals | - | 0.600* | 2.250*** | 2.019*** | 1.969*** | 1.947*** |
| (=1 if yes) | - | (0.318) | (0.334) | (0.357) | (0.355) | (0.353) |
| Expected loss | -0.051** | -0.040* | -0.040* | -0.035 | -0.032 | -0.028 |
| (% of total) | (0.021) | (0.022) | (0.022) | (0.021) | (0.021) | (0.022) |
| Year & season controls | no | no | yes | yes | yes | yes |
| Location controls | no | no | no | yes | yes | yes |
| Household characteristics | no | no | no | no | yes | yes |
| Asset Score | - | - | - | - | 0.274** | 0.259** |
| (1 point for each asset owned) | - | - | - | - | (0.112) | (0.113) |
| Farm characteristics | no | no | no | no | no | yes |
| $\beta_0$ | 3.925*** | 6.414*** | 11.110*** | 13.551*** | 12.407*** | 12.534*** |
| | (0.285) | (0.435) | (0.650) | (1.569) | (1.916) | (1.975) |
| F-test: coefficient on expected loss is equal to 1 | 208.47*** | 272.93*** | 274.28*** | 293.93*** | 295.96*** | 285.27*** |
| $R^2$ | *0.5363* | *0.5554* | *0.5903* | *0.6015* | *0.6044* | *0.6048* |

[7]Table 1—7, columns 5 and 6 are reproduced in Table 1—12 of Appendix with a term that interacts use of other improved storage and farmer experience, to show that the effectiveness of improved storage increases as the household head has more experience. As a household head gains more experience, storage length would be no different than if traditional storage was used.

## 1.6 Conclusion

This study estimated storage loss and factors affecting it along with duration of storage, using cross-sectional data from five countries in SSA. Our results suggest that even though estimates are low, simply looking at storage loss independent of farmers' storage practices does not capture all of the costs incurred by smallholder farmers. There is continuous speculation in the literature that smallholder farmers employ adaptation strategies to reduce storage loss, such as planting local maize varieties that store better than hybrid varieties, using chemical insecticides to kill insect pests, and selling maize earlier in the season at lower prices to avoid losses. However, to date there is limited evidence to suggest that the use of these strategies is actually driven by the purpose of reducing losses. Therefore, our study sought to provide some new evidence that the use of these strategies are in fact related to storage loss.

Our results suggest that there is heterogeneity across the countries in our sample in terms of cultivating traditional rather than improved maize varieties, applying storage chemicals, and selling earlier than intended for mitigating storage loss. Differences in the approaches to storage loss mitigation are likely affected by farmers' expectations, and we see that actual outcomes deviate from expectations. We can attribute some of the variation in storage loss and length to application of storage chemicals. Storage chemicals have the largest effect of reducing loss, however only about 40% of our sample used storage chemicals, likely because of reasons related to access, effectiveness, and concerns about health, as discussed previously.

However, we find little evidence that planting more land with traditional varieties equates to less loss, despite high use of traditional storage methods. Omotilewa et al. find that storing in a hermetic PICS bag increases the probability that farmers in Uganda plant improved varieties the following seasons (2018). Their findings suggest that the decision to plant improved maize is in part affected by excess loss incurred in traditional storage, but the storage loss problem is addressed by more effective storage. In this case, an investment in one improved input (storage) induces an increased investment in other improved inputs (seeds). Based on our results, it does not seem that households use traditional maize varieties as a substitute for more effective storage methods. Rather, unobserved heterogeneity, likely in income and cash constraints, could be driving the finding that planting local maize decreases storage length.

We also do not find that selling maize earlier than intended actually reduces loss. Households do tend on average to sell earlier than intended, but not because of storage loss. This may be because other such as cash liquidity are more visible to the farmer and therefore have a bigger role in determining when to sell. As a market good exchangeable for cash, stored maize can be considered a form of savings account and inter-seasonal price fluctuations are comparable to a flexible interest rate. At such low levels of storage loss, incurring additional marginal levels of loss are likely not enough to induce farmers to sell earlier at lower prices. Our model only measures the length of storage for maize that is actually stored, but does not measure the decision to sell directly at harvest or store for sale later in the season.

Future work should include teasing out the effect from storage loss on storing maize for consumption and the decision to sell right away to avoid storage. Such analysis can inform appropriate solutions to make hermetic storage technologies more accessible and cost-effective, thereby helping smallholders take advantage of the inter-seasonal price arbitrage. Some of this work is already being conducted within the households in our sample. In Tanzania, some households were given PICS bags, and others were given PICS bags with a loan at harvest, in an attempt to target this liquidity constraint farmers face at harvest. The study concludes this year, but preliminary findings suggest that the loan induces farmers to store more for longer compared to just the PICS bag alone (Channa et al., 2019).

Our study considers only the use or absence of use of specific adaptation strategies, but does not quantify the costs or benefits of each. Sheahan and Barrett discusses the need to assess an 'optimal' level of storage loss: the point at which applying additional costs to reduce storage loss is equivalent to the benefit of the mitigated loss (2017). Such an optimization model must consider that as information becomes available over time, expected loss and intended storage length would be continuously re-estimated. This would require collecting data of expected and actual values and storage decisions not just before and after storage, but also frequently during storage.

In addition, the quality loss in maize due to observable threats like insects and unobservable food safety threats such as aflatoxin and chemical residues should be considered. Over- or under-estimating storage loss, which we do find in our study, could be a signal that in general, farmers are on one side or the other of this optimal level, and could take steps to move closer to optimal with a better understanding of all costs involved. Better technology, information and resources could lead to a more optimal solution by decreasing costs, both direct and indirect, of storage loss mitigation. There is yet to be such an extensive accounting study to quantify not only direct costs, but also indirect costs, especially health and income effects.

## 1.7 References

Affognon, H., Mutungi, C., Sanginga, P., Borgemeister, C. "Unpacking Postharvest Losses in Sub-Saharan Africa: A Meta-Analysis." *World Development,* vol. 66, 2015, pp. 49-68.

Ambler, K., de Brauw, A., Godlonton, S. "Measuring postharvest losses at the farm level in Malawi." *Australian Journal of Agricultural and Resource Economics,* vol. 62, 2018, pp. 139-160.

Boyer, S., Zhang, H., Lempérière, G. "A review of control methods and resistance mechanisms in stored-product insects." *Bulletin of Entomological Research,* vol. 102, no. 2, 2012, pp. 213-229.

Burke, M., Bergquist, L. F., Miguel, E. "Sell low and buy high: arbitrage and local price effects in Kenyan markets." *The Quarterly Journal of Economics,* vol. 134, no. 2, 2019, pp. 785-842.

Cairns, J. E., Hellin, J., Sonder, K., Araus, J. L., MacRobert, J. F., Thierfelder, C., Prasanna, B. M. "Adapting maize production to climate change in sub-Saharan Africa." *Food Security,* vol. 5, no. 3, 2013, pp. 345-360.

Channa, H., Ricker-Gilbert, J., Shiferaw, F., Abdoulaye T., "Helping smallholder farmers make the most of maize through harvest loans and storage technology: insights from a randomized control trial in Tanzania." Working paper, 2019.

"Country tables: Maize." *African Postharvest Losses Information System,* www.aphlis.net/en/page/2/country-tables#/datatables/country-tables?lang=en&metric=prc&crop=3&year=2012. Accessed 23 April 2019.

D'agostino, R. B., Belanger, A., D'agostino, R. B. Jr. "A suggestion for using powerful and informative tests of normality." *The American Statistician,* vol. 44, no. 4, 1990, pp. 316-321.

De Groote, H., Kimenju, C. S., Likhayo, P., Kanampiu, F., Tefera, T., Hellin, J. “Effectiveness of hermetic systems in controlling maize storage pests in Kenya.” *Journal of Stored Products Research,* vol. 53, 2013, pp. 27-36.

“Descriptive statistics using the summarize command | STATA annotated output.” *UCLA: Statistical Consulting Group,* stats.idre.ucla.edu/stata/output/descriptive-statistics-using-the-summarize-command/. Accessed 21 June 2019.

Hayes, W.J. “Dosage and other factors influencing toxicity.” *Handbook of Pesticide Toxicology,* vol. 1, 1991, pp. 39-105.

Kaminski, J., Christiaensen, L. “Post-harvest loss in sub-Saharan Africa – what do farmers say?” *Global Food Security,* vol. 3, nos. 3-4, 2014, pp. 149-158.

Ng’ang’a, J., Mutungi, C., Imathiu, S. M., Affognon, H. “Low permeability triple-layer plastic bags prevent losses of maize caused by insects in rural on-farm stores.” *Food Security,* vol. 8, no. 3, 2016, pp. 621-633.

Omotilewa, O.J., Ricker-Gilbert, J., Ainembabazi, J. H., Shively, G. E. “Does improved storage technology promote modern input use and food security? Evidence from a randomized trial in Uganda.” *Journal of Development Economics,* vol. 135, 2018, pp. 176-198.

Ricker-Gilbert, J. and Jones, M. “Does storage technology affect adoption of improved maize varieties in Africa? Insights from Malawi’s input subsidy program.” *Food Policy,* vol. 50, 2015, pp. 92-105.

“Rural Population.” *World Development Indicators,* www.data.worldbank.org/indicator/SP.RUR.TOTL?locations=ET, *The World Bank*. Accessed 21 June 2019.

Sheahan, M. and Barrett, C. B. “Review: Food loss and waste in Sub-Saharan Africa.” *Food Policy,* vol. 70, 2017, pp. 1-12.

Stephens, E. C. and Barrett, C. B. “Incomplete credit markets and commodity marketing behavior.” *Journal of Agricultural Economics,* vol. 62, no. 1, 2011, pp. 1-24.

Tubbs, T., Woloshuk, C., Ileleji, K. “A simple low-cost method of determining whether it is safe to store maize.” *AIMS Agriculture and Food,* vol. 2, no. 1, 2017, pp. 43-55.

Williamson, S. “Pesticide provision in liberalized Africa: Out of control?” *AgREN Network,* no. 126, 2003, Overseas Development Institute, London, United Kingdom.

Williamson, S. “Understanding the full costs of pesticides: experience from the field, with a focus on Africa.” *Pesticides – The Impacts of Pesticide Exposure*, 2011, pp. 25-49.

Williamson, S., Ball, A., Pretty, J. “Trends in pesticide use and drivers for safer pest management in four African countries.” *Crop Protection,* vol. 27, no. 10, 2008, pp. 1327-1334.

# 1.8 Appendix

**Table 1–8. Description of variables used in dataset**

| Variable | Unit | Description |
|---|---|---|
| **Storage** | | |
| Expected storage loss | % | Loss expressed as percent of total maize stored |
| Actual storage loss | % | Loss expressed as percent of total maize stored |
| Intended storage length for sale | Weeks | |
| Actual storage length for sale | Weeks | |
| Storage | Binary | =1 if maize was stored using hermetic or other improved storage (see Table 2) |
| **Adaptation strategies** | | |
| Plant traditional maize variety | Hectares | Share of maize cultivated land planted for local maize varieties |
| Apply storage chemicals to maize stored for sale | Binary | =1 if household applied storage chemicals to maize stored |
| Sell earlier than intended | Binary | =1 if intended storage length for sale is greater than actual storage length for sale |
| **Year and season** | | |
| Season | Binary | =1 if major agricultural season |
| Year | Categorical | Surveys conducted 2013-2015; 2013 used as reference year |
| *2014* | | |
| *2015* | | |
| **Location** | | |
| Country | Categorical | Ghana used as reference country |
| *Ethiopia* | | |
| *Nigeria* | | |
| *Tanzania* | | |
| *Uganda* | | |
| Within-country geographical identifiers | Categorical | Two categorical variables |

**Table 1—8 continued**

| | | |
|---|---|---|
| **Household characteristics** | | |
| Age of household head | Years | |
| Gender of household head | Binary | =1 if household head is male |
| Education of household head | Years | |
| Farm experience of household head | Years | |
| Size of household | # | |
| Household members under the age of 10 | # | |
| Asset Score | Index | 1 point is added for each asset the household owns |
| *Mobile phone* | | |
| *Radio* | | |
| *Television* | | |
| *Bicycle* | | |
| *Motorbike* | | |
| *Savings account* | | |
| *Access to tractor or animal draught power* | | |
| **Farm characteristics** | | |
| Total land area used for crop production | Hectares | |
| Total land area used for maize production | Hectares | |
| Total quantity of maize stored | Kilograms | |
| Distance to nearest market | Kilometers | |

**Table 1–9. Storage method use, by type (% of total sample)**

| | Ethiopia | Ghana | Nigeria | Tanzania | Uganda | All |
|---|---|---|---|---|---|---|
| *Hermetic storage* | | | | | | |
| Hermetic bags | 1.2% | 1.0% | 2.8% | 1.3% | 0.1% | 1.6% |
| Airtight drum/silo/jerrycan | 0.3% | 0.0% | 2.0% | 0.3% | 0.7% | 1.2% |
| **Hermetic storage total** | **1.5%** | **1.0%** | **4.8%** | **1.7%** | **0.9%** | **2.8%** |
| *Other improved storage* | | | | | | |
| Improved granaries | 0.3% | 4.7% | 0.6% | 0.5% | 1.0% | 1.0% |
| Metal silo/drum | 0.0% | 0.0% | 2.7% | 0.3% | 0.2% | 1.3% |
| **Other improved storage total** | **0.3%** | **4.7%** | **3.3%** | **0.8%** | **1.2%** | **2.3%** |
| *Traditional storage* | | | | | | |
| Single layer plastic bag | 62.0% | 26.6% | 0.0% | 4.0% | 71.0% | 29.5% |
| Traditional granaries | 13.6% | 18.8% | 14.2% | 11.9% | 7.0% | 11.7% |
| Woven bag/sisal bag | 0.3% | 25.3% | 77.7% | 66.3% | 0.0% | 42.9% |
| Heaped in house | 0.3% | 4.7% | 0.0% | 2.3% | 10.7% | 4.2% |
| Open-air hanging | 0.0% | 0.0% | 0.0% | 12.9% | 0.9% | 1.5% |
| Other storage | 21.9% | 19.0% | 0.0% | 0.0% | 8.4% | 5.1% |
| **Traditional storage total** | **98.1%** | **94.3%** | **91.9%** | **97.5%** | **97.9%** | **94.9%** |
| *Other storage* | | | | | | |
| Private off-farm storage | 0.0% | 0.0% | 0.0% | 0.0% | 1.8% | 0.6% |
| Community storage facility | 0.0% | 0.0% | 0.0% | 0.0% | 0.1% | 0.0% |
| Other | 21.9% | 19.0% | 0.0% | 0.0% | 6.5% | 4.5% |
| **Other storage total** | **21.9%** | **19.0%** | **0.0%** | **0.0%** | **8.4%** | **5.1%** |
| **Number of observations** | **324** | **384** | **2922** | **597** | **2215** | **6442** |

**Table 1–10. Effect of expected storage loss and adaptation strategy use on actual storage loss: all variables (% of total maize stored)**

| N=6,442 | | | | | | |
|---|---|---|---|---|---|---|
| Variables | 1 | 2 | 3 | 4 | 5 | 6 |
| Expected loss | 0.562*** | 0.561*** | 0.561*** | 0.561*** | 0.562*** | 0.559*** |
| (% of total) | (0.062) | (0.061) | (0.062) | (0.062) | (0.063) | (0.063) |
| Used hermetic storage | 0.892 | 0.718 | 0.824 | 0.920 | 0.991 | 0.958 |
| (=1 if yes) | (0.930) | (0.943) | (0.940) | (0.936) | (0.933) | (0.933) |
| Used other improved storage | -0.506 | -0.404 | -0.485 | -0.895** | -1.025** | -1.016** |
| (=1 if yes) | (0.432) | (0.437) | (0.436) | (0.447) | (0.453) | (0.452) |
| Share of land cultivated using traditional varieties | - | -0.002 | -0.002 | -0.005* | -0.003 | -0.004 |
| (% of maize land cultivated) | - | (0.002) | (0.002) | (0.003) | (0.003) | (0.003) |
| Applied storage chemicals | - | -0.906*** | -0.700*** | -1.125*** | -1.080*** | -1.047*** |
| (=1 if yes) | - | (0.247) | (0.268) | (0.297) | (0.300) | (0.298) |
| Sold maize earlier than intended | - | -0.004 | 0.084 | 0.439 | 0.406 | 0.383 |
| (=1 if yes) | - | (0.313) | (0.314) | (0.310) | (0.313) | (0.313) |
| Stored maize for sale | -0.611** | -0.518** | -0.593** | -0.647*** | -0.675*** | -0.597** |
| (=1 if yes) | (0.245) | (0.244) | (0.247) | (0.238) | (0.245) | (0.244) |
| Season | - | - | -0.404* | -0.488** | -0.507** | -0.530** |
| (=1 if major agricultural season) | - | - | (0.223) | (0.227) | (0.230) | (0.230) |
| Year | - | - | -0.692*** | -0.245 | -0.249 | -0.248 |
| (=1 if 2014) | - | - | (0.234) | (0.229) | (0.228) | (0.228) |
| Year | - | - | -0.272 | -0.278 | -0.101 | -0.223 |
| (=1 if 2015) | - | - | (0.339) | (0.677) | (0.669) | (0.672) |
| Ethiopia | - | - | - | 0.181 | 0.198 | 0.034 |
| (=1 if yes) | - | - | - | (1.082) | (1.098) | (1.096) |
| Nigeria | - | - | - | 0.174 | 0.241 | 0.027 |
| (=1 if yes) | - | - | - | (1.187) | (1.192) | (1.196) |

**Table 1—10 continued**

| | | | | | | |
|---|---|---|---|---|---|---|
| Tanzania | - | - | - | -0.657 | -0.653 | -0.774 |
| (=1 if yes) | - | - | - | (1.772) | (1.783) | (1.782) |
| Uganda | - | - | - | -4.075* | -3.758* | -3.923* |
| (=1 if yes) | - | - | - | (2.289) | (2.262) | (2.260) |
| Geo ID 1 | - | - | - | -0.206* | -0.160 | -0.148 |
| (Categorical) | - | - | - | (0.106) | (0.116) | (0.116) |
| Geo ID 2 | - | - | - | 0.131*** | 0.113*** | 0.108** |
| (Categorical) | - | - | - | (0.042) | (0.042) | (0.042) |
| Age of household head | - | - | - | - | 0.033** | 0.033** |
| (Years) | - | - | - | - | (0.014) | (0.014) |
| Gender of household head | - | - | - | - | 0.781** | 0.820** |
| (=1 if male) | - | - | - | - | (0.362) | (0.367) |
| Size of household | - | - | - | - | -0.030 | -0.022 |
| (# of individuals living at home) | - | - | - | - | (0.030) | (0.030) |
| Education level of household head | - | - | - | - | 0.129 | 0.125 |
| (Years) | - | - | - | - | (0.091) | (0.091) |
| Children under the age of 10 | - | - | - | - | -0.054 | -0.054 |
| (# of individuals in household) | - | - | - | - | (0.063) | (0.063) |
| Farm experience of household head | - | - | - | - | -0.016 | -0.016 |
| (Years) | - | - | - | - | (0.014) | (0.014) |
| Asset Score | - | - | - | - | -0.026 | -0.005 |
| (1 point for each asset owned) | - | - | - | - | (0.076) | (0.076) |

**Table 1—10 continued**

| | | | | | | |
|---|---|---|---|---|---|---|
| Total land cultivated | - | - | - | - | - | 0.000 |
| (ha) | - | - | - | - | - | (0.003) |
| Maize land cultivated | - | - | - | - | - | -0.001 |
| (ha) | - | - | - | - | - | (0.006) |
| Total quantity of maize stored | - | - | - | - | - | -0.0001*** |
| (kg) | - | - | - | - | - | (0.000) |
| Distance to nearest market | - | - | - | - | - | -0.007 |
| (km) | - | - | - | - | - | (0.010) |
| $\beta_0$ | 2.470*** | 2.96*** | 3.904*** | 2.690* | 0.784 | 1.007 |
| | (0.320) | (0.429) | (0.521) | (1.378) | (1.541) | (1.515) |
| F-test: coefficient on expected loss is equal to 1 | 50.01*** | 50.94*** | 50.44*** | 49.28*** | 48.59*** | 49.04*** |
| $R^2$ | *0.3191* | *0.3219* | *0.3240* | *0.3361* | *0.3392* | *0.3408* |

**Table 1–11. Effect of intended storage length and adaptation strategy use on actual storage length for maize sold: all variables (weeks)**

| N=5,015 | | | | | | |
|---|---|---|---|---|---|---|
| Variables | 1 | 2 | 3 | 4 | 5 | 6 |
| Intended storage length for sale | 0.768*** | 0.725*** | 0.724*** | 0.716*** | 0.714*** | 0.713*** |
| (weeks) | (0.016) | (0.017) | (0.017) | (0.017) | (0.017) | (0.017) |
| Used hermetic storage | 0.083 | 0.318 | 0.875 | 0.942 | 0.976 | 1.016 |
| (=1 if yes) | (1.234) | (1.214) | (1.187) | (1.179) | (1.180) | (1.180) |
| Used other improved storage | -0.824 | -0.284 | -0.816 | -1.320 | -1.388* | -1.392* |
| (=1 if yes) | (0.899) | (0.854) | (0.857) | (0.830) | (0.826) | (0.825) |
| Share of land cultivated using traditional varieties | - | -0.040*** | -0.045*** | -0.054*** | -0.053*** | -0.052*** |
| (% of maize land cultivated) | - | (0.004) | (0.004) | (0.004) | (0.004) | (0.004) |
| Applied storage chemicals | - | 0.600* | 2.250*** | 2.019*** | 1.969*** | 1.947*** |
| (=1 if yes) | - | (0.318) | (0.334) | (0.357) | (0.355) | (0.353) |
| Expected loss | -0.051** | -0.040* | -0.040* | -0.035 | -0.032 | -0.028 |
| (% of total) | (0.021) | (0.022) | (0.022) | (0.021) | (0.021) | (0.022) |
| Season | - | - | -1.572*** | -2.247*** | -2.244*** | -2.222*** |
| (=1 if major agricultural season) | - | - | (0.296) | (0.292) | (0.290) | (0.293) |
| Year | - | - | -5.126*** | -4.023*** | -4.000*** | -3.996*** |
| (=1 if 2014) | - | - | (0.360) | (0.328) | (0.328) | (0.329) |
| Year | - | - | -3.335*** | -5.974*** | -5.993*** | -5.873*** |
| (=1 if 2015) | - | - | (0.573) | (1.014) | (1.017) | (1.017) |
| Ethiopia | - | - | - | -4.134*** | -3.959*** | -4.057*** |
| (=1 if yes) | - | - | - | (1.176) | (1.203) | (1.234) |
| Nigeria | - | - | - | -2.928* | -2.620 | -2.350 |
| (=1 if yes) | - | - | - | (1.625) | (1.637) | (1.648) |

**Table 1—11 continued**

| | | | | | | |
|---|---|---|---|---|---|---|
| Tanzania | - | - | - | -3.343 | -2.614 | -2.345 |
| (=1 if yes) | - | - | - | (2.165) | (2.187) | (2.196) |
| Uganda | - | - | - | -8.643*** | -7.762*** | -7.387** |
| (=1 if yes) | - | - | - | (2.926) | (2.959) | (2.976) |
| Geo ID 1 | - | - | - | -0.124 | -0.077 | -0.092 |
| (Categorical) | - | - | - | (0.147) | (0.149) | (0.150) |
| Geo ID 2 | - | - | - | 0.117* | 0.091 | 0.088 |
| (Categorical) | - | - | - | (0.060) | (0.061) | (0.061) |
| Age of household head | - | - | - | - | -0.019 | -0.019 |
| (Years) | - | - | - | - | (0.017) | (0.017) |
| Gender of household head | - | - | - | - | -0.408 | -0.415 |
| (=1 if male) | - | - | - | - | (0.941) | (0.940) |
| Size of household | - | - | - | - | 0.146*** | 0.141*** |
| (# of individuals living at home) | - | - | - | - | (0.044) | (0.044) |
| Education level of household head | - | - | - | - | 0.051 | 0.047 |
| (Years) | - | - | - | - | (0.108) | (0.108) |
| Children under the age of 10 | - | - | - | - | -0.186** | -0.182** |
| (# of individuals in household) | - | - | - | - | (0.086) | (0.085) |
| Farm experience of household head | - | - | - | - | 0.021 | 0.021 |
| (Years) | - | - | - | - | (0.018) | (0.018) |
| Asset Score | | | | | 0.274** | 0.259** |
| (1 point for each asset owned) | - | - | - | - | (0.112) | (0.113) |

**Table 1—11 continued**

| | | | | | | |
|---|---|---|---|---|---|---|
| Total land cultivated | - | - | - | - | - | -0.029 |
| (ha) | - | - | - | - | - | (0.060) |
| Maize land cultivated | - | - | - | - | - | 0.042 |
| (ha) | - | - | - | - | - | (0.060) |
| Total quantity of maize stored | - | - | - | - | - | 0.000 |
| (kg) | - | - | - | - | - | (0.000) |
| Distance to nearest market | - | - | - | - | - | -0.017 |
| (km) | - | - | - | - | - | (0.016) |
| $\beta_0$ | 3.925*** | 6.414*** | 11.110*** | 13.551*** | 12.407*** | 12.534*** |
| | (0.285) | (0.435) | (0.650) | (1.569) | (1.916) | (1.975) |
| F-test: coefficient on expected loss is equal to 1 | 208.47*** | 272.93*** | 274.28*** | 293.93*** | 295.96*** | 285.27*** |
| $R^2$ | *0.5363* | *0.5554* | *0.5903* | *0.6015* | *0.6044* | *0.6048* |

Table 1—12 includes an interaction term between use of improved storage and farming experience of the household head. The significance of this interaction term shows that the effectiveness of improved storage to store for longer increases with more experience. If the household head has no or little farming experience, storage length is significantly shorter than if traditional storage methods were used. As experience increases, however, the difference in storage length between improved and traditional storage methods diminishes. At about 35 years of experience, the difference is zero.

**Table 1–12. Effect of improved storage use and farming experience on actual storage length for maize sold (weeks)**

N=5,015

| Variable | 5 | 6 |
|---|---|---|
| Intended storage length for sale | 0.714*** | 0.713*** |
| (weeks) | (0.017) | (0.017) |
| Used hermetic storage | 0.968 | 1.009 |
| (=1 if yes) | (1.165) | (1.165) |
| Used other improved storage | -3.849*** | -3.876*** |
| (=1 if yes) | (1.333) | (1.332) |
| Used other improved storage*Farming experience | 0.113** | 0.114** |
| | (0.048) | (0.048) |
| Share of land cultivated using traditional varieties | -0.053*** | -0.053*** |
| (% of maize land cultivated) | (0.004) | (0.004) |
| Applied storage chemicals | 1.959*** | 1.938*** |
| (=1 if yes) | (0.355) | (0.353) |
| Expected loss | -0.030 | -0.027 |
| (% of total) | (0.021) | (0.021) |
| Year & season controls | yes | yes |
| Location controls | yes | yes |
| Household characteristics | yes | yes |
| Asset Score | 0.275** | 0.259** |
| (1 point for each asset owned) | (0.112) | (0.113) |
| Farm characteristics | no | yes |
| $\beta_0$ | 12.541*** | 12.708*** |
| | (1.920) | (1.979) |
| F-test: coefficient on expected loss is equal to 1 | 296.17*** | 285.45*** |
| $R^2$ | *0.6048* | *0.6053* |

# CHAPTER 2. IS THERE A MARKET FOR THIRD-PARTY QUALITY VERIFICATION IN RURAL GRAIN MARKETS? EVIDENCE FROM AN EXPERIMENTAL AUCTION FOR MOISTURE TESTING IN KENYA

## Abstract

Drying maize is costly and moisture may not be fully observable to buyers in most rural markets. Traders in informal grain markets are discouraged from providing good quality maize due to weak regulation and lack of low-cost moisture testing technology that allows buyers and sellers to accurately determine if grain is dried to a level safe for storage. This study evaluates a third-party moisture testing service that provides external quality verification, encourages safe drying practices and reduces asymmetric information between producers and consumers in western Kenya. We utilize a Becker-Degroot-Marschak auction to elicit maize traders' willingness to pay for the service, offered with two types of moisture meters. The first device is a low-cost hygrometer that measures relative humidity and costs about $2.50 (250 KSH) and the second is a compact, commercial grade moisture meter that costs $170 in the United States (upwards of 17,000 KSH with import tax and price markups). We find that on average, traders are willing to pay $.39 (39 KSH) for the moisture meter service and $.28 (28 KSH) for the hygrometer service. Although traders are willing to pay more for the commercial moisture meter service, the hygrometer service is a more cost-effective investment for a testing service because of the low cost of the device. An additional take-it-or-leave-it auction to purchase the hygrometer reveals that about 15% of traders are willing to purchase the device at market price, but those who are willing are not sensitive to small fluctuations around this price. A third party moisture testing service using a hygrometer seems to be a viable way to make moisture testing more widely accessible and standard practice. This can help improve the quality and level of food safety available in rural grain markets.

**Keywords:** Maize, drying, Kenya, sub-Saharan Africa, maize traders, moisture content, moisture testing service, experimental auction

## 2.1 Introduction

With no enforced regulations for moisture content or aflatoxin levels, informal grain markets in most of sub-Saharan Africa (SSA) lack incentive to supply maize that has been dried to a level safe for storage. If maize is stored when it is too wet, above 13% moisture content (MC), the moisture produces fungi that cause aflatoxins, which can pose serious health risks to those who consume it. Because aflatoxin is unobservable without testing for moisture content or aflatoxin levels directly, consumers and producers do not have enough information to accurately determine the quality of maize in informal grain markets. Even if suppliers are consciences of safe drying practices and would prefer to supply dry maize, drying it costs money, and moisture testing devices are often too expensive or inaccessible for small- and medium-sized farmers and traders. Determining if maize is at or below the safe limit is difficult with only the traditional moisture testing methods commonly used by buyers and sellers in rural markets, including touching, shaking and/or biting the maize kernels to see if they are dry.

The scale of the problem associated with insufficient drying in rural markets of sub-Saharan Africa (SSA) is large. Kenya has experienced a number of aflatoxin outbreaks in recent years, so the maize markets are perhaps more advanced in terms of awareness of aflatoxins and the need to properly dry maize ("Alert over maize…," 2008; "Bumper Kenya maize…," 2010; Extreme weather increasing…," 2016). Even so, a study by Gachara et al. finds that 85% of maize samples were stored at moisture levels above 13% MC in three counties in southwestern Kenya (2018). This exemplifies the need for more education, and affordable and accurate moisture testing solutions in informal grain markets. Contrarily, maize sold in the formal markets, primarily to millers, the National Cereals and Produce Board (NCPB), or for export, are limited to no more than 10 parts per billion (ppb) of aflatoxin (De Groote et al., 2016). The NCPB will not purchase maize that has a MC above 13.5%. Though the NCPB and large-scale millers can more easily bear the burden of costly moisture testing devices, small- and medium- sized suppliers in informal markets who buy and sell the majority of maize that is consumed in Kenya require creative, low-cost solutions to encourage moisture testing as standard practice.

The asymmetric information between the formal and informal grain markets and the inability of producers and consumers to distinguish between safe and unsafe maize in the informal market exemplify the well-known lemons market problem described by Akerlof (1970). Many consumers in Kenya know aflatoxin exists and are willing to pay a premium for aflatoxin-tested maize, however no aflatoxin or moisture content information currently exists (De Groote et al., 2016). This uncertainty disadvantages both suppliers and consumers, as suppliers face lower prices and consumers have no way to distinguish maize quality. Therefore, in this article, we propose a simpler, cheaper substitute to aflatoxin testing or purchasing expensive moisture meters: a third-party moisture testing service. Such a service can potentially provide external validity for moisture readings and therefore build trust between consumers and suppliers; reduce information asymmetry between the informal and formal grain markets; and encourage demand for good quality maize to drive the use of safe drying practices.

Our study uses a revealed preference, Becker-Degroot-Marschak (BDM) auction to elicit willingness to pay (WTP) from traders for this third-party moisture testing service that can provide needed information on the quality of their maize. We test the service provider model with the idea that some people, perhaps rural youth, could purchase the moisture devices and bring them to farms and markets to provide accurate, unbiased readings of moisture content before people buy and sell maize in the market. Our sample consists of 199 traders from around Uasin Gishu county, a major maize producing and trading area in Kenya.

We use two user-friendly devices that detect moisture content. The first device is a small, low-cost hygrometer that gives a relative humidity and temperature reading for the environment that the maize is stored in, and the second device is a more expensive commercial-grade moisture meter that gives a more precise, direct moisture content reading of the grains. No product similar to the hygrometer is currently available in our study area, to our knowledge. There are many moisture meter models available on the market in Kenya, but they are not feasible investments for the average smallholder farmer or small-scale trader to purchase because of the high upfront cost. Anecdotal evidence suggests that the cheapest moisture meters cost about $300 in our study area.

A major benefit to the service provider model is that it could offer buyers and sellers an unbiased moisture test from an independent third party not involved in the transaction. This is key for consumers to trust the validity of the testing service. Without an unbiased third party, traders could be incentivized to falsify moisture content tests conducted by themselves in order to take advantage of price premiums that some consumers are willing to pay for labeled, quality maize. In addition, the service provider model makes otherwise inaccessible devices available through a third party, and could spur demand for maize that has been dried to a level safe for storage. As these devices (and the service provider model) are not currently used in our study area, little is known about the actual demand.

Therefore, we first derive demand curves for moisture detection services using both moisture testing devices. We test for a difference in WTP between the two services using ordinary least squares models, because they differ in functionality and market price ($2.50[8] (about 250 KSH)

[8] Hygrometers are currently being sold in Kenya by Bell Industries for a price of 250 KSH ($2.50). However, during the time of study hygrometers were not available for sale in our study area.

for the hygrometer and \$170[9] (about 17,000 KSH) for the moisture meter model used in our study).[10] We selected two devices that differ widely in price and functionality because start-up costs are a major factor for any new business. A moisture meter is a large initial investment and would take time for the service to become profitable. The hygrometer is a low-cost alternative that can make it easier for potential service providers such as rural youth to start their business.

We also use three variations of the BDM auction procedure to test if the way we ask questions about WTP affects respondents' valuation. This can inform how best to conduct precise, unbiased auctions in future research. Lastly, we held a take-it-or-leave-it auction at the end of the survey where traders could purchase one hygrometer at one of three randomly offered prices. This helped us determine whether a slight change in the price of the device around the current suggested retail price of \$2.50 changes respondents' willingness to purchase a hygrometer. In doing so, we can consider the feasibility of traders adopting the hygrometer device if made available in the market, alongside of assessing the viability of the service model. One goal of this study is to increase information on moisture content in informal grain markets and encourage moisture testing as standard practice, thus it is important to understand how receptive traders are to paying current market price for the hygrometer.

The present article makes two main contributions to the literature. First, to our knowledge, we are the first, or one of the first, to test the viability of a third party verification service for testing product quality in a rural market of a developing country. We build on Channa et al.'s study[11] in

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[9] We purchased the moisture meter for \$170 in the United States and brought it to Kenya. If the same meter were available in Kenya the price would certainly be much higher.
[10] Throughout this paper, we use the approximate exchange rate that 1 USD is equivalent to 100 KSH, unless otherwise stated.
[11] Channa et al.'s study was conducted as part of the same FPL project as this study (2018).

Kakamega County, Kenya in 2017, where the authors conducted auctions to elicit WTP for purchasing the DryCard™ developed at UC Davis and the hygrometer identified by Purdue University (the same hygrometer used in our study) (2018). Previous to Channa et al., we are unaware of any studies that use an auction to derive demand for a moisture detection device or service. Our study expands on Channa et al.'s findings by adding the more cost-accessible service model component to a new sample of traders. Further, while the previous study assessed demand for the hygrometer, we assess traders' receptiveness to the device at and around market price. This can provide us with a benchmark to which we can compare receptiveness of the service model.

Shimamoto et al.'s study in 2018 measured adoption of moisture meters given risk preferences for rice farmers in Cambodia, but did not elicit willingness to pay for the devices. Similar studies (De Groote et al., 2016; Hoffmann and Moser, 2017; Prieto et al., 2018) have examined WTP for price premiums in the maize market in Kenya, but no other studies to our knowledge elicit WTP for a service model that could provide means to certify good quality maize. Hoffmann and Moser consider only aflatoxin testing in the formal maize sector where it is more stringently enforced (2017). Millers often sell maize above 10 ppb in the informal market, since there are no testing regulations. Without accessible devices to test aflatoxin levels in the informal market, producers encourage market segmentation based on maize quality and it is often the poorest consumers who rely on the informal market that are afflicted.

Our second contribution is methodological for how best to elicit WTP using a BDM action for an item that is almost completely new to participants. We use two Random Binary Choice (RBC) variants on the BDM auction mechanism, where participants are asked if they would be willing to pay for the device over a series of increasing or decreasing price values (Healy, 2016). Theory suggests that the starting point may anchor the bid in the direction of the starting value, causing participants to over- or under-bid (Hanemann et al., 1991; Flachaire and Hollard, 2007). We expand Channa et al.'s analysis of starting point bias by comparing the RBC variants to a third methodology, the standard BDM (2018). If the RBC variant procedures do not bias bids, they may offer more precise values as they allow the respondent to compare their true WTP to price levels in small increments.

We find that traders demand the moisture meter service at $0.39 and hygrometer at $0.28, on average. The moisture meter service maximizes gross revenue at $0.50, while the hygrometer maximizes gross revenue at $0.30. However, the hygrometer service would start generating profit sooner, as it would only cost a service provider $2.50, compared to at least $300 for the moisture meter. Further, only a small percentage of traders were willing to buy the hygrometer at market price of $2.50, suggesting that purchasing the hygrometer service can provide necessary moisture testing to more traders than if traders have to purchase the device for themselves. Finally, we find no evidence that eliciting WTP in different ways affects the respondents' bids after the respondent is given a chance to practice the auction procedure. This indicates that future studies can consider using alternate auction methods to the standard BDM elicitation procedure.

## 2.2 Background

### *2.2.1 Maize moisture content*

Excess moisture leads to mold and mycotoxin growth without proper drying and storage practices that ensure maize is dried to a safe level post-harvest. Fungi (*Aspergillus flavus* and *Aspergillus parasiticus*) produce aflatoxins that can cause liver damage, cancer, or even death if consumed at high levels. Aflatoxins can cause nutritional and immunological damage if consumed consistently at low levels (Williams et al., 2004). Since aflatoxin are not observable by sight or taste alone, the most reliable proxy, outside of costly aflatoxin tests, is moisture content. Below 13% moisture content (equivalent to 65% relative humidity), aflatoxin-producing fungi cannot grow[12] (Tubbs et al., 2017).

However, reliable and cost-effective solutions for aflatoxin or moisture content testing remains an unexplored niche in the informal grain markets in Kenya. Most farmers and traders rely on traditional methods of moisture detection such as touching, biting, or shaking maize kernels. Current literature and anecdotal evidence suggest that these methods can help distinguish between 'wet' and 'dry,' but not small differences, for example the crucial threshold between 12% and 14% moisture content. Prieto et al. find that Senegalese farmers and traders, while able to discern between wet and dry unlabeled maize using traditional methods, still discounted wet labeled maize more than wet unlabeled maize (2018). This indicates that there is uncertainty in traditional moisture detection methods and labeling maize is risk-reducing. Channa et al. finds substantial demand for the hygrometer and DryCard™ in Kakamega County, neighboring our study area, suggesting that farmers and traders would prefer more accurate methods to measure moisture content (2018).

### *2.2.2 The Kenyan context*

Kenya has experienced three lethal aflatoxicosis outbreaks since 1981, with the latest outbreak in 2004 resulting in a 39% case fatality rate (Probst et al., 2007). Recent research suggests the threat of future outbreaks is still present. Aflatoxin levels are limited in formal markets to 10 ppb, but

[12] Moisture content can test whether maize is safely dry at the time of testing, but cannot guarantee maize safety prior to testing. Aflatoxins can be present from in-field exposure or from storage prior to testing if not dried properly. Therefore, while moisture content is positively correlated with the possibility of aflatoxin production, it is not a perfect indicator.

regulation is weak in informal markets, where most consumers buy their maize for at-home consumption, and there is currently no certification that provides a price premium label for aflatoxin-safe maize in Kenya (De Groote et al., 2016). This is likely related to the steep cost and sparse locations for testing aflatoxin levels. De Groote et al. reported that aflatoxin testing from a private lab in Kenya costs up to 3,500 KSH ($41) per sample at the time of the study (2016). Hoffmann and Moser tested maize flour in the field with a $6 test, but this is still expensive for smallholder farmers and traders in the informal maize sector and does not factor in shipping or lab testing fees (2017).

There is currently no third-party service providing grain moisture content readings in Kenya. A study from the AflaSTOP project implemented by the International Food Policy Research Institute (IFPRI) elicited WTP for a mobile grain drying service and found that 28% of farmers in the North Rift region and about 50% of farmers in the Eastern Province of Kenya would be willing to pay for a drying service that costs up to $29.41/metric ton. In its concluding implications, the project highlights the need for the "establishment of a credible and low-cost system for testing and labeling grain" (Walker and Davies, 2013). Consumers are receptive to the idea of price premiums for tested and labeled aflatoxin-safe maize in Kenya markets, but there still is currently no formal, recognizable certification system in place, and producers lack the means to accurately and cost-effectively test their maize (De Groote et al., 2016). A third-party service provider could be such a feasible system.

### *2.2.3 Moisture detection devices in our study*

The hygrometer was identified as an option for measuring moisture content in maize by the Food Processing and Post-Harvest Handling Innovation Lab of Purdue University and is a small, batteryoperated device that can be imported to Kenya from China and sold at a wholesale price of $0.90 (90 KSH). Hygrometers sell in other locations in SSA for a retail price of 250 KSH (about $2.50). The device displays the air humidity level and temperature, so a humidity reading of 65% would correspond to the critical maize moisture content between 12.5% and 13.5% when stored at 20-30 degrees Celsius (Tubbs et al., 2017).

To obtain an accurate reading from the hygrometer, the maize sample must be placed in a small hermetic bag with the hygrometer and left to calibrate for 15 minutes before obtaining an accurate reading. The hygrometer is always on and the battery is not easily replaceable[13], so users may need to replace the device every few years. The service provider model can eliminate the need for many users to re-purchase the hygrometer every several years, and maximizes the amount of time the device is actually used during the battery's life span. Channa et al. found that on average, farmers were willing to pay 130 KSH ($1.27) and traders were willing to pay 120 KSH ($1.17) for the hygrometer, notably less than market price (2018). Their study area was in Kakamega county, directly west of Uasin Gishu county. The hygrometer service we offered consisted of one sample reading.

One benefit of the moisture meter over the hygrometer is that it measures moisture content directly, so the user does not need to convert between humidity and moisture content. In addition, the device is quick, more accurate, and does not require a plastic bag. The service provider saves valuable time for traders by providing instantaneous, accurate readings without the steep upfront cost of purchasing the device. Additionally, the quick reading time allows multiple samples to be

[13] The hygrometer requires a watch battery, which is difficult to find in rural areas of SSA.

taken, to increase accuracy across a wider maize sample. In our study, we provided the average of three sample readings using the commercial moisture meter, if the respondent's bid was successful.

We chose the AgraTronix™ MT-16 Portable Grain Moisture Tester for our study, based on functionality (easily produces readings for 16 different grain scales, including maize within 5-40% moisture content); accuracy (±0.5%); cost ($170 purchased in the United States); and portability (weighs 2 kilograms) ("MT-16"). It is important to note here, for future discussion on replicability of this service provider model, that this model is on the cheaper end of moisture detection devices, and does not provide additional functions such as temperature, weight, etc. Additionally, import taxes would increase cost if the device were purchased and exported from the United States. Based on conversations with traders, millers, and Ministry of Agriculture officials, it is likely that a moisture meter of equivalent quality would sell for more than $170 in Kenya.

## 2.3 Methods

### *2.3.1 Data collection*

The survey auction was conducted in March 2019 in markets across Uasin Gishu county, in the southwest region of Kenya, where aflatoxin contamination is present and maize production is high. Uasin Gishu has one long-rain season for maize, with harvest October through November ("Country brief: Kenya"). Anecdotal evidence suggests that most wet maize is traded from September to December, depending on the year. At the time our study was conducted, wet maize was only coming from some small pockets in Uasin Gishu and surrounding counties.

This study was conducted as part of the Feed the Future Innovation Lab for Food Processing and Post-harvest Handling (FPL) at Purdue University, in collaboration with the

International Maize and Wheat Improvement Center (CIMMYT) and the Kenya Agricultural and Livestock Research Organization (KALRO). We sampled 199 traders across all six sub-counties from over 50 small and medium markets. Our sampling framework was limited in scope by the lack of a centralized market list at the county level, as many are small, informal and change daily.

However, our target sample were small- to medium-sized maize traders that populate these informal markets because (1) the main consumer base of these markets are local households, and (2) traders in these markets lack access to moisture detection devices. Thus, we had to continuously search for markets without official market days by traveling around the county. Within each market, market size was estimated upon arrival and approximately 80% of maize traders were randomly selected to participate. The questionnaire asked traders about demographics, their maize trading business, most important criteria they consider when purchasing maize, drying practices, assets, knowledge on aflatoxin, and prior knowledge of the hygrometer and moisture meters.

### *2.3.2 Auction mechanism*

We chose the Becker-Degroot-Marschak auction mechanism for several reasons. First, it allowed us to conduct the auction on individuals rather than in large groups, which was ideal for our sample across such a large area. Second, the BDM is theoretically proven to be incentive compatible, meaning the participant achieves his best outcome by stating his true preference. Third, it allows the respondent to bid on both services, but ensures that the bid on one service does not affect the bid on the other (Becker et al., 1964). The main drawback is that the BDM is notoriously complex compared to other auction mechanisms when the respondent is asked to bid on more than one good (Healy, 2016). We overcame this by starting with a practice auction using pens and pencils, during and after which participants were able to ask questions.

We utilized two Random Binary Choice (RBC) variants of the BDM, in addition to the standard BDM mechanism. Under the RBC variants, rather than asking for a single bid, the participant is asked a series of questions about willingness to pay, and all he must answer is "yes" or "no." Each question asks the participant if he is willing to pay some amount for the product, in ascending or descending order with amounts varying by some increment (see Table 2—6, in Appendix A). The "switch point" (true value) is the amount at which he would rather have the money than the product (Healy, 2016). Azrieli et al. show that this mechanism is also incentive compatible, assuming monotonicity (the participant never chooses a higher bid over a lower bid) (2016). Thus, the respondent's WTP is reached by incrementally increasing or decreasing the offered price until there comes a point where he is willing to pay no more on the margin.

The RBC mechanism allows the respondent to consider his true value by comparing it to prices directly lower or higher to it. This mechanism may offer a more precise estimate, compared to the standard BDM where the respondent is asked to simply supply some bid. The only caveat of the RBC variant is that the question order may anchor the bid so that a low-to-high (high-to-low) question order may lead the participant to understate (overstate) their true value (Hanemann et al., 1991). Flachaire and Hollard find that under uncertainty, participants tend to answer "yes," so as the values approach the participant's true value and indifference or uncertainty arises, the bid would be biased upwards in either RBC variant (2007).

### *2.3.3 Identification Strategy: Auction Procedure*

The auction procedure we followed ensured that traders reported their true willingness to pay. In addition, any varying aspects in implementation was random, observable and independent of the traders' WTP, and therefore can be controlled for in a regression model. Participants bid in a randomized order for two moisture testing services: (1) the hygrometer and (2) the moisture meter. The auction method (Low-High, High-Low or Standard BDM) was randomly selected for each trader and the same method was used for all rounds.

Before the real auction for the service took place, respondents participated in a practice auction, where they bid on pens and pencils. The practice auction was identical in both method and procedure as the real auction. This helped the respondents become familiar with the auction procedure, and understand that bidding their true value was the strategic approach. This ensured that learning about the auction structure did not interfere with the respondent's valuation of the technology, and that the respondent did not try to win the auction by some means other than stating his true value.

At the beginning of the survey, traders were given a demonstration of both devices. The enumerator explained how each device worked and how to determine if maize is safely dry based on the device's output. For the hygrometer, a 65% relative humidity reading corresponds with the ~13% safe moisture content threshold, and the commercial moisture meter gives a direct moisture content reading. Following the device introduction, the enumerator performed demonstrations with wet and dry maize for each device. The enumerator placed a hygrometer in a bag of wet maize, and another hygrometer in a bag of dry maize. The bags were left to sit for at least 15 minutes to allow time to calibrate and the final readings were shown to the respondent prior to starting the auction. For the commercial moisture meter, the trader was able to see immediately the results.

Following a short questionnaire, the auction began, first with a practice auction and then the real auction. If the low-high method was selected, the respondent was asked if he is willing to pay 5 KSH (about $.05) for the service. If he answers yes, he was then asked if he would be willing to pay 10 KSH. As long as he answered yes, the enumerator increased the bid amount by 5 KSH for each question. Bidding stopped once the respondent answered no, and the last amount he was willing to pay was recorded as his value. Alternatively, bidding stopped once the value reached 75 KSH. If the high-low method was selected, the bidding started at 75 KSH. As long as the participant responded that he was not willing to pay, the enumerator decreased the bid by 5 KSH. Once the participant responded that he would be willing to pay a certain amount, bidding stopped and this amount was recorded as his value.

For the standard BDM method, the respondent was asked how much he is willing to pay for the service, as an open-ended question, where he could give any value. To stay consistent with the RBC variants, we limited the price range to no greater than 75 KSH. If the respondent indicated he was not willing to pay even 5 KSH, his WTP was 0. In this case, the respondent was asked to record why he is not willing to pay for the service. For either method, the participant's value is the highest he is willing to pay. Question order for each auction method is outlined in Table 2—6 of Appendix A.

After the participant placed bids on both services, the binding auction was randomly chosen with a coin toss. The respondent then drew a piece of paper from an envelope to determine the 'market price' used to compare to his bid. The envelope contained pieces of paper, each with a price from 5 KSH to 75 KSH, where each price level was represented once (Healy, 2016). If his bid was greater than or equal to the price on the paper, he won the bid and purchased the service at the lower price (Becker et al., 1964). Thus, the higher the bid, the greater the chance of winning.

# 2.4 Empirical Framework

### *2.4.1 Willingness to pay for moisture reading services*

Respondents were offered two services that test the moisture content of their maize: (1) a reading using the hygrometer, and (2) a reading using the commercial moisture meter. Recall that the main difference between the two in functionality is that while the hygrometer is reliable and cheaper, the moisture meter is quicker and more accurate. We are interested in whether willingness to pay differs between the two. For each service, we generate a demand curve by plotting the percent of traders willing to pay at or above each price level, where price levels range from 0 KSH to 75 KSH in increments of 5 KSH (about $.05). From here, we can analyze the elasticity of demand along the demand curve using the following equation:

$$\varepsilon_D = \frac{\%\Delta Quantity}{\%\Delta Price} \tag{2.1}$$

Next, our analysis of traders' willingness to pay for moisture reading services uses OLS regression to test the difference, if any, in what participants are willing to pay for the two services. The linear model is presented as follows:

$$WTP_{ij} = \beta_0 + \beta_1 Hygrometer_{ij} + \beta_2 LH_i + \beta_3 HL_i + \beta_4 Order_i + \beta_5 PracticeSuccess_i + \beta_6 X_i + \varepsilon_i + \omega_{ij} \tag{2.2}$$

Where $WTP_{ij}$ is individual $i$'s willingness to pay for service $j$; $Hygrometer_{ij}$ is a binary variable equal to 1 for individual $i$ if bid $j$ refers to the hygrometer service (and 0 for the moisture meter service); $LH_i$ is equal to 1 if the low-high auction method was used by individual $i$; $HL_i$ is equal to 1 if the high-low auction method was used by individual $i$; $Order_i$ indicates the order that bids were placed in and is equal to 1 if respondent $i$ bid first on the hygrometer service;

$PracticeSuccess_i$ is equal to 1 if the trader purchased a pen or pencil in the practice auction; $X_i$ is a vector of control variables including trader demographics, maize trading demographics, drying practices, and prior knowledge of aflatoxin, the hygrometer, and commercial moisture meters (listed in Table A2 of Appendix A); $\varepsilon_i$ is the error term specific to individual *i*; and $\omega_{ij}$ is an error term corresponding to individual *i*'s perception of service *j*. Both error terms are assumed to be uncorrelated with the covariates from the experimental auction. Based on Equation (2.2), the null hypothesis follows:

*$H_0$1: WTP is the same for the hygrometer and moisture meter services.*

We expect that traders are willing to pay more for the moisture meter reading, as the device is more familiar (and therefore perceived to be more reliable), more accurate, and takes less time. Coefficient $\widehat{\beta_1}$ in Equation (2.2) allows us to test Hypothesis 1.

### *2.4.2 Testing for biasedness in the auction mechanism*

Next, we expand on Channa et al.'s research by comparing starting point bias between a standard BDM auction mechanism and two RBC variants (2018). We randomize how the WTP questions are presented to the respondent to determine if the auction method leads to under- or over-valuation. While Channa et al. did find evidence that starting at higher values anchors the respondent's bid higher relative to starting at lower values, our interest here is to determine which, if either, RBC variant stays consistent with the standard method of framing the respondent's value. We assess biasedness first within the real auction only, where respondents bid on the two moisture testing services, with Equation (2.2). For comparison, we also assess outcomes within the practice auction, where respondents bid on a pen and a pencil, to determine if biasedness is present with less experience. For the practice auction, we use the following linear model:

$$WTP_{ij} = \beta_0 + \beta_1 Pen_{ij} + \beta_2 LH_i + \beta_3 HL_i + \beta_4 Order_i + \beta_5 Z_i + \varepsilon_i + \omega_{ij} \quad (2.3)$$

Where $Pen_{ij}$ is a binary variables equal to 1 for individual $i$ if bid $j$ is for the pen; $Order_i$ indicates the order that bids were placed during the real auction and is equal to 1 if respondent $i$ bid first on the pen; $Z_i$ is a vector of control variables that include trader demographics, assets and maize trading demographics; and all other variables remain the same as in Equation (2.2).

If there is no starting point bias when using an RBC variant compared to the standard BDM, it may offer a more precise tool for researchers to incrementally approach respondents' WTP. If the price starting point does matter in influencing the participants' valuations, however, our demand curve could be affected. The null hypothesis is expressed as follows:

*$H_0$3: The auction method has no effect on WTP.*

Coefficients $\widehat{\beta_2}$ and $\widehat{\beta_3}$ in Equations (2.2) and (2.3) allow us to test Hypothesis 3 by comparing outcomes from the Low-high and High-low methods to the standard BDM, respectively, for both real and practice auction outcomes. In both Equations (2.2) and (2.3), we employ F-tests to test if coefficients $\widehat{\beta_2}$ and $\widehat{\beta_3}$ within each model are statistically different from each other. This tests if WTP is different between the Low-high and High-low methods.

As suggested by Channa et al.'s results, we expect to see some indication of starting-point bias (2018). Therefore, we predict participants bid lower than they would have otherwise when using the low-high method, and bid higher than they would have otherwise when using the high-low method.

*2.4.3 Willingness to purchase the hygrometer*

Lastly, we consider the results of the take-it-or-leave-it auction where we offered the traders an opportunity to purchase the hygrometer device. With this auction, we test traders' sensitivity to being offered different price levels. Traders were offered the hygrometer for either 200, 250 or 300 KSH (market price ± 50 KSH) at random. We first use the following linear probability model (LPM) to test traders' propensity to purchase the hygrometer based on the offered price:

$$Purchase_i = \beta_0 + \beta_1 Price200_i + \beta_2 Price300_i + \beta_3 WTPhygrometer$$

$$+\beta_4 WTPmm + \beta_5 RealSuccess + \beta_6 PracticeSuccess + \beta_7 X_i + \varepsilon_i \qquad (2.4)$$

Where $Purchase_i$ is a binary variable equal to 1 if respondent *i* chose to purchase the hygrometer at the offered price; $Price200_i$ is equal to 1 if the price offered was 200 KSH and 0 otherwise; $Price300_i$ to 1 if the price offered was 300 KSH and 0 otherwise; $WTPhygrometer_i$ and $WTPmm_i$ are trader $i$'s values of the hygrometer and moisture meter services, respectively; $RealSuccess_i$ and $PracticeSuccess_i$ are binary variables equal to 1 if trader *i* was successful at purchasing a moisture reading service or practice item, respectively; and the vector $X_i$ and the individual error term $\varepsilon_i$ remain the same as in Equation (2.2).

Next, we compare results of the LPM regression with those from a probit and logit estimator which account for the possible non-linearity in the probability that a trader will purchase a hygrometer, based on the offered price. The probit and logit models are expressed as follows, respectively:

$$Prob(Purchase_i = 1|(Price_i, Z_i, X_i) = \Phi(Price_i{}'\beta + Z_i{}'\alpha + X_i{}'\gamma) \qquad (2.5)$$

$$Prob(Purchase_i = 1|(Price_i, Z_i, X_i) = \Lambda(Price_i{}'\beta + Z_i{}'\alpha + X_i{}'\gamma) \qquad (2.6)$$

Where $Purchase_i$ and $X_i$ are the same as in Equation (4); $Price_i$ is a vector equal to $(Price200_i, Price300_i)$ ; and $Z_i$ is a vector consisting of the terms ($WTPhygrometer_i$, $WTPmm_i$, $RealSuccess_i$, $PracticeSuccess_i$) as in Equation (2.4). Equations (2.4)-(2.6) will be tested with and without control vector $X_i$.

If traders are indifferent to price changes in the 200-300 KSH range, it may indicate a strong demand for more accurate moisture detection methods than the traditional methods currently used. The null hypothesis we test is stated as:

*$H_0$2: Hygrometer price has no effect on willingness to purchase the device.*

To test Hypothesis 2, we are interested in coefficients $\widehat{\beta_1}$ and $\widehat{\beta_2}$ in Equation (2.4) and $\hat{\beta} = (\widehat{\beta_1}, \widehat{\beta_2})$ in Equations (2.5) and (2.6). These coefficients determine whether the probability of purchasing a hygrometer differs between 200 and 250 KSH, and 250 and 300 KSH. To see if there is a significant difference in probability between 200 and 300 KSH, we use an F-test for the results from Equation (2.4) and a Chi-squared test for Equations (2.5) and (2.6), which test if $\widehat{\beta_1}$ and $\widehat{\beta_2}$ are different from each other. We expect to find that a lower price offer does induce traders to purchase more than if the price was higher.

## 2.5 Results

Descriptive statistics for key variables including auction outcomes are reported in Tables 2—8 and 2—9 in Appendix B. Following the descriptive statistics, a breakdown of the categorical variables used as control variables in the regressions are provided in Tables 2—10 through 2—15. These variables include the criteria that traders consider most important for purchasing maize, greatest challenges they face when drying maize, methods used for checking if maize is dry, most visible sign of aflatoxin, strategies for managing aflatoxin contamination, and the reason for not purchasing the hygrometer device in the take-it-or-leave-it auction.

### *2.5.1 Deriving the demand curve for moisture reading services*

The demand curve is derived using monotonicity, i.e., we include all individuals in the quantity willing to pay until their switch point (the recorded value) is reached. As Figure 2—1 shows, traders are willing to pay more for the testing service using a commercial moisture meter than they are for the hygrometer at all price levels. This is expected, given the advantages that the moisture meter has over the hygrometer, in all major aspects except the cost of the device.

The slopes of the demand curves for the moisture testing services using the hygrometer and commercial moisture meter are similarly inelastic, although the moisture meter service exhibits less elasticity between 5 and 50 KSH (elasticity for the moisture meter service is approximately -0.54 while elasticity for the hygrometer service is -0.83). Both demand curves show a steep drop in number of respondents willing to pay when the price increases from 50 to 55 KSH, where the curve is considerably elastic (elasticity is about -3.21 for moisture meter service and -1.55 for hygrometer service). Of the 199 traders, 90.5% (78.4%) are not willing to pay more than 50 KSH for the hygrometer (moisture meter) service. In general, quantity is not very responsive to changes in price up to 50 KSH. Above 50 KSH, the number of traders willing to purchase either service decreases but after this shift remains relatively unresponsive to price changes. This is evident in Figures 2—2 and 2—3, which display the frequency of each price level reported.

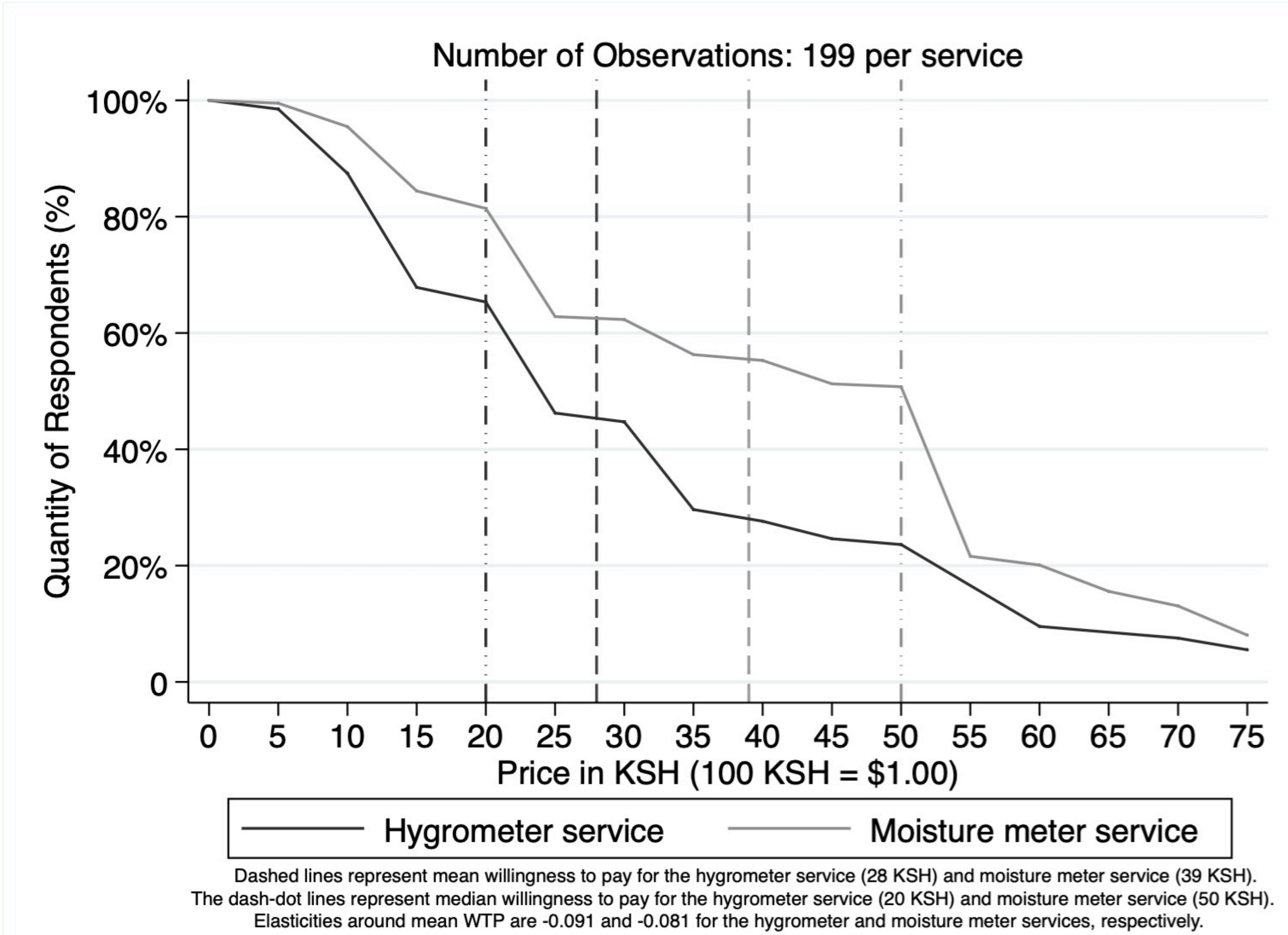


**Figure 2–1. Willingness to pay for moisture testing services**

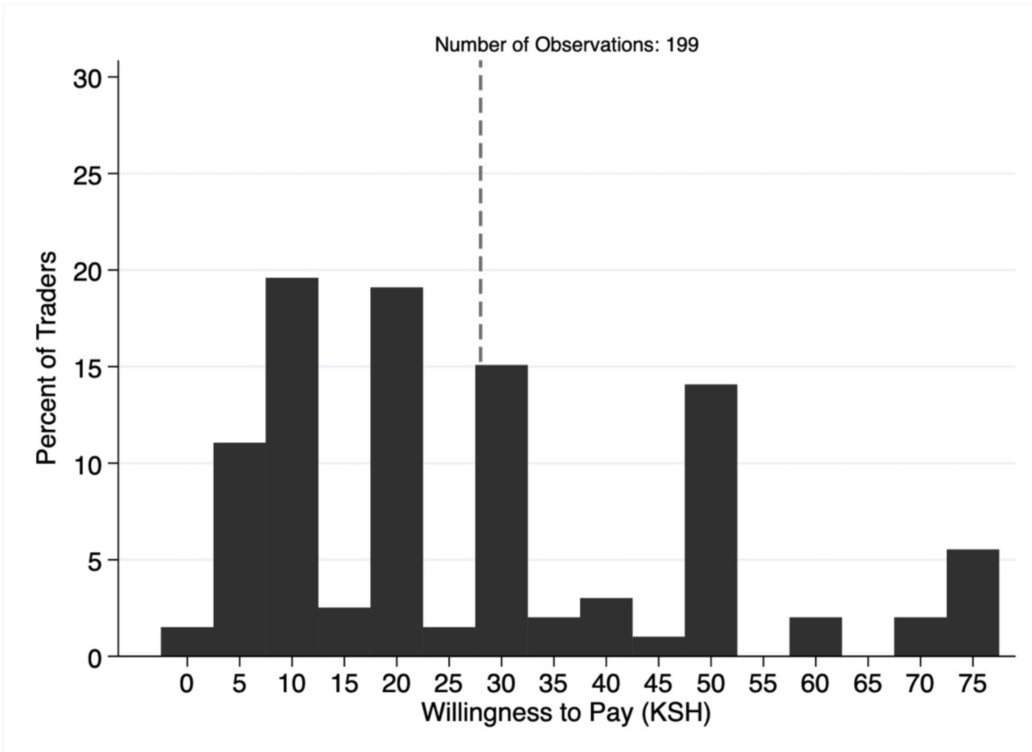


**Figure 2–2. Distribution of WTP for hygrometer service**

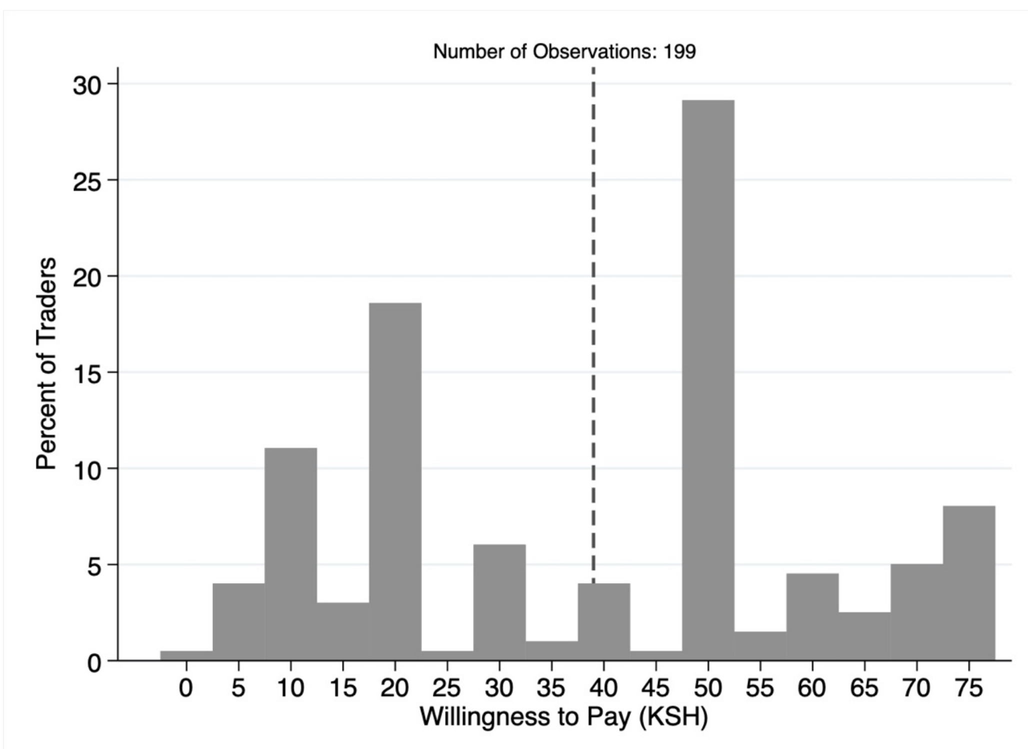


**Figure 2–3. Distribution of WTP for moisture meter service**

Tables 2—1 and 2—2 estimate the gross revenue for each service at prices ranging from 5 to 75 KSH, calculated using the number of 200 potential customers, which is nearly the size of our sample.[14] At the transition between a price per moisture reading of 50 and 55 KSH, gross revenue more than halves for both services. The results shown in these tables indicate that 50 KSH per moisture reading is the revenue maximizing price for the moisture meter service (5,076 KSH maximum profit); raising the price any further results in large revenue losses. Revenue is maximized (2,684 KSH) for the hygrometer service at 30 KSH per moisture reading price. The higher maximizing price and revenue for the moisture meter service is consistent with traders valuing this service higher than the hygrometer service.

**Table 2–1. Estimated revenue for moisture meter service**

| Price (KSH) | % of respondents willing to pay | Quantity of respondents willing to pay (out of sample size 200) | Total Revenue (KSH) |
|---|---|---|---|
| 75 | 8.04% | 16 | 1,206 |
| 70 | 13.07% | 26 | 1,830 |
| 65 | 15.58% | 31 | 2,025 |
| 60 | 20.10% | 40 | 2,412 |
| 55 | 21.61% | 43 | 2,377 |
| **50** | **50.76%** | **102** | **5,076** |
| 45 | 51.26% | 103 | 4,613 |
| 40 | 55.28% | 111 | 4,422 |
| 35 | 56.29% | 113 | 3,940 |
| 30 | 62.32% | 125 | 3,739 |
| 25 | 62.82% | 126 | 3,141 |
| 20 | 81.41% | 163 | 3,256 |
| 15 | 84.43% | 169 | 2,533 |
| 10 | 95.49% | 191 | 1,910 |
| 5 | 99.51% | 199 | 995 |

*Maximum revenue bolded in red*

[14] The purpose of this market population size is to be able to calculate and compare gross revenue between the two services. Relative gross revenue would be the same if a different market population is used.

**Table 2–2. Estimated revenue for hygrometer service**

| Price (KSH) | % of respondents willing to pay | Quantity of respondents willing to pay (out of sample size 200) | Total Revenue (KSH) |
|---|---|---|---|
| 75 | 5.53% | 11 | 830 |
| 70 | 7.54% | 15 | 1,056 |
| 65 | 7.54% | 15 | 980 |
| 60 | 9.55% | 19 | 1,146 |
| 55 | 9.55% | 19 | 1,051 |
| 50 | 23.62% | 47 | 2,362 |
| 45 | 24.63% | 49 | 2,217 |
| 40 | 27.65% | 55 | 2,212 |
| 35 | 29.66% | 59 | 2,076 |
| **30** | **44.74%** | **89** | **2,684** |
| 25 | 46.25% | 93 | 2,313 |
| 20 | 65.35% | 131 | 2,614 |
| 15 | 67.86% | 136 | 2,036 |
| 10 | 87.46% | 175 | 1,749 |
| 5 | 98.52% | 197 | 985 |

*Maximum revenue bolded in red*

### *2.5.2 Willingness to pay for moisture reading services*

The primary interest of this study focuses on traders' WTP for moisture reading services offered by a third party. Table 2—3 contains the results from the linear model estimated via OLS in Equation (2.2), which measures the outcomes from our BDM auction for both services. Each trader has two recorded observations, one for each service. We present results with and without the control vector $X_i$ as a robustness check and report robust standard errors clustered at the trader level. We first observe that results do not change when control variables are added, which suggests that the demand for more effective moisture testing is relatively independent of observable trader-specific characteristics. Further, the constant term is significantly greater than zero, implying that regardless of the individual trader characteristics or the device used for the service, traders on average exhibit some level of demand for moisture testing services.

We are interested in $\widehat{\beta_1}$, the difference in WTP between the moisture meter and hygrometer service, and we find that traders are willing to pay about 11 KSH ($.11) less for the hygrometer service than the moisture meter service. The significance of $\widehat{\beta_1}$ with 99% confidence allows us to reject the null of Hypothesis 1 and conclude that there is a significant difference in WTP between the two services offered. This result is robust even when including trader-specific variables, and consistent with what we see in the demand curves in Figure 2—1.

Using Equation (2.2), we can calculate that traders value the moisture testing service at 39 KSH and the hygrometer service at 28 KSH on average, based on the insignificance of all other coefficients. However, the hygrometer sells at about $2.50 (250 KSH) each, while the AgraTronix™ MT-16 Portable Grain Moisture Tester cost $170 to purchase in the United States. Assuming some import taxes, and price markups we estimate that this would sell for a minimum of $300 (30,000 KSH) in Kenya. At 50 KSH per reading, it would take 600 readings to break even on the moisture meter. Assuming a 51% success rate for selling the service (based on Table 2—1), meeting this target sales quantity would require a market population of 1,177 traders. For the hygrometer service at 30 KSH per reading, it would take only 9 readings to break even and start generating profit. Assuming a 45% success rate at 30 KSH (based on Table 2—2), the service provider would only require a market population of 19 traders to meet his goal. Thus, the hygrometer service is more cost-effective for a third-party service provider, despite the lower valuation of the service and relative disadvantages when compared with the moisture meter, namely time and precision.

**Table 2–3. Willingness to pay for moisture reading services**

| | *No controls* | *Controls* | *Fixed Effects* |
|---|---|---|---|
| Service (=1 if observation is for hygrometer service) | -11.131*** | -11.131*** | -11.131*** |
| | (1.226) | (1.267) | (1.218) |
| Low-high method used (=1 if yes) | -2.04 | -1.22 | - |
| | (3.675) | (3.518) | - |
| High-low method used (=1 if yes) | 0.40 | -0.15 | - |
| | (3.383) | (3.069) | - |
| Real auction order (=1 if hygrometer was bid on first) | 3.95 | 3.80 | - |
| | (2.731) | (2.791) | - |
| Respondent purchased a pen or pencil in practice auction (=1 if yes) | -4.88 | -5.40 | - |
| | (3.308) | (3.413) | - |
| Respondent has heard of or seen hygrometer previously (=1 if yes) | - | 6.22 | - |
| | - | (4.235) | - |
| Respondent has heard of or seen commercial moisture meter previously (=1 if yes) | - | 1.53 | - |
| | - | (2.847) | - |
| Respondent has owned or currently owns a commercial moisture meter (=1 if yes) | - | -12.97 | - |
| | - | (8.927) | - |
| $\beta_0$ | 38.215*** | 38.903*** | 38.894 |
| | (3.324) | (14.168) | (0.861) |
| Trader demographics included | no | yes | no |
| Assets included | no | yes | no |
| Maize trading business demographics included | no | yes | no |
| Drying & aflatoxin variables included | no | yes | no |
| Number of observations | 398 | 398 | 398 |
| $R^2$ | *0.0840* | *0.2466* | *0.0663* |
| F-statistic: WTP is the same if low-high or high-low method is used | 0.60 | 0.11 | - |

Robust standard errors, clustered at the trader level, are shown in parentheses. See Table 2—7 in Appendix A for a full list of variables included as controls. ***p<0.01, **p<0.05, *p<0.1

### *2.5.3 Testing for biasedness in the auction mechanism*

The auction procedure used in the study consisted of three variations of the BDM auction method, randomly assigned across traders. This allows us to test if one or more of these variations leads to significantly under- or over-stated WTP values. We compare the Low-high and High-low methods against the Standard BDM method where respondents are asked to state a price that they are willing to pay for the services in Equation (2.2) and the practice items in Equation (2.3). In both equations, $\widehat{\beta_2}$ and $\widehat{\beta_3}$ are the coefficients of interest. Results are reported in Tables 2—3 and 2—4 for the real and practice auctions, respectively. Two model specifications are used to check for robustness in each table: the first uses only auction outcomes and the second adds trader and business characteristics.

We first look at results from Equation (2.2) where only real auction outcomes were considered. In both specifications in Table 2—3, neither the Low-high or High-low methods result in a significantly different WTP value than the Standard BDM method. We discern if the coefficients corresponding to the Low-high and High-low methods are statistically different from each other using an F-test. Results of the F-test are reported at the bottom of Table 2—3 and suggest that $\widehat{\beta_2}$ and $\widehat{\beta_3}$ are not significantly different from each other either. Therefore, there was no biasedness in WTP in the real auction due to auction method.

Next, we compare these results to outcomes from the practice auction using Equation (2.3). When considering outcomes from the practice auction only in Table 2—4, we find that there is still no difference in WTP between the Standard BDM and either RBC variant. However, WTP values are significantly lower with the Low-High compared to the High-Low auction method, as indicated by the significant F-statistic in Table 2—4. The level of significance decreases slightly when controlling for trader demographics, suggesting that some of the biasedness is correlated with trader-specific characteristics. The results in Tables 2—3 and 2—4 signify that there is biasedness between the two RBC variants, but only in the practice auction, which could be due to the learning curve of the auction procedure. The question order may induce the respondent to under- or over-bid during their first attempt if using the Low-High or High-Low methods. The disappearance of this effect when considering only observations from the real auction highlights the importance of practicing the auction beforehand, as the auction procedure can seem complex initially.

**Table 2–4. Effect of auction method on willingness to pay for practice items**

| | *No controls* | *Controls* |
|---|---|---|
| Practice Item (=1 if observation is for pen) | 1.28*** (0.437) | 1.28*** (0.444) |
| Low-high method used (=1 if yes) | -1.60 (1.450) | -0.99 (1.442) |
| High-low method used (=1 if yes) | 3.20 (2.005) | 3.25 (2.013) |
| Practice auction order (=1 if pen was bid on first) | -1.07 (1.567) | -0.79 (1.475) |
| $\beta_0$ | 14.365*** (1.479) | 11.923* (6.278) |
| Trader demographics included | no | yes |
| Assets included | no | yes |
| Maize trading business demographics included | no | yes |
| Number of observations | 398 | 398 |
| $R^2$ | *0.0378* | *0.1029* |
| F-statistic: WTP is the same if low-high or high-low method is used | 7.49*** | 5.47** |

Robust standard errors, clustered at the trader level, are shown in parentheses. For maize trading business demographics, only quantity of maize bought and sold monthly were included as a proxy for income. See Table 2—7 in Appendix A for a full list of variables included as controls. ***p<0.01, **p<0.05, *p<0.1.

We cannot reject the null hypothesis of no difference in WTP as a result of auction method, according to Table 2—3. While both RBC variants do not bias WTP compared to the standard BDM, they are biased compared to each other. However, this biasedness disappears with experience after the respondent practices the auction procedure. Thus, auctions that use an RBC variant should be sure to include at least one practice auction. Given this result, we can conclude that our demand curve is not affected by biasedness in WTP elicitation method. Future work that uses the BDM auction procedure should consider using an RBC variant, as the marginal changes in price can provide benchmarks to answer a simpler 'yes' or 'no' question rather than an open-ended question. Specifically, the Low-High auction method may be more useful as most respondents bid in the lower range of 0 to 75 KSH, and anecdotally respondents tended to be frustrated by the continued questioning in the High-Low method to reach their WTP.

### *2.5.4 Willingness to purchase the hygrometer*

Next we compare linear probability, probit, and logit models to assess whether traders are sensitive to the price offered for purchasing the hygrometer device in the take-it-or-leave-it auction. The prices of 200 KSH and 300 KSH are compared to the current market price, 250 KSH, using the coefficients $\widehat{\beta_1}$ and $\widehat{\beta_2}$, respectively, in Equations (2.4)-(2.6). Table 2—5 shows that the probability of a trader purchasing the device does not change if he is offered 200 or 300 KSH, rather than 250 KSH. This does not change across model specifications, with or without control variables. Next, we conduct F-tests in the LPM and Chi-Squared tests in the probit and logit models on $\widehat{\beta_1}$ and $\widehat{\beta_2}$ to see if the probability of purchasing the hygrometer differs between offer prices of 200 and 300 KSH. All F-Statistics and Chi-Squared values show that $\widehat{\beta_1}$ and $\widehat{\beta_2}$ are not statistically different from each other. Therefore, we cannot reject the null Hypothesis 3 that the offered price affects the probability a trader will purchase the hygrometer.

While Table 2—5 suggests that traders are not sensitive to price changes around market price, it is necessary to keep in mind that only 15% of traders were willing to purchase the hygrometer in this price range. Therefore lowering the price slightly would not encourage more traders to purchase the device. This study did not test traders' WTP for the hygrometer below 200 KSH, but Channa et al. found that traders in the neighboring county of Kakamega were willing to pay on average 120 KSH for the hygrometer, suggesting that a supplier would need to lower the price substantially to increase its customer base (2018). Unless such a price decrease is more profitable, it is unlikely that a supplier would be motivated solely by increasing its sales quantity. Therefore, it is not probable that selling hygrometers in the market would achieve our goal of making moisture testing common practice, without some form of subsidy or price support.

**Table 2–5. Willingness to purchase the hygrometer**

| | Linear Probability Model | | Probit Model | | Logit Model | |
|---|---|---|---|---|---|---|
| | *Without controls* | *With controls* | *Without controls* | *With controls* | *Without controls* | *With controls* |
| 200 KSH price offered (=1 if yes) | -0.015 | -0.012 | -0.018 | 0.065 | -0.056 | 0.036 |
| | (0.070) | (0.071) | (0.277) | (0.324) | (0.505) | (0.638) |
| 300 KSH price offered (=1 if yes) | -0.087 | -0.059 | -0.389 | -0.270 | -0.748 | -0.524 |
| | (0.056) | (0.059) | (0.274) | (0.333) | (0.514) | (0.657) |
| WTP for hygrometer service | -0.007 | 0.001 | -0.025 | 0.035 | -0.063 | 0.070 |
| | (0.010) | (0.011) | (0.046) | (0.045) | (0.092) | (0.091) |
| WTP for moisture meter service | 0.019** | 0.013 | 0.088** | 0.064 | 0.169** | 0.116 |
| | (0.009) | (0.009) | (0.042) | (0.045) | (0.080) | (0.089) |
| Respondent purchased moisture reading service (=1 if yes) | 0.063 | 0.055 | 0.268 | 0.277 | 0.547 | 0.369 |
| | (0.064) | (0.067) | (0.271) | (0.353) | (0.521) | (0.785) |
| Respondent purchased a pen or pencil (=1 if yes) | 0.005 | 0.002 | 0.065 | -0.072 | 0.083 | -0.197 |
| | (0.065) | (0.066) | (0.308) | (0.385) | (0.592) | (0.911) |
| Respondent heard of/saw hygrometer prior (=1 if yes) | - | 0.085 | - | 0.526 | - | 0.995 |
| | - | (0.090) | - | (0.400) | - | (0.829) |
| Respondent heard of/saw moisture meter prior (=1 if yes) | - | 0.020 | - | 0.238 | - | 0.499 |
| | - | (0.063) | - | (0.303) | - | (0.628) |
| Respondent owned/currently owns moisture meter (=1 if yes) | - | -0.123 | - | - | - | - |
| | - | (0.105) | - | - | - | - |

**Table 2—5 continued**

| | | | | | | |
|---|---|---|---|---|---|---|
| $\beta_0$ | 0.045<br>(0.048) | -0.254<br>(0.247) | -1.666***<br>(0.280) | -4.525***<br>(1.380) | -2.891***<br>(0.533) | -8.217***<br>(2.959) |
| Trader demographics included | no | yes | no | yes | no | yes |
| Assets included | no | yes | no | yes | no | yes |
| Maize trade demographics included | no | yes | no | yes | no | yes |
| Drying & aflatoxin variables included | no | yes | no | yes | no | yes |
| Number of observations | 199 | 199 | 199 | 185 | 199 | 185 |
| $R^2$ | *0.0693* | *0.2500* | *0.0849* | *0.3354* | *0.0863* | *0.3374* |
| Test: Propensity to purchase hygrometer is the same if offered at 200 or 300 KSH | 1.18 | 0.50 | 1.42 | 0.82 | 1.37 | 0.49 |

Robust standard errors are shown in parentheses. See Table 2—7 in Appendix A for a full list of variables included as controls. Respondent owns/rents trade store and respondent owned/own a moisture meter are omitted from the probit and logit specifications due to collinearity. The coefficient test reports the F-Statistic for the LPM specifications and the Chi-Squared value for the probit and logit specifications.
***p<0.01, **p<0.05, *p<0.1

## 2.6 Conclusion

In this article we conducted an individual BDM auction with 199 small-scale traders in rural Kenya for two maize moisture reading services (a low-cost hygrometer and a rapid, precise commercial moisture meter). Our purpose was to estimate if this service provider model that we estimated could be a solution for the lack of reliable moisture testing in SSA. Without valid moisture testing of maize, it is nearly impossible for consumers and buyers to distinguish between maize that has and has not been properly dried (Akerlof, 1970). This is problematic, as aflatoxin contamination resulting from wet maize is not directly observable, but has been linked to adverse health outcomes (Williams et al., 2004). In such a lemons market, everyone is worse off, as farmers and traders may receive lower prices than if maize was observably safe, and consumers are unsure about food quality. With a third-party verification system, traders could be more accountable for the quality of their products, and consumers more aware and confident of the foods they eat.

We find that traders value the moisture reading service about 11 KSH ($.11) more than the hygrometer service. Based on the demand curves, revenue is maximized at 50 KSH ($.50) for the moisture meter service and 30 KSH ($.30) for the hygrometer service. Although traders do value the moisture meter service greater than the hygrometer service, the vast cost difference between the two technologies makes the hygrometer service more profitable for service providers. While WTP is less for the hygrometer service, it is much more profitable for the supplier. This is assuming, however, that substitutes for the hygrometer service (say, a competing moisture meter service) do not crowd out demand.

Placing these results in context, it is important to note that this study was conducted in the lean season, when only 10% of respondents were still purchasing wet maize (Table 2—8,

Appendix B). Thus, the WTP values (and therefore the derived demand curve) are likely lower at this point in the season compared to directly after harvest. We would expect demand to peak in the months following harvest (October through December), when maize is fresh and farmers sell predominantly wet maize. Knowing the moisture content of the maize that traders intend to buy may influence their drying decisions, or may even influence the decision of who to buy from. To further develop a feasible third-party service provider model, future work should consider implementing studies during the peak season directly following maize harvest to assess seasonal demand.

Moving forward would require developing the third-party service model further, including potential service providers, a means to certify that service providers are legitimate and unbiased, and the target consumer base. Farmers may be a more applicable demographic than traders to sell the moisture testing service to. Because farmers usually consume what they produce, bypassing farmers ignores their health and livelihood. Farmers may be willing to pay more to sample their maize for personal consumption as it has a direct connection to the households' overall productivity. Moreover, farmers are integral actors for ensuring quality maize in every stage of production up to the farmgate. Aflatoxin could be present from in-field exposure or poor drying and storage practices prior to moisture content testing, therefore it is crucial to consider testing at multiple stages throughout production and post-harvest management. Testing moisture content on-farm as early as possible reduces the chances that fungi can grow and produce aflatoxin by informing farmers if maize should be dried further to a safe level.

This article has demonstrated that introducing third-party service providers for testing maize moisture content can provide opportunities for farmers, traders, and other market actors to make their products more attractive to consumers. This verification service model is a feasible first step in encouraging traders to supply verified safe maize that is already in demand. The service model offers advantages that simply selling hygrometers cannot accomplish, namely the unbiased, third-party component, and encouraging moisture testing as common practice.

Next steps could include researching whether consumers are willing to pay a premium for maize labeled and tested specifically with the hygrometer and the moisture meter. Recent studies find that consumers are ready and willing to pay premiums on labeled maize in Senegal and Kenya, but WTP in these studies were not derived based on the specific method of testing (Prieto et al., 2018; De Groote et al., 2016). It is also important that consumers understand the difference between aflatoxin testing and moisture testing. A safe moisture content label would indicate that maize was safe at the time of testing, but cannot guarantee that maize was always stored at a safe level throughout production and post-harvest. Continued research into the feasibility and implementation of the service model is warranted, as it could serve as a trusted verification system to standardize moisture testing and ensure that aflatoxin contamination is no longer a safety threat.

## 2.7 References

Akerlof, George A. "The market for 'lemons': quality uncertainty and the market mechanism." *The Quarterly Journal of Economics, vol.* 84, no. 3, 1970, pp. 488-500.

Azrieli, Y., Chambers, C.P., Healy, P.J. "Incentives in experiments: a theoretical analysis." *Journal of Political Economy,* vol. 126, no. 4, 2018, pp. 1472-1503.

Becker, G.M., DeGroot, M.H., Marschak, J. "Measuring utility by a single-response sequential method." *Behavioral Science,* vol. 9, no. 3, 1964, pp. 226-232.

"Bumper Kenya maize harvest contaminated by toxins." *British Broadway Corporation: Africa*, 2 June 2010, www.bbc.com/news/10219505. Accessed 16 May 2019.

Channa, H., Ricker-Gilbert, J., De Groote, H., Marenya, P., Bauchet, J. "Willingness to pay for a new farm technology given risk preferences: evidence from an experimental auction in Kenya." 2018 Conference, July 28-August 2, 2018, Vancouver, British Columbia 277406, International Association of Agricultural Economists.

"Country brief: Kenya." *FAO Global Information and Early Warning System,* 8 May 2018, www.fao.org/giews/countrybrief/country.jsp?code=KEN. Accessed 16 May 2019.

De Groote, H., Narrod, C., Kimenju, S., Bett, C., Scott, R., Tiongco, M., Gitonga, Z. "Measuring rural consumers' willingness to pay for quality labels using experimental auctions: the case of aflatoxin-free maize in Kenya." *Agricultural Economics,* vol. 47, no. 1, 2016, pp. 33-45.

"Extreme weather increasing level of toxins in food, scientists warn." *The Standard Digital: Business,* 31 May 2016, www.standardmedia.co.ke/article/2000203586/n-a. Accessed 16 May 2019.

Flachaire, E. and Hollard, G. "Starting-point bias and respondent uncertainty in dichotomous choice contingent valuation surveys." *Resource and Energy Economics,* vol. 29, no. 3, 2007, pp. 183-194.

Gachera, G., Nyamache, A., Harvey, J., Gnonlonfin, G., Wainaina, J. "Genetic diversity of *Aspergillus flavus* and occurrence of aflatoxin contamination in stored maize across three agro-ecological zones in Kenya." *Agriculture & Food Security,* vol. 7, no. 52, 2018, pp. 1-10.

Gathura, Gatonye. "Alert over maize poisoning." *Daily Nation Kenya*, 1 Oct. 2008, www.nation.co.ke/news/regional/1070-476454-bvyofpz/index.html. Accessed 16 May 2019.

Hanemann, M., Loomis, J., Kanninen, B. "Statistical efficiency of double-bounded dichotomous choice contingent valuation." *American Journal of Agricultural Economics,* vol. 73, no. 4, 1991, pp. 1255-1263.

Healy, P. "Explaining the BDM – or any random binary choice elicitation mechanism – to subjects." *Mimeo,* 2016, pp. 1-10.

Hoffmann, V. and Moser, C. "You get what you pay for: the link between price and food safety in Kenya." *Agricultural Economics,* vol. 48, no. 4, 2017, pp. 449-458.

"MT-16." *AgraTronix™ ,* www.agratronix.com/shop/grain/mt-16/. Accessed 16 May 2019.

Prieto, S., Ricker-Gilbert, J., Bauchet, J. "Incomplete information and product quality in rural markets: evidence from an experimental auction for maize in Senegal." 2018, Working paper.

Probst, C., Njapau, H., Cotty, P. "Outbreak of an acute aflatoxicosis in Kenya in 2004: identification of the causal agent." *Applied and Environmental Microbiology*, vol. 73, no. 8, 2007, pp. 2762-2764.

Shimamoto, D., Yamada, H., Wakano, A. "The effects of risk preferences on the adoption of post-harvest technology: evidence from rural Cambodia." *The Journal of Development Studies,* vol. 54, no. 10, 2018, pp. 1819-1837.

Tubbs, T., Woloshuk, C., Ileleji, K. "A simple low-cost method of determining whether it is safe to store maize." *AIMS Agriculture and Food,* vol. 2, no. 1, 2017, pp. 43-55.

Walker, S. and Davies, B. "Farmer perceptions of aflatoxins: implications for intervention in Kenya." In Aflatoxins: finding solutions for improved food safety, eds. Unhevehr, L. J. and Grace, D. *2020 Vision Focus*, vol. 20, no. 7, 2013, International Food Policy Research Institute (IFPRI).

Williams, H., Phillips, D., Jolly, P., Stiles, J., Jolly, C., Aggarwal, D. "Human aflatoxicosis in developing countries: a review of toxicology, exposure, potential health consequences, and interventions." *American Journal of Clinical Nutrition,* vol. 80, no. 5, 2004, pp. 1106-22.

# 2.8 Appendices

### *2.8.1 Appendix A. Auction Methodology & Variables*

**Table 2–6. Question order for BDM auction variations**

| ***Low-High Method*** | ***High-Low Method*** | ***Standard BDM Method*** |
|---|---|---|
| Are you willing to pay **5** KSH? | Are you willing to pay **75** KSH? | How much are you willing to pay for ______ service? |
| Are you willing to pay **10** KSH? | Are you willing to pay **70** KSH? | |
| Are you willing to pay **15** KSH? | Are you willing to pay **65** KSH? | |
| Are you willing to pay **20** KSH? | Are you willing to pay **60** KSH? | |
| Are you willing to pay **25** KSH? | Are you willing to pay **55** KSH? | |
| Are you willing to pay **30** KSH? | Are you willing to pay **50** KSH? | |
| Are you willing to pay **35** KSH? | Are you willing to pay **45** KSH? | |
| Are you willing to pay **40** KSH? | Are you willing to pay **40** KSH? | |
| Are you willing to pay **45** KSH? | Are you willing to pay **35** KSH? | |
| Are you willing to pay **50** KSH? | Are you willing to pay **30** KSH? | |
| Are you willing to pay **55** KSH? | Are you willing to pay **25** KSH? | |
| Are you willing to pay **60** KSH? | Are you willing to pay **20** KSH? | |
| Are you willing to pay **65** KSH? | Are you willing to pay **15** KSH? | |
| Are you willing to pay **70** KSH? | Are you willing to pay **10** KSH? | |
| Are you willing to pay **75** KSH? | Are you willing to pay **5** KSH? | |
| *Questions stop once respondent answers 'No'* | *Questions stop once respondent answers 'Yes'* | *Respondent is only asked one question* |
| *The last price level to which respondent answers 'Yes' to is his/her true value* | *The first price level to which respondent answers 'Yes' to is his/her true value* | *The price level given by respondent is his/her true value* |

**Table 2–7. List of variables in control vector X**

| | |
|---|---|
| ***Trader demographics*** | |
| | Subcounty (categorical) |
| | Gender (=1 if male) |
| | Age (years) |
| | Education (years) |
| ***Assets (owns/has access to)*** | |
| | Car (=1 if yes) |
| | Lorry (=1 if yes) |
| | Trade store (=1 if yes) |
| | Tractor (=1 if yes) |
| | Motorcycle (=1 if yes) |
| | Bicycle (=1 if yes) |
| ***Maize trading business demographics*** | |
| | Trade experience (years) |
| | Average maize bought during peak season (kg/month) |
| | Average maize sold during peak season (kg/month) |
| | First most important criteria for buying maize (categorical) |
| | Second most important criteria for buying maize (categorical) |
| | Third most important criteria for buying maize (categorical) |
| ***Drying & Aflatoxin*** | |
| | Greatest drying challenge faced was rain (=1 if yes) |
| | Determines if maize is dry by biting (=1 if yes) |
| | Determines if maize is dry by listening (=1 if yes) |
| | Determines if maize is dry by visual observation (=1 if yes) |
| | Trader has heard about aflatoxin (=1 if yes) |
| | Trader manages aflatoxin contamination by disposing of maize (=1 if yes) |
| ***Moisture reading devices*** | |
| | Trader has heard of or seen previously the hygrometer (=1 if yes) |
| | Trader has heard of or seen previously a moisture meter (=1 if yes) |
| | Trader has owned or currently owns a moisture meter (=1 if yes) |

### *2.8.2 Appendix B. Descriptive Statistics & Other Data Tables*

**Table 2–8. Trader characteristics**

| ***Variable name*** | ***Mean*** | ***Standard deviation*** |
|---|---|---|
| Gender (=1 if male) | 0.41 | 0.49 |
| Age (years) | 40.29 | 12.25 |
| Education (years) | 10.48 | 3.25 |
| Assets (owns/has access to) (=1 if yes) | | |
| Car | 0.84 | 0.36 |
| Lorry | 0.77 | 0.42 |
| Trade store | 0.95 | 0.21 |
| Tractor | 0.72 | 0.45 |
| Motorcycle | 0.24 | 0.43 |
| Bicycle | 0.36 | 0.48 |
| Maize trading experience (years) | 8.43 | 7.93 |
| Average maize quantity purchased during peak season (kg/month) | 13,061 | 27,829 |
| Average maize quantity sold during peak season (kg/month) | 11,195 | 24,667 |
| Average number of counties traders buy from | 1.46 | 0.73 |
| Trader buys from farmers (=1 if yes) | 0.92 | 0.26 |
| Trader sells to consumers in the market (=1 if yes) | 0.92 | 0.27 |
| Share of maize bought from farmers (%) | 72.37 | 34.10 |
| Share of revenue from maize trading (%) | 51.34 | 27.96 |
| Trader currently buys wet maize (=1 if yes) | 0.10 | 0.30 |
| Trader dried maize (=1 if yes) | 0.62 | 0.49 |
| Trader used own labor to dry maize (=1 if yes) | 0.31 | 0.46 |
| Trader used hired labor to dry maize (=1 if yes) | 0.38 | 0.49 |
| Trader has heard of aflatoxin (=1 if yes) | 0.91 | 0.29 |
| Trader has heard of or seen hygrometer previously (=1 if yes) | 0.15 | 0.35 |
| Trader has owned/owns hygrometer (=1 if yes) | 0.01 | 0.07 |
| Trader has heard of or seen moisture meter previously (=1 if yes) | 0.38 | 0.49 |
| Trader has owned/owns moisture meter (=1 if yes) | 0.03 | 0.16 |
| *Number of observations* | *199* | |

**Table 2–9. Auction outcomes (BDM and Take-it-or-leave-it)**

| ***Variable Name*** | ***Mean*** | ***Standard Deviation*** |
|---|---|---|
| Average WTP for hygrometer service (KSH) | 27.8 | 20.19 |
| Average WTP for moisture meter service (KSH) | 38.9 | 21.65 |
| | ***Percent of total*** | |
| Auction method used | | |
| Low-high | 30.15% | |
| High-low | 39.70% | |
| Standard | 30.15% | |
| Auction order | | |
| Hygrometer service first | 47.74% | |
| Moisture meter service first | 52.26% | |
| Auction outcomes - purchases (=1 if successful) | 44.22% | |
| Hygrometer service | 33.73% | |
| N= 83 | | |
| Moisture meter | 51.72% | |
| N= 116 | | |
| Willingness to purchase hygrometer (=1 if purchased) | 15.08% | |
| 200 KSH price offered | 16.67% | |
| N= 48 | | |
| 250 KSH price offered | 18.75% | |
| N= 80 | | |
| 300 KSH price offered | 9.86% | |
| N= 71 | | |
| Number of observations (if not specified) | 199 | |

**Table 2–10. Most important criteria for purchasing maize (% of total)**

| ***Criteria*** | ***1st Most Important*** | ***2nd Most Important*** | ***3rd Most Important*** |
|---|---|---|---|
| Mold | 21.61% | 26.63% | 18.59% |
| Insects | 16.08% | 29.15% | 22.11% |
| Rotten kernels | 30.65% | 22.11% | 14.57% |
| Color | 9.55% | 10.55% | 18.09% |
| Price | 21.11% | 10.55% | 25.63% |
| Sells own maize only/ does not buy | 1.01% | 1.01% | 1.01% |
| Number of observations | | 199 | |

**Table 2–11. Greatest challenges faced when drying maize (only traders who dry maize)**

| ***Challenge*** | ***Greatest Challenge*** | ***2nd Greatest Challenge*** | ***3rd Greatest Challenge*** |
|---|---|---|---|
| Lack of access to/money for drying technology | 3.25% | 0.81% | 3.25% |
| Lack of labor to monitor drying | 11.38% | 26.02% | 21.95% |
| Lack of space for solar drying | 6.50% | 8.13% | 7.32% |
| Pests/ animals | 14.63% | 22.76% | 9.76% |
| Rain | 58.54% | 17.07% | 3.25% |
| Other | 0.81% | 0.81% | 4.87% |
| Did not face any drying challenges | 4.88% | 22.76% | 49.59% |
| Number of observations | | 123 | |

**Table 2–12. Methods used for checking if maize is dry**

| *Method* | *Percent of total* |
|---|---|
| Biting kernel | 47.74% |
| Listening to the sound | 30.15% |
| Visual observation | 26.63% |
| Salt and bottle | 1.01% |
| Uses commercial moisture meter | 2.51% |
| Compares weight before and after drying | 6.03% |
| Feels dryness in hand | 14.07% |
| Other | 3.53% |
| Number of observations | 199 |

*Note: respondents could select more than one option*

**Table 2–13. Most visible sign of aflatoxin for traders that know about aflatoxin**

| *Visible sign* | *Percent of total* |
|---|---|
| Moldy grain | 21.55% |
| Broken maize kernels | 0.55% |
| Rotten kernels | 14.36% |
| Change of color | 53.59% |
| Bad smell | 1.66% |
| Sour taste | 0.55% |
| None/ Does not know | 7.73% |
| Number of observations | 181 |

**Table 2–14. Strategies traders use to manage aflatoxin contamination**

| *Management strategy* | *Percent of total* |
|---|---|
| Dispose of contaminated maize | 49.75% |
| Report to authorities/ NCPB | 1.51% |
| Re-dry | 14.07% |
| Sell as livestock feed | 14.57% |
| Use as livestock feed | 13.07% |
| Sell anyway/ does nothing | 5.53% |
| Does not know/ has no experience w/ aflatoxin | 3.02% |
| Number of observations | 199 |

*Note: respondents could select more than one option*

**Table 2–15. Reason for not purchasing hygrometer device**

| *Reason reported* | *Percent of total* |
|---|---|
| I would want it only if it was free | 17.65% |
| I own/can access a different type of moisture meter | 2.35% |
| I am not interested in using/purchasing device | 28.82% |
| Too expensive | 6.47% |
| I don't sell to NCPB/I have no use for it | 0.59% |
| Hygrometer takes too long to read moisture content | 4.71% |
| I do not have enough money at this time | 21.18% |
| I do not have a use for it outside of peak season | 3.53% |
| I would buy later but not at this time of year | 11.18% |
| I would prefer to purchase the moisture meter | 3.53% |
| Number of observations | 169 |