Willingness to Pay for a new farm technology given Risk Preferences. Evidence from an experimental auction in Kenya.

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Abstract:

This paper describes an experimental auction conducted among maize traders and farmers in Western Kenya to measure adoption for two low-cost technologies that can measure grain moisture content. Willingness-to-pay auctions (WTP) were combined with a risk preference lottery, allowing an opportunity to study the impact of risk preferences on technology adoption. The specifics of this technology also allows us to identify the impact of risk aversion on willingness to pay for a technology when production uncertainty is not part of the equation. We also randomized two variations of the BDM method for collecting WTP data allowing for a mechanism by which to study the impact of the method on valuation data. We find some evidence that risk aversion increased willingness to pay. Another result with implications in implementation of field experiments in the developing world is that farmers were sensitive to the method in which the auction was presented but traders were not.

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Abstract

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Introduction

Increasing usage of new farm technologies in the developing world is an important part of moving to more sustainable and productive farming systems, and contribute potentially a mechanism through to providing which small holders with options to can break out of the poverty cycle. Insights that help explain the pattern behind farm technology adoption can be very useful for practitioners.

However, empirical work on the role of risk and uncertainty affecting technology adoption is complicated by the challenges associated with using survey data to measure risk aversion and technology adoption. It is to be noted that the applied economics profession in response to the challenges associated with working with survey data in general, has recognized that in many scenarios experimental data will offer more insights. Randomized Controlled Trials, for example, offer a mechanism by which to deal with endogeneity caused by self-selection when measuring causal impacts. (Duflo et.al.,2008) Similarly, incentive compatible methods of eliciting willingness to pay (WTP) provide a way of avoiding hypothetical bias and strategic bidding when eliciting valuations(Lusk & Schroeder, 2004). Cardenas & Carpenter (2008) in a review of field experiments in the develop world make the point that economic experiments can result in insights that might even be contrary to traditional perspectives.

This paper contributes to the existing literature by using experimental methods to look at the impact of risk preferences on willingness to pay for a new farm technology. We use an incentive compatible method to measure farmer valuations for a new technology that they were not initially familiar with, the Becker De Groot Maschak (BDM). In addition to the auction we also conduct a Ordered Lottery Selection (Binswanger, 1980)style lottery) in which respondents select a lottery from an ordered set. The lottery choices(which vary in terms of mean and variance of outcome) reflect the risk preferences of the respondents.

Using incentive compatible methods are is considered less biased than compared to stated preference methods, which is what the previous literature has relied on.(List & Gallet, 2001) Some of the recent literature that has examined this issue includes Asrat et.al (2013) who carry out a choice experiment in Ethiopia to determine the impact of risk preferences on farmer seed choices. Liu (2013) using survey data finds that Chinese farmers who are more risk and ambiguity averse are less likely to adopt Bt (Bacillus thuringiensis) technology. Since in the context of Liu's study Bt technology is not riskier than traditional cotton, what appears to matter are farmer's own perceived benefits and losses.

This paper is concerned with two low-cost technologies called the Hygrometer and the DriCard respectively. These devices are both low cost tools for measuring moisture content in maize costing $1.50 and 25 cents respectively, compared to the traditional moisture meters which cost upwards of US $100. The devices can therefore offer a more affordable alternative which is potentially more accurate then traditional methods of determining moisture. (e.g. biting, sound of the maize)

The outcomes of the technologies used in this paper are not dependent on any external risk factors (like rainfall for example). The devices reduce the uncertainty associated with maize moisture content. This is useful because when considering other technologies i.e seed or fertilizer, it is hard to differentiate between outcome uncertainty associated specifically with the technology versus just a cautiousness with respect to using a new technology.[1] As such, a risk averse individual should place a greater value on this reduction of uncertainty(be willing to pay more for the insurance essentially).

A closely associated study to this work is Shimamoto et.al. (2017) who look to measure the impact of risk preferences on the use of moisture meter devices in rural Cambodia. The authors use an experimental mechanism to measure risk preferences and supplement this with survey data looking into whether the farmer had used moisture meters for rice seeds. They find that more risk averse farmers are more likely to be using the moisture meters.[2] We extend this work concerning the role of risk preferences on technology adoption in a few different ways. We use an incentive compatible design to measure willingness to pay. Additionally the nature of our design was such that the technology was completely new for the respondents. This is helpful because respondent exposure to the technology (how they heard about it, which can impact adoption decisions) is consistent across the sample.

The other contribution of this article is related to the process of conducting valuation experiments in the field. The Becker De Groote Maschak (BDM, 1964) has been shown to be theoretically incentive compatible, yet concerns regarding its application in the field remain despite its long history of use. Cason & Plott (2014) attribute the failure of the BDM in their case as a type of game misconception. DeShazo (2012) uses data from multiple studies using contingent valuation to measure willingness to pay. He finds that when questions are asked in ascending order this leads to lower average valuations versus when questions are organized in a descending way. We make a slight variation in the process that we used to conduct the BDM (Healey 2017) to test if these type of effects persist when using incentive compatible methods. We randomly allocate each individual to either an ascending series or descending series of questions to elicit willingness to pay. The randomization allows us to test if the order of the questions has an impact on participant valuation.

[1] For example when examining adoption of a new seed variety it is hard to take apart the impact of the increased production uncertainty versus wariness associated with the newness of the technology
[2] The study also finds that loss aversion and probability weighting does not appear to affect moisture meter use

This discussion leads to the following null hypotheses:

$H_0$1: An individual's level of risk aversion does not affect his or her willingness to pay for either a hygrometer or dricard

In order to test how the process used effects valuations we need to compare WTP outcomes from the two methods used:

$H_0$2: The process by which the auction is conducted does not affect Participant valuations. (High Low versus Low High)

We have two different respondent types(farmers and traders) in our sample and there is empirical evidence from Senegal(McCoy 2016) that traders are better informed about maize moisture content then buyers. While this study is comparing farmers and traders, we expect that since traders have to value maize more frequently they would be better at estimating moisture content. This in turn would suggest that they value the devices less :

$H_0$3: Farmers and traders have the same valuation for both devices

In addition to these main hypotheses the data allows us to study some correlates of demand that might be useful for policymakers and suppliers/marketers engaged in marketing new technology to farmers in the developing world. We develop demand curves for both devices and also study specific farmers and trader characteristics to determine their impact on willingness to pay.

We find that higher levels of risk aversion are associated with increasing willingness to pay for both devices, however this result is sensitive to model specification. We reduce the uncertainty regarding the actual functioning of the device by conducting a demonstration, and since these devices reduce uncertainty(by providing more information) regarding the moisture content in maize, more risk averse individuals are willing to pay more.

Another useful finding is that farmers in our sample are very sensitive to the way in which the auction questions are presented to them, while traders are not. This could be an important finding for practitioners using the BDM mechanism to measure valuations. It makes the case that there is some form of game misconception or framing effect, which however does not appear to be present in the trader populations.

Background

Post Harvest Losses Issues

Post-harvest losses can be a major source of loss in the grain supply chain in the developing world (FAO 2010). In maize which is the major cereal, in East Africa, losses just due to pests can be as high as 20-30%. (Boxall, 2002). In addition to these losses there is also depreciation in the economic value of damaged maize.

Another non-economic consideration with improperly stored grain is the presence of dangerous toxins. The impact of aflatoxins a highly carcinogenic toxins produced by the Apergillus fungi is a serious concern in the developing world and Kenya in particular. There were major outbreaks of aflatoxicisis in the early 2000's which resulted in more than 500 deaths that were attributed to contaminated maize. (Lewi et al. ,2005)

Its chronic presence in food items like maize (the main cereal consumed in Kenya) can result in serious harm to the body with effects including liver damage, abortion and malabsorption of micronutrients by the body. One of the main factors that effects the growth rate of fungus in stored maize is the presence of water in stored grain. This indicates that a straightforward way of managing the growth of fungi that produces this toxin is to manage the moisture content at which maize is stored. However, moisture meters are expensive, costing more than a US $100 and not easily available in many parts of the world.

Moisture Detection Technologies: Hygrometer and the DriCard

The DriCard is a laminated strip of cobalt chloride paper (which has the property of changing color with humidity levels in the atmosphere). The card works through a color change that can be calibrated with a humidity level. The Hygrometer, calibrated by the team at Purdue University, is a cheap standard household device that provide humidity and temperature readings.

The conversion of humidity reading to a specific moisture content requires both a temperature reading and a humidity reading. However Tubbs et. al. (2017) have established that for maize grain specifically a humidity reading of 65% indicates a moisture content in maize of between 12.5 % and 13.5% if the temperature is between 20-30 degrees Centigrade. This allows farmers and traders to use the 65% as a critical value for moisture content in maize (since below 13.%is considered sufficiently dry). The hygrometer provided a numeric humidity reading, while for the DriCard a color change to purple implies that the humidity is in this range. These are available at a retail cost $1.50/unit and $0.50/unit in the US respectively. The Hygrometer is considered to be more accurate because its output is numerical and it avoids the subjectivity of the DriCard which requires interpreting a color reading.

Methodology

Site and participant selection

In order to assess the demand for both of these items in rural Kenya, a willingness to pay auction was conducted in Kakamega district (redrawn to Kakamega County- which includes additional areas) in March 2017, which is more humid then other parts of Kenya. This area is one of the sites for a project being conducted by Purdue's Food Processing Lab[3]. The sample consisted of 589 individuals, which include 305 farmers and 284 maize traders. The farmers in our sample had already been surveyed on issues related to post harvest issues in the previous year. (March 2016) It was the first time however that the traders were approached.

Kakamega district has two seasons with the major one going on from March-September and the other smaller one going from November-Jan. So this experiment occurred when the processing and

[3] https://ag.purdue.edu/ipia/fpl/Pages/default.aspx

storage decisions for maize harvested from the short rain season had already occurred. Farmers were beginning to prepare for harvest for the long rain season.[4]

Auction structure

(Insert Table 1 here)

Farmers were approached in their homes and traders were approached in the market, and then given a brief introduction to the activity after which verbal consent was obtained.

Since both devices were completely new for the participants, an explanation of how they both worked was necessary. The enumerators therefore started the survey by introducing the participants to the devices and explaining the purpose of the devices. Each enumerator carried two small plastic bags of wet and dry maize each. They put in the DriCard and the Hygrometer in the dry and wet maize each. The enumerators then told the participants that while they waited for the devices to calibrate they would like to ask the participants some questions regarding their household and maize production. After the questionnaire was completed (questionnaire available on request), the enumerators conducted the auction to determine the maximum willingness to pay for both the devices.

The auction followed the incentive compatible BDM (1964) design. The process of conducting it were adapted from Healey (2017) for participants that are not directly interacting with the questionnaire and for whom an intermediary in the form of an enumerator is present. The participants were asked in form of a series of questions whether they were willing to pay a certain amount for the Hygrometer/DriCard.

(Insert Table 3 and 4 here)

These questions were setup in two different ways. In the first method the farmers were asked if they would be willing to pay for the DriCard/Hygrometer starting from a price of 3.00 USD (300 KSh),

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[4] This is relevant to note because the auction timing did not coincide with when there would be increased demand for post-harvest technology

where approximately 100 KSh is equivalent to $1. If the participant indicated that they would be willing to buy the item (tool?) at this price then the questions stopped for the particular device. If the participant said they were not willing to buy then the price was lowered by 20 KES (approximately 20 US$ cents) and so on until the price went to 20 KES. The second method worked the same way except the prices began at 20 KES) and if the participants were willing to buy at this price and the price went up by 20 cents until it reached a maximum of 300 KES (3.00 USD).

Following this, participants were asked to toss a coin and the final device was picked depending on the outcome of the toss. After this, participants picked a price from a brown paper bag, which had slips of paper ranging from 20 to 300 (indicating prices from 20 cents to 3.00 USD, 20 KES to 300 KES). According to the standard BDM method if the random price was higher than the price bid by the participant, the participant lost the auction and the chance to buy the device. Conversely, if the randomly chosen price was lower than the price bid by the respondent, then he or she bought the device at the lower price. The randomization of the specific method allows us to test if there is an effect depending on if we use Low-High or High-Low with the WTP questions.

Risk Aversion Experiment

(Insert Table 2 here)

Following the willingness to pay exercise the participants played a Binswanger style lottery. Participants played four games with the order of the game randomized. The games consisted of sets of 6 lotteries each which varied in degrees of riskiness. The participants had to choose one of the 6 lotteries in each of the games. The maximum possible amount that the participant could win is $1.60 (160 KES).

The participants choose an option in each game, but only one of the games was binding with real payouts. After the game was chose, the option the participant had picked out in the game was played through the flip of a coin and a payout was made based on the outcome of the toss.(Table 2)

In each part of the willingness to pay and lottery game, any random selection was done through strips of paper in a brown paper bag. However before the randomization the strips were taken out of the bag, hown to the participant (who were encouraged to pick them up and check them if they wanted) and then put back in the bag (to convince the participants of the transparency of the design). *Conceptual Framework for Willingness to pay and risk aversion*

We start with the following expression for willingness to pay[5]

$$\int_{z\_min}^{z\_max} U(y - WTP, z) gdz = \int_{z\_min}^{z\_max} U(y - WTP, z) gdz' \quad (1)$$

In the expression we assume that gdz' is a mean preserving spread of gdz, in which case a risk averse individual would prefer gdz to gdz'. We take 'z' to be the quality of stored maize. By investing in the hygrometer/DriCard the respondent is essentially purchasing information that would reduce the uncertainty associated with the quality of stored maize. This would mean that the amount that the respondent is willing to pay for the device is dependent on their level of risk aversion. A more risk averse individual would be willing to pay more to reduce this uncertainty

Empirical Model

The dataset in this sample is structured so that we have two "WTP" observations per household. (one for each device). It is not possible to run a fixed effect regression because all the variables of interest including the method used and the risk parameter are invariant across the two WTP observations.

We run an ordinary least squares regression[6] to help better understand the factors affecting respondent willingness to pay and to test the hypothesis discussed in the earlier section. Clustered standard errors at the participant level are used because we have two observations per participant. Using an OLS with clustered standard errors is more robust then using a random effect regression because it allows for a more flexible error structure. (Greene, 2012)

$$WTP_{d,i} = \beta_1 F_i + \beta_2 D_{d,i} + \beta_3 \theta_i + \beta_4 R_i + \beta_5 M_i + \beta_x * X_i + \beta_6 (F_i * M_i) + \beta_7 (F_i * D_{d,i}) + \beta_4 \theta_i * F_i + u_i + w_{ij} \quad (1)$$

In the equation above, the terms are defined as the following:

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[5] The section above has been adapted from (Bateman & Willis,2001)

[6] We also present results from a tobit regression(censored at Ksh 0 and 300) but since the main conclusion do not change we present the results from the OLS regression.(tobit regression results are shown in Appendix)

"$WTP_{d,i}$" is the willingness to pay for each device for each individual. This is in KES(Kenyan shillings). "d" is the index for the device type (Hygrometer, DriCard) and "i" indicates the individual.

F_i is an indicator variable for whether the respondent was farmer or trader. (Farmer-0, Trader-1)

$D_{d,i}$ is an indicator variable for which device willingness to pay was being elicited. (Hygrometer-1, Drycard-0)

θ_i is the risk parameter estimated using the lottery experiment.

R_i is the highest reliability ranking that the respondent gave for an alternate method.

M_i is an indicator variable for the method used. (High-Low-1, Low-High-0)

$u_{i,} w_{ij,}$ The error term is split into the respondent effect($u_{i,}$) and the respondent and device effect ($w_{ij,}$).

X_i is a vector of control variable such as maize harvested, size of land cultivated, asset score for the individual, the household size, previous knowledge of aflatoxin and the respondent gender. The asset score is an aggregation of 5 questions that asks the respondent about ownership of various assets.

The expression β_3+ $\beta_4 \overline{F_i}$ allows us to test our first hypothesis. An increasing θ_i implies an increasing level of risk aversion(assuming a CRRA utility function).

The expression $\beta_5 + \beta_{6*}\overline{F_i}$ allows us to test whether the method used has a significant impact on the valuation.

The expression $\beta_1 + \beta_{6*}\overline{M_i} + \beta_{7*}\overline{D_{d,i}} + \beta_4\bar{\theta}_i$ allows us to test whether farmers and traders have different willingness to pay for the technology.

We also extend this analysis by splitting the sample with respondent types. This is not comparable to the previous regression and does not really permit for comparison of results between the two groups like with the interaction terms. However, it allows us to include additional controls for each sample. We include size of land cultivated and maize harvested for farmers and the proportion of maize bought from traders outside Kakamega for the traders in our sample. Both of these variables could possibly impact willingness to pay. It is likely that farmers who harvest more maize are likely to have greater demand for both devices and therefore bid more(+). Traders who buy more of their maize from traders outside Kakamega are likely to bid lower(-) for these devices. This hypothesis is based on anecdotal evidence which suggested that when buying from larger scale traders the quality was expected to be more consistent.

$$WTP_{d,i} = \beta_2 D_{d,i} + \beta_3 \theta_i + \beta_4 R_i + \beta_5 M_i + \beta_x * X_i + \beta_f * X\_F_i \qquad (2)$$

Results

Respondent Characteristics

(Insert Table 5 here)

Our sample had 589 respondents with 305 farmers and 289 traders. The farmers belonged to 13 different "sub locations"[7] in Kakamega district. The traders were from 13 different market centers from all over Kakamega district. Traders tend to be wealthier then farmers as indicated by non-maize sales income and the asset score. They are also more likely to be slightly better educated and have smaller families. Despite this for both devices, traders are willing to pay slightly less, although the difference is within 5 KSh

(Insert Table 6 here)

We can see this reflected in our sample because farmers tend to cultivate more land in the March-September(long rain), and a smaller proportion of this land is devoted to maize(38% vs 56%) when compared to the short rain season.

(Insert Table 7 here)

The data in the table provided above helps develop an interesting pattern on the maize market in Kakamega. Following the long rain season (after September) traders tend to buy most of their maize from farmers outside Kakamega district (44%) but following the short rain season (January onwards) almost all of the maize bought by traders comes from traders outside Kakamega (67%)[8.] While we do

[7] A sub location is an administrative unit in Kenya that is smaller then a district but consists of multiple villages within.

[8] Unfortunately, the totals in the table do not add up exactly, the total for the short rain season is larger by 700 kg and the total for the long rain season is larger by 300 kg. While this is problematic and suggests enumerator error it is not large enough to be a matter of serious concern

not ask about this in our survey, in-depth discussions with some traders suggests that most of this maize is bought from very large scale trading operations in bulk.

Traders who are buying from large scale traders are less likely to have bargaining power and therefore less interested in a device like the hygrometer. The auction was conducted in February-March 2016 (after the short rain harvest) when most traders appear to be buying maize this way. This might be a possible explanation of why traders on average were willing to pay a smaller amount for the hygrometer and DriCard. We might expect therefore that traders who tend to buy more in bulk from larger maize operations will be willing to pay less. We will explore this possibility in the regression model discussed in the following sections.

Auction Data: Willingness to pay-Demand and Profitability

(Figure 1 here)

We noted from the means reported in Table 5 that respondents were willing to pay for the hygrometer then for the DriCard. We now use histograms of the raw willingness to pay data(Figure 1) to check for obvious differences in their distribution .

The higher mean for the hygrometer comes from a sample of the population that there is a larger proportion of the population in the 200-300 KSh range as compared to the hygrometer. If we take a closer look at the distribution this point comes across in the fact that difference in the median willingness to pay (100 KSh for the Hygrometer and 60 KSh for the DriCard) is smaller than the difference in willingness to pay at the 75th percentile for both devices. (180 KSh for the Hygrometer and 120 KSh for the DriCard).

(Figure 2 and 3 here)

The figures show demand curves for the hygrometer and DriCard split by farmer and traders. The demand curves are made by plotting out the proportion of respondents willing to buy the device at each level. The demand for the hygrometer is similar between the farmer and trader demand curves, but there are more farmers willing to buy the DriCard at each price point. We also use this demand to calculate elasticities around the mean.

$$\varepsilon = \frac{\%\text{Change in proportion}}{\%\text{Change in Price}} \qquad (3)$$

We find that the demand for the elasticity for the hygrometer is around one when the price increases from 100 to 120 Ksh. For the DriCard demand falls more steeply with an elasticity of 1.7 as price rises from 60 to 80 Ksh.

Risk Aversion Parameters

We utilize the risk data to estimate a parameter for each individual in our sample. The method briefly described here has been covered (along with many others) in a manual prepared by Harrison and Rustrom (2014).In our experiment each participant makes four choices and the expected utility of any one choice assuming a CRRA utility function (Constant Relative Risk Aversion) is equivalent to :

$$EU_i = \exp(0.5\big(wealth + outcome_l{}^{1-\theta}/1-\theta\big) + 0.5\big(wealth + outcome_h{}^{1-\theta}/1-\theta\big))(4)$$

In the equation above 0.5 comes from the fact that each outcome in the choice has equal probability, the l, h index indicates the low and high outcome. The wealth variable is the hourly income for each individual. This is calculated by dividing a household's total reported income with 365*8, assuming an 8-hour workday. The probability of choosing anyone choice from the 6 choices in each lottery are:

$$EU_i = \frac{eu^i}{eu^1+eu^2+eu^3+eu^4+eu^5+eu^6} \qquad (4)$$

The next step is then to write out a maximum likelihood procedure that returns the risk aversion parameter for each individual that maximizes the probability of the choice actually made by the participant.

(Insert Figure 4 here)

The figure above provides a snapshot of the raw data from the lottery game. Six different categories of risk preference are defined to show that varying levels of risk aversion. They go from the safest option which shows an extreme level of risk aversion (Extreme) to the last option which reflects risk-seeking behavior(Neutral to Preferring). We can see that approximately the same number of individuals prefer the safest option in each game, although there is a higher number in Game D (highest stake game) The proportion of individuals who prefer the "Moderate option" falls in the higher stake games (Game C and D) with an increasing number of subjects at the extremes ("Extreme" and "Neutral to Preferring").

(Insert Figure 5 here)

This figure shows the histogram for the distribution of the risk parameter assuming a constant relative risk aversion model.

We can see that approximately one third of the population (192) is risk seeking while the remaining population is risk averse.[9]

Risk Aversion

Table 8 presents results from six different regression models, which move from sparse specifications to the fullest specification presented in the last column. The joint hypothesis test for significance of the risk parameter and the interaction with the risk parameter and the respondent type is not significant at the 10% level. This suggests that risk aversion does not play a significant role in determining willingness to pay. However it is important to note that the sign for the coefficient (β_3) is in the hypothesized direction. When we split the regression into farmers and traders however the risk parameter is positive and significant in the farmer only regression.

Method Used to elicit valuation

[9] With a CRRA utility function increasing values reflect increasing levels of risk aversion.

In the overall sample willingness to pay dropped by 39 Ksh when we elicit valuation using the Low-High method .However farmers seem to more affected by the method in which willingness to pay is elicited. In fact there is evidence that for traders there is a small positive effect when we move from Low-High to High-Low, however this is just 6 Ksh. It is possible that traders who are more used to valuing commodities are more likely to pick up the mechanics of the BDM game faster.

Comparing Farmers and Traders

The hypothesis test[10] specified above suggests that farmers and traders are different in terms of their willingness to pay for both devices. Traders bid almost 54 Ksh lower than farmers overall.

Other Factors affecting Willingness to Pay

None of the other variables that we discussed appear to be significant in the regression models discussed above. Specifically the additional variables that we include in the sample wise regression namely maize harvested and proportion of maize bought from traders outside Kakamega is not significant.

(Insert Table 8 and 9 here)

Discussions and Conclusions

The paper looks to make contributions in two main areas. The first one is the impact of risk aversion on willingness to pay for a new technology. A great deal of the evidence suggests that increasing levels of risk aversion result in lower rates of adoption for a new technology. Shimamto et. al (2017) find that increasing levels of risk aversion result in increasing use of a moisture meter. This study, which has the advantage of measuring demand in an incentive compatible design for a completely new technology, finds similar results. However in our models, while the sign of the risk aversion parameter is

[10] Significance level of less then 1%

positive in all the specifications, it is only significant in the farmer only regression. These findings provide some evidence that when systematic training and demonstration(as in our study) reduces the uncertainty surrounding the use and performance of a new technology, then more risk averse farmers value a risk reducing technology higher.

Another contribution of this study is to modify the BDM mechanism to examine if that has an impact on valuations. The BDM has the advantage of being incentive compatible and being able to get at specific valuations for each individual, but it is harder to explain in the field as shown by Cason & Plott (2014). The DeShazo (2012) paper using contingent valuation data shows that ascending question sequences are susceptible to "framing and loss aversion". However this is not clear from the results of this paper. Firstly because since we are using an incentive compatible mechanism different and secondly because this affect does not persist for traders in the sample. One of the shortcomings of this study, and a possible area for further research is to examine if this effect persists with different populations, and to better explain the mechanisms driving the difference.

This study also makes a contribution to the literature looking at demand and elasticities for new technologies, which can be useful for policy makers and practitioners marketing new farm technologies in the developing world. We find that demand for the Hygrometer, which is a more expensive product, is higher than demand for the DriCard. The profitability analysis also suggests that market segmentation(i.e-marketing the Hygrometer to richer consumers and the DriCard to the lower end of the market) could potentially be a profitable strategy. Related to this are our results that farmers and traders value the devices differently, which also makes a case for segmentation.

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Tables

Table 1-Steps followed in survey

Steps					
Recruit Participant	Demonstrate functioning of both items, hygrometer and DriCard Fill out remaining survey as items are being shown	Randomly allocate participant to 1) WTP(up-down) 2)WTP(down-up)	Conduct two practice rounds with stationery	Conduct actual exercise with both items	Play lottery for elicitation of risk aversion parameters

Table 2-Lottery Game

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	60	60
2	48	96
3	36	144
4	24	180
5	12	228
6	0	240

Table 3-WTP(Up-down/High-Low)

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

Table 4- (Down-up/ Low-High)

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

Table 5-Summary Statistics

	Mean					
	Farmer		Trader		Total	
Household Size(No)	6.216	(2.497)	5.820	(2.455)	6.025	(2.483)
Years of Education of the Respondent	7.675	(3.920)	8.335	(3.568)	7.993	(3.766)
Have you ever heard of hermetic bags?-Proportion of sample	0.544	(0.499)	0.546	(0.499)	0.545	(0.498)
Have you heard about aflatoxin(Yes=1, No=0)	0.934	(0.248)	0.937	(0.244)	0.935	(0.246)
Maize sold from September 2016-November 2016(kg)	119.7	(367.4)	8851.9	(40950.4)	4291.4	(28614.1)
Maize sold from January 2017-onwards(kg)	9.486	(50.70)	8317.9	(46596.3)	3978.7	(32443.6)
Total Revenue besides revenue from maize sold	115613.0	(246243.6)	184845.3	(237436.1)	148995.0	(244297.5)
Asset score of household	1.784	(1.054)	1.933	(1.033)	1.856	(1.046)
Risk Parameter assuming power utility function	0.839	(0.074)	0.972	(0.096)	0.903	(0.0604)
Highest reliability ranking from methods currently used to check dryness	2.839	(0.041)	2.926	(0.0413)	2.881	(0.0292)
Willingness to pay for hygrometer	121.4	(82.93)	115.8	(80.40)	118.7	(81.70)
Willingness to pay for DriCard	92.85	(74.43)	80.42	(68.93)	86.86	(72.04)
Observations	589					

Table 6-Additional Summary Statistics for Farmers

	Mean	
Total land cultivated for September 2016 harvest season(Acres)	1.146	(0.954)
Total land cultivated for Jan 2017 harvest season(Acres)	0.644	(0.765)
Total land cultivated for maize for September 2016 harvest season(Acres)	0.841	(0.714)
Total land cultivated for maize Jan 2017 harvest season(Acres)	0.358	(0.507)
Observations	305	

Note: Standard deviations are in brackets

Table 7-Additional Summary Statistics for Traders

	Mean	
Maize bought in September-November 2016 period?(kg)	11120.9	(47269.0)
Maize bought Jan 2017 onwards?(kg)	9991.0	(50957.9)
Maize bought from farmers in Kakamega district-September-November 2016 period?(kg)	2788.0	(8735.4)
Maize bought from farmers in Kakamega district-Jan 2017 onwards?(kg)	1382.0	(6284.1)
Maize bought from other traders in Kakamega district-September-November 2016 period(kg)?	940.6	(3831.0)
Maize bought from other traders in Kakamega district-Jan 2017 onwards?(kg)	1001.8	(2352.8)
Maize bought from farmers outside Kakamega district-September-November 2016?(kg)	4915.2	(30648.8)
Maize bought from farmers outside Kakamega district-Jan 2017 onwards?(kg)	1463.5	(7207.0)
Maize bought from traders outside Kakamega district-September-November 2016?	2728.3	(23041.5)
Maize bought from traders outside Kakamega district-Jan 2017 onwards?(kg)	6689.8	(49110.0)
Observations	278	

Note: Standard deviations are in brackets

Table 8 - Regression results for Essay 1

Variable Description	Willingness to Pay for each device					
Dummy for Respondent Type Farmer=0, Trader=1	-38.91**					-54.66***
	(19.59)					(20.74)
Binary Variable for device 0=DriCard 1=Hygrometer		31.92***				28.59***
		(2.735)				(3.750)
Method Used, 1-High Low, 2-Low High			-16.83***			-39.21***
			(5.732)			(7.825)
Risk Parameter assuming power utility function				2.150		3.857*
				(1.717)		(2.213)
Highest reliability ranking of traditional methods					2.542	2.604
					(3.101)	(3.018)
Years of Education of the Respondent(Years)	0.546	0.546	0.705		0.496	0.614
	(0.774)	(0.774)	(0.774)		(0.774)	(0.763)
Maize sold from September 2016-November 2016(kg)	2.81e-05	2.81e-05	2.12e-05	8.22e-06	2.90e-05	2.83e-05
	(4.70e-05)	(4.70e-05)	(4.60e-05)	(4.54e-05)	(4.74e-05)	(4.78e-05)
Household Size(No)	0.765	0.765	0.876	0.610	0.802	0.723
	(1.208)	(1.208)	(1.208)	(1.210)	(1.200)	(1.172)
Sex of the respondent	7.156	7.156	6.669	6.831	6.889	5.934
	(6.682)	(6.685)	(6.553)	(6.758)	(6.725)	(6.559)
Asset score of household	1.782	1.782	2.184	2.263	1.836	1.820
	(3.185)	(3.187)	(3.149)	(3.058)	(3.185)	(3.083)
Total Revenue besides revenue from maize sold	-4.83e-06	-4.83e-06	-5.65e-06	-8.22e-06	-5.99e-06	-1.48e-05
	(1.09e-05)	(1.09e-05)	(1.08e-05)	(1.16e-05)	(1.12e-05)	(1.18e-05)
Interaction Term between Device and Trader Dummy						6.965
						(5.487)
Interaction between Method and Trader Dummy						45.93***
						(11.10)
Interaction between risk parameter and Trader Dummy						-2.042
						(3.260)
Constant	108.6***	92.65***	113.7***	106.8***	99.81***	85.99***
	(18.58)	(18.59)	(18.58)	(18.82)	(21.93)	(17.64)
Observations	1,168	1,168	1,168	1,168	1,168	1,168
R-squared	0.058	0.099	0.069	0.061	0.059	0.114
Hypotheses Tests (χ2)						

Robust(clustered at household level) standard errors in parentheses
Sub location/Market level Fixed Effects included
*** p<0.01, ** p<0.05, * p<0.1

Table 9-Split sample Regression Results

Variable Description	Willingness to Pay for each device Traders	Farmers
Binary Variable for device 0=DriCard 1=Hygrometer	35.02***	28.59***
	(4.305)	(3.766)
Method Used, 1-High Low, 2-Low High	6.904	-39.11***
	(8.473)	(8.025)
Risk Parameter assuming power utility function	2.667	4.008*
	(2.463)	(2.181)
Highest reliability ranking from methods currently used to check dryness	-0.270	4.536
	(4.461)	(4.185)
Maize sold from September 2016-November 2016(kg)	2.39e-05	0.000902
	(5.93e-05)	(0.00920)
Years of Education of the Respondent	1.675	-0.450
	(1.235)	(1.003)
Household Size(No)	0.642	0.602
	(1.935)	(1.539)
Sex of the respondent	14.85	3.686
	(11.02)	(8.626)
Asset score of household	7.260	-3.196
	(5.113)	(4.077)
Total Revenue besides revenue from maize sold	-3.92e-05	-9.82e-06
	(2.58e-05)	(1.21e-05)
Maize Harvested in Jan 2017(Kgs)		-0.00369
		(0.0252)
Total land cultivated for Jan 2017 harvest season(Acres)		7.127
		(6.271)
Proportion of maize bought from traders outside Kakamega		0.599
		(0.376)
Observations	514	610
R-squared	0.132	0.165

Robust standard errors in parentheses
Sub location/Market level Fixed Effects included
*** p<0.01, ** p<0.05, * p<0.1

Figures

Figure 1- Histogram distribution of Hygrometer and DriCard

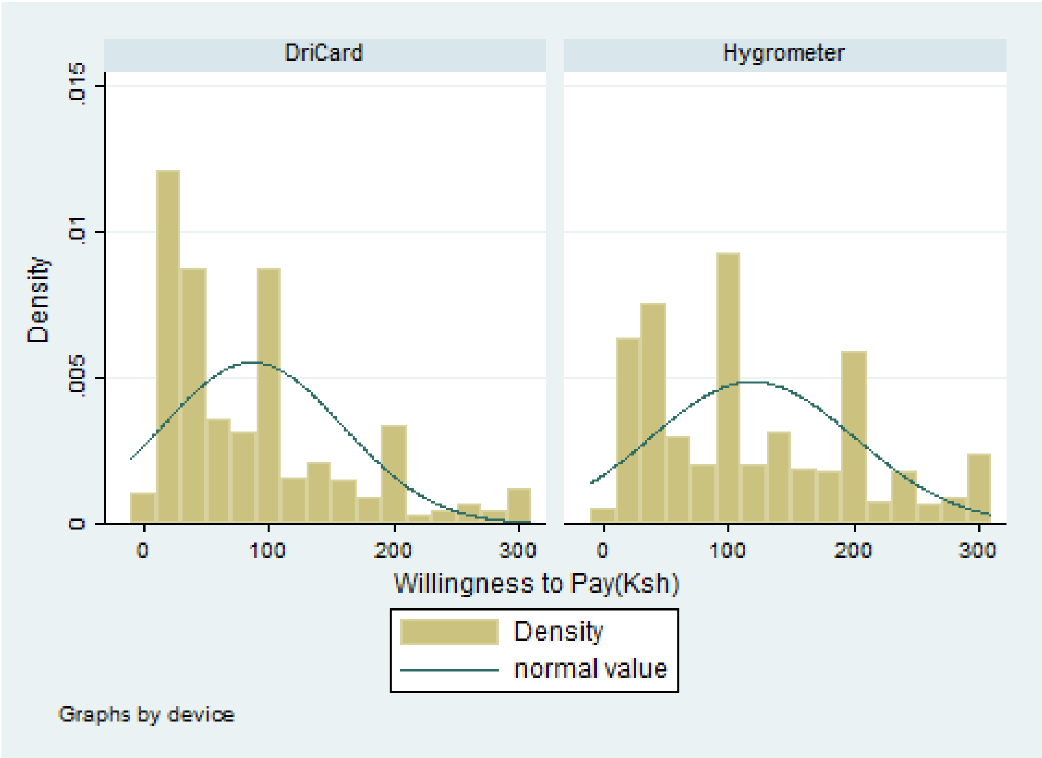
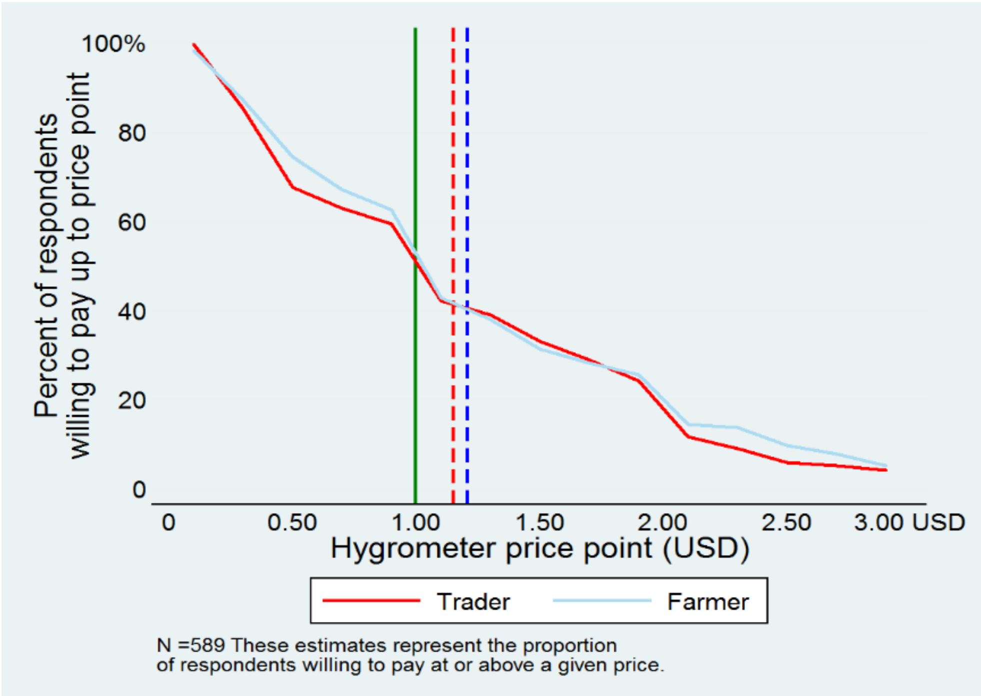
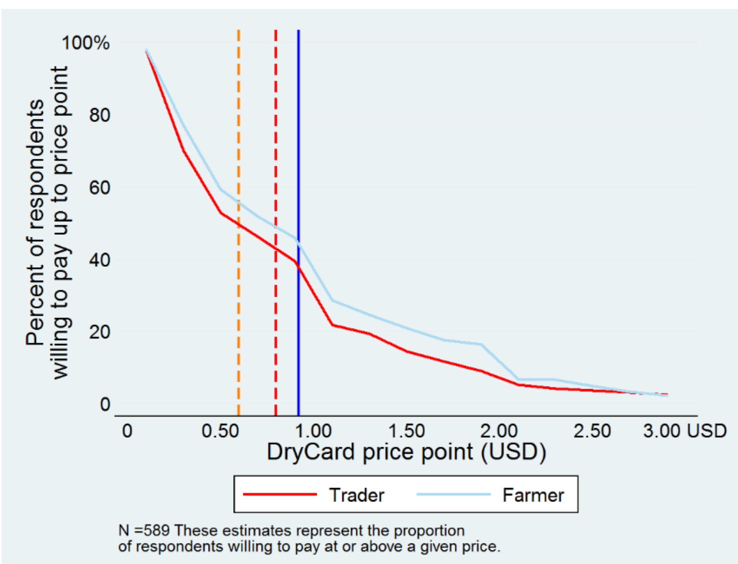


Figure 2-Demand Curve for Hygrometer



Notes-The green line reflects the median willingness to pay for both the farmer and trader. The red and and blue dotted line mark out the the mean willingness to pay for the trader and farmer respectively

Figure 3- Demand Curves for DriCrad



Notes-The blue line marks the mean willingness to pay for farmers and the orange line marks out the mean for the traders. The red dotted line in the middle shows the median willingness to pay for both farmers and traders.

Figure 4-Risk Aversion Data

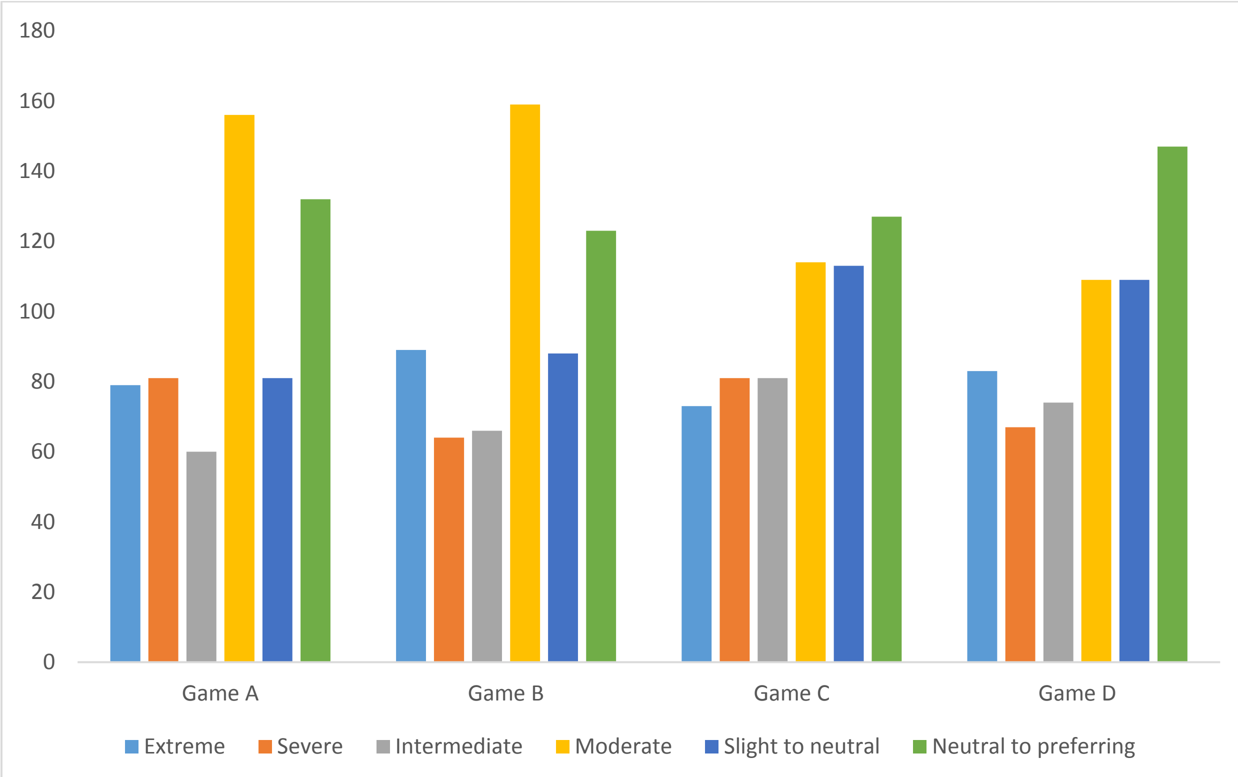
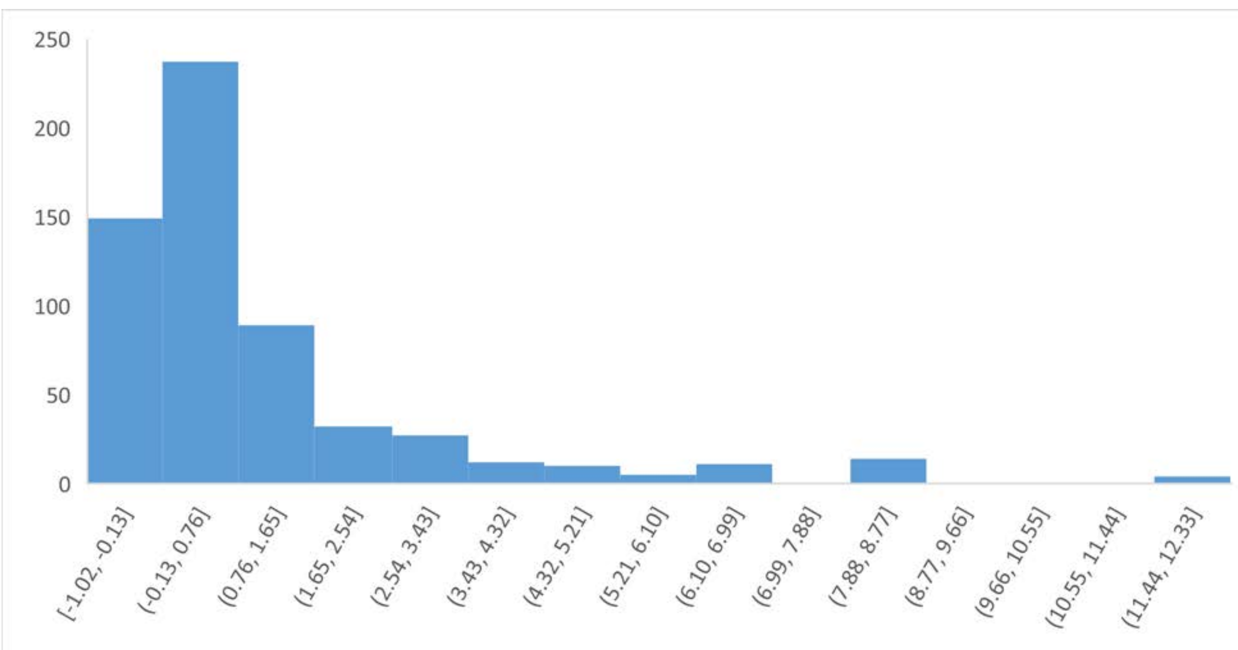


Figure 5-CRRA Parameter Estimate Distribution



Appendix 1-Tobit Results

Variable Description	Willingness to Pay for each device						
Dummy for Respondent Type Farmer=0, Trader=1	-41.74**					-32.36**	-57.28***
	(21.04)					(14.79)	(22.13)
Binary Variable for device 0=DriCard 1=Hygrometer		33.23***				31.92***	29.77***
		(2.842)				(4.334)	(3.904)
Method Used, 1-High Low, 2-Low High			-17.81***			-16.81***	-40.63***
			(5.903)			(4.419)	(8.092)
Risk Parameter assuming power utility function				2.513		2.298**	4.260*
				(1.823)		(1.115)	(2.305)
Highest reliability ranking of traditional methods					2.515	2.967	2.677
					(3.199)	(2.281)	(3.112)
Have you heard about aflatoxin(Yes=1, No=0)	11.68	11.67	11.20	11.43	11.56	11.10	7.725
	(11.86)	(11.88)	(11.62)	(11.94)	(11.93)	(9.163)	(12.21)
Maize sold from September 2016-November 2016(kg)	2.43e-05	2.40e-05	1.63e-05	4.37e-06	2.53e-05	8.03e-07	2.15e-05
	(4.98e-05)	(4.98e-05)	(4.87e-05)	(4.79e-05)	(5.01e-05)	(8.08e-05)	(4.95e-05)
Household Size(No)	0.717	0.720	0.814	0.680	0.761	0.750	0.689
	(1.248)	(1.247)	(1.247)	(1.252)	(1.239)	(0.938)	(1.209)
Sex of the respondent	6.659	6.675	6.266	6.595	6.365	6.128	5.593
	(7.088)	(7.084)	(6.945)	(7.072)	(7.136)	(4.956)	(6.955)
Asset score of household	2.848	2.845	3.425	2.719	2.858	2.804	2.954
	(3.198)	(3.197)	(3.174)	(3.175)	(3.196)	(2.277)	(3.109)
Total Revenue besides revenue from maize sold	-4.68e-06	-4.65e-06	-5.09e-06	-9.37e-06	-5.93e-06	-1.04e-05	-1.49e-05
	(1.07e-05)	(1.07e-05)	(1.07e-05)	(1.18e-05)	(1.11e-05)	(1.01e-05)	(1.17e-05)
Interaction Term between Device and Trader Dummy							7.261
							(5.679)
Interaction between Method and Trader Dummy							46.49***
							(11.45)
Interaction between risk parameter and Trader Dummy							-2.124
							(3.430)
Constant	108.6***	92.65***	113.7***	106.8***	99.81***	85.99***	99.66***
	(18.58)	(18.59)	(18.58)	(18.82)	(21.93)	(17.36)	(22.27)
Observations	1,168	1,168	1,168	1,168	1,168	1,168	1,168

Robust(clustered at household level) standard errors in parentheses
Sub location/Market level Fixed Effects included
*** p<0.01, ** p<0.05, * p<0.1

Appendix 2-Manufacturer/Reseller Profitability

Taking a closer look at the manufacturer/reseller profitability for these products is useful from a policy perspective . We assume a fixed cost of 90Ksh(0.9 USD) for the hygrometer and 15 Ksh for the DriCard. For each device we calculate the price point at which the supplier(or manufacturer) would maximize profitability. We find that the most profitable selling price for the Hygrometer is 190 Ksh while for the DriCard this is 90Ksh. Overall because of the low cost of the DriCard it is 1.3 times more profitable.

Figure 4-Profitablity Curve Hygrometer

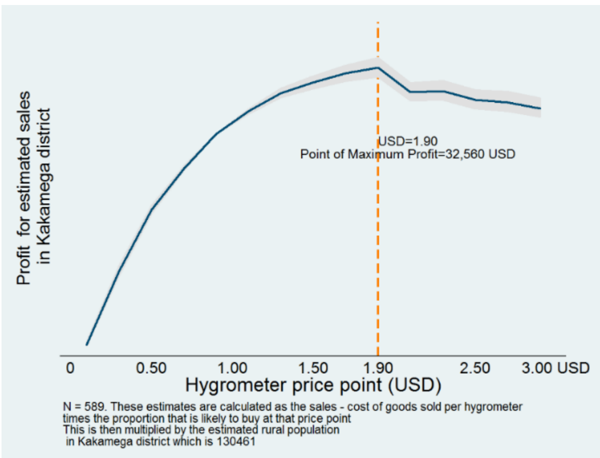


Figure 5-Profitability Curve DriCard