BEHAVIORAL RESPONSES TO POST-HARVEST CHALLENGES IN EAST AFRICA: LESSONS FROM FIELD EXPERIMENTS

by

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This is dedicated to my parents, Professor Ghulam Asghar Channa and Professor Yasmin Channa, and to my three brilliant sisters Dr. Roomasa Channa, Dr. Yamna Channa and Dr. Hajra Channa. I can never be grateful enough for their love and support.

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The first essay “What drives smallholder farmers’ willingness to pay for a new farm technology? Evidence from an experimental auction in Kenya” has been co-authored with Amy Z Chen, Dr. Patrcia Pina, Dr. Jacob Ricker-Gilbert (committee chair) and Dr. Daniel Stein.

The second essay “Willingness to pay for a new farm technology given risk preferences: Evidence from an experimental auction in Kenya” has been co-authored with Dr. Jacob Ricker-Gilbert (Committee Chair), Dr. Hugo De Groote and Dr. Jonathan Bauchet (committee member).

The third essay “Helping Smallholder Farmers Make the Most of Maize through Harvest Loans and Storage Technology: Insights from a Randomized Control Trial in Tanzania” has been co-authored with Dr. Jacob Ricker-Gilbert (committee chair), Dr. Feleke Shiferaw and Dr. Tahirou Abdoulaye.

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ABSTRACT

Author: Channa, Hira. PhD
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Title: Behavioral Responses to Post-Harvest Challenges in East Africa: Lessons From Field Experiments
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This dissertation consists of three different essays evaluating solutions to postharvest challenges faced by farmers in Kenya and Tanzania. In the first essay we see that demand for a new storage technology the Purdue Improved Crop Storage (PICS) bags in Western Kenya, a completely new technology for almost the entire sample, was highly elastic and that a small proportion of the population would buy at the current market price. In the second essay we find evidence that farmers, who are primarily growing for maize consumption are more concerned about food safety in maize than traders, who are willing to pay less to keep the maize safer. In the third essay in Tanzania, we find that liquidity concerns at harvest prevent farmers from optimizing maize storage and sales decisions.

CHAPTER 1. INTRODUCTION

This dissertation consists of three separate but related essays evaluating solutions to post-harvest issues in East Africa. The first essay measures Willingness to Pay (WTP) for a hermetic storage technology (Purdue Improved Crop Storage (PICS) bag), that has been shown to reduce grain losses and maintain maize quality, amongst farmers in Western Kenya, and compares the impact of three different mediums of communication about the technology (text, audio and video) on its demand. This essay makes two contributions to the literature in this area. First, it uses incentive-compatible methods to measure demand for a new hermetic storage technology, showing that demand is highly elastic (4.3). Second, it randomizes the medium by which farmers learn about the technology before eliciting demand, allowing for comparison between different mediums on demand. In this setting, the medium used to communicate information has no statistically significant impact on demand. This leads to the recommendation that policy-makers should rely on the cheapest and most scalable method for communicating information about new technologies (text messages in this context).

The second essay measures WTP for two low-cost moisture meters (USD<3 as opposed to USD>100 for other moisture meters) amongst smallholder maize farmers and traders in Western Kenya. Effectively managing moisture content before storage, plays an important part in containing the growth of fungi that produce dangerous toxins like aflatoxin. This essay makes three contributions. The first is to measure demand for two low-cost moisture meters using incentive-compatible methods for both farmers and traders. 80% of the sample was willing to pay more than the wholesale cost for at least one of the moisture meters, suggesting high potential demand for these technologies. Second is to study the impact of experimentally elicited risk preferences on demand for these technologies. Higher levels of risk aversion are correlated with higher levels of demand for the moisture meters, which are risk-reducing technologies. The third contribution is with regards to the method of eliciting WTP in a field setting. We use a Multiple Price List (MPL) format to elicit WTP instead of the open-ended BDM questions. While this format has been shown to be easier to understand, it can also be more susceptible to framing effects (Anderson et al.,2008). A comparison of two different list types (increasing prices versus decreasing prices) shows us that the list type can play a significant role on elicited WTP. Farmers bid 37% less when WTP is elicited using the increasing price list (versus the decreasing price list), while traders bid 6% more when WTP is elicited using the increasing price list.

The third essay describes the results from a Randomized Control Trial (RCT) in southern Tanzania, which evaluates two different post-harvest interventions targeted towards maize farmers in this region. Previous research suggests that farmers in much of Sub-Saharan Africa, face two main post-harvest challenges. The first is safely storing grain, minimizing losses due to insects and rodents, and reducing the growth of fungi that produce dangerous toxins. Limited access to improved storage technology might result in sales earlier in the year, because of high-expected losses (Kadjo et al.,2018). Second is managing the persistent price seasonality in grain markets in this region. In Mbeya Tanzania, where this research was conducted prices rose by 80% on average in 2015 and 2016 from harvest time in June, into the next planting season in January. Farmers may be unable to take advantage of this intertemporal arbitrage opportunity because of cash demands at harvest (harvest expenses, school fees etc.) and lack of a credit market (Stephen and Barrett, 2011).

In this essay the storage constraint is addressed using a triple layer hermetic storage bag (the PICS bag). The credit constraint is addressed via a loan product that is offered to randomly selected participants at harvest and is due back six months from then at an interest rate of 12%. The loan worth TSh 80,000 (USD 36), equivalent to the value of two bags of maize at that time it was offered) is collateralized with maize stored in the hermetic storage technology.

The main finding is that the loan intervention results in farmers storing 30% and selling 50% more maize later in the year. However the results from our study are likely attenuated by the unusual maize price pattern during our intervention year, no maize price rise in the lean season due to an export ban imposed by the Tanzanian government. We also find evidence for heterogeneity in our treatment effect, where farmers who were more credit constrained at baseline, benefited more from the interventions.

CHAPTER 2. WHAT DRIVES SMALLHOLDER FARMERS' WILLINGNESS TO PAY FOR A NEW FARM TECHNOLOGY? EVIDENCE FROM AN EXPERIMENTAL AUCTION IN KENYA[1]

2.1 Abstract

We use an incentive compatible experimental auction to measure demand for a new agricultural technology, a triple layered hermetic storage bag. When used properly, the bag creates an airtight seal that reduces storage loss from insect pests and neutralizes aflatoxin contamination in stored grain. We find that demand for this new technology is highly elastic (4.3) and that the wholesaler could increase profit by lowering the price. We also find that farmers' valuation for the bag is not significantly different based on the medium through which information about it is communicated to them, either text, audio or video messages. This suggests that practitioners should use the cheapest option for disseminating information, which is text messaging in this context. In addition, we find that farmers who have prior awareness of the bag are willing to pay 20% more on average than those previously unaware of it. In total, the highly elastic demand for the improved bags, along with the fact that prior awareness of the bag leads to higher willingness to pay, suggests that a one-time price subsidy for the new technology could spur demand and increase future adoption.

2.2 Introduction

What drives the adoption of new farm technologies amongst smallholder farmers in the developing world? This is an important question for policymakers and researchers, because new technologies can increase agriculture productivity, improve food security and help enhance the economic status of farming households. Better understanding of farmer characteristics and policy mechanisms that drive technology adoption help practitioners create programs that target those most likely to adopt a technology and benefit from using it.

Although the literature on agricultural technology adoption is extensive, very few studies have estimated demand for technologies using experimental auctions. Experimental auctions allow

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[1] This paper has been co-authored with Amy Z Chen, Dr. Patricia Pina, Dr. Jacob Ricker-Gilbert (committee chair) and Dr. Daniel Stein. This essay is available for citation as a published article in Food Policy. It is accessible at: https://www.sciencedirect.com/science/article/pii/S0306919218306353

precise measurement of willingness-to-pay (WTP), using real stakes and products. The objective of the present article is to measure demand for a new agricultural technology, a triple layered hermetic (airtight) storage bag amongst smallholders in Kenya using an experimental BDM auction (following Becker, Degroot, and Marschak, 1964). When used properly, the bag, called a Purdue Improved Crop Storage (PICS) bag, creates an airtight seal that reduces storage loss from insect pests and neutralizes aflatoxin contamination in stored grain. While the PICs bag is effective at reducing storage losses, it is significantly more expensive than traditional woven bags that offer no protection from insects or aflatoxin {roughly KSh 250 for a 90 kilogram PICS bag vs. KSh 80 for a 90 kilogram woven bag}. Therefore, adoption may not be automatic amongst limited resource smallholder farmers and they may be sensitive to price.

With this in mind, we answer three research questions related to the adoption and willingness to pay for this new storage technology: 1) How elastic is demand for the new bag? 2) Does prior awareness of the bag affect willingness to pay? 3) Is the average WTP affected by the information medium (i.e. by video, text or audio) by which farmers learn about the technology?

We answer these questions by conducting an experiment in which we randomize the medium of information through which the participant learns about the bag, and then subsequently measure their WTP using a BDM auction. This allows us to clearly measure the impact of the information medium on farmer valuations. Almost none of the 682 smallholder farmers in our sample from western Kenya had ever used the PICS bags before our auction, though some had heard about it.

Our article makes an empirical contribution to the vast literature on technology adoption, using a PICS bag as an example. Our work most closely fits in with previous studies on how farmer characteristics and behavior affect agricultural technology adoption amongst smallholders in the developing world. Work by Feder et al. (1985) point out that adoption rates are heterogeneous across farmer characteristics with risk preferences, education and tenancy status all playing a role. Recent work by Suri (2011) confirms the role of heterogeneity in returns on technology adoption among smallholders in Kenya. Fuglie and Kascak (2001) highlight the role of land quality and farm size, while Cunguara and Damhofer (2011) find that market access can affect returns to technologies and thereby affect adoption rates. There is also growing literature documenting the role of one's own experience, social networks and learning (Besley and Case, 1993; Foster and Rosenzweig, 1995; Conley and Udry, 2010) as possible determinants of the factors that drive adoption amongst farmers.

Our article specifically builds upon existing literature related to farmer WTP for new technologies, most of which uses stated preference methods. For example, Bell et al. (2014) use choice experiments to make the case that farmers in Pakistan will pay for irrigation services. Qaim and De Janvry (2003) and Horna et al. (2007) also use choice experiments to estimate demand for seed variety traits, while Hill et al. (2011) estimate demand for an insurance product. The challenge surrounding stated preferences methods is the inherent hypothetical bias due to the lack of actual transactions.[2] Another problem with stated preference methods is that the difference between actual and hypothetical bids is very context specific (List and Shogren, 1998).

Recognizing this issue, the present article is among a relatively small group of papers that use experimental auctions to measure demand for agricultural products in the developing world. Stein and Tobacman (2016) measure demand for an innovative agriculture insurance product in a lab setting using BDM amongst Indian farmers. Cole et al. (2016) measure valuations for a new agriculture insurance product and an information service using two methods, BDM and the fixed price method. One of their main findings is that valuations elicited using the two different methods are largely similar. Lybbert et al. (2018) measure WTP for laser land levelling services in India to determine what type of discounts would be the most cost-effective. Waldman et al. (2014) use a Vickrey auction to determine that demand for new crop varieties is overstated when stated preference methods are used to elicit farmer WTP.

Results from our BDM auction reveal that demand for the PICS bag is highly elastic, with an elasticity estimated at 4.3 between the price range of KSh 200 and KSh 250.[3] This high elasticity suggests that the wholesaler for PICS bags in Kenya could increase their profit by 29% if they lower the suggested retail price from KSh 250 to KSh 200. We also find that WTP is not significantly different for people who learned about the technology through either text or video messages, compared to audio messages. Prior awareness of the bag is the most important factor correlated with willingness to pay, as farmers with previous awareness of the PICS bags have a

[2] In some contexts cost and/or logistics concerns might make BDM or other revealed preference methods impossible to conduct, leaving stated preference methods as the only option.
[3] Ksh 100= US $1.00

WTP that is around 20% higher on average than those with no previous knowledge of the technology.

2.3 Background

2.3.1 The technology - PICS Bag

The present article is specifically concerned with estimating WTP among smallholders for a new, improved storage technology designed to reduce losses from insects, mold and rats during on-farm storage. The PICS bag developed at Purdue University in the United States is a three-layer hermetic bag that consists of an outside layer of woven polypropylene and two inner layers of polyethylene.

Without hermetic storage or other effective technologies, quantity losses due to insects, mold and rats can be a major source of loss in the grain supply chain in the developing world. For maize specifically, insect pests alone can damage 20-30% of a stored crop after six months (Boxall, 2001). In addition to these losses, there is also depreciation in the economic value of damaged maize. In a study in Benin, Kadjo et al. (2016) use revealed preference methods to measure price discounts and find that damaged grain is discounted by 3% on average, although these price discounts for damaged maize disappear as people grow desperate in the lean season.

Government response in many countries has been to advocate the use of storage insecticides like Actelic. However, one serious drawback is that use of insecticides can be extremely dangerous for consumer health if insecticide treated maize is consumed before the latency period of around three months ends (Tefera, 2012).

There is evidence that farmers who use PICS bags use the technology in place of storage chemicals. Omotilewa et al. (2018) find in Uganda using experimental data that giving the PICS bags to farmers reduces the likelihood of using storage chemicals by 4%, and increases the length of storage. In addition, the airtight seal of the PICS bag stops mold growth and prevents the spread of aflatoxin in stored grain that is properly dried (Williams et al., 2014). Using a RCT that involved nearly 2,000 smallholder households in southern Senegal, Prieto et al. (2017) compare various post-harvest technologies to find that the PICS bag is the most effective at reducing aflatoxin levels in stored maize.

PICS bags were initially disseminated on a large scale in West and Central Africa and investments were made to develop commercial supply chains of the bags. By 2014, nearly 2.5

million bags had been sold in the regions, with continued demand for more (Murdock et al., 2014). As a more specific example, PICS bags were introduced in 2015 to Kenya, and a recent study in Kakamega district of western Kenya found that after just two calendar years 6% of the sample had purchased a hermetic bag (Channa and Ricker-Gilbert, 2017). It should be noted that the PICS bag can be utilized for multiple grain and legume crops.

As mentioned in the introduction, the potential drawback relative to the single layer woven bag is the PICS bag's higher upfront cost {KSh 250 per one 90 kg bag, vs. KSh 80 for a single layer woven 90 kg bag that offers no protection against insects, molds or other pests}. However, research indicates that hermetic bags are more cost effective than alternate storage methods in the longer run. For example, Ndegwa et al. (2016) find using randomized control trial (RCT) data from Kenya that the bags are profitable if used for four seasons.[4]

2.4 Experimental Design

Our experiment took place in the Western and Rift Valley province (older administrative divisions) of Kenya. The areas where the survey was conducted are major maize producers in Kenya (ICPAC Geoportal, 2017), and have two major maize seasons. The long rain season starts with planting in March-April and ends with the harvest in August-September. The short rain season (where a much smaller proportion of farmers plant maize) starts with planting in October-November and ends with the harvest in March-April. The original sample consisted of 723 farmers in our sample from six counties: Trans Nzoia, Uasin Gishu, Bungoma, Elgeyo Marakwet and Nandi. Out of this sample, 682 farmers agreed to participate in the study and provided their willingness to pay for PICS bags.[5] The sample of farmers consisted of customers from a local microfinance bank, most of whom were taking part in a separate evaluation of an agricultural information service.[6]

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[4]To get a sense of the PICS bag usage cost versus the standard gunny when pesticide is used:
Cost of 1 synthetic bag= KSh 80+ Cost of Pesticide per bag= KSh 13 +Application Labor per bag= KSh 38 =Total Cost= KSh 131 /bag. This is smaller than the cost of the PICS bag at KSh 250. However, even assuming that both methods provide equivalent protection against loss, this simple back of the envelope calculation suggests that the PICS bag is more cost effective if it is used for at least two years. Anecdotal evidence suggests that it can last 3 years

[5] 20 farmers were surveyed but did not enter the BDM part of the study because they withdrew consent. Frequently this was because they gave moral/ethical/religious reasons for not wanting to participate in the auction. Additionally 21 of those who had a successful bid for the bag and agreed to pay later but then did not pay. We do not consider any of these respondents so we have 682 bids out of the 723 surveyed.

[6] In order to increase the sample size for this study, we recruited additional farmers were not part of the agricultural information evaluation to participate in this study. These participants were also customers of the local microfinance back, and consist of 146 of the 723 farmers in our sample. And it included 123 out of the 682 farmers from whom we got the final

Farmers were not paid a participation fee, so any purchase of PICS bags came from their own money. There is a trade-off with regards to participation fees: providing farmers money to participate eases any temporary liquidity constraints that may lessen WTP, but also might increase WTP by heightening social desirability bias. In this work we address farmer liquidity concerns at the time of the auction by allowing farmers to pay later when they could raise the money for the bag (within the next week).

Researchers from IDinsight, a non-profit research organization, managed the implementation of the auction. Prior to eliciting their WTP, farmers were presented information on the hermetic storage bags using a randomly assigned medium. One of these was a text message, the other an audio message and the third a video message (all of the messages were in Swahili).[7] Each message was delivered to the respondent by the enumerator conducting the auction on an Android smartphone before the respondents were asked to place their bids. The content of the message across the different mediums was kept very similar. The key point of the message in each medium was that the PICS bag allowed for storage without chemicals.

After this, the participants were given an outline of the auction process and were told that it would be in their best interest to bid their maximum true valuation for the bag. Participants were also told that the bags were available in the nearby markets at prices starting from KSh 250.[8] The participants had a practice round with biscuits, which followed the same steps as the final auction with the bag.

Briefly, the BDM auction was implemented as follows: After the practice round the participants were told to bid for the bag in multiples of ten shillings. After the bid, the enumerators explained to the participant exactly what would happen in different scenarios when the offer price was drawn, and gave them a chance to adjust their bid. For example, if the participant bid 50 shillings, the enumerators told them that if the random price that was drawn was higher, such as 60 shillings, then they would not be able to purchase the bag. If however the price drawn was lower for example 40 shillings, then they would get to purchase the bag at 40 shillings. This was

bid. Reported WTP for PICS bags was not significantly different between the farmers who were part of the separate evaluation and the others recruited solely for this study (p value=0.6687).

[7] The specific messages used were developed from a Bell flyer, a PICS audio jingle made for Tanzania (https://www.youtube.com/watch?v=vAgQMAKOHO8&feature=youtu.be), and a PICS video made for Tanzania

[8] The reason we decide to inform participants about the market price, is because we have heterogeneity in our sample regarding how well informed the participants are about the market. In order to control for this heterogeneity with regards to market information, everyone was informed about the current market price. Although stating a market price may anchor WTP, we believe that having some concept of an accepted price for an item provides a realistic context for people to make valuations.

repeated until the participant settled on a final bid. After the bid, the enumerator presented the participant with a bag full of sealed envelopes, and the participant chose one envelope from the bag. The participant then opened the envelope and read the price, and then the enumerator instructed the participant on the outcome of the game, which resulted in no sale or the participant purchasing the PICS bag.

If the participants did not have the required money to purchase the bag at the time of the experiment, they could arrange a time to meet with the research team in the next two weeks in order to make the purchase. The vast majority (56/58) of farmers who purchased bags did so using the mobile money service M-PESA.

2.5 Empirical Model

2.5.1 Elasticity Estimation

The first objective of our study is to estimate the elasticity of demand for improved storage bags. To do so, we estimate the market demand curve for the PICS bags using the WTP data from respondents in our sample. We estimate the elasticity for the bags as the proportion of individuals willing to purchase at each price using survival analysis. [9] Equation 1 shows the formula we used to calculate this proportion. [10]

$$S_j = \prod_{k=1}^{j} \frac{n_k - d_k}{n_k} \tag{1}$$

In the equation above n_k denotes the number still willing to purchase at price point k, and d_k denotes those whose WTP was less than k. The standard errors for the proportions calculated in equation 1 are estimated using equation 2.

$$st_j = S_j * \sqrt{\sum_{k=1}^{j} \frac{d_k}{n_k(n_k - d_k)}} \tag{2}$$

[9] The proportion of participants willing to pay at each price is equivalent to the quantity demanded since each participant had the option to bid for only one bag.

[10] Equation 1 and 2 have been taken from StataCorp. 2014. STATA survival Analysis Release Manual. Release 14 College Station, TX: Stata Press. The equations in this manual have been adapted from Kalbfleisch and Prentice 2002.

It is a simple extension to calculate the elasticity using the proportions estimated in equation 1 with equation 3 below.

$$\varepsilon_s = \%\Delta S_j / \%\Delta Price_j \tag{3}$$

The standard error for the elasticity estimate using the delta method estimated in equation 4 is as follows:

$$\varepsilon_{st_s} = st_j * (1/\Delta Price_j)^2 \tag{4}$$

The proportion of individuals willing to purchase at each price is plotted against the price in Figure 2.1, and the standard errors from equation 2 are then used to calculate the confidence intervals, also shown in Figure 2.1.

2.5.2 Estimation of the determinants of WTP

The second objective of the article is to test which factors affect an individual's WTP for the improved storage bags. We do so by estimating a model of demand for PICS bags by individual i as follows:

$$WTP_i \ = \ \boldsymbol{M_i}\gamma + A_i\delta + \ \boldsymbol{X_i}\beta + \varepsilon_i, \quad \varepsilon_i \sim N(0, \sigma^2) \tag{5}$$

WTP is the amount the respondent is willing to pay for one bag (between 0 and 300 KSh). The vector of dummy variables M, indicates the medium in which the respondent learned about the PICS bags; either through text, audio, or voice. The coefficient estimate of $\hat{\gamma}$ tests the hypothesis about whether WTP for PICS bags differs based on the medium in which information is presented to the respondent. Similarly, A is an indicator variable for whether the farmer had any prior awareness about the PICS bags before being approached for the auction, and the coefficient $\hat{\delta}$ tests the hypothesis about whether prior awareness of the technology affects WTP for it. We also include other variables that could affect farmer WTP in the vector X. This vector of variables includes respondent gender, size of farming area, quantity of maize harvested in the previous long rain season, length of period in months for which the maize was stored following the previous season and a dummy for whether the participant won in the practice round. The error term in equation 5 is denoted by ε. Given the experimental nature of our auction, we assume that ε is i.i.d (independent and identically distributed) normal.

2.5.3 Estimator choice

Nearly 38% of the observations in our sample have a WTP of zero, suggesting that the dependent variable exhibits properties of a corner solution variable (Wooldridge, 2010). This suggests that a linear specification estimated via Ordinary Least Squares (OLS) is likely to be biased.

The tobit specification provides an opportunity to deal with the corner solution nature of our dependent variable, WTP. However, a concern with the tobit is that it assumes the same underlying process for those who bid zero, and those who bid values greater than zero.

Fortunately, hurdle models are more flexible because they separate out the underlying decision into two. The first step involves the decision to "participate"; in our case this would be the decision on whether to bid for the bag at all. The next step is then the decision of how much to pay. We use the Cragg (1971) hurdle model which he specified to explain demand for durable goods.

$$s_i = \begin{cases} 1 \text{ if } \boldsymbol{M_i}\gamma + A_i\delta + \boldsymbol{X_i}\beta + \varepsilon_i > 0 \\ 0 \; otherwise \end{cases} \tag{6}$$

The continuous variable WTP_i is observed only if $s_i = 1$, and is modeled as in Cragg (1971):

$$WTP_i = \boldsymbol{M_i}\gamma + A_i\delta + \boldsymbol{X_i}\beta + v_i \tag{7}$$

In the specification above v_i has a truncated normal distribution, where it is truncated at $\boldsymbol{M_i}\gamma_v + A_i\delta_v + \boldsymbol{X_i}\beta_v$.

2.6 Results and Discussion

2.6.1 Data Description

Table 1 presents the key descriptive statistics for our sample of 682 respondents. We present the means and standard deviations for six key variables for all our respondents and by information medium (audio, text, and video) through which they received information about PICS bags.[11] The average WTP for the entire sample is KSh 83. A little more than half of the sample is female and the average farm size is 2 acres. Almost all the respondents (87%) stored some grain in the previous

[11] We also present these statistics by those presented the data by those who bid zero and those who bid above zero in Appendix 2.11.2.

season, and the average maize harvested was 2,717 kg for the previous season.[12] Additionally 38% of the respondents had a final bid of zero for the bag. We check for balance amongst the different media groups by using a multinomial logit regression, following Mckenzie (2015). Results suggest that we are unable to reject the null that these characteristics are the same for households across the different categories (information types) at a p-value of 0.51.

2.6.2 Demand and Profitability Analysis

Figure 1 presents the demand curve for PICS bags from our sample, which is based on the proportions estimated from the survival analysis at each price point. We use equations 3 and 4 discussed above to measure elasticity and the associated standard error. The price elasticity between the prices of KSh 200 and KSh 250 (the current retail price, and the suggested retail price based on the profitability calculation described below) is 4.3 [0.81][13] suggesting highly elastic demand. As the price falls by KSh 50 demand increases from 8.9 % to 16.7% of the sample who are willing to purchase the bag (Figure 2.1).

Based on the demand curve, we now consider whether the wholesaler of the bags could increase profit by lowering the wholesale and through this the retail price of the bags. [14] This analysis focuses on the retailer's and wholesaler's profit, and assumes that the ratio of the wholesale price to the retail price remains constant no matter what price the wholesaler sets.
At the time of the auction the wholesale price for retailers to purchase one PICS bag was KSh 190, equivalent to 76% of the current suggested retail price of KSh 250. We assume that the ratio of the wholesale to retail price always stays the same at 76%. This simplified analysis also ignores potential economies of scale in production costs, and assumes a fixed production cost of KSh 70 per bag. We assume KSh 70 to be the cost per bag to the wholesaler, since in our scenario the wholesaler and manufacturer are one entity. Figure 2 provides the profit of the wholesaler under these assumptions at price points ranging from KSh 0 to KSh 300. The profit is scaled by dividing it with the profit of the wholesaler at the current price of KSh 250. It turns out that the profit (in

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[12] We focus only on maize as our primary control and not beans which is the other main crop in this area that could be stored in PICS bags. Unfortunately, we do not have bean storage related data for 329 of our respondents. This occurred because for a random subsample the questionnaire size was reduced due to time issues. However, the remaining data suggests that this not a major issue because a majority of the remaining households, 85%, do not store any beans at al.

[13] The elasticity estimate is 4.3 and 0.81 is the associated standard error.

[14] In this scenario since Bell Industries manufacturers and then distributes to retailer, we assume that the manufacturer and wholesaler is one entity. In the rest of the paper we refer only to the wholesaler.

this simplified scenario) is highest when the retail price is KSh 200, and the wholesale price is KSh 152, 76% of KSh 200.

If the retail price is lowered from KSh 250 to KSh 200 (by lowering the wholesale price KSh 190 to KSh 152), the price decrease of 20% is accompanied by an increase in demand from 8.9% to 16.7%. For the wholesaler this works out to a 51% increase in revenue and 1.29 times more profit. (Figure 2.2).

In order to further illustrate this point we develop a scenario imagining that we have a total potential market (number of farmers who could buy PICS bags) of 1000. We use this scenario to show how sales and profit, of the retailer and the wholesaler, would change if the retail price is lowered from KSh 250 to KSh 200. In the status quo, the suggested retail price for one PICS bag is KSh 250, and the wholesale price is KSh 190. Our demand analysis indicates that 9% of the potential market purchases the bag at a retail price of 250, so 90 bags are sold. With 90 bags sold, the retailer's revenue is KSh 22,500 {KSh 250*90 bags} and her profit is KSh 5400 {(KSh 250-190)*90 bags}. In this situation the wholesaler's revenue is KSh 17,100 {KSh 190*90 bags} and her profit is KSh 10,800 {(KSh 190-70)* 90 bags}.

Now we look at what happens when the retail price of PICS bags is lowered to KSh 200, and the wholesale price to KSh 152. Demand would now go up to approximately 170 bags sold. Now the retailer's revenue is KSh 34,000 {KSh 200*170 bags} and her profit is KSh 8160 {(KSh 200-152)*170 bags}. The wholesaler's revenue is KSh 25,840 {KSh 152*170 bags} and her profit is KSh 13,940 {(Ksh 152-70)*170 bags}.

This example shows us that by lowering the retail and wholesale price of PICS bags by 20% demand goes up from 8.9% to 16.7%, the retailer profit goes up by 51% {(8160-5400)/5400} and the wholesaler profit goes up by 29% {(13,940-10,800)/10800}.

One limitation should be noted with regards to our demand and profit calculations. The result from the BDM auction cannot be extrapolated to a scenario where participants are purchasing multiple bags, because we elicit willingness to pay for only the first bag. It is possible that the willingness to pay for any bags thereafter is different. This is especially the case given the fact that the average farmer needs more than one 90 kg bag to store all of his or her maize.

2.6.3 Factors affecting willingness to pay for hermetic bags

Table 2.2[15] presents results from multiple empirical specifications of factors that affect WTP for hermetic bags. The first two columns present results from a parsimonious specification of a linear model estimated via OLS, while the next column is a full specification using OLS. The next two columns present the result from the tobit and Cragg's hurdle model respectively. All specifications give similar results.

Our results suggest that regardless of estimator and/or specification, the WTP for PICS bags is not different between text message, video message and audio message. The finding that the different mediums for marketing messages are not associated with different WTP has practical implications for policymakers and businesses looking to inform farmers about new technology. Given that the WTP is not statistically different across communication mediums, the focus should be on the medium which is least expensive in terms of reaching the most individuals per dollar or Shilling spent. For example, within the context of this study, it costs KSh 31,250 to send two text messages to 5,000 farmers per week, equivalent to KSh 3.13 per text message. It costs KSh 72,500 to send two audio messages to 5,000 farmers per week, equivalent to KSh 7.25 per audio message. Sending video messages is much more expensive and it would cost approximately KSh 105,000 to send just one video message to 5000 farmers, equivalent to KSh 21 per video message.[16]

Our findings predict that text messages have the same impact on demand, while being considerably cheaper than marketing based on audio or video messages. Another factor that might affect the medium used is the literacy level of the households that are being targeted as potential customers. In our case this does not appear to be a major concern as 90% of the respondents in our survey stated that they were able to read the text message, so text message appears to be a cheap (in terms of KSh spent on reaching a respondent) and accessible medium in this context. However if scaling up to a less literate population, then audio messages might be the most suitable medium to reach the most people.

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[15] Table 2.2 provides the result for 664 observations, because of incomplete data for a few variables. As a robustness check we run the same regressions with the mean of the missing value and regress with 682 observations. The results provided in Appendix 2.11.1 are qualitatively the same.

[16] Costs for audio and text estimated using EchoMobile's pricing for Kenya (https://www.echomobile.org/public/platform), which includes a fixed monthly service subscription cost plus cost per message sent. Costs for video messages are based on cost of sending a MMS through Airtel. We estimate that the smallest size of the compressed vide would be 300 KB which would mean three MMS to send the video. One MMS costs KSh 7. (http://africa.airtel.com/wps/wcm/connect/africarevamp/kenya/home/business/messaging-mms)

Results from Table 2.2 also indicate that across specifications, having previous awareness of hermetic bags increases the average respondent's WTP for PICS bags by KSh 15.12-20.95 compared to those who are unaware. This result is robust and statistically significant (p-value<0.05) across the different specifications, and corresponds to a relative increase in mean WTP of around 20%.

We also find that the dummy for winning in the practice round is highly significant. This is an interesting find, and it seems likely that this is significant in the model is because WTP for biscuits and PICS bags is positively correlated. If an individual is willing to pay more for one, he or she is also willing to pay more for the other. Also naturally, in a BDM auction, if you bid more you are more likely to win.

None of the coefficients on additional individual characteristics that we include in the regression, (i.e. gender, farm size, months maize was in storage and quantity of maize harvested), are significantly different from zero. While there may be other factors affecting the variation in WTP that we do not observe in our model, our experimental design should control for concerns about biased coefficient estimates. Recall from table 1 that the medium of information shown to a particular farmer (audio, video, text) was randomly chosen, so demographic variables are balanced across medium of information as shown in table 1 which we discussed earlier.

2.7 Conclusions and Policy implications

The present article uses a Becker-DeGroote-Marshack (BDM) auction to estimate willingness to pay (WTP) for a new farm technology (PICS hermetic storage bags), amongst a sample of 682 smallholder maize farmers in western Kenya. The hermetic storage technologies are more effective than traditional woven bags at eliminating insect, mold and other pests during storage, but are significantly more expensive than other bags available at the market. Awareness was low and adoption was non-existent among our sample during the time of the auction, making this a useful case study on WTP and adoption for researchers and practitioners working towards improving farm technology adoption in the developing world.

We find that demand for the hermetic bags in our sample is highly elastic (elasticity is 4.3). High elasticity of demand for the bags is understandable in this context as people may be unsure of the technology's benefits relative to its price. A simple analysis of profit suggests that the manufacturer of PICS bags in Kenya can increase their profits by lowering wholesale prices. For example, lowering the bag's price by 20% from KSh 250 to KSh 200 would increase profit for the retailer by 51% and profits for the wholesaler by 29%.

Another key finding is that the medium of information about the technology (text, video or voice) does not affect willingness to pay. This finding holds significant practical value. If there is no differential impact on willingness to pay for the technology between all mediums, then practitioners should use the most cost-effective method to spread awareness about new technologies. While text-messages are clearly the most cost-effective method in our context, audio and video messaging could be more appropriate in different places depending on relative costs of using text, vs. audio, vs. video messaging and the literacy of the target population.

While most of the observed individual characteristics do not affect farmer valuation, the one exception is that prior awareness is a statistically and economically significant factor positively correlated with willingness to pay for the bag. This finding is closely linked with the results from a RCT in Uganda examining the impact of initial subsidies on adoption of a new hermetic storage technology (Omotilewa et al. 2018). Their results (based on the same hermetic technology described in this paper) suggest that when there is uncertainty surrounding a new technology, a one-time subsidy can raise demand. This is a useful lesson for those who are looking to introduce new technologies to farmers, suggesting that initial (and temporary) subsidies for a new technology can be an effective way of scaling up adoption.

In addition, it should be noted that awareness and use of hermetic technology among our sample is low. Recall from table 1 that only 23% of respondents are aware of hermetic technology, while only three respondents in the sample actually use hermetic technology (0.04%). It is possible that once these respondents become more aware and have experience using hermetic bags their WTP will increase, and the profit maximizing price for the bag for manufacturers and retailers may also increase. This would suggest that some investment in extension and advertising by actors in the PICS supply chain to raise awareness about the technology could be profitable for them.

2.8 Funding Declaration

IDinsight has partnered with PICS and Bell Industries to conduct a willingness to pay exercise with farmers surrounding Kitale and Eldoret to determine smallholder farmers' willingness to pay for PICS bags in these areas, and whether demand varies by which informational message farmers receive about the PICS bag (text, audio, or video).

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2.10 Tables and Figures

Table 2.1 Summary Statistics by media type

	Audio	Text	Video	All
PICS WTP bid for analysis (KSh)	81	90	81	83
	(92)	(90)	(81)	(92)
Prior PICS awareness	0.27	0.24	0.19	0.23
	(0.45)	(0.42)	(0.39)	(0.42)
Respondent is female (binary)1=Female	0.56	0.54	0.56	0.55
	(0.50)	(0.50)	(0.50)	(0.50)
Total Maize Harvested(metric tons)	2.70	2.40	2.50	2.50
	(4.50)	(2.90)	(4.70)	(4.10)
Farm Size(Acres)	1.95	2.00	1.90	2.00
	(2.10)	(2.30)	(2.30)	(2.30)
Months the maize was left in storage during the previous season(months)	1.60	1.60	1.60	1.60
	(1.50)	(1.80)	(1.60)	(1.60)
Individual won biscuit in demonstration round (Won=1)	0.58	0.56	0.62	0.59
	(0.49)	(0.5)	(0.49)	(0.49)
Observations	229	194	241	664

Standard deviations in parentheses; Notes-In order to check for balance across categories we run a multinomial logit using the media type as the dependent variable. See Mckenzie (2015) . The p- value for a joint hypothesis test is 0.505 indicating that we cannot reject the null hypothesis that that the means of each of these variable is not statistically different across the different groups.

Table 1 includes statistics from 664 observation, for which complete data was available for all variables

Table 2.2 Factors affecting Willingness to Pay for PICS bags (in Kenya Shillings)

	(2) OLS (parsimonious specifications)		(3) OLS (Full Model)	(4) Tobit	(5) Hurdle Model
Prior PICS awareness (binary)1=Aware	20.95** (8.89)		15.93** (7.864)	20.19* (11.99)	15.12** (7.420)
Respondent is female (binary)1=Female			-0.926 (6.747)	2.159 (10.37)	-0.122 (6.686)
Total Maize Harvested (metric tons)			-0.000281 (0.00159)	-0.000221 (0.00242)	-8.32e-05 (0.00173)
Farm Size (Acres)			3.244 (2.706)	4.076 (4.122)	2.882 (2.483)
Shown a text message explaining the technology¥		8.88 (9.24)	10.57 (8.355)	18.21 (12.87)	10.27 (8.408)
Shown a video explaining the technology¥		-0.095 (8.39)	-1.255 (7.900)	3.544 (12.19)	-0.317 (7.674)
Months the maize was left in storage during the previous season (months)			1.809 (2.045)	4.600 (3.145)	1.814 (2.055)
Individual won biscuit in demonstration round (Won=1)			70.77*** (6.741)	132.9*** (11.11)	60.70*** (6.155)
R-squared	0.013	0.005	0.024	0.0025	0.0039

Robust standard errors in parentheses; OLS results and tobit and double hurdle marginal effects reported; Dummies for two areas of Eldoret and Kitale are included in the specification.
¥ Compared to a control of audio message; Total number of observations in each specification is 664; *** p<0.01, ** p<0.05, * p<0.1; McFadden’s pseudo R-squared reported for the tobit and Craggs hurdle regression

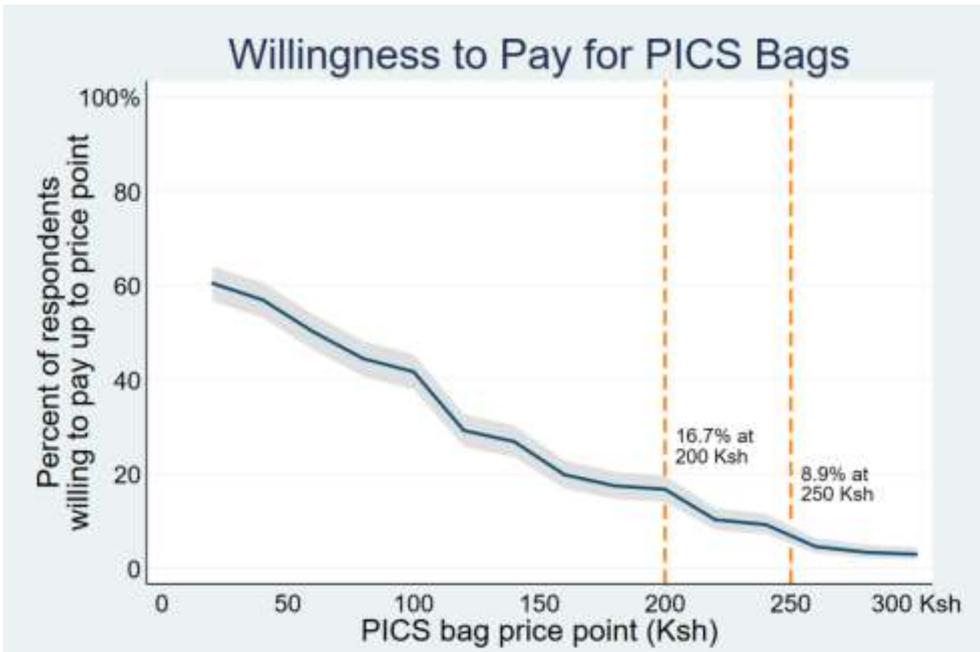

Figure 2.1 Willingness to Pay for bags

The graph above is built using survival analysis. N = 682. These estimates represent the proportion of farmers willing to pay at or above a given price. Gray shaded region represents 95% confidence interval. 41 survey respondents not included in these WTP estimates because of various reasons including 6 cases where the enumerator explained the activity incorrectly. Orange lines mark out the proportion of individuals willing to buy at KSh 200 and KSH 250.

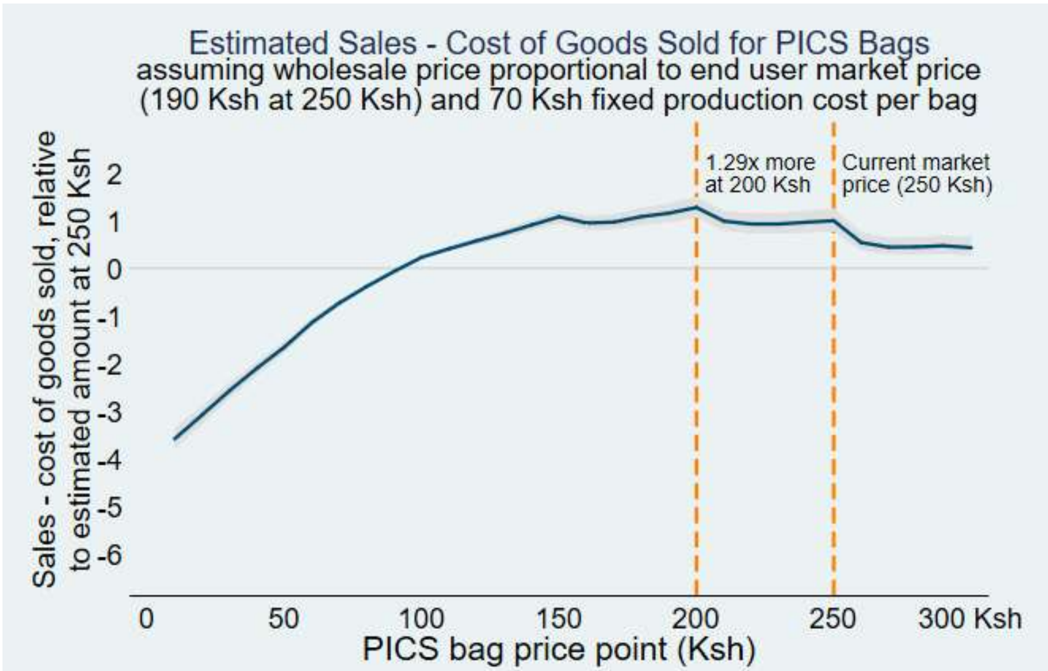

Figure 2.2 Profitability Analysis

N = 682. These estimates are calculated as the sales - cost of goods sold per bag (price point * 190 Ksh (Bell wholesale price) / 250 Ksh (end user market price) - 70 Ksh (fixed production cost per bag)) multiplied by the percentage of respondents willing to pay at that price. The estimates are then divided by the estimated profit at 250 Ksh. This model does not incorporate varying production costs by volume, nor other marketing and distribution costs. This model does not incorporate varying production costs (input and manufacturing costs) by volume, nor other marketing and distribution costs. Gray shaded region represents 95% confidence interval.

2.11 Appendix

2.11.1 Appendix -Factors affecting Willingness to Pay for PICS bags using full sample (in KSh)

	OLS(Full Model)	Tobit	Hurdle Model
Prior PICS awareness (binary)1=Aware	19.83**	25.47**	17.89**
	(8.485)	(12.92)	(8.116)
Respondent is female (binary)1=Female	-1.832	-2.498	-1.431
	(7.287)	(11.15)	(7.080)
Total Maize Harvested (metric tons)	-0.000133	0.000487	9.21e-05
	(0.00172)	(0.00261)	(0.00189)
Farm Size(Acres)	3.573	3.840	2.982
	(2.86)	(2.81)	(2.78)
Shown a text message explaining the technology¥	8.998	10.67	6.231
	(9.023)	(13.77)	(8.862)
Shown a video explaining the technology¥	1.758	7.555	2.118
	(8.527)	(13.15)	(8.337)
Months the maize was left in storage during the previous season (months)	1.418	4.170	1.601
	(2.209)	(3.413)	(2.261)
R-squared	0.022	0.0025	0.0039

Robust standard errors in parentheses; OLS (parsimonious specification) results and tobit and double hurdle marginal effects reported; Dummies for two areas of Eldoret and Kitale are included in the specification. ¥ Compared to a control of audio message; Total number of observations in each specification is 682; *** p<0.01, ** p<0.05, * p<0.1; McFadden's pseudo R-squared reported for the tobit and Craggs hurdle regression; This table is added as a robustness check by rerunning the specifications with means of the missing values added. The coefficients do not change qualitatively

2.11.2 Appendix- Summary Statistics by bid

	Bid greater than Zero	Bid is zero	Total
Prior PICS awareness	.25 (.43)	.22 (.41)	.23 (.42)
Respondent is female (binary)1=Female	.55 (.5)	.56 (.5)	.56 (.5)
Total Maize Harvested(kg)	2,668 (4,152)	2,167 (3,052)	2,478 (3,780)
Farm Size(Acres)	2.1 (2.4)	1.7 (1.9)	1.9 (2.2)
Months the maize was left in storage during the previous season(months)	1.7 (1.6)	1.4 (1.6)	1.6 (1.6)
Observations	413	251	664

Standard deviations in parentheses; Table includes statistics from 664 observation, for which complete data was available for all variables

CHAPTER 3. WILLINGNESS TO PAY FOR A NEW FARM TECHNOLOGY GIVEN RISK PREFERENCES: EVIDENCE FROM AN EXPERIMENTAL AUCTION IN KENYA[17]

3.1 Abstract

Encouraging adoption of tools that measure crop moisture content is important for food safety, because aflatoxin growth (dangerous toxins produced by the Aspergillus family of fungi) can be stopped by drying crops to 13.5% moisture content or below before storage. However, farmers and traders who do not have access to moisture measurement tools may not be able to fully observe moisture content in their grain. This may inhibit the effectiveness of rural markets to deliver safe quality grain to consumers. Several low-cost devices (USD<3 as opposed to USD>100 for moisture meters) have recently been developed that can accurately test moisture content in maize and thus contribute to increased food safety, and market participation for millions of low-income households. This article (i) estimates the demand for two such devices among smallholder farmers and small-scale traders in Western Kenya, (ii) measures the impact of individuals' risk aversion on willingness to pay for these devices, and (iii) measures framing effects, by eliciting valuations with two different frames (increasing versus decreasing price lists), when using a multiple price list format to conduct auctions in the field. We find that more than 80% are willing to pay more than cost for the cheaper of the two devices and that farmers, who tend to be growing maize primarily for own consumption, are willing to pay more than traders. We interpret this finding as evidence that food safety concerns, rather than quantity losses, are driving demand for these technologies. More risk averse individuals report a slightly higher WTP for these risk-reducing devices. Finally, farmers, who value these devices based on their food safety benefits, are very sensitive to framing effects mean bids elicited with an increasing price list were 37% higher than those with a decreasing price list.

[17] **This work has been has been co-authored with Dr. Jacob Ricker-Gilbert (committee Chair), Dr. Hugo De Groote and Dr. Jonathan Bauchet (committee member).**

3.2 Introduction

Aflatoxins are toxins produced by the Aspergillus family of fungi that are known to cause liver cancer, and have been linked to malabsorption of nutrients and stunting in children (Williams et al. 2004; Hoffmann, Jones, and Leroy 2018; Liu and Wu 2010). In addition, nearly 20,000 deaths were attributed to aflatoxins poisoning in 2010 by the World Health Organization (WHO) (Havelaar et al. 2015). As many fungi, Aspergillus thrive in wet and warm conditions. Therefore, a key tool for reducing aflatoxins contamination, is effective management of the moisture content of maize after harvest (Chulze 2010; Oyebanji and Efiuvwevwere 1999).

The challenge is that moisture content is imperfectly observable to potential buyers in developing countries, where moisture meters are priced out of range of most smallholder farmers and small-scale traders (McCoy et al. 2016). With moisture content not fully observable, sellers have little incentive to dry maize to levels that are safe for storage and consumption, because drying is costly in terms of labor hours (potentially up to 4-5% of the value of the maize)[18]. In fact there is a disincentive to dry in many sub-Saharan Africa countries, in which maize is sold by volume or weight, because drier maize weighs less and has lower volume than wet maize. Both these factors combined suggest that the unobservable nature of moisture content in maize creates a "lemons" market (Akerlof 1970). In this context, nobody is incentivized to produce, dry, and sell quality, safe maize.

This article primarily aims to estimate demand for two low-cost technologies (USD<3) that remove most of the uncertainty in measuring maize moisture content, thus potentially solving the "lemons market" problem. Specifically, we use experimental auctions to estimate willingness to pay (WTP) for a hygrometer and a DryCard™ among 584 smallholder farmers and traders in Western Kenya. The devices do not directly provide grain moisture content readings, but measure relative humidity in the air, which can be then translated into moisture content readings. The hygrometer offers a numerical reading for the humidity, as opposed to the DryCard™ which changes color in response to humidity. The hygrometer however is more expensive (Figure 3.1;

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[18] This estimate is based on self-reported farmer WTP of $1.85/bag for a new drying service in a survey conducted by ACVIDOCA. However his rough estimate can vary depending on the weather. For example, it would be more costly during wetter years.
The price of maize per 90kg bag is taken to be $35, based on wholesale maize prices in February 2016.
https://agricultureauthority.go.ke/wp-content/uploads/2016/06/AFA-e-bulletin-Q4-2016-17.pdf ("4th Quarter E-News Bulletin April – June 2017" 2017)
http://www.acdivoca.org/wp-content/uploads/2017/05/Kenya-Feasibility-Final.pdf (Walker and Davies n.d.)

detailed descriptions of devices are provided in Section 3.5.1). For ease in writing, we refer to these devices as moisture meters in the rest of the paper.

The hygrometer and DryCard™ have been shown to be effective moisture meters in a lab setting, however there is no information so far on their demand amongst smallholder farmers and traders for whom they were designed (Tubbs, Woloshuk, and E. Ileleji 2017; Thompson et al. 2017). Akter et al. 2018 measure demand for a moisture meter amongst 140 farmers in Bangladesh, but the moisture meter used was expensive, costing upwards of US $70 as opposed to the upper range of US $3 for the devices used in this paper. Another important contribution of our study is to include both maize traders and farmers in our sample. This is useful in terms of better understanding drivers of demand for these technologies, since farmers and traders might value the meters for different reasons. We also measure demand for two different devices that vary in terms of cost and accuracy, which allows us to measure respondent valuation for specific characteristics of moisture meters.

In addition to estimating demand for moisture meters, we examine how risk preferences affect WTP for the two new (to the participants) technologies. An extensive literature has shown that farmers' risk preferences are major determinants of production and technology adoption decisions (for example, Feder, Just, and Zilberman 1985; Foster and Rosenzweig 2010; Karlan et al. 2014; Cardenas and Carpenter 2008; Cole, Giné, and Vickery 2017).

Examining the role of risk preferences on WTP make for an interesting case study in our context because the moisture meters are perhaps more intuitively seen as an insurance device rather than a production technology, which implies that increased levels of risk aversion should result in increased demand for the technology. Notably Shimamoto et al. (2017) find ,using a sample of 142 farmers in Cambodia, that being more risk averse increases the probability of using moisture meters to measure the moisture content of rice seed (Shimamoto, Yamada, and Wakano 2017).
We build on existing evidence by experimentally eliciting WTP to measure demand for moisture meters, instead of previous use of the technology, and by eliciting risk preferences using real payoffs. In addition, in our setting awareness and knowledge of the products are null at the onset, therefore they are consistent across the sample.

The third and final goal of our article is to provide empirical insights on the method of conducting experimental WTP auctions in the field. We use a multiple price list format (MPL) to conduct the auction instead of the Becker-DeGroot Marschak (BDM) mechanism. In contrast to the BDM mechanism, which uses open-ended questions about the price that participants are willing to pay for an item, in the MPL format participants are asked a series of binary questions about their willingness to pay various amounts. After all questions are answered, one question is picked randomly, and the answer taken as binding. The MPL mechanism was first used to elicit valuations in the well-known paper by Kahneman et al. (1990) to study the Willingness to Accept (WTA) \Willingness to Pay (WTP) gap (Kahneman, Knetsch, and Thaler 1990). This approach has been used recently in the field in a developing country context to estimate valuations for laser land leveling services in India (Lybbert et al. 2018).The main advantage of the MPL format is its ease of explanation to participants compared to other elicitation mechanisms, a feature that was attractive given the population we study.

However, one of the challenges with using MPL are framing effects, where respondent valuations are affected by how the list is presented. Framing effects might be a reflection of the respondents utilizing all available information to value commodities and not necessarily a violation of economic models (Harrison, Glenn W.; Hastard, Ronald M.; Rutstrom 2004). Anderson et al. (2006) suggest that one way to address the impact of framing effects on valuations is to use more than one frame, and to control for the effect in the statistical analysis. We measure framing effects by randomizing the list type across participants: increasing or decreasing list type. The price range is the same in both lists, but the starting price and the question order (decreasing versus increasing) vary depending on the list.

The mean WTP in our sample is $1.20 for the hygrometer, and $0.87 for the DryCard™. Fifty percent and eighty percent of participants are willing to pay more than the wholesale cost of the hygrometer and DryCard™, respectively. While respondents are willing to pay more for the hygrometer which is perceived to be more accurate than the DryCard™, there is a larger proportion of the population willing to pay above cost for the DryCard™.

Farmers are willing to pay 30% more on average for either device compared to traders. We expect that farmers, only 30% of whom are selling any maize, are driven by food safety concerns such as aflatoxin contamination, even if grain damage is not apparent. This is unlike traders, who are likely to be driven primarily by concerns of more visible losses. We take this result then to suggest that quality concerns are a bigger driver of demand than quantity losses. The fact that volume of maize sales is not a significant factor in explaining WTP also seems to point in this direction.

Our results show that those who are more risk averse have higher WTP for the moisture meters, although this effect is small in magnitude. This result is in line with the fact moisture meters are risk-reducing, and can be seen analogously to an insurance device.

Finally, we find that the specific list type used to elicit WTP does affect valuations. Farmers bid 37% less than the average WTP when we use the increasing price list. We find a much smaller effect for traders, who bid 6% more than the average when we use the increasing price list. This result indicates that traders have more precise valuations, potentially because their demand is driven by relatively easier to monetize physical grain losses.

Our results show that framing effects can be large, especially when valuing something like food safety, on which it might be challenging to place a monetary value. While this requires more research one possible implication is to use multiple frames which allows for measurement of these effects.

3.3 Background on moisture content and aflatoxin

The disease burden created by the presence of aflatoxins in a staple commodity like maize can have severe implications for the economic productivity and health of millions of low-income families in developing countries (Bloom, Canning, and Sevilla 2004; Bhargava et al. 2001; Well 2007). Field conditions such as high humidity, and inappropriate post-harvest practices such as insufficient drying of the maize before storage can spur the growth of the fungi that produce aflatoxins (Kaaya, Kyamuhangire, and Kyamanywa 2006; Mahuku et al. 2019). Generally wetter maize stored in warmer weather will see higher rates of fungus growths during storage, and managing moisture content is therefore an important tool for ensuring food safety (Spanjer 2019)

There is evidence from our sample {as measured by reliability rankings for traditional methods, such as touching and biting kernels (see figure 3.2)}, and from research in Senegal that moisture content, which can be a signal for the presence of aflatoxins, is mostly unobservable or imperfectly observable to potential buyers (McCoy et al. 2016). The study from Senegal found, using an incentive compatible auction that respondents were willing to pay a premium for maize of moisture content of 14-16% that was explicitly labelled with the moisture content reading, as compared to maize that was unlabeled but of the same moisture content and identical in every other way. This suggests, that at least to some extent, maize within this moisture range is not perfectly observable to the buyers. In a separate study researchers in Kenya found, using experimental on-farm field trials, that aflatoxin concentration was almost double after 35 weeks when maize moisture content was above 14%, as compared to aflatoxin concentration in maize that was at moisture content between 13-14%, before it was put into storage (Ng'ang'a et al. 2016).

Maize markets in the developed world have at least partially resolved the issue of moisture content being unobservable in grains by standardizing moisture content grades at the time of purchase. These standards however are almost non-existent in rural markets in the developing world. A possible reason for this is that the grain moisture meters used in the developed world are relatively expensive, costing upwards of US $70, which is likely too expensive for small-scale farmers and traders in the developing world.

3.4 Conceptual Framework

This section provides a simple conceptual framework to develop the intuition behind the hypotheses that we test in this paper, which are related to (i) the determinants of demand for these devices, (ii) the impact of risk preferences on demand and (iii) the impact of framing effects on demand.

The moisture measurement devices discussed in this paper provide information about moisture content of maize. This information can translate into two benefits for users. First if the seller can find a market that offers a premium for maize dried below 13%, this would suggest that there is a financial benefit to him or her for having more accurate information about the moisture content of maize before sale. However, this is unlikely in our setting where such markets are limited. The other benefit, likely to be more relevant in this context, and discussed in the previous section, is that drying maize to below 13.5% has been shown to be effective at controlling aflatoxin growth and reducing losses during storage of maize (Oyebanji and Efiuvwevwere 1999).

$$(1 - \mathrm{p})\mathrm{U}(\mathrm{y}) + \mathrm{pU}(\mathrm{Y} - \mathrm{L}) = \mathrm{U}(\mathrm{Y} - \mathrm{X}) \qquad (1)$$

The equation above is an expression indicating willingness to pay amount X to avoid a loss "L". The "p" expresses the probability of the loss. In our context we see this as the probability of loss that the respondent will experience after storage if she does not purchase the moisture meter, and X is the amount that she is willing to pay for the moisture meter to avoid these losses. For simplicity we see L as only the loss that she will attribute to inaccurate moisture content information, and no other reason.

$$(1-\mathrm{p})\mathrm{U}(\mathrm{y})+\mathrm{pU}(\mathrm{Y}-\mathrm{L})-\mathrm{pLU}'(\mathrm{Y})+0.5\mathrm{pL}^2\mathrm{U}''(\mathrm{Y})=\mathrm{U}(\mathrm{Y})-\mathrm{XU}'(\mathrm{Y}) \tag{2}$$

We use a Taylor series expression around U(Y) to get the standard expression above shown in equation 2.

$$X = pL + 0.5\mathrm{pL}^2\mathrm{A} \tag{3}$$

We then solve for X (the willingness to pay to avoid loss) which is a function of the probability of loss, the value of the loss, and the individual's absolute risk aversion "A".

$$X = p(L^1(Qu) + L^2(Qa)) + 0.5\mathrm{p}(L^1(\mathrm{Qu}) + L^2(\mathrm{Qa}))\hat{}\,^2\mathrm{A} \tag{4}$$

We make a small extension to the expression in equation 3, and break L into quality and quantity losses of grain. By quality losses, we refer to maize that still appears undamaged but might be contaminated with high levels of aflatoxin, and by quantity losses, we refer to a physical loss in grain value. We treat the value of the loss as a flexible function of the grain quantity, with the form depending on individual preferences. We can then use this expression to develop some intuition about how each element of these equations effect X (the WTP for the devices).

$$\frac{dX}{dA} = 0.5p(L^1(Qu) + L^2(Qa))\hat{}\,^2 \tag{5}$$

First, we examine how increases in levels of risk aversion affect WTP. We assume that $\mathrm{p} \geq 0$ and $\mathrm{L} \geq 0$, since the probability of loss will be within [0 1], and L is the loss in terms of value attributable to inaccurate moisture content information. The result here is intuitive, that willingness to pay to avoid loss is increasing in levels of risk aversion.

$$\frac{dX}{dQu} = (\mathrm{p} + \mathrm{p}(L^1(\mathrm{Qu}) + L^2(\mathrm{Qa}))\mathrm{A}) * (L^{1\prime}(\mathrm{Qu})) \tag{6}$$

The sign of the derivative in equation 6, showing how willingness to pay 'X" changes with regards to quantity losses, depends on $(\mathrm{L}'(\mathrm{Qu}))$ since each component in $(\mathrm{p} + \mathrm{p}(L(Qu) + L(Qa))\mathrm{A})$ is ≥ 0. We define *Qa* as the quantity of grain that the respondent might perceive as being dangerous to consume because of contamination, and *Qu* as the quantity of grain that the respondent expects to be visibly damaged. This implies that $\frac{dX}{dQu} \geq 0$ and $\frac{dX}{dQa} \geq 0$. The more grain that the individual perceives will be damaged in either way, then the greater the value of the loss.

The specific form of $\frac{dX}{dQu}$ and $\frac{dX}{dQa}$ in our setup would depend on individual preferences, which is captured in their loss function. For example, the loss function for quality loss will determine the weight the individual places on the health concerns related to aflatoxin contamination. The loss function for the quantity of grain will determine the value of the loss, based on the market price faced by the individual. Farmers in our sample, who are growing mostly for own consumption (only 30% sell any maize), are likely to care about both quality and quantity losses in their own stored maize.

However, traders are likely to be less sensitive to non-visible damage for grain that they are selling and focused primarily on physical damage to the grain. This implies that traders would have lower valuations for the moisture meters. Another implication is that because it is easier to place a monetary value on a quantity loss compared to a quality loss, traders are also likely to have more precise valuations than farmers, who are putting relatively more weight on quality losses than traders. If these implications hold, and traders have more precise valuations, then traders should be less sensitive to the way that the auction is framed than farmers. This is because framing effects might create a reference point, which is less likely to be important if the individual can easily monetize the benefit of the technology that she is considering buying.

3.5 Experimental Design

The following section discusses the devices used in this study and the respondents. Then it describes the brief survey that was conducted, the auction to elicit WTP, and finally the lottery game. The process followed for each respondent is summarized in Figure 3.3.

3.5.1 Devices used in this study

We measured WTP for two low-cost moisture detection devices: a hygrometer, and a DryCard™. The hygrometer is a simple household device that measures humidity and temperature in the air. When placed in a small hermetic bag with a handful of grain, grain and air moisture come to an equilibrium within 15 to 30 minutes (Tubbs, Woloshuk, and E. Ileleji 2017).[19] For maize, a relative air humidity of 65% at temperatures between 20-30 degrees Centigrade indicates that moisture content in maize is between 12.5 % and 13.5%. This is the temperature range in most tropical and sub-tropical areas. In Kakamega for example, the location of the study, the average temperature is within a one degree variation of 20 degrees Centigrade for the entire year (CLIMATE-DATA.ORG n.d.). This means that the hygrometer users can use the 65% relative humidity reading as a critical value for moisture content in maize: readings of 65% of below indicate that maize

[19] In contrast, moisture meters measure grain moisture content directly, and provide a quasi-instant reading.

moisture content is below 13.5% and maize is considered sufficiently dry, while readings above 65% indicate that additional drying is required before putting the maize into storage.

The DryCard™, developed by the Horticulture Innovation Lab at the University of California – Davis, is a laminated strip of cobalt chloride paper, which changes color with humidity levels in the atmosphere. The color change has been calibrated with specific humidity levels. A blue-colored strip indicates that maize is sufficiently dry for storage, and a pink-colored strip indicates that maize is too wet for storage (Thompson et al. 2017).

The hygrometers used were calibrated by researchers from the USAID funded Feed the Future (FtF) Innovation Lab (IL) for Food Processing and Post-Harvest Handling at Purdue University, and the demonstration was based on the instructions of these researchers. The DryCards™ were provided to the team by researchers from the USAID funded FtF Horticulture IL at UC Davis.

Each moisture meter discussed above has its own strength and weaknesses. The hygrometer's moisture reading is numerical and does not require interpreting a color reading. In addition to being more accurate and unaffected by the light, the numerical reading can be particularly useful in a trading context, in which objective readings are required. However, the color reading of the DryCard™ may be preferable for people with limited education and knowledge of numbers. The DryCard™ also has the advantage of being much cheaper to manufacture. We estimate that the DryCard™ can be produced locally for about 15 cents/unit. The hygrometers must be imported from China; at a wholesale price of 90 cents. Essentially, the hygrometer provides more accuracy for a higher price than the DryCard™.

3.5.2 Sample

The study was conducted in Kakamega district in Western Kenya, where the main food crop grown by smallholder farmers is maize, and rainfall and humidity are high through the year (precipitation ranges from 61 mm-211 mm). To constitute the sample, we built upon a previous sample of farmers designed to be representative of the district. The initial sample of 312 farmers was representative of farmers in district in December 2015[20], and was chosen with a three-stage sampling design. Thirteen sublocations were randomly selected from the district, from which four villages were selected in each sublocation and six households from each village.

[20] This is a subsection of the current Kakamega county in Kenya

This experiment was conducted with 584 participants, 305 farmers (all those available from the original 312), and 279 maize traders. To develop a sample of traders, all the markets in Kakamega district were identified through collaboration with an extension officer from KALRO based in Kakamega city. After obtaining permission from the government representative at the market, the number of maize traders in each market was counted. If there were fewer than 30 traders, every trader in the market was interviewed. When there were more than 30, then enumerators were assigned to different parts of the market. They walked from one end to the other of the part assigned to them and approached every other maize trader they saw, described the project to them, and asked them if they would be willing to participate.[21]

3.5.3 Auction

The field work was conducted by a team of ten enumerators and two supervisors during February-March 2017. CIMMYT Kenya (International Maize and Wheat Improvement Center) hired the team of enumerators. KALRO Kakamega (Kenya Agriculture and Livestock Research Organization) helped establish contacts with the farmers and traders in the region.

Enumerators approached farmers in their homes and approached traders in the market. The enumerators explained that they were working with CIMMYT and would be discussing a new technology which could help tell the moisture content in maize. Enumerators told the respondents that they would have an opportunity to purchase the devices after a demonstration and a 20-minute household survey. Each participant was told that they would be given a participation fee of $3, but that this in no way obligated them to answer all the questions or purchase any of the items. The participation fee was given right after the respondent agreed to participate, before any of the activities began.

After the respondents agreed to participate, enumerators introduced the hygrometers and DryCard™, and explained the purpose and features of each of them. Each enumerator carried four small plastic bags, two each with wet and dry maize, and two hygrometers and DryCards™. They always started the demonstration by putting a DryCard™ and a hygrometer each in a bag of wet and dry maize. The enumerators then told the participants that while they waited for the devices to equilibrate, they would like to ask them some questions regarding their household, their maize

[21] Except for 15 cases all traders agreed to be surveyed. Additionally, they were 5 cases where the interview began but traders turned out not to be maize traders. We drop these from our sample.

production and post-harvest activities. Specifically, the survey included questions on household demographics, asset ownership and crops grown in the last long-rain season. The respondents were also asked about maize sales, storage practices, and knowledge of aflatoxins. The auctions for both devices were conducted after the survey.

We used the multiple price list format (MPL) to conduct the auction.[22] The MPL consists of a list of binary questions out of which one question is chosen randomly for payout. In our case respondents were not shown the entire table, and the questions shown in Table 3.1 were read out to them one by one, because we were unsure if all our sample would be literate.

We opted for the MPL over the BDM with open-ended questions because there is some evidence that the open-ended BDM can be challenging to explain to respondents. Cason & Plott (2014) found that American college students did not fully understand the BDM mechanism, and mistook it as a first price auction (Cason and Plott 2014). Berry et al. (2015) compared the BDM and take-it-or-leave-it design (TIOLI) in field experiments in Ghana and found that while the BDM can deliver relatively more precise valuations, it comes at the added cost of increased complexity during explanation. They found that BDM estimates are systematically lower then TIOLI valuations (Berry, Fischer, and Guiteras 2015). A supporting reason for choosing the MPL was also that the moisture meters were a completely unfamiliar item for our sample. Not only was our specific technology unfamiliar to respondents, only 7/584 respondents had used any type of moisture meter at all. The only other reference for measuring moisture content in maize being the traditional methods, such as biting the maize, or listening to the rattle of the maize. This made the implementation of the open-ended BDM even more challenging.

However, as we discuss earlier the MPL can be susceptible to framing effects. We utilize the suggestion by Anderson et al. (2006) of varying the frame in the elicitation tool to quantify these effects. We use two different price lists, the first where the price starts at 20 cents and increases to $3 (increasing), and another where the price starts at $3 and decreases to 20 cents (decreasing). The status quo for each of these lists is the same i.e. no moisture meter. We use this design to examine if there could be an anchoring effect due to the starting price (Ariely and Simonson 2003), or order effects because of the direction of the questions. These effects may be

[22] For guidelines on implementation we borrow from the manual produced by Healy (2018) for the specifics of conducting the auction, where he refers to these sets of exercises as the Random Binary Choice mechanisms. Azrieli et al. (2018) discuss some of the underlying assumptions necessary for incentive compatibility (Azrieli, Chambers, and Healy 2018; Healy 2017).

stronger when consumers are valuing unfamiliar goods, as they are in our study (Bateman et al. 2007). A shortcoming of our design is that we cannot differentiate between the effect of the starting price (20 cents or $3), and the order which the questions follow (increasing or decreasing). However, we opted for this design to retain the same price range (20 cents-$3), and the same interval length between questions (20 cents), which could also have affected outcomes.

We randomly divided respondents into each of these price lists before the experiment (using an excel random number generator) to cleanly measure the impact of the type of list on the valuations. 291 respondents responded to questions from the list with the increasing prices, and the remaining 293 responded to questions from the list with the decreasing prices[23]. We used a between-subjects design to measure the impact of the lists, so that any one respondent only saw one type of list, including in the practice rounds.

In the group who responded to questions with the increasing prices, respondents were asked if they would be willing to buy the item at a starting price of 20 cents. If the respondent answered "no", then the auction ended there. If the respondent answered "yes", the price was raised by 20 cents and the question repeated, this continued until either the respondent refused to purchase the item at the stated price, or until the price reached a maximum of $3. In the group with the decreasing prices, respondents were asked if they would be willing to buy the item at a starting price of $3. If the respondent answered "yes", then the auction ended there. If the respondent answered "no", the price was lowered by 20 cents and the question was asked again and the procedure was repeated until the respondent was willing to buy, or until the price reached a low of 20 cents.

We elicited valuations for both the hygrometer and the DryCard™ but gave respondents the option to only buy one item. To ensure this, the respondents first bid on both items after which one item was randomly selected. The selection was done using a coin toss. Following this, a price was randomly selected.

To draw the price, the respondent drew a slip of paper from a brown paper bag, containing 15 slips marked with numbers from 20 to 300 in increments of 20. If the drawn number was lower than their bid (the maximum price they had indicated they would be willing to buy), they bought

[23] We check whether the randomization worked by running a regression of willingness to pay on all of the covariates included in the regression. We used an F-test to check whether the variables jointly affected what question order the respondent was allocated too. We fail to reject the null, that the variables did not jointly affect the order, at a p value of 0.73.

the device at the random lower price. If the random price was higher than their bid they did not purchase the device.

To ensure the respondents fully understood the MPL procedure, two practice rounds were played with pencils and pens. The practice rounds followed the exact same procedure as the auction for the moisture meters, except that the price ranges were different to reflect the value of the stationery items. Each round involved bids on two pencils or two pens each, and within each round, the bid for only one item (randomly determined as described above) was binding.

3.5.4 Risk Aversion Experiment

After the auction we elicited risk preferences using the four choice-sets shown in Figure 3.4 in random order.[24] (Figure 3.4). Each choice-set consisted of six alternates in which outcomes varied in both mean and variance, and participants selected one according to their preferences. The first alternate in each of the four choice-sets had the lowest pay-out and zero variance, and can therefore be considered the "safest." Only one of the four choice-sets was binding, randomly selected by the participant by picking a slip of paper from a brown paper bag. After selecting the binding choice-set the participants played out the alternate they had picked for that set by flipping a coin. Table 3.2 provides the associated range of constant relative risk aversion (CRRA) coefficients, assuming a power utility function ($({}^{1}/_{1-\theta})c^{1-\theta}$), for each choice.[25] Six different categories of risk preference are defined to show the varying levels of risk aversion. They start from the safest option which shows an extreme level of risk aversion ("extreme"), with a CRRA coefficient starting from infinity. The last option has coefficients going from zero to negative infinity, which reflects risk-seeking behavior ("neutral" to "preferring").

The responses are used to estimate risk aversion parameters for each participant, following Harrison and Elisabet Rutström (2008), and assuming CRRA preferences, a common assumption in the risk aversion literature (Cardenas and Carpenter 2008). The expected utility of any one of the six alternatives in each choice-set is:

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[24] As a robustness check we regress whether the respondent won a device on the estimated risk parameter. We fail to reject the null that winning did not affect the parameter at a p value of 0.428.

[25] We arrive at the range of CRRA coefficients in Table 4 by equating the expected utility for two options. For example, an individual with a power utility function with θ =3.3 is indifferent between the first and the second lottery in each of the games.

$$EU_i = \exp(0.5(outcome_l{}^{1-\theta}/1-\theta) + 0.5(outcome_h{}^{1-\theta}/1-\theta)) \quad (6)$$

In the equation above 0.5 represents the equal probability of each outcome, and the l and h index indicates the low and high outcome. The participant will choose the alternate in each of the four choice-sets that maximizes her expected utility from Equation 2. The probability of choosing lottery *j* is therefore:

$$\mathrm{prob_j} = \frac{\mathrm{eu^j}}{\mathrm{eu^1 + eu^2 + eu^3 + eu^4 + eu^5 + eu^6}} \quad (7)$$

As each participant selected the preferred alternate for each game, the data contains four observations (probabilities) for each participant. The risk aversion parameter θ that maximizes the probability of the actual choices made was calculated using maximum likelihood estimation.[26]

3.6 Empirical Model

The data includes 1168 observations: two WTP bids for each participant, one for each device, and participant-level data from the survey. The empirical analysis consists of two parts: a descriptive analysis of the WTP, and results from linear regressions estimated via Ordinary Least Squares (OLS) to test our main hypotheses.

First, we utilize the proportions of individuals willing to buy at each price point to plot demand curves for each of the devices. We then calculate demand elasticities for each of the devices. Second, we use the following regression models[27] to test the hypotheses discussed in these papers.

$$\begin{aligned} WTP_{d,i} = \alpha + \beta_1 TRADER_i + \beta_2 MAIZE\ SOLD_i + \beta_3 HYGROMETER_{d,i} + \beta_4 \theta_i \\ + \beta_5 INC\_ORDER_i + \gamma X_i + u_{ij} \end{aligned} \quad (8)$$

[26] The maximum likelihood function is the sum of the logged probabilities from each of the four games. We use the *fmisnsearch* function in matlab to estimate the theta parameter. In another specification we also include back ground wealth/consumption (hourly earning) in the utility function when estimating theta. The results do not change qualitatively.

[27] A fixed effect specification would not allow us to measure the impact of individual characteristics such as respondent type or risk preferences on WTP, which is why we do not consider it. However we cluster standard errors at the individual level (Greene 2012). As a further robustness check we run a tobit and random effects. Results are qualitatively the same . Please see Appendix 3.11.1.

In the equation above, $WTP_{d,i}$ is the WTP (in Kenyan Shillings[28]) of each individual i for each device d. $TRADER_i$ indicates the respondent type (=1 for traders, =0 for farmers) and β_1 measures the difference in WTP between farmers and traders. $MAIZE\ SOLD$ is the kg of maize sold by the farming household or by the trader, in the period from September 2016-November 2016 (following the main long rain season). β_2 is the impact of a kg increase in maize sold on WTP. $HYGROMETER_{d,i}$ indicates the device that the bid applies to (=1 for hygrometers and =0 for DryCard™) and β_3 measures the impact of the device type on valuations. These three coefficients allow us to test three different hypotheses, which offer more insights into demand drivers for these devices. The first two hypotheses (i) farmer and trader WTP is the same and (ii) maize sold has no impact on WTP, allow us to understand what factors drive demand for these devices. β_3 which tests whether (iii) hygrometer and DryCard™ WTP is the same. θ_i is the estimated risk parameter and β_4 measures the impact of a one unit increase in the risk aversion parameter on WTP. The null hypothesis is (iv) risk preferences as measured by the parameter θ_i do not have an impact on WTP.

INC_ORDER_i indicates the order used in the list presented (=1 for increasing and =0 for decreasing order of the bids) and β_5 is the impact of bids elicited with increasing list as opposed to the decreasing list. The null hypothesis is (v) that list type used has no impact on WTP.

To estimate the differential effects between farmers and traders we also estimate a model including three interaction terms.

$$\begin{aligned} WTP_{d,i} = \alpha + \delta_1 TRADER_i + \delta_2 HYGROMETER_{d,i} + \delta_3 MAIZE\ SOLD_i + \delta_4 \theta_i \\ + \delta_5 INC\_ORDER_i + \delta_6 (TRADER_i * HYGROMETER) + \delta_7 (TRADER_i \\ * \theta_i) + \delta_8 (TRADER_i * ORDER_i) + \gamma X_i + u_{ij} \end{aligned} \quad (9)$$

The interaction terms are $(TRADER_i * HYGROMETER)$, $(TRADER_i * ORDER_i)$ and $(TRADER_i * \theta_i)$. δ_6 measures the additional WTP that a trader would be willing to pay (over farmer) for a hygrometer. The null hypothesis is (vi) device type has the same impact on farmer and trader WTP. Similarly δ_7 is the additional impact of a one unit increase in the risk aversion parameter on a trader and (vii) risk preferences have the same impact on farmer and trader WTP. lastly δ_8 measures the additional impact on traders of being assigned to the increasing list and, (viii) list type has the same impact on farmer and trader WTP.

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[28] KSH 100= USD 1.00 during our study

X_i and γ is a vector of seven control variables and the associated vector of coefficients respectively. Specifically the controls are i) maize harvested; ii) size of land cultivated; iii) the total number of television, motorbike and bicycle, mobile money accounts, and savings accounts owned by the household (asset score); iv) household size (number of individuals); v) previous knowledge of aflatoxins, denoted by a dummy indicator for self-reported awareness; and vi) a binary variable equal to one if the respondent was female and zero if he was male. Standard errors are clustered at the participant level.

3.7 Results and Discussion

In this section we provide descriptive statistics of the participants included in the experiment, the results from the choices in the lotteries, followed by the analysis of the WTP data to estimate demand curves for each device. Finally, we present the OLS regression estimates.

3.7.1 Description of Participants

Participants had an average household size of 6 members and nearly 8 years of education, and while the total revenue from other sources was the same for farmers and traders, traders sold substantially more maize then farmers, 8800 kg on average compared to 120 kg by farmers. (Table 3.3). Almost all participants had previously heard of aflatoxins.

We now move onto the data from the risk game. Analysis indicates that 13 to 15% of respondents chose the option that indicates extreme risk aversion across all the games (Table 3.4) and the mean CRRA estimate in our sample is 0.25. These results appear to be comparable to those elicited in different countries from similar experiments in a field setting. For example Yesuf and Bluffstone (2009) found that 15-37% of Ethiopian farmers choose the extremely risk averse category (in gains-only games). Cardenas and Carpenter (2008) reviewed the literature measuring risk preferences and reported mean CRRA estimates from nine different studies with estimates ranging from 0.05 to 2.57, which include our estimate.

3.7.2 WTP, elasticity and demand curve estimates

Overall, respondents were willing to pay 37% more for the hygrometer ($1.19) than the DryCard™ (87 cents). Traders were on average willing to bid less for both the hygrometer and the DryCard™ ($1.16 and 80 cents), compared to the farmers ($1.21 versus 93 cents, Table 3). However, the difference in WTP between the hygrometer and the DryCard™ was higher for traders (45%) than for farmers (30%).

Figure 3.5 shows the demand curves for the hygrometer and DryCard™, by respondent type. At the median price, the demand elasticity for the hygrometer is one: demand (proportion willing to purchase) goes from 43% to 38% of the sample when the price rises from $1.00 to $1.20. The elasticity of demand for the DryCard™ is smaller, at 0.69: demand goes from 52% to 46% of the sample when the prices rises from 60 to 72 cents[29] (Figure 3.5).

It is interesting that the DryCard™ is more profitable for an actor on the supply-side of the market, while farmers and traders on the demand-side of the market overwhelmingly appeared to favor the hygrometer when asked to choose one of the devices assuming both technologies were available at the prices that they bid. The most common reason offered for this was the increased accuracy offered by the hygrometer.

3.7.3 Regression Results

We present the regression results in six different columns in Table 3.5. We move from parsimonious specifications to a fuller specification which includes all the key variables with the interactions and the control variables (Column 6 in Table 3.5).

Our first goal is to assess the determinants of the demand for these devices. The first hypothesis we test is whether farmer and trader WTP for these devices is the same (β_1). In the parsimonious specification with no controls (Column 1) we find that traders are willing to pay 43 cents ($p = 0.030$) less than the farmers. This effect persists in the specification with the controls, trader WTP is 33 cents lower, which is approximately 30% less than the overall average. (Column 5, $p = 0.09$).

We then look at the effect of market orientation (as defined by amount of maize sold) on WTP for these devices (β_2). We find no statistically significant of the impact of quantity of maize sold on farmers and traders. (Column 5 in Table 5). These empirical findings are in line with farmer demand being driven by quality losses (food safety concerns), in addition to the quantity losses. Farmers' in our sample grow maize primarily for own consumption.

[29] Because of the nature of the way our data was collected, we do not have an actual number of respondents willing to pay 72 cents, so we utilize the value number of respondents willing to pay 80 cents.

The third hypothesis is that there are no differences in valuations between the two devices (β_3). We find that on average respondents were willing to pay 32 cents more for the hygrometer ($p<0.001$) then the DryCard™ (Column 2). This effect remains even after we add the controls in Column 5.

To examine if there is a difference between farmers and traders in their WTP for each of the devices we look at the coefficient of the interaction term. The coefficient on the interaction term (δ_6,between hygrometer and trader dummy), which is interpreted as the additional impact on WTP for the hygrometer by a trader is not significant at the 10% level ($p=0.205$). This suggests that we cannot reject the null hypothesis that the premium paid for the hygrometer is the same for farmers and traders.

The increased valuation for the hygrometer could be driven by two factors. The first is, as we see in Figure 3.7, buyers overwhelmingly believe that the hygrometer is more accurate. Second, anecdotal evidence suggests that buyers perceive the hygrometer as lasting longer than the DryCard™, which would suggest that the valuation for the hygrometer includes possible savings for multiple periods.

The second goal for this paper is to determine the role of risk preferences on WTP. The devices discussed in this study provide participants with additional, new information about moisture content in maize, an excess of which (above 13.5%) can be harmful before storage. Our conceptual framework suggests that we should expect to see a positive relationship, a more risk averse individual would value this information more than a less risk averse individual, ceteris paribus.

We find that the coefficient for the risk parameter (β_4) in the sparse specification and the one with the added controls is not significant at the 10% level (column 4 and 6 respectively). We extend this by looking at differences between farmers and traders using the interaction term (trader dummy and the risk aversion parameter). In this specification we find that a 1 unit increase in theta is correlated with a 10 cent (10% of average WTP) increase in WTP for farmers ($p = 0.030$). Considering that a 1 unit increase in theta reflects a relatively large increase in risk preferences, our mean CRRA is 0.25, the impact of risk preferences is relatively small. However, this does provide evidence that risk preferences are positively correlated with the WTP. There does not appear to be a statistically significant difference on the change in WTP caused by an increase in risk aversion (as measured by the theta parameter) between farmers and traders (β_7, $p=0.232$).

This finding suggests that context of the technology is important when considering the role of risk preferences[30].

The final goal for this study is to examine the role of question order on WTP when using the multiple price list format. We find that the list type does affect WTP (β_5). Respondents who answered questions presented in the increasing order offered lower bids, on average 16 cents less ($p = 0.005$, Column 3). This effect is robust to the addition of the controls and in fact becomes slightly larger at 17 cents (16.5 % of average WTP, $p = 0.001$, Column 6). We reject the null hypothesis that list type does not affect WTP.

The next step is to examine differences between farmers and traders by using the interaction terms (trader dummy and increasing price dummy). Here we find that for farmers the effect is highly negative, with the ascending order of bids resulting in average bids that are 40 cents lower ($p < 0.001$), a 37% drop from the average WTP. The effect is the opposite for traders, who on average bid 6 cents higher ($\beta_2+\beta_{(8,)}$ $p=0.000$) more when the increasing price list is used. The list type does have a very different impact on farmer and trader WTP, with traders bidding 46 cents more than farmers (β_8) when the increasing price list is used.

This finding indicates that systematically including framing effects, by eliciting valuations with more than one frame type, can help quantify framing effects. Framing effects can make a significant impact on valuations, this appears to be especially true when buyers are trying to quantify the value of intangibles such as food safety or improved quality.

3.8 Conclusion

The information asymmetry in maize markets in Kenya, a staple commodity, has serious health and economic implications. Insufficiently dried maize is more susceptible to fungi growth which results in increased aflatoxin growth, which in turn have serious short and long-term health implications. This article analyzes the demand for moisture measurement devices amongst smallholder farmers and traders in Western Kenya that address this information asymmetry by providing an objective source of information on moisture content.

[30] We also utilize the raw responses to the risk game as a robustness check. We create an index by aggregating all the responses to the four games, so that a higher number indicates a less risk averse individual. The result is qualitatively the same and significant at $p=0.078$

We find that farmers, who are growing primarily for own-consumption, value these devices more than the traders in our sample. Our framework suggests that this higher valuation is attributable to greater concern by farmers about food safety. Supporting evidence for this is also found in the empirical result that market orientation, measured by the quantity of maize sold, does not appear to be driving demand.

The lower valuation by traders not only highlights the presence of an information asymmetry, but also the low incentive for traders to invest in a technology that can address this issue. This also confirms that technological interventions cannot independently address a market failure. Government intervention in the form of quality standards, combined with technological subsidies, which allow smaller-scale producers to meet these requirements, might be an effective strategy in dealing with the food safety concerns related to maize. Other research based in Uganda on demand for new post-harvest technologies, suggests that initial subsidies for new technologies can actually crowd-in demand as it reduces uncertainty (Omotilewa, Ricker-Gilbert, and Ainembabazi 2019).

Fifity percent and eighty percent of participants report a WTP higher than the wholesale cost of the hygrometer and the DryCard™ respectively. Bell Industries (a national supplier of agricultural technologies in Kenya), which has begun a pilot to sell a modified version of the hygrometer at a retail price of approximately $2.50, which would mean that less than 10% of the sample would buy at this price.

We provide evidence that increasing risk preferences are associated with an increase in WTP, although this effect is relatively small. This finding corroborates the insight that experimentally elicited risk preferences are correlated with agricultural decisions as shown in previous literature. However, our work adds the insight that even for a completely unfamiliar technology, the function of the technology (risk-reducing in this context), drives this relationship.

Our final goal is to offer a methodological contribution to the process of eliciting valuations in the field. We use a Multiple Price List format which elicits valuations through a series of ascending or descending (in terms of price) binary questions. There are two main findings of note. First, the list type by which values are elicited matters: the list with ascending bids results in lower average valuations than the list with decreasing bids, for our combined sample of farmers and traders. However, this impact varies depending on the respondent type, with the ascending questions causing a strong downward bias in valuations for farmers, but resulting in a much smaller upward bias for traders. This finding supports the discussion that traders are motivated primarily by minimizing physical losses in grain which are easier to quantify. Finally, our results suggest that framing effects should be systematically included in valuation exercises, especially in contexts when valuations are driven primarily by intangibles like quality losses.

3.9 References

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3.10 Tables and Figures

Table 3.1 WTP Bidding for moisture detection devices

Decreasing

1	Would you be willing to pay?	300 KSh
2	Would you be willing to pay?	280 KSh
3	Would you be willing to pay?	260 KSh
4	Would you be willing to pay?	240 KSh
…	…	…
14	Would you be willing to pay?	40 KSh
15	Would you be willing to pay?	20 KSh

Increasing

1	Would you be willing to pay?	20 KSh
2	Would you be willing to pay?	40 KSh
3	Would you be willing to pay?	60 KSh
4	Would you be willing to pay?	80 KSh
…	…	…
14	Would you be willing to pay?	280 KSh
15	Would you be willing to pay?	300 KSh

Table 3.2 - Game A with CRRA coefficients

Risk aversion	Heads	Tails	CRRA Coefficient Range	
Extreme	10	10	∞	3.3
Severe	8	16	3.3	1.3
Intermediate	6	24	1.3	0.7
Moderate	4	30	0.7	0.6
Slight to neutral	2	38	0.6	0.0
Neutral to preferring	0	40	0	-∞

Table 3.3 - -Summary statistics

	Farmer		Trader		Total	
Household size (no)	6.2	(2.5)	5.8	(2.471)	6.0	(2.490)
Years of education of the respondent	7.7	(3.9)	8.3	(3.6)	8.0	(3.8)
Have you ever heard of hermetic bags?-Proportion	0.5	(0.5)	0.5	(0.5)	0.5	(0.498)
Have you heard about aflatoxin (Yes=1, No=0)	0.9	(0.3)	0.9	(0.2)	0.9	(0.2)
Maize sold from September 2016-November 2016 (kg)	120	(368)	8852	(40,950)	4291	(28,614)
Maize sold from January 2017-onwards (kg)	9.5	(50.7)	8318	(46,596)	3978.7	(32,443)
Total revenue besides revenue from maize sold (USD)	1,156	(2462)	1,846	(2371)	1,485	(2442)
Asset score of household	1.8	(11)	1.9	(1.0)	1.9	(1.048)
Willingness to pay for hygrometer (USD)	1.21	(0.82)	1.16	(0.81)	1.19	(81.75)
Willingness to pay for DryCard™ (USD)	0.93	(0.74)	0.81	(0.69)	0.87	(0.72)
Acres of land cultivated for September 2016 harvest	1.1	(0.9)				
Acres of land cultivated for Jan 2017 harvest	0.6	(0.8)				
Acres of land cultivated for maize for September 2016	0.8	(0.7)				
Acres of land cultivated for maize Jan 2017	0.4	(0.5)				
Maize bought in September-November 2016 period (kg)	11,326	(47698)				
Maize bought Jan 2017 onwards (kg)	10,181	(51,434)				
Maize bought from farmers in Kakamega district- Sept-Nov 2016	2819	(8781)				
Maize bought from farmers in Kakamega district- Jan 2017 onwards?(kg)	1394	(6319)				
Maize bought from other traders in Kakamega district-Sept-Nov 2016 (kg)	951	(3852)				
Maize bought from other traders in Kakamega district-Jan 2017 onwards (kg)	991	(2349.4)				
Maize bought from farmers outside Kakamega district-Sep-Nov 2016 (kg)	4966	(30821)				
Maize bought from farmers outside Kakamega district-Jan 2017 onwards (kg)	1464	(7207)				

Note: 1) Standard deviations are in brackets. 2) The first set of variables include summary figures for all 584 respondents. 3) The next set includes statistics only for farmers (**305 observations**) and traders (**279 observations**).

Table 3.4 - -Percent of individuals selecting each option in every game

	Extreme	Severe	Intermediate	Moderate	Slight to neutral	Neutral to preferring
Game A-Max payoff 40	13.41	13.75	10.19	26.49	13.75	22.41
Game B-Max payoff 80	15.11	10.87	11.21	26.99	14.94	20.88
Game C—Max payoff 120	12.39	13.75	13.75	19.35	19.19	21.56
Game D—Max payoff 160	14.09	11.38	12.56	18.51	18.51	24.96

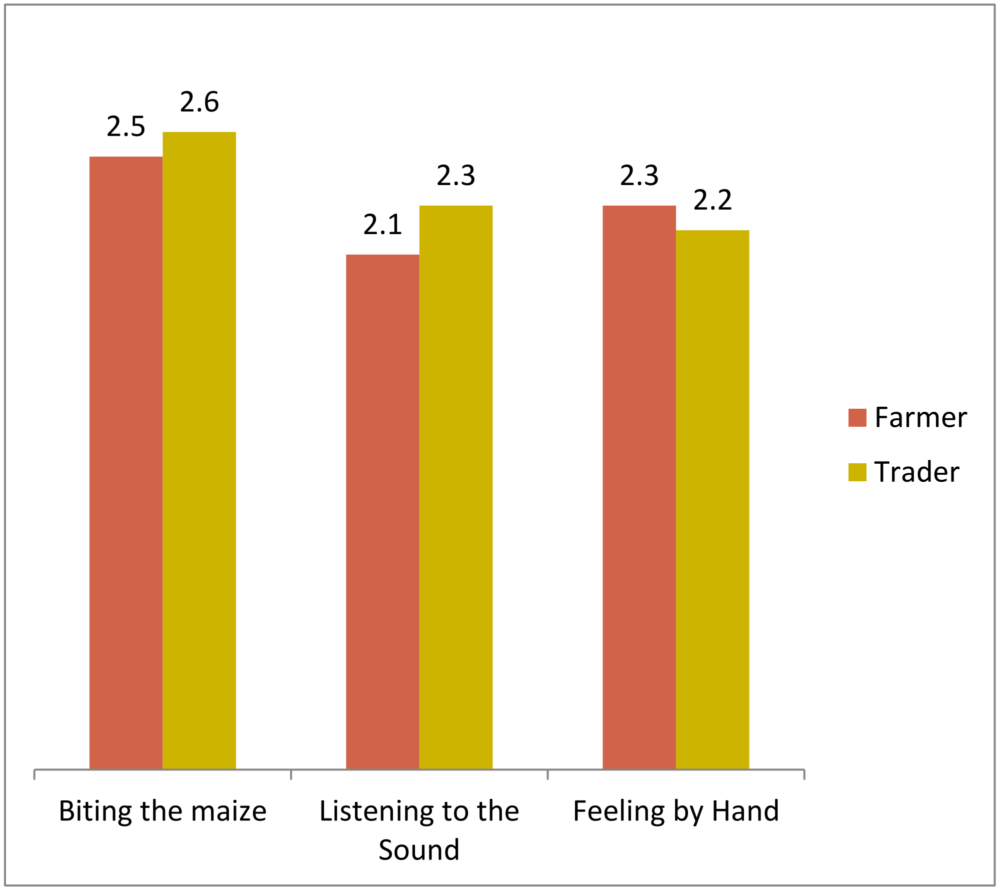
Table 3.5 - -Regression estimates

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
			Willingness to Pay ($)			
Trader Dummy: Farmer=0, Trader=1	-0.43**				-0.33*	-0.55***
	(0.20)				(0.20)	(0.20)
Hygrometer Dummy: DryCard™=0 Hygrometer=1		0.32***			0.32***	0.29***
		(0.03)			(0.03)	(0.04)
Maize sold from September 2016-November 2016 (kg)					0.00	0.00
					(0.00)	(0.00)
Risk Parameter assuming power utility function				0.04	0.05	0.10**
				(0.03)	(0.03)	(0.05)
Increasing List Dummy: Decreasing=0, Increasing=1			-0.16***		-0.17***	-0.40***
			(0.06)		(0.06)	(0.08)
Interaction Term between trader and hygrometer dummy						0.07
						(0.05)
Interaction between trader dummy and risk parameter						-0.08
						(0.07)
Interaction between trader dummy and increasing list dummy						0.46***
						(0.11)
Years of Education of the Respondent					0.01	0.01
					(0.01)	(0.01)
Household Size					0.01	0.01
					(0.01)	(0.01)
Male Dummy: Female=0, Male=1					0.07	0.06
					(0.07)	(0.06)
Asset score of household					0.02	0.02
					(0.03)	(0.03)
Total household revenue besides revenue from maize sold					-0.00	-0.00
					(0.00)	(0.00)
Constant	1.32***	1.16***	1.38***	1.29***	1.01***	1.11***
	(0.15)	(0.15)	(0.15)	(0.15)	(0.17)	(0.17)
Observations						
R-squared	1,168	1,168	1,168	1,168	1,168	1,168

Notes: 1) *** $p<0.01$, ** $p<0.05$, * $p<0.1$
2) Standard errors clustered at the individual level.
3) Average WTP for entire sample, for both devices is $1.03.
4) Power utility function is of the form $((1/_{1-\theta})c^{1-\theta})$.
5) Asset Score is calculated by adding the total number of television, motorbike and bicycle, mobile money accounts, and savings accounts owned by the household.6) Each regression has 1168 observations

Figure 3.1 Hygrometer and DryCard™

Notes- The figure above shows the DryCard™ at the top and the Hygrometer at the bottom. The DryCard™ and the Hygrometer on the left are in a bag of dry maize and vice versa



Reliability – Scale

Very Reliable	5
Reliable	4
Somewhat Reliable	3
Can make mistakes sometimes	2
Not reliable at all	1

Figure 3.2 Self Reported rankings of traditional moisture detection methods

Notes-The graph shown above is based on responses to the question “How would you rate the reliability of this method?” The ranking chart shown on the right was read out to respondents.

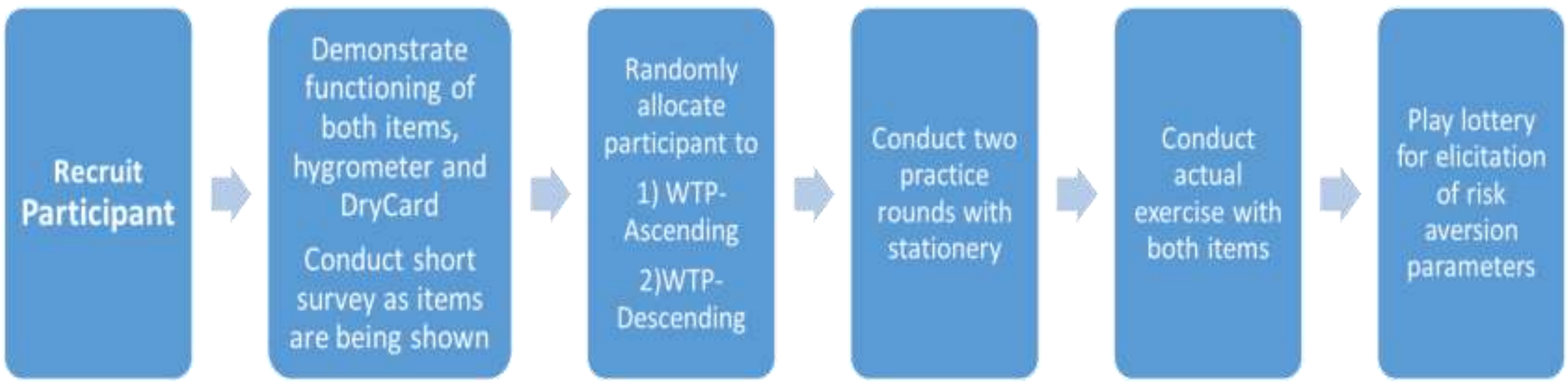


Figure 3.3-Steps followed in the research

Lottery A

Choice No		
1	10	10
2	8	16
3	6	24
4	4	30
5	2	38
6	0	40

Lottery B

Choice No		
1	20	20
2	16	32
3	12	48
4	8	60
5	4	76
6	0	80

Lottery C

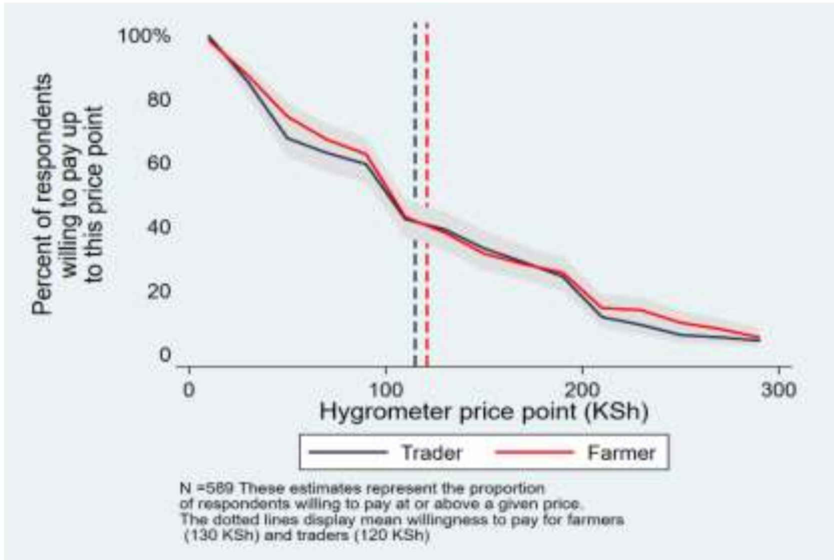
Choice No		
1	30	30
2	24	48
3	18	72
4	12	90
5	6	114
6	0	120

Lottery D

Choice No		
1	40	40
2	32	64
3	24	96
4	16	120
5	8	152
6	0	160

Figure 3.4-Lottery Game

Notes- Each game has six options, each option offering an outcome for flipping a coin, either head, left column, or tail, right column; each participants chooses one option for each lottery



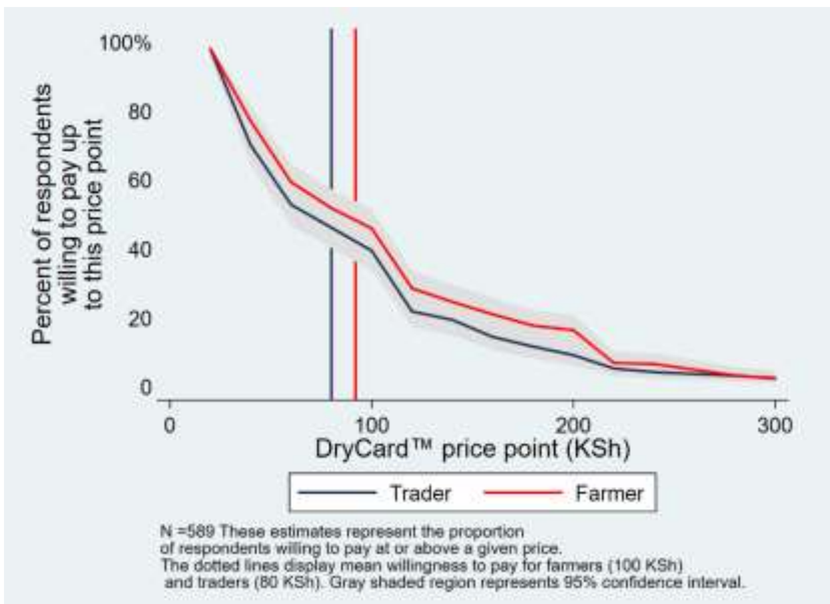


Figure 3.5 Demand Curves for Hygrometer and DryCard™

Notes-These figures are based on the raw WTP data elicited in the auction. The standard errors represented by the gray area are calculated using survival analysis.

$$st_j = S_j * \sqrt{\sum_{k=1}^{j} \frac{d_k}{n_k(n_k - d_k)}} \quad (2)$$

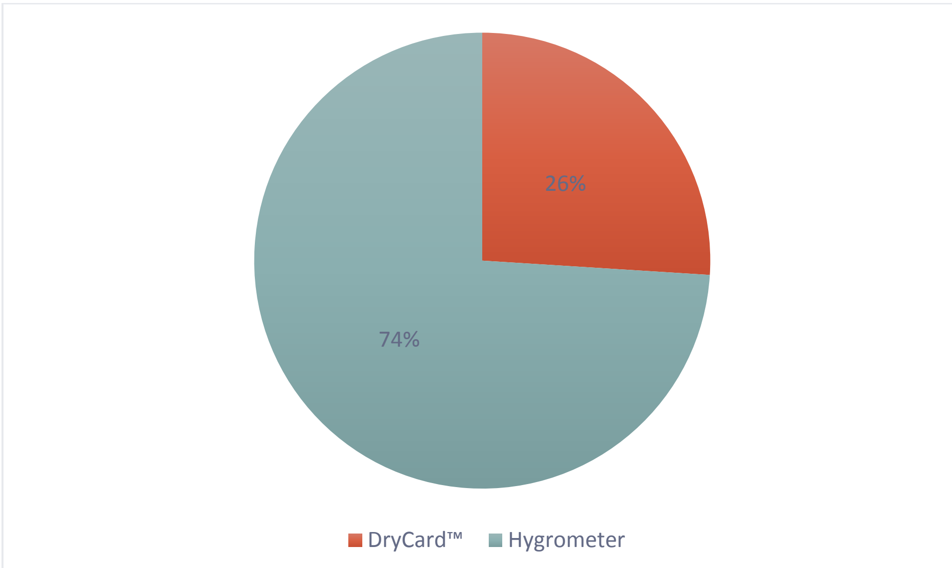


Figure 3.6-Device preference

Notes-This graph is based on responses following the question. The question asked was “If both devices were available to you at the price you bid which one would you prefer?”

3.11 Appendix

3.11.1 Robustness check

	Random Effects	Tobit Regression
VARIABLES	Willingness to Pay for each device	
Respondent Type Farmer=0, Trader=1	-54.66*** (20.74)	-57.85*** (22.05)
Device DryCard™=0 Hygrometer=1	28.59*** (3.750)	29.77*** (3.904)
Method Used, 0=Decreasing, 1-Increasing	-39.21*** (7.825)	-41.14*** (8.121)
Risk Parameter assuming power utility function	3.857* (2.213)	4.286* (2.305)
Highest reliability ranking from methods currently used to check dryness	2.604 (3.018)	2.550 (3.119)
Years of Education of the Respondent	0.614 (0.763)	0.607 (0.786)
Maize sold from September 2016-November 2016(kg)	2.83e-05 (4.78e-05)	2.42e-05 (4.98e-05)
Household Size (No)	0.723 (1.172)	0.806 (1.210)
Sex of the respondent Female=0, Male=1	5.934 (6.559)	5.595 (6.852)
Asset score of household	1.820 (3.083)	2.343 (3.185)
Total Revenue besides revenue from maize sold	-1.48e-05 (1.18e-05)	-1.59e-05 (1.19e-05)
Interaction Term between respondent and device dummy	6.965 (5.487)	7.254 (5.678)
Interaction between method and respondent dummy	45.93*** (11.10)	46.89*** (11.45)
Interaction between risk parameter and respondent dummy	-2.042 (3.260)	-2.147 (3.421)
Constant	103.8*** (20.07)	105.8*** (21.24)
Observations	1,168	1,168

CHAPTER 4. HELPING SMALLHOLDER FARMERS MAKE THE MOST OF MAIZE THROUGH HARVEST LOANS AND STORAGE TECHNOLOGY: INSIGHTS FROM A RANDOMIZED CONTROL TRIAL IN TANZANIA[31]

4.1 Abstract

Farmers in Sub-Saharan Africa face two main post-harvest challenges: maintaining the quantity and quality of staple grains throughout the year, and managing the persistent price seasonality in grain commodity markets. We use a Randomized Control Trial (RCT) to evaluate two interventions among smallholder maize farmers in Southern Tanzania, a storage technology and a loan product, that address these challenges. The storage technology offered to participants is a triple layered hermetic (airtight) storage bag, which can reduce quantity and quality losses in maize due to insects and mold without the use of storage chemicals. One of the reasons farmers are unable to exploit the price seasonality, is because of a liquidity crush at harvest. We address this issue with a loan distributed at harvest. The loan, collateralized with maize stored in the hermetic bags, is due six months from harvest when maize prices traditionally rise. Those who were offered the loan product stored 29 percent more and sold 50 percent more maize on average in the lean season, compared to those who were not offered either of the two treatments. The maize price rise was unexpectedly small in our intervention year due to an export ban on maize, which likely attenuated the outcomes of the intervention. This also highlights the challenges surrounding agricultural financial products in the developing world.

Keywords: Randomized control trial, hermetic Storage, microfinance, Tanzania, price seasonality, maize markets, credit groups

4.2 Introduction

While improving staple crop production remains a major challenge in Sub-Saharan-Africa (SSA), it is important to realize that the food security challenge does not end at harvest. Smallholder

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[31] **This work has been co-authored with Dr. Jacob Ricker-Gilbert (committee chair), Dr. Feleke Shiferaw and Dr. Tahirou Abdoulaye.**

farmers growing maize and other grains face two main post-harvest issues. One is an entomological challenge because storage pests such as the maize weevil and the large grain borer (LGB) can cause tremendous post-harvest dry weight loss (DWL). This means that households have less grain to sell and consume later in the year, and what they have is of lower value due to decreased quality over time (Boxall 2002, Abass et al., 2014). The second challenge is an economic issue, because grain prices are usually lower at harvest than they are later in the season. Unfortunately, storage constraints and pressing liquidity demands means that households are often unable to exploit the significant price seasonality that exists in many grain markets in SSA. In fact, they may end up in a situation where they sell their maize for low prices at harvest to pay off debts, only to buy back grains for household consumption when prices are at their highest. In combination, pest damage and economic constraints create a situation that undermines food security and reduces income for smallholder farmers in SSA.

The present article provides empirical evidence to determine which intervention can enable smallholder farmers in SSA to store more maize to sell or consume later in the year when prices normally rise. We conduct a randomized control trial (RCT) in the southern highlands of Tanzania to examine the potential role of two interventions in relieving smallholders' post-harvest liquidity, and their physical quantity and quality loss constraints. The first addresses the entomological challenge faced by smallholder farmers by providing an initial subsidy for a new storage technology, two hermetic (airtight) storage bags that hold up to 100 kg of shelled maize each. The hermetic bag protects stored grain by killing insects and neutralizing mold growth. It is a way to store grain effectively without the use of storage chemicals.

The second intervention addresses the liquidity issue by offering farmers access to a new credit product. The credit product uses maize stored in a hermetic storage bag as collateral for a loan that is distributed during the harvest season, and is due back 6 months from harvest with 12% interest, when maize prices are typically much higher. The credit intervention incorporates our storage intervention since the loan is collateralized with grain stored in hermetic storage bags. However, we treat this intervention as separate rather than cumulative, because the hermetic bags used to collateralize the loan could not be used for additional storage.

Our working hypotheses are: the intervention that relieves the most pressing constraint for farmers, either storage or liquidity, will have the greatest impact on maize storage decisions, and the timing and size of maize sales. Specifically, if these constraints prevent farmers from storing and selling maize in the lean season, then we should see increased maize inventory in the lean season and a transfer of maize sales from the harvest season to the lean season.

This article builds upon the limited previous experimental research that has tried to understand and test mechanisms behind the persistence of these challenges and evaluate different interventions that look to address these concerns. Burke et al. (2019) implement a credit intervention like the one in the present study, but the collateralized maize is stored using traditional storage bags that offer no protection from insects and mold. The authors find that providing credit immediately after harvest increases maize sales profit, although this gain is smaller in areas where treatment intensity of the intervention is higher.

In addition to credit constraints, a lack of improved storage technologies also play a potentially critical role in affecting smallholders' decisions at harvest. Aggarwal et al. (2018) address storage constraints in Kenya by providing farmers the option to store their maize collectively (in hermetic bags) with members of their village savings group. Households, who accepted this treatment stored maize longer, sold 23% more maize on average, and those who sold did so later in the season at higher prices. Omotilewa et al. (2018) also finds that providing improved storage technology (also hermetic bags) to farmers in Uganda results in farmers storing more maize for a longer period.

Basu and Wong (2015) evaluate a food storage program through the introduction of a new storage technology and a food credit program, using an RCT in Indonesia. The food credit program provides credit in the form of food during the lean season, which is then repaid at the time of harvest. They find that the credit intervention increases income and minimizes seasonal gaps in consumption, although neither program affects average staple food consumption.

We exogenously relieve the storage constraint, by providing hermetic storage bags and relieve the liquidity constraint at harvest by providing a loan. Our contribution is then to compare the impact of both these interventions to the control group, which allows us to understand the role of each of these constraints in preventing farmers from optimizing maize storage and sale practices.

Our experiment covered seven districts in the Mbeya region of the southern highlands of Tanzania, with a sample size of 1,250 respondents. The randomization occurred at the level of individual credit clubs, where 131 clubs participated in total. Of the total, 44 clubs were randomly allocated to the storage intervention (involved training and receiving 2 hermetic storage bags), 43 clubs were randomly allocated to the credit intervention (offered access to the loan product described above), and another 44 were randomly allocated to the control group. In each treatment group, 10 individuals were randomly selected to be treated.[32] Similarly, from the control group 10 individuals were randomly selected to be surveyed

We find that there was a great deal of interest in the loan product as well as the storage intervention. Eighty percent of the farmers to whom we offered the loan product accepted, which is more than the already high acceptance rate of 60-65% found by Burke et al. (2019). We find evidence that the credit intervention allowed farmers to store 29% more maize until later in the year and resulted in a 50% increase in the quantity of net maize sales. While the impacts of the credit intervention are larger and more precise than the impacts of the storage intervention, when compared to the control group, we cannot reject the null that storage and credit treatment had the same treatment effect. This suggests that both constraints to some extent drive farmer maize storage and sale behavior, but that liquidity constraints at harvest play a bigger role. We also find that a subsample that was credit constrained before our intervention benefited more from our treatments compared to those who were not credit constrained.

However, the statistical significance of these results weakens when we account for multiple hypothesis testing. We primarily attribute this to the maize price behavior during our intervention year. Maize prices did not rise in the lean season, in contrast to previous years' price pattern because the government of Tanzania imposed an export ban on maize. The government intervention introduced additional price uncertainty in the maize market. This added uncertainty, along with the depressed maize prices, likely attenuated the outcomes related to maize sales, purchases and storage.

4.3 Setting and Project Design

4.3.1 Maize Price Seasonality in Tanzania

Maize is the main cereal consumed by most Tanzanians, providing an estimated 60% of the calorie requirement. Most of the maize produced is used for home consumption, while the remaining is primarily sold in local markets. While yields have been growing (1.4 Mt/ha), production growth has primarily been driven by increases in land allocated to maize or conversion of fallow land to

[32] We have a great deal of variation in the number of people who turned up across clubs We use inverse probability weights in all our regressions tocontrol for this variation.

the maize crop. Mbeya region where our research is focused, is a surplus producing region responsible for 11% of maize production in Tanzania. (Wilson and Lewis, 2015)

Using maize price data from the Mbeya region in Tanzania, we find that for the last 17 years, average maize prices in the planting season (December-January) were nearly 35% higher than they were at harvest time (June). This seasonality was particularly sharp for the last two years, when the prices were nearly 80% higher in the lean season (Figure 4.1). Additionally, we find that seasonality in maize prices is high compared to other crops like beans and rice, and that seasonality in Mbeya region is higher than it is in other regions (Figures 4.2 and 4.3)

Baffes et al. (2015) study maize prices in Tanzania to better understand the drivers behind the price patterns in grain markets there. Since Tanzania is a net exporter of maize in most years, the authors find that regional prices (for example the retail price of maize in Nairobi) drive nearly a third of the price variation in the country. The remaining price variation is attributable to domestic factors such as production shocks, maize harvest cycles, and government policies such as export bans. Gilbert et al. (2017) use pricing data for various food commodities across seven countries in Africa and find significant price seasonality especially for maize (around 33% on average), which is almost three times larger than an international reference price. In an associated study, Kaminski et al. (2016) show that price seasonality is still very much present, and additionally that it has a significant impact on household consumption.

4.3.2 Storage Technology Intervention

We use the Purdue Improved Crop Storage (PICS) bag developed at Purdue University for the storage component of our intervention. The PICS bag is a three-layer hermetic bag that consists of an outside layer of woven polypropylene, and two inner layers of polyethylene. There is also evidence to suggest that the airtight seal of bags can play a role in containing the spread of aflatoxin in stored grain, compared to the standard gunny (Williams et al., 2014).

One disadvantage of the PICS bag is its high cost relative to the single layer woven bag. One PICS bag, which holds 100 kg of shelled maize, costs roughly \$2.3[33], while one single layer woven bag with the same capacity, costs only \$0.70. However, the PICS bag can be reused for multiple years[34]. Additionally the bag does not require application of storage chemicals to kill

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

[34] In Niger for example, a survey of 121 farmers using PICS bags for cowpea storage, found that up to 79% of farmers found that the bag was effective for storage even after 3 years of use (Baributsa et al., 2010).

insects, which reduces operating costs and also mitigates the potential negative health effects associated with those chemicals.

4.3.3 Loan Intervention

To examine the role of the liquidity constraint at harvest, the authors worked with their partners Phiretajo to design a loan product. Phiretajo is a local NGO responsible for the registration and training of the credit clubs, called Village Savings Cooperative Bank (VICOBA) in the Mbeya region of Tanzania. The term VICOBA (kikundi in Swahili) refers to a group of individuals (15-30) who come together so that they can access credit (for most formal credit is inaccessible) and save and invest money. The group meets every week or every other week, and each member buys "shares" in the VICOBA. This is a form of saving for the group members, who then lend this money out to other group members. Occasionally, if resources allow the VICOBA also makes investments in small businesses using this pool of money.

The members elect a chairperson, secretary and accountant from each VICOBA. To be officially registered, the VICOBAs must pay a sum of TSh 300,000 (USD 137) in total to Phiretajo and the district government. Phiretajo assists the VICOBAs in their region with registration, trains them so that the VICOBAs function more effectively, and helps them open bank accounts. VICOBA membership is exclusive except for a few cases. [35]

The loan product offered to VICOBA members as part of the intervention was approximately worth the value of the grain in two PICS bags of maize. Each PICS bag holds 100 kilograms of shelled maize, so 200 kilograms were valued at about TSh 80,000 (USD 36) at the time of harvest in June 2017. The money was given to farmers in cash at the time of harvest, and they had the choice of either purchasing additional maize or using maize from their own harvest to store as collateral for the loan. The maize was stored in a central location, either a government office or the home of one of the group leaders. The expectation was that the farmers would sell their maize in six months to pay back the loan to Phiretajo with 12% interest. The 12% interest rate is higher than the 10% internal lending rate of the credit group but is much lower than the 20-25% interest rate which would be the cheapest outside option for farmers (a group loan from CRDB

[35] In our case there were only three cases in one (Ileje) district where there were individuals in our selected groups who were also members of other groups which were also included in our sample. In that case the researcher randomly selected them into either one of the two groups.

Bank, however only 2% of our sample indicated that they had access to any formal sources of credit).

Our loan intervention also included a storage intervention. However we do not consider this as a cumulative intervention, since the hermetic bags used for collateral were tied to the credit intervention and could not have been used for any other purpose. The main reason for collateralizing the loan with hermetic bags was that our partners believed that the storage losses would be too high if farmers used traditional technology, and therefore repayment would be poorer.

4.3.4 Power Calculations

We used LSMS (Living Standards Measurement Survey, 2014-15) Tanzania data to conduct power calculations for this study. Using this dataset we find that average maize stored currently with the household, asked at the time of the survey, is 339 (549)[36] kg, and average maize harvested is 836 (986) kg. Unfortunately, we do not have maize inventory specifically for the lean season, since the survey occurred throughout the year. This level of inventory should be considered an upper limit, since it also includes maize harvested throughout the year.

The storage intervention consists of two bags worth 100 kg each; we therefore use 200 kg as the size of the treatment effect. The credit intervention also consists of a loan worth two bags of maize, so we expect a similarly sized effect.

We use these effects and baselines values to calculate sample sizes to be powered at the 80% level. For lack of a better value we use intra cluster correlation within the village (according to the LSMS data) of 0.02 as a proxy for group level intra-cluster correlation.

These calculations assume that a treatment effect of 200 kg results in a MDE of 0.36. With a sample size of 400 individuals in 40 groups, we are powered to pick up a MDE of 0.30. This is considered a small to medium range for MDE when designing experiments (Duflo et al., 2007) Also, since these outcomes are correlated across time, the use of a baseline survey should help substantially increase power.

4.3.5 Project Implementation

The activities were conducted in collaboration with Purdue University, International Institute of Tropical Agriculture (IITA) and Phiretajo. The paragraphs below describe the outline of the

[36] Standard errors provided in parenthesis.

randomization which is also summarized in Figure 4.5. From April 24-May 31, 2017 a team of enumerators (10 enumerators and 2 supervisors), and a team of three trainers visited the randomly selected VICOBAS in seven districts from the Mbeya region. 131 VICOBAs were visited during this time as shown. VICOBA groups were randomly selected into three groups:

1. Control-This group did not receive any training, bags or loans. Ten randomly selected individuals from this group were selected and surveyed. (Group 1)
2. Storage-The entire group received training on the use of the PICS bags. Subsequently, 10 individuals within the group were randomly selected in an open lottery to receive two free bags. (Group 2)
3. Storage+Credit- The entire group received training on the use of the PICS bags. Subsequently, 10 individuals within the group were randomly selected in an open lottery and were offered a loan at the time of harvest worth approximately TSh 80,000 (USD 36). The loan was collateralized with grain stored in two PICS bags. If the respondents accepted the offer of the loan the bags were given for free. We refer to this as alternately as the credit group, and the storage+credit group in the discussion. (Group 3)

The participants who received the PICS bags (in the storage group) or the PICS bags and the loan (in the credit group) constitute the treated individuals in Group 1 and Group 2, respectively. The training for Group 2 and Group 3 involved a demonstration on how the bag should be used, followed by a video that explained the benefits of the bag. Group 1 was told that 10 individuals would be randomly selected for a simple survey on maize production, consumption, and sales and other questions on household demographics. Additionally, these individuals would receive two hermetic storage bags each. It was explained to the groups that this activity was just a pilot for better understanding the benefits of the bags and the loans. We also explained that from the following year, the bags will be available in more markets, and possibly the loans would be more widely available to those interested.

For group 2, the 10 individuals who received the bag were encouraged to store maize in the bag but there were no restrictions placed on the use of the bag. For group 3 the members were told that individuals would receive two bags and be offered a loan of TSh 80,000 (USD 36) at the time of harvest. The loan was for 6 months at an interest rate of 12%. The collateral for the loan would be two bags of maize stored in the hermetic bags. The two bags of maize would be stored at a central location, which would be either a village office or the home of one of the group leaders (or a senior member as agreed upon by the group).

For transparency, the randomization within the groups occurred when the team arrived. Slips of papers were distributed in a bowl with numbers from one to total number of members present. Those who got slips with the numbers from 1-10 would receive the bags, or the bags and the loan. All groups that participated in the intervention (including the control) received combined gifts of stationery worth Tsh 20,000 (USD 11)[37]. Additionally, all the participants who took part in the survey received a journal which they were asked to fill before or after their weekly meetings for the next year[38].

The end line survey was held after a full calendar year in May 2018. We were able to re-interview 1238 out of the 1250 originally interviewed during the baseline survey, with attrition of less than 1%. To minimize attrition, we also conducted phone interviews if respondents were not available for interviews in their homes or meeting space after two visits by the team. Of the total interviews conducted for the end-line 21% were conducted over the phone.[39]

4.4 Initial Baseline Statistics

Table 1 provides the mean and standard deviations for 12 key variables. We winsorize the top and bottom 1 % of the observations for all these variables. A standard procedure to check for balance, is to run t-tests comparing groups to check if the randomization worked correctly. In our case however, since we have multiple treatment groups this greatly increases the number of t-tests that we would need to do, increasing the probability of a positive significance by chance (Type 1 error). Instead, we utilize a statistic recommended by Imbens and Rubin (2015) as a method for checking balance which reflects the size of the difference, referred to as the normalized difference.

$$t = (\mu_1 - \mu_0)/(\sqrt{(\sigma_1^2 + \sigma_0^2)}) \tag{3}$$

We find that this statistic is smaller than 0.25 for all our variables, implying that the differences if present are small. As an additional check we also provide F-statistics for joint

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

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

[39] As a robustness check we check if results were statistically significant for those interviewed over the phone. Results are qualitatively the same (Appendix 4.12.2)

orthogonality for each variable across all the four arms. These regressions include district fixed effects with standard errors clustered at the VICOBA level. Using this F-test we find that all variables are balanced.

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

Farmers in our sample had a maize harvest 1503 kg of maize. This falls to 626 kg around the time the next planting season begins in January, which is when prices traditionally rise. We do not show self-reported maize losses during storage in the table because they are almost negligible in our sample (averaging at 13 kg). Additionally, this average is driven by a few observations with higher losses, and 90% of the sample reporting zero losses. This is lower than the estimates ranging from 1.4-5.9 % provided by Kaminski and Christiansen (2014), which they calculated using household survey data from Malawi, Uganda and Tanzania. Generally, farmers take precautionary measures to reduce losses including applying storage chemicals and selling earlier because of the risk of storage losses. Around 56% of our sample was using storage chemicals in the baseline year, and average storage chemical expenditure amongst users was TSh 7000 (USD 3)[40].

The simple poverty scorecard index is developed from a series of 10 questions. The index was developed using Tanzania's Household Budget Survey data and is meant to predict the likelihood of the household being below the poverty line (Schreiner 2012). The average score in our table shows for our sample, using the $1.90/ day poverty line, that the average household's likelihood of being below the poverty line is 31%.[41]

4.5 Empirical Model

We examine three main outcomes that could be affected by the intervention: maize inventory held by the household six months after harvest (beginning of January 2018 (kg)), and net maize sales

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

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

in terms of monetary value (TSh), and quantity (kg). We estimate the following model for the dependent variables of interest for individual i in VICOBA group j as follows:

$$y_{i,j} = \alpha + \beta_1 storage_{ij} + \beta_2 credit_{ij} + D_d + e_{i,t} \quad (2)$$

Where storage and credit, are indicator variables for the storage credit treatment received by individual i in group j respectively. $\boldsymbol{D_d}$ is a vector of district level dummies. The coefficient vector β measures the Intent-to-Treat estimate, and is identified by the difference between the control and treatment groups during the intervention year. Standard errors are clustered at the VICOBA level. This specification is noted as POST in the tables.

Additionally, to utilize the baseline data, we use an Analysis of Covariance (ANCOVA) specification, which can be more precise than a difference-in-difference specification in a setting like ours where we have a single baseline and follow-up survey (Mckenzie, 2012). This specification is the same as the one shown in equation 2, except that it adds in the previous period's outcome value as a control.[42]

Equation 2 does not allow the treatment dummy to vary across quarters, however for net maize sales we might expect the treatment effect to vary considerably across the quarters. For example, we might hope that for the treated group sales fall in the quarter following harvest but are higher later in the year. To examine if treatment effects vary across quarters, we also estimate:

$$y_{i,q,j} = \alpha + \sum_{q=1}^{q=4} storage_i \, \beta_{q,1} \sum_{q=1}^{q=4} credit_i \, \beta_{q,2} + Q_q + D_d + e_{i,t} \quad (3)$$

In the equation above Q_q are the quarter level dummies and the treatment values vary by each quarter, for example, the credit intervention has a treatment vector $\beta_{q,2}$, which consists of 4 different values.

We also conduct heterogeneity analysis by interacting the treatment dummies with a dummy indicating if the household was borrowing constrained in the baseline year.

$$y_{i,j} = \alpha + \beta_1 storage_{ij} + \beta_2 credit_{ij} + \beta_3 * (storage_{ij} * con_{ij}) + \beta_4 (credit_{ij} * con_{ij}) + D_d + e_{i,t} \quad (4)$$

[42] Calculations shown by Mckenzie (2012) show that that if the correlation is between 0.25-0.5 then there can be increased power by using ANCOVA instead of DID or just a "POST" method. The POST method is equivalent to the SMD method in our paper. The correlations between the baseline outcome and the intervention year outcome is 0.45 and 0.4 for net sales through the year (TSh), and maize inventory in the beginning of January (kg) respectively.

In equation 4 above β_1, β_2 are interpreted as the treatment effects for the storage and credit intervention respectively for those who were not credit constrained at baseline. While $\beta_{3,} and\ \beta_4$ are interpreted as the treatment effects for the storage and credit intervention respectively for those who were credit constrained at baseline.

4.6 Results

4.6.1 Take-up

All of the respondents except one accepted the hermetic storage bags that were offered as part of the storage intervention. Unfortunately, two groups who were selected did not receive the PICS bags because of miscommunication with our implementing partners. In total 95% (403) of the respondents who were selected received the storage intervention.

Of the total respondents offered the loan 81% (330) accepted it. This is higher than the 60-65% that Burke et al. (2019) find for a comparable product in Kenya, which is already much higher than adoption of micro-credit products in general, which ranges from 2-55%. This high uptake is perhaps explained by the fact that farmers recognized the arbitrage opportunity, and because they were already members of credit groups and familiar with the lender Pheretajo.

We also find that the most common use of the loan, larger than 40% of those who took the loan, was to purchase additional maize to store in the PICS bag (Figure 4.5). Anecdotal evidence suggested that this was because many farmers recognized that the investment opportunity created by the price arbitrage. This combined with the high take-up suggests that farmers in our sample were aware of the intertemporal arbitrage opportunity.

4.6.2 Primary Effects of the Intervention

We have two main outcomes of interest that we hypothesize would be affected by the intervention. If storage or liquidity constraints were preventing farmers from exploiting the price seasonality then we would hypothesize that farmers who received the intervention would have more maize inventory stored later in the year, and they would delay sales later into the year when maize prices are generally higher (Figure 4.1).

We present two specifications for each of the two outcomes. The first specification presents the POST estimates. This involves an OLS (ordinary least squares) regression of the outcome variable for the intervention year on the treatment dummies, following the specification in equation

1. We then present results from the ANCOVA specification. In our discussion we focus primarily on the ANCOVA specification.

We start by examining the impact on maize inventory held by the household in the beginning of January 2018, the January following the intervention (Column 1 and 2 of Table 2.2). This is when maize prices tend to be at the highest in this region (Figure 4.1). We find that the credit treatment increases the amount of maize stored on average by 223 kg (p=0.021), which is 30% more than the control groups inventory (ANCOVA specification). The coefficient associated with the storage treatment is not significant at the 10 % level (p=0.189).

We see that for the credit intervention net maize sales increased by 233 kg (p=0.05), which is a 50% increase in net maize sold compared to the control group in the intervention year. We next look at net maize sales in terms of value. This is the net maize revenue in TSh for the year, total maize sales minus total maize purchases, and we adjust the balance for the credit group by subtracting the amount of interest (9600 TSh/4 USD) on the loan. We find no statistically significant impact on net maize sales for any of the interventions in any specifications in Table 4.2.

The dummies for net maize sales for the storage treatment, either in terms of net value or net quantity are not significant at the 10% level. However, as with the inventory outcome we cannot reject the null that the coefficients for the storage and the treatment coefficients are the same. We interpret these results to indicate that there is an impact of the storage intervention in comparison to the control group, because we cannot reject the null that the coefficients are equivalent to the credit intervention, but that these impacts are smaller and noisier in comparison to the credit group.

These results indicate that the credit intervention resulted in farmers storing longer and selling more maize overall. However, we do not observe an overall effect on net maize sales profit with these specifications. We extend this analysis in Table 4.3 by allowing the treatment effect on net sales to vary across the quarters. This implies separating the net maize sales data for each quarter (instead of the aggregate in the earlier regression) and pooling them together in a regression. We utilize this specification to disaggregate the effect quarter wise.

While these results are noisy, the coefficients suggest that the treatment results in a transfer of sales later into the year. Net sales in quantity are higher on average by 135 and 128 kg for the credit group in the latter half of the year and so are net maize sales in terms of value by TSh 38,195 and TSh 30,759 (a total of USD 31), when compared to the control group. We also see an average decrease in sales worth TSh 16,356 (USD 8) in the April-June quarter when harvest begins, although though this is not statistically significant at the 10% level (p=0.12). This suggests an increase in net maize sales of TSh 52,418 (USD 23).

4.6.3 Exploring treatment heterogeneity

In this section we explore the possibility that there is a subpopulation that may have benefited a great deal because of the interventions.[43] One possible source of heterogeneity could be that treatment effects are different for those who were less credit constrained at the time of the intervention. Since we worked with credit groups, all farmers already had an additional source of credit. However, the amount that they could possibly borrow varied depending on the size of the VICOBA (in number and wealth of the members), and the individual wealth of the members.

Anecdotal evidence suggests, as we would expect, that wealthier and more established members find it easier to borrow. This is confirmed with the results presented in Table 4.4. We find that being credit constrained (as indicated by a dummy if you borrowed less than the median from the VICOBA) has a significant effect on the treatment effect especially for the storage treatment. Those who were credit constrained in the year prior to the intervention had a much higher treatment effect in response to both to our treatments. It appears that this effect is driven by an increase in the net quantity of maize sold by the household. We see that the group that was credit constrained in our sample and was offered the credit intervention on average sold 533 kg more maize, compared to the control group that was also credit constrained at the baseline.

A possible area of future research is to use the results from this work and others (Aggarwal et al., 2018; Burke et al., 2019 and Omotilewa et al., 2018) to further explore sources of heterogeneity.

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[43] We use the non-parametric tests developed by Crump et al. (2008) to examine the presence of hetrogeniety. We test the main outcome variables, mainly maize inventory in January following the intervention (kg) and net maize sales during the intervention year (TSh), Appendix 4.11.3 presents the results for both these tests. The last four columns also present results from a test for a zero Average Treatment Effect (ATE). This is essentially what we tested in the previous regressions and confirms the results that we have already found.
Appendix 4.12.5 suggests that there is heterogeneity in the treatment effect for the storage and credit intervention on net maize sales during the intervention year. This implies that there is a subpopulation who benefited from the loan, in terms of increased sales, and some who potentially reduced maize sales because of the intervention.
Crump allows for a chi-square distribution and a normal distribution for the tests. Both the results are shown in the table and are qualitatively similar for each test.

4.7 Impact of Maize price pattern on outcomes

As discussed earlier, the estimated magnitude of our intervention's impact was likely attenuated because maize prices did not rise in Tanzania during December-February 2018, as has been traditionally observed (Figure 4.6). While maize prices across the last 17 years have risen by an average of 40% in the months of January-February following the harvest in June, this year's prices did not rise and were close to where they were in June.

Anecdotal evidence suggests that an export ban put in place around harvest time combined with a bumper harvest in Zambia could have contributed to the price depression. Previous research work in Tanzania shows us that maize export bans can result in lower maize prices. Baffes et al. (2015) finds that an export ban reduces maize prices by 3.1%. Diao and Kennedy (2016) use a computable general equilibrium model to show that maize producer prices fall significantly following a ban, hurting poor rural households and benefitting urban households.

Our communications with government officials and a review of news reports suggests that the stated reason behind the placement of the bans was to prevent a maize shortage (Kamndaya, (2017), Ng'wanakilala (2017)). Between January-March 2017 maize prices in Tanzania were 80% higher than the prices at harvest in June 2016. The perception amongst government officials was that uncontrolled exports to Kenya were responsible for this price rise.

The lack of maize price rise affected the loan repayment rates associated with the credit intervention. Loan repayment was at 85% as of August 2018, which is lower than expected. However, the proportion of respondents who have repaid at least partially is higher at 90%.

The lack of maize price rise reduced the intertemporal benefit that could be accrued by producers by storing maize across into the lean season. This has clear implications for the outcomes of our project in two different ways. First, through creating behavior change in the months after harvest. If farmers realized that the export ban would prevent a price rise, then the incentive to store longer and sell later is lower. Even if our intervention relieves the storage or liquidity constraint which was preventing farmers from optimizing the quantity stored, the optimal maize quantity that the farmer might want to store is now lower.

Another impact would be in the form of sales later in the year. If they could afford to, farmers might hold onto the maize even longer delaying sales, or sell at lower than expected prices, reducing the revenue gains from the intervention.

These explanations suggest a strong attenuation effect on the observed outcomes. Our results are sensitive to accounting for multiple hypothesis tests (Table 4.5). The False Discovery rate adjusted p-values are larger (Anderson, 2008), and none of the results found above are significant at the 10% level.

4.8 Conclusions

This paper provides insights from an RCT, which provided a storage and a credit intervention to smallholder farmers in Southern Tanzania at harvest. The unique contribution of the present article is that it is the first to offer RCT estimates on the impact of both storage and credit constraints and compares each one to a control group to evaluate the differential impact of each group.

Our results indicate that the credit intervention, which is possible only because of the storage technology allows farmers to store 29% more maize in the lean season and increases quantity of maize sold (adjusted for maize purchases) by 50% compared to the control group later in the year. We also find evidence, when allowing for treatment effects to vary across quarters that sales were transferred later into the year, and farmers were able to increase maize sales profit with this transfer.

However our results our noisy and not robust to multiple hypothesis testing. It is likely that these findings were attenuated by the fact that maize prices did not rise this year during the lean season. Our experiences highlight that government intervention in maize markets, in the form of an export ban in this case, can create uncertainty about investments in maize, and is possibly one of the reasons behind the persistent price seasonality in grain markets in East Africa. It also serves to point out the high uncertainty associated with agriculture credit products, the returns on which are affected by many uncontrollable factors.

Despite these attenuated results the loan product appears to have been received well. The main take-away for our partners in the field was the increased security of collateral offered because the loan product was combined with a technological innovation. Despite the uncertainty because of the unexpected maize prices, which presumably led to a lower repayment rate, they independently scaled up the credit product to 200 credit groups in the next season. They offered credit collateralized with two bags of beans stored in hermetic bags. The hermetic bag technology considerably reduces the risk of loss of grain/legume (which serves as collateral) for the lender. This lowered risk is transferred to the borrowers in the form of lower interest rates. Additionally, technologies such as mobile money allow repayment to be more flexible, which proved to be useful since the lack of price rise meant that some individuals delayed repayment.

We also find evidence for treatment effect heterogeneity, with those who were credit constrained at baseline benefiting more from our treatment compared to those who were relatively less credit constrained. This is likely because those farmers who were less constrained were already able to optimize storage and sales decisions, reducing the treatment effect.

Despite the unexpected maize price pattern, the high take-up, the scaling-up by our partners, and the impact on maize inventory and sales suggest that these constraints affect farmer maize storage and sales decisions. The presence of these constraints has broader implications for understanding the persistence of price seasonality in this region and other neighboring areas.

4.9 References

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4.10 Tables and Figures

Table 4.1-Summary Statistics

	1	2	3	4	5	6	7
Variables	Control	Storage	Stor age+Credit	(1)-(2)	(1)-(3)	(2)-(3)	F-test
Maize harvested in June 2016 (kg)	1536.333 [134]	1379 [129]	1600 [158]	0.1	-0.038	-0.134	1.284
Total maize consumed by household	419 [17]	392 [16]	393 [15]	0.118	0.112	-0.005	1.292
Net maize Sales by Household (TSh)	304,000 [50839]	289,000 [53679]	410000 [67095]	0.022	-0.137	-0.153	1.667
Proportion of households who were net sellers	0.189 [0.019]	0.23 [0.025]	0.175 [0.024]	-0.016	0.04	0.056	0.402
Proportion of autarkic households	0.3 [0.026]	0.31 [0.028]	0.282 [0.031]	-0.09	0.039	0.129	1.292
Spent on storage chemicals (TSh)	7580 [605]	6742 [709]	6521 [738]	0.084	0.105	0.023	1.082
Fertilizer Expense of Household (TSh)	147,000 [19490]	123000 [15487]	130000 [19932]	0.127	0.082	-0.036	0.367
Total cost of maize seed purchased (TSh)	3030 [665]	1792 [460]	2771 [630]	0.119	0.022	-0.098	1.634
Maize inventory beginning of January 2017(kg)	628 [54]	625 [54]	625 [644]	0.005	0.004	-0.001	0.019
Number of hermetic bags owned before intervention	0.338 [0.11]	0.17 [0.09]	0.13 [0.05]	0.135	0.179	0.045	1.52
Progress out of Poverty Index score of the household	48 [1]	48 [1]	49 [1]	-0.043	-0.098	-0.052	1.019
Money borrowed from the VICOBA (TSh)	234,000 [48752]	224000 [54446]	237000 [68238]	0.018	-0.004	-0.021	0.121

Notes-(1) The table above shows the summary statistics by treatment categories from column 1-3.
(2) Imbens and Rubin suggest an alternate normalized difference statistic comparing each treatment category with the others that we show her from column 4-6.
(3)We show results from an F-test for joint orthogonality for each of the variables. Standard errors are clustered at the VICOBA level and fixed effects for district dummies are included in all estimation regressions for F tests.
(4) ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.
(5)This data was winsorized at the 1st and 99th percentile.

Table 4.2- Main outcomes post-intervention

VARIABLES	Maize Inventory in January 2018 (kg)		Net maize sales during April 2017-March 2018 (TSh)		Net maize sales during April 2017-March 2018 (kg)	
	POST	ANCOVA	POST	ANCOVA	POST	ANCOVA
Group2=Training+Storage	142	137	17,811	11,782	123	129
	(105)	(103.8)	(52,999)	(44,270)	(122.9)	(97.11)
Group3=Training+Storage+Credit	247*	223**	84,796	42,339	327**	233*
	(127)	(95)	(66,297)	(51,918)	(162)	(118.2)
Maize inventory beginning of Jan-March 2017		0.54***				
		(0)				
Net maize sales during April 2016-March 2017 (TSh)				0.289***		
				(0.0457)		
Net maize sales during April 2016-March 2017 (kg)						0.439***
						(0.0723)
Total maize consumed during April 2016-March 2017 (kg)						
Control mean and standard deviation	753		198,739		478	
	(1018)		(501,732)		(1231)	
Observations	1,238	1,238	1,238	1,238	1,238	1,238
R-squared	0.090	0.222	0.131	0.298	0.122	0.274
Group 2=Group 3	0.403	0.401	0.239	0.470	0.175	0.332

Notes (1) The table presents Intention to Treat Estimates from a SMD (Simple Mean Difference) and an ANCOVA regression on the treatment dummies.
(2) By SMD we mean a regression of the post-intervention variable on the treatment dummies. ANCOVA estimation includes the baseline year's value of the outcome variable
(3) The outcome variables respective are
Maize Inventory in Jan 2018 (kg),
Net maize sales in TSh through the year (maize sales-maize purchases-interest rate paid by credit group)
Net maize sales in kg through the yea
Maize consumed in kg through the year
(4) Standard errors clustered at VICOBA Level.
(5) District Fixed Effects and constant included in all specifications.
(6) Observations have also been probability weighted by the likelihood of them being selected for any treatment, or for being surveyed.
(7)*** p<0.01, ** p<0.05, * p<0.1

Table 4.3- Quarter level analysis

	(1)	(2)	(3)	(4)
Variables	Net Maize Sales (TSh)	Net Maize Sales (TSh)	Net Maize Sales (kg)	Net Maize Sales (kg)
	POST	ANCOVA	POST	ANCOVA
Group 2= Storage group before harvest (April-June)	-19,947	-19,938	-53.23	-51.85
	(13012)	(13002)	(36)	(34)
Group 2= Storage group during harvest (July-Sept)	8,725	8,722	22.69	19.78
	(19311)	(19303)	(52)	(49)
Group 2= Storage group in quarter after harvest (Oct-Dec)	27,561	27,636	64.81	76.87
	(21,601)	(21,590)	(67)	(63)
Group 2= Storage group two quarters after harvest (Jan-Mar)	13,333	13,290	33.61	28.12
	(13489)	(13478)	(40)	(39)
Group 3= Storage+Credit group before harvest (April-June)	-16,338	-16,356	-49.85	-51.37
	(12,228)	(12,223)	(33)	(31)
Group 3= Storage+Credit group during harvest (July-Sept)	8,826	8,190	36.34	5.019
	(18451)	(18353)	(52)	(48)
Group 3= Storage+Credit group after harvest (Oct-Dec)	38,179*	38,195*	134.6*	128.4*
	(21392)	(21378)	(71)	(69)
Group 3= Storage+Credit group after harvest (Jan-Mar)	30,801*	30,759*	96.00*	91.13*
	(17065)	(17007)	(53)	(47)
Net Maize Sales in quarter of baseline year (TSh)		0.000859		
		(0)		
Net maize sales in quarter of baseline year (kg)				0.222***
				(0)
Maize inventory in quarter of baseline year				
Constant	4,561	4,603	1.086	10.59
	(11,651)	(11,640)	(32)	(30)
Observations	4,952	4,952	4,952	4,952
R-squared	0.051	0.052	0.057	0.092
Group2=Group3 in April-June	0.704	0.707	0.903	0.985
Group2=Group3 in July-Sept	0.996	0.978	0.796	0.755
Group2=Group3 in Oct-Dec	0.637	0.639	0.331	0.442
Group2=Group3 in Jan-Mar	0.279	0.279	0.217	0.181

Notes (1) The table presents Intention to Treat Estimates from a SMD (Simple Mean Difference) and an ANCOVA regression on the treatment dummies, interacted with the quarter level dummies
(2) By SMD we mean a regression of the post-intervention variable on the treatment dummies. ANCOVA estimation includes the baseline year's value of the outcome variable
(3) The outcome variables respective are
Net maize sales in TSh through the year (maize sales-maize purchases-interest rate paid by credit group)
Net maize sales in kg through the yea
(4) Standard errors clustered at VICOBA Level and district Fixed Effects and constant included.
(6) Observations have also been probability weighted by the likelihood of them being selected for any treatment, or for being surveyed. (7)*** p<0.01, ** p<0.05, * p<0.1 (8) All treatment effects are in reference to control group. (Group 1)

Table 4.4-- -Treatment heterogeneity with respect to credit constraints

Variables	(1) Net Maize Sales (TSh)	(2) Net Maize Sales (kg)	(3) Maize Inventory in Jan 2018 (kg)
Group = 2, Storage	-99,117*	-70	26
	(54,688)	(118)	(110)
Group = 3, Storage+Credit	-60,284	-33	10
	(49,426)	(120)	(107)
Did not borrow from Vicoba in baseline year=1	-171,219***	-293**	-141.7
	(56,210)	(128.0)	(115)
Interaction term for storage intervention dummy and dummy for not borrowing from Vicoba in baseline year	228,754***	412**	229.3*
	(67,552)	(171)	(138)
Interaction term for credit intervention dummy and dummy for not borrowing from Vicoba in baseline year	214,846***	566**	453.3**
	(81,752)	(219)	(202)
Net maize sales during April 2016-March 2017 (Tsh)	0.288***		
	(0.0448)		
Net maize sales during April 2016-March 2017 (kg)		0.433***	
		(0.0711)	
Maize inventory beginning of Jan-March 2017			0.533***
			(0.0881)
Constant	89,379**	73	263**
	(44,932)	(104)	(115)
Observations	1,238	1,238	1,238
R-squared	0.307	0.281	0.229
Group 2 when credit constrained	0.00338	0.0264	0.152
Group 3 when credit constrained	0.0341	0.0195	0.0212
Group 2=Group3 (when credit constrained)	0.673	0.242	0.214

Notes (1) The table presents ANCOVA estimates
(2) ANCOVA estimation includes the baseline year's value of the outcome variable
(3) The treatment variable has been interacted with a dummy variable signifying credit constraint. The dummy is , whether the individual borrowed from the vicoba in the baseline year. We use this variable because for 78 % of the sample the vicoba is the main source of credit. Borrowing amount is also positively correlated with land cultivated (0.07) and household revenue (0.14) in the baseline year.
(3) The outcome variables respective are
Maize Inventory in Jan 2018 (kg),
Net maize sales in TSh through the year (maize sales-maize purchases-interest rate paid by credit group)
Net maize sales in kg through the yea
(4) Standard errors clustered at VICOBA Level and district Fixed Effects and constant included.
(6) Observations have also been probability weighted by the likelihood of them being selected for any treatment, or for being surveyed.
(7)*** p<0.01, ** p<0.05, * p<0.1
(8) All treatment effects are in reference to control group. (Group 1)

Table 4.5-- -Unadjusted P values compared to sharpened q values

	Storage		Storage+Credit	
Variables	Unadjusted p values	Sharpened q values	Unadjusted p values	Sharpened q values
Maize Inventory in January 2018 (kg)	0.189	0.69	0.021	0.113
Net maize sales during April 2017-March 2018 (TSh)	0.791	0.909	0.416	0.217
Net maize sales during April 2017-March 2018 (kg)	0.318	0.771	0.046	0.13
Hetrogeniety-Net maize sales during April 2017-March 2018 (TSh)	0.072	0.563	0.225	0.168
Hetrogeniety-Net maize sales during April 2017-March 2018 (TSh)	0.001	0.018	0.01	0.104
Hetrogeniety-Net maize sales during April 2017-March 2018 (kg)	0.551	0.909	0.78	0.35
Hetrogeniety-Net maize sales during April 2017-March 2018 (kg)	0.017	0.158	0.011	0.104
Hetrogeniety-Maize Inventory in January 2018 (kg)	0.811	0.909	0.099	0.139
Hetrogeniety-Maize Inventory in January 2018 (kg)	0.922	0.954	0.027	0.113
Quarter Level-Net maize sales during April 2017-March 2018 (TSh)				
Quarter before harvest-April-June	0.128	0.624	0.183	0.168
Quarter during harvest-June-September	0.652	0.909	0.656	0.35
Quarter after harvest-October-December	0.203	0.69	0.076	0.13
Two quarters after harvest-January-March	0.326	0.771	0.073	0.13
Quarter Level-Net maize sales during April 2017-March 2018 (kg)				
Quarter before harvest-April-June	0.128	0.624	0.103	0.139
Quarter during harvest-June-September	0.687	0.909	0.917	0.37
Quarter after harvest-October-December	0.224	0.69	0.066	0.13
Two quarters after harvest-January-March	0.472	0.909	0.055	0.13

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

Figure 4.6 - Maize price change from harvest Mbeya Tanzania

Notes-Graph made by Authors based on city level maize price data provided by the Ministry of Industry (Tanzania). The graph was calculated by averaging prices for each month across the different years. The y axis represents how much higher the average price in that month was compared to the average price in June. Mbeya region is primarily a unimodal maize production area, and June is generally when the harvest begins and maize prices are lowest in the Mbeya region.

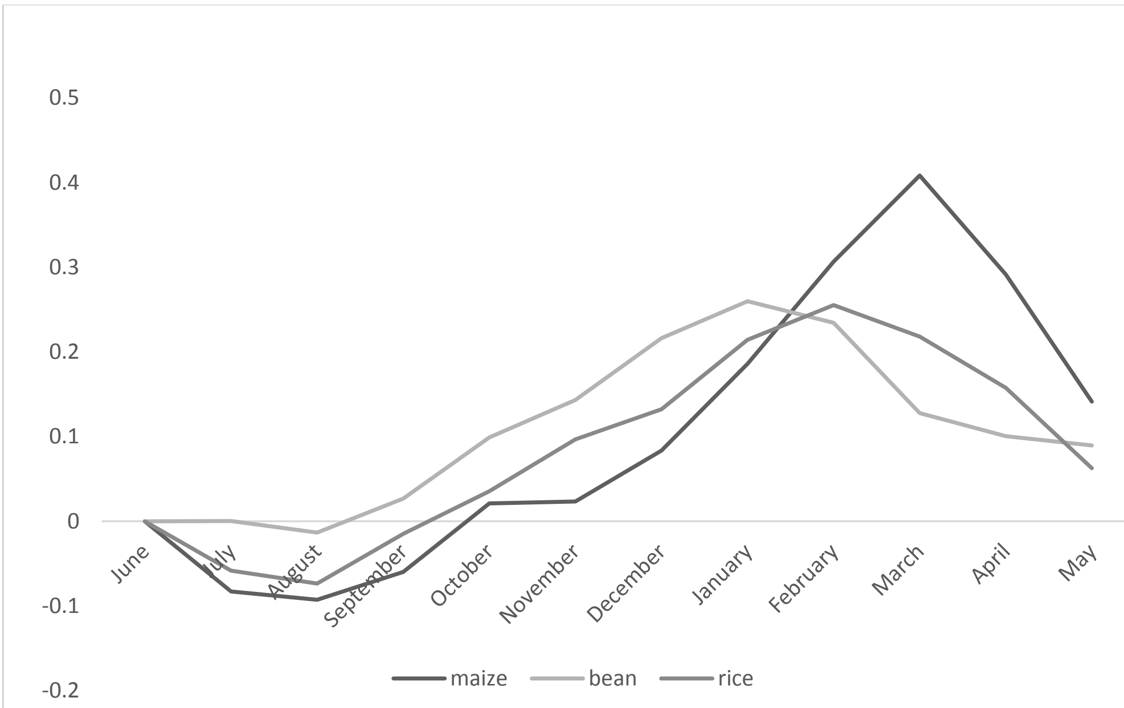


Figure 4.7 - Price behavior of maize, compared to bean and rice in Mbeya region

Notes-Graph made by Authors based on city level price data provided by the Ministry of Industry (Tanzania). The graph was calculated by averaging prices for each month across the different years. The y axis represents how much higher the average price in that month was compared to the average price in June.

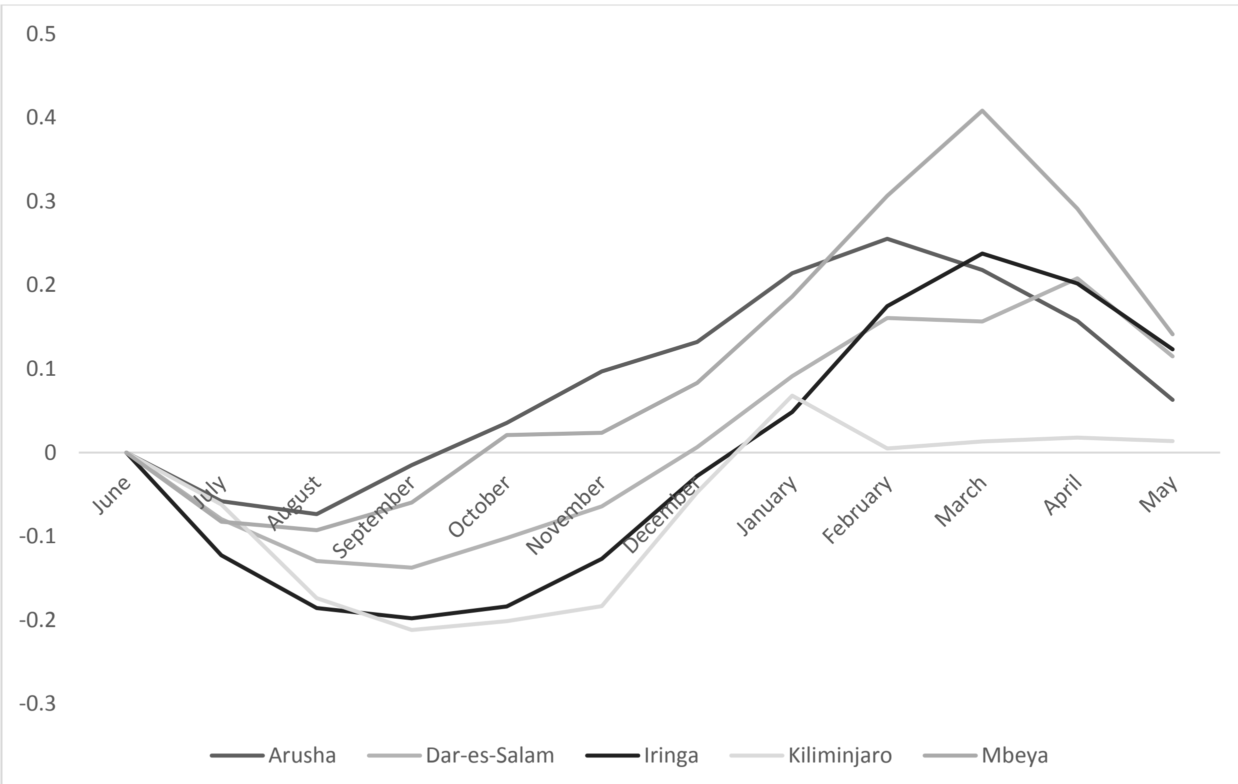


Figure 4.8 - Price behavior of maize in Mbeya compared to other regions

Notes-Graph made by Authors based on city level price data provided by the Ministry of Industry (Tanzania). The graph was calculated by averaging prices for each month across the different years. The y axis represents how much higher the average price in that month was compared to the average price in June.

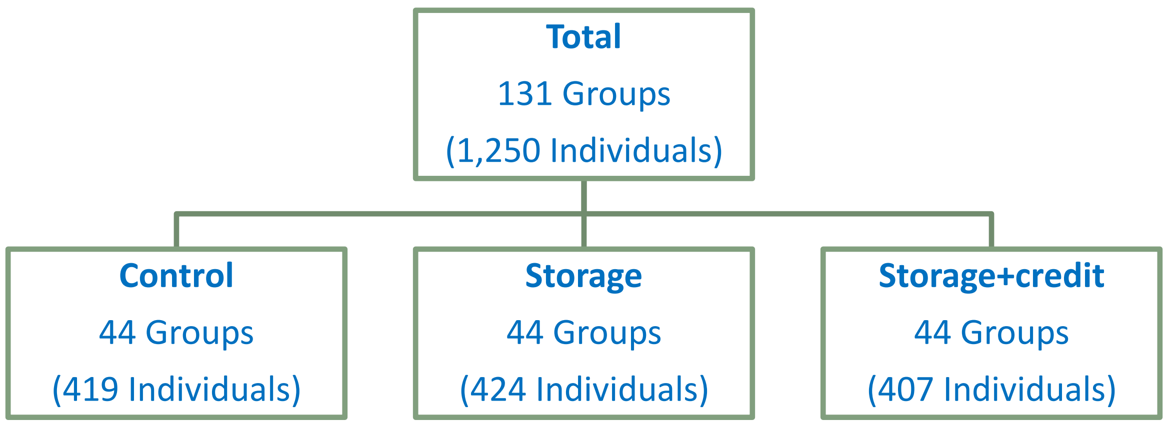


Figure 4.9 -- Design of Randomized Control Trial

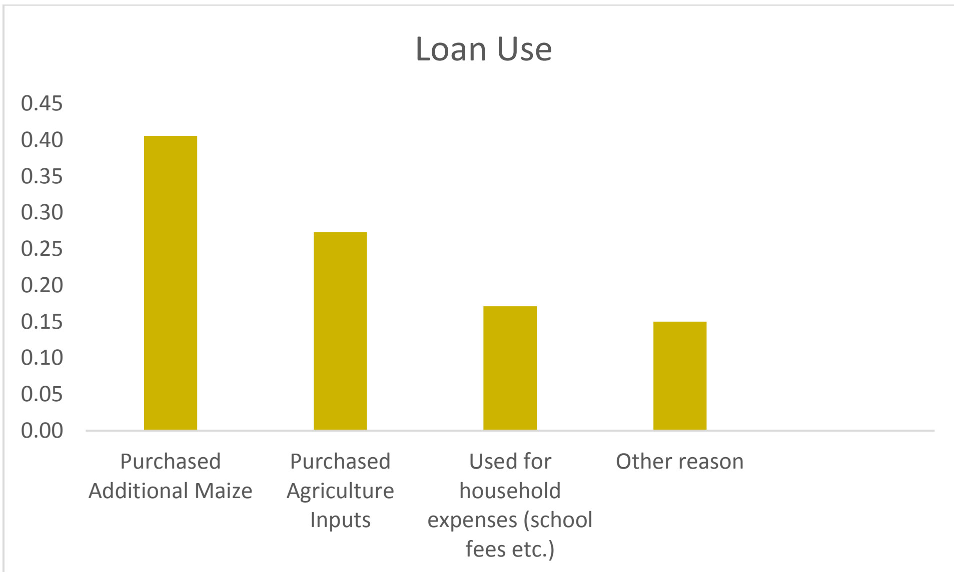


Figure 4.10 -- -Loan Utilization

Notes-This is in response to a question asked from those who took up the loan. In the case that the loan was utilized for additional purposes, the major use has been presented here. Other reason includes investment in non-agricultural business and home repairs.

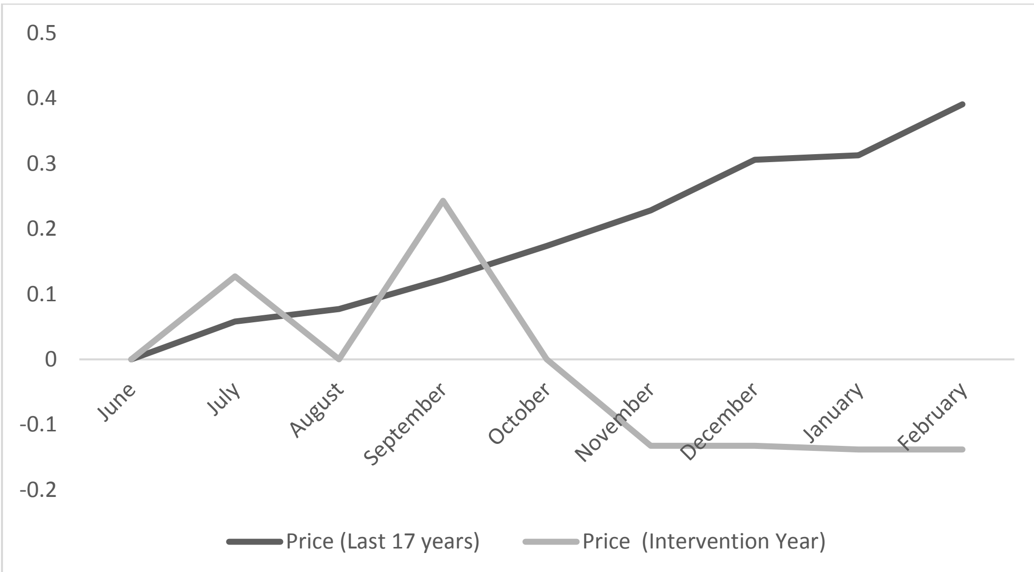


Figure 4.11 -Price behavior for last 17 years, compared to intervention year

Notes-The graph showing price data from the intervention year was taken from the USDA GAINS Report on Tanzania, from June 2017-February 2018. This data is representative for all of Tanzania and not Mbeya. This graph will be updated when we are able to get data for Mbeya city from Ministry of Industry and Trade for the year 2017-2018.

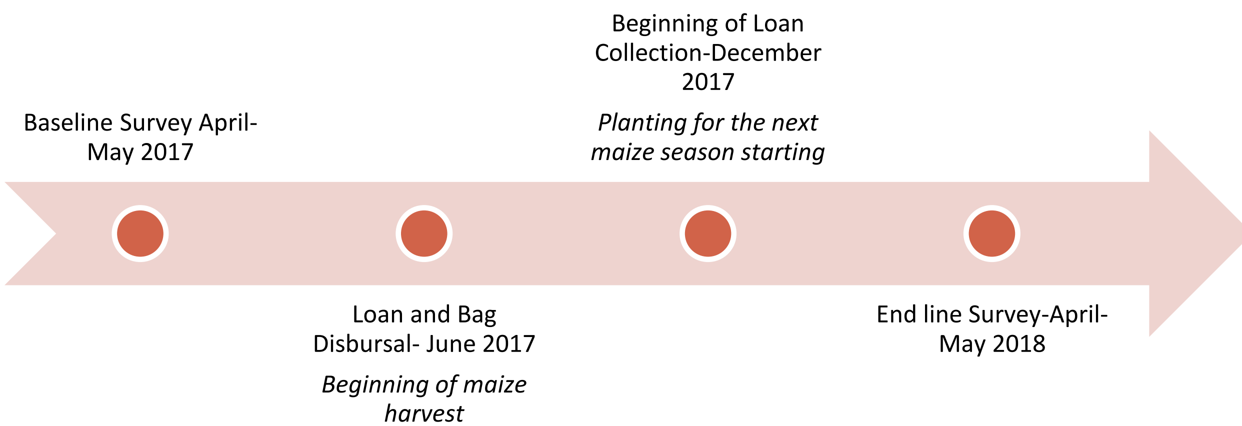
4.11 Appendix

4.11.1 Phone interview dummy for robustness check

VARIABLES	(1) Net Maize Sales (TSh)	(2) Maize in January 2018 (kg)	(3) Net Maize Sales (kg)
Storage	11,232	141.4	127.1
	(44,153)	(105.0)	(97.08)
Storage+ Credit	42,319	222.3**	233.3*
	(52,024)	(94.99)	(118.4)
Interview was conducted over phone (Yes=1)	16,857	-134.3	66.74
	(41,363)	(82.68)	(116.7)
Net maize sales (TSh)	0.290***		
	(0.0453)		
Net Maize Sales (kg)			0.272***
			(0.0346)
Amount of maize stored with household at the beginning of Jan-March 2017	-58.09	0.136	-0.00286
	(55.74)	(0.108)	(0.0134)
Constant	4,216	216.4**	-79.56
	(39,290)	(94.61)	(95.55)
Observations	1,238	1,238	1,238
R-squared	0.275	0.224	0.298

Notes (1) The outcome variable is net maize sales in TSh, maize inventory in January 2018 in kg and maize consumption in kg (2) We include control variables , maize consumed maize harvested, maize inventory and sales in all three specifications.(3) Phone interview is included as a dummy variable in all three specification. (4) Standard errors clustered at VICOBA Level. (5) District Fixed Effects and Constant included in all specifications. (5) Observations have also been probability weighted by the likelihood of them being selected for any treatment, or for being surveyed. (6)*** p<0.01, ** p<0.05, * p<0.1

4.11.2 Timeline



4.11.3 Crump Test for heterogeneity

	Zero Conditional Average Treatment Effect				Constant Conditional Average Treatment Effect				Zero Average Treatment Effect			
	Chi-Sq_Test	p-val_Chi-sq	Norm_Test	p-val_Norm	Chi-Sq_Test	p-val_Chi-sq	Norm_Test	p-val_Norm	Chi-Sq_Test	p-val_Chi-sq	Norm_Test	p-val_Norm
	1	2	3	4	5	6	7	8	9	10	11	12
Credit												
Net Maize Sales over intervention year (TSh)	30.2625	0.0167	2.5213	0.0058	28.833	0.0169	2.5255	0.0058	2.4296	0.1191	1.5587	0.1195
Maize Inventory held in January 2018 (kg)	19.6463	0.2366	0.6446	0.2596	18.6179	0.2316	0.6605	0.2545	3.7804	0.0519	1.9443	0.0522
Maize consumed over intervention year (kg)	17.0851	0.3801	0.1918	0.4239	16.3346	0.3602	0.2437	0.4037	1.1543	0.2827	-1.0744	0.283
Storage												
Net Maize Sales over intervention year (TSh)	35.9371	0.003	3.5244	0.0002	34.924	0.0025	3.6376	0.0001	0.0369	0.8477	-0.192	0.8478
Maize Inventory held in January 2018 (kg)	15.9693	0.4551	-0.0054	0.5022	15.3521	0.4264	0.0643	0.4744	0.8171	0.366	0.9039	0.3663
Maize consumed over intervention year (kg)	13.4872	0.6369	-0.4442	0.6716	13.1529	0.5905	-0.3372	0.368	0.4061	0.524	-0.6373	0.5241

Notes 1) The table provides results for the tests described in Crump et al. (2008). The paper describes two hypothesis tests. The first one if there is a zero conditional ATE, meaning that across the covariate space the treatment effect is zero (first 4 columns). The second one checks if the conditional average treatment effect is the same for the entire covariate space (columns 5-8). The last four columns essentially checks the average treatment effect which we have previously examined in our earlier regressions (last 4 columns). 2) We test for each of the three main variables net maize sales (TSh), maize inventory in January (kg) and maize consumed over intervention year (kg). 3) We also test separately for each treatment category, so in total there are 9 rows. 4) All of the variables presented in the baseline statistic are used for this test