Male and Female Risk Preferences and Maize Technology Adoption in Kenya

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ABSTRACT

Risk is pervasive in developing country agriculture, and risk preferences are though to impact seed and technology choice. Empirical research on risk preferences and technology adoption typically only consider the risk preferences of a single household member. In this paper experimental techniques based on prospect theory (PT) to elicit risk aversion, loss aversion, and nonlinear probability weighting parameters from husbands and wives in Kenyan agricultural households. We also use survey data about their maize seed choice from these same respondents. We find that all three PT parameters are significant in different model specifications, and that risk preferences affect adoption differently for men and women in the same households, and also differently in the eastern and western regions of the country.

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1. Introduction

Farmers in developing countries face an extremely difficult situation when deciding whether or not to adopt a new agricultural technology. Governmental agencies, research groups, private firms, and non-governmental organizations, however, continue to develop new technologies that could improve the livelihoods of rural farming communities in developing nations. What then, is causing farmers to delay or reject new technologies? Factors including wealth, education, credit constraints, access to information and risk aversion have been identified as key variables in the technology adoption process (Feder, Just, and Zilberman 1985, Sunding and Zilberman 1999).

Risk is an essential factor in the technology adoption decision. Farmers depend on the success of their crops for consumption and income. The uncertain returns on technological investments make the decision to change technologies, such as switching from a local maize variety to a high yielding (but high cost) hybrid, an inherently risky decision. Furthermore, because farmers in developing countries rarely have formal insurance or savings to fall back on, failures in agricultural production can have dire and lasting consequences. A number of studies have tied risk preferences to technology adoption (Lybbert 2006, Marra, Pannell, and Abadi Ghadim 2003, Saha, Shumway, and Talpaz 1994, Liu 2008, Binswanger 1980, Feder 1980, Feder, Just, and Zilberman 1985, Engle-Warnick, Escobal D'Angelo, and Laszlo 2007, Liu 2013). To our knowledge, this is one of the first papers to incorporate test the impact of men and women's risk preferences in same household on technology adoption.

Economists typically assume unified households make technology adoption decisions. However, households are composed of individuals that may have different tastes, preferences, and objectives when it comes to agricultural production and consumption. Despite theoretical and empirical evidence that production and consumption decisions are not made by unified households (Fisher, Warner, and Masters 2000, McElroy and Horney 1981, Manser and Brown 1980, Schultz 1990), little attention has been paid to how divergent female and male risk preferences and gender roles within the household fit into the technology adoption process.

Another common assumption in the technology adoption literature is that the curvature of the utility function affects adoption. While this is likely true, it may not be the complete story. Loss aversion and nonlinear probability weighting—parameters based in prospect theory (PT) (Kahneman and Tversky 1979, Prelec 1998)—may also be significant determinants of adoption (Liu 2008). Eliciting risk aversion, loss aversion, and probability weighting measures from farmers in Kenya, and understanding how each of these affect technology adoption decisions, can aid those involved in crop development and dissemination in choosing the most effective technology interventions.

This study uses experimental techniques to elicit risk preferences from both males and females (typically husbands and wives) in Kenyan farming households in order to do the following: (i) test whether expected utility theory (EU) or prospect theory (PT) is more appropriate when defining a Kenyan farmers' utility function under risk, (ii) explore intra-household differences in male and female risk preferences to; (iii) determine if the unitary household model is sufficient to explain Kenyan household technology decisions with respect to risk preferences. The paper is organized as follows. Section 2 contains background information on risk preferences and our experimental design. Section 3 uses the risk experiment data, in addition to household, individual, and subplot-level data, to examine maize technology adoption in Kenya. In Section 4 we offer some concluding remarks.

2. Background

Maize technology in Kenya

Agricultural accounts for 51% of Kenya's GDP (Feed the Future 2014). Agriculture employs over 70% of Kenya's population, particularly in rural areas, and is the main source of income for rural households (FAO 2014). Maize is also the staple of the Kenyan diet, particularly in rural areas. Kenyan farmers have adopted a number of improved varieties, but overall maize production is still mid-range in comparison to its East African counterparts. From 2000-2012, the average maize yield each year was 1619 kg/ha whereas Ethiopia's and Tanzania's were 2145 kg/ha and 1554 kg/ha, respectively (FAOSTAT 2014). For a broader comparison, South Africa and the United States produced 3537 kg/ha and 9157 kg/ha, respectively, over the same time period.

While there are obvious socioeconomic, technological, and climatic differences between the United States and Kenya, there is unmistakably room for improvement in Kenyan maize production. A number of research institutions and private companies have put research and development into breeding improved maize varieties suitable for Kenya's diverse and overpopulated land. This study evaluates whether farmers choose a non-hybrid (i.e., local or "improved" seed) or a particular type of hybrid seed. Cross breeding male and female plants from separate lines produces hybrid maize seeds. The result of this pairing is a hybrid seed that has hybrid vigor, leading to increased yields. While yields from hybrid seeds can be greater than from open-pollinated varieties (OPV), costs associated with hybrids are also higher. In addition, hybrid seeds must be purchased new each season to maintain their vigor.

In rain-fed environments, hybrid maize can be a very risky technology. Seeds are expensive, and if there is no rain farmers will incur substantial losses. Furthermore, hybrid seeds perform best with other costly inputs from which there is no return without sufficient rain. However, some hybrid seeds are conceived specifically to help farmers manage risk.

Drought and gray leaf spot (GLS) are two stresses relevant to Kenyan farmers. In the arid East, there have been eight notable droughts in the last 15 years (EM-DAT 2014), making drought tolerant hybrids extremely relevant in the eastern region. In the West, rain is more prevalent and maize is susceptible to GLS, a disease caused by the *Cercospora zeae-maydis* fungus (Wise 2010). The fungus thrives in moist, warm climates and reduces yields through legion formation on maize leaves that reduces photosynthesis. In Kenya, drought tolerant hybrids and hybrids resistant to grey leaf spot (GLS) have been developed. Risk preferences are therefore an important factor in determining whether or not a household will adopt hybrid seeds, however the expected relationship between risk preferences and technology choice is somewhat ambiguous.

Risk experiments

Risk experiments are common in the economics literature, especially in developing countries. Two common experimental methods are the Binswanger (1980) and Holt and Laury (2002) methods. The Holt and Laury (2002) method presents respondents with a series of pairwise lottery choices with positive payoffs differing in expected payoffs and variance. Respondents' choices in these lotteries determine their risk parameters. Binswanger (1980) asks respondents to choose one of eight pairwise lotteries where each payout has an equal chance of being chosen.

Tanaka, Camerer, and Nguyen (2010) recently developed a method to measure PT parameters: risk aversion, loss aversion, and nonlinear probability weighting. Tanaka, Camerer, and Nguyen (hereafter TCN) present Vietnamese respondents with 35 pairwise lottery choices, seven of which contain gains as well as losses, and use farmers' choices in these pairs to estimate the three PT parameters. Liu (2013) uses the TCN approach with cotton farmers in China. She finds that more risk-averse and more loss-averse farmers adopt *Bt* cotton later. In addition, farmers that overweight small probabilities are more likely to adopt *Bt* cotton earlier. The importance of loss aversion and nonlinear probability weighting in Liu's study enforce the hypothesis that PT may be more appropriate than EU in characterizing farmer decision making under risk. This study expands on TCN and Liu's work by incorporating intra-household gender dynamics and performing the experiments with farmers in an African context, where both agriculture and gender norms are substantially different than in Asia.

Numerous studies have found correlations between gender and risk aversion. In particular, being male is repeatedly associated with lower risk aversion (Holt and Laury 2002, Liu 2008, Wik et al. 2004, Bauer and Chytilová 2009, Liu 2013). Croson and Gneezy (2009) perform an extensive literature review of experimental evidence revealing gender differences in risk preferences, social preferences, and reaction to competition and conclude that women are more risk-averse than men. Experimental studies done with students in the U.S. (Holt and Laury 2002), villagers in Northern Zambia (Wik et al. 2004), and villagers in India (Bauer and Chytilová 2009) conclude that females are more risk-averse than males.

A few reasons for this may be emotional reaction to uncertain outcomes (Croson and Gneezy 2009), number of children under the care of the mother (Bauer and Chytilová 2009), confidence differences between males and females (Croson and Gneezy 2009), and different interpretations of uncertain situations (Arch 1993). Eckel and Grossman (2008) review risk attitudes between women and men in a number of experiments involving choices among gambles and also draw the general conclusion that women are more risk-averse than men.

Prospect theory

The EU framework weights losses and gains equally and a single risk aversion parameter (σ) captures risk preferences. PT, however, includes three parameters that define an individual's risk preferences: risk aversion (σ), loss aversion (λ), and nonlinear probability weighting (α) (Kahneman and Tversky 1979, Prelec 1998). Nonlinear probability weighting involves overweighting small probabilities and therefore placing a premium on outcomes that are considered certain. Loss aversion defines the curvature of the utility function below zero and measures how individuals react towards potential losses compared to potential gains. The PT model is flexible because EU is nested within it when the loss aversion and probability weighting parameters both equal one.

TCN use an experiment to derive PT to model risk preferences for Vietnamese households and test whether probability weighting and loss aversion, in addition to risk aversion, shape individuals' utility functions. Liu (2013) uses the same experiment with Chinese cotton farmers. Both studies find loss aversion and probability weighting parameters to be significantly different than one, suggesting concavity of the utility function is insufficient in defining risk preferences.

Following TCN (2010) and Liu (2013), the utility function is of the following form:

$$(1)\ U(x,p;y,q) = \begin{cases} v(y) + \pi(p)\big(v(x) - v(y)\big) & for\ \ x > y > 0\ or\ x < y < 0 \\ \pi(p)v(x) + \pi(q)v(y) & for\ x < 0 < y \end{cases}$$

$$\text{where } v(k) = \begin{cases} k^{\sigma} & for\ k > 0 \\ -\lambda(-k^{\sigma}) & for\ k < 0 \end{cases},\ k = x, y \quad \text{and} \quad \pi(m) = \exp\,[-(-\ln m)^{\alpha}],\ m = p, q$$

In this utility function, x and y are the possible outcomes and p and q are the probabilities associated with these outcomes, respectively. The parameter σ represents risk aversion; when $\sigma > 1$, respondents are risk-loving, $\sigma = 1$, risk-neutral, and $\sigma < 1$, risk-averse. λ represents loss aversion; theoretically, λ defines the curvature of the utility function below zero relative to the curvature above zero (Liu 2013). As λ increases, the individual is more loss-averse. Finally, α represents nonlinear probability weighting, and is extended from a model in Prelec (1998) and employed by TCN (2010) and Liu (2013). The probability weighting function is $\pi(m)$. If $\alpha > 1$, the weighting function is S-shaped and characterizes individuals who overweight high probabilities and underweight low probabilities. When $\alpha < 1, \pi(m)$ is inverted S-shaped, and defines individuals who underweight high probabilities and overweight low probabilities. If $\alpha = 1$ and $\lambda = 1$, the model reduces to EU. We use experimental techniques to estimate each of these parameters and test whether EU is sufficient to explain individuals' utility functions.

Intra-household bargaining and technology adoption

The Beckarian unitary household model assumes households are a unified body where income from individuals is pooled and preferences are identical (Becker 1981). In the context of African households, however, where the roles of women and men are distinct, there are different economic spheres, and preferences may differ, it may be more appropriate to model the household decision-making process as a bargaining model (Manser and Brown 1980, McElroy and Horney 1981). If household members do in fact have varying preferences, the unitary model may misrepresent the technology adoption process and its impacts on individuals' welfare within the household. Few studies, however, thoroughly examine how divergent preferences and bargaining roles within the household affect technology choice. Thus, a focus of this study is to examine the roles of both women and men in the household and how their relative bargaining power affect the decision to adopt a new technology.

Zepeda and Castillo (1997) study adoption of intensive rotational grazing among dairy farmers in Wisconsin. They model the adoption decision as the conventional unitary household model as well as a cooperative bargaining model, where the husbands and wives in the household make the decision jointly. The bargaining model better explains IRG adoption; women's wages are significant and households making joint decisions are more likely to adopt (Zepeda and Castillo 1997). Fisher, Warner, and Masters (2000) model the adoption of stabling in Senegal as a function of gender-specific factors and find that women's age, additional wives in the household, and farm income of the first wife affect the husband's decision to adopt stabling. This suggests that including variables specific to the husbands and wives can enhance technology adoption models' explanatory power. To incorporate the preferences of both men and women in the same households in the maize technology adoption decision, we include gender-specific risk preferences into our empirical technology adoption model. In the following section we provide a conceptual model to guide our empirical analysis.

3. Model

We begin with a household utility maximization problem under uncertainty. In the case of maize production in the study region, **t**he sources of uncertainty are stochastic events of drought or GLS infestation. For simplicity, we will call both a drought or GLS infestation a "stress". Farmers make their seed decision prior to knowing the occurrence and severity of a stress in each particular season. If the probability is known with certainty and all possible outcomes are positive, EU is sufficient to model each respondent's utility function. However, in the case of unknown probabilities and potential losses, PT provides a better utility function.

We assume a farmer's decision at the beginning of the season is between using a non-hybrid seed (NH), his or her status quo, adopting a HY hybrid, or adopting a ST hybrid. The two types of hybrids target different needs. HY seeds are a risky investment; they do not insure against stresses, but will increase yields when the climatic conditions are suitable. ST hybrids, however, are used as insurance against a stress. Thus, the resultant varietal selection process is complex.

In the study area, seed and input costs for HY seeds are greater than ST and NH seeds. In addition, ST costs (*C*) are higher than NH, i.e., $C_{NH} < C_{ST} < C_{HY}$. We assume two possible states of the world: stress (drought or GLS infestation), which occurs with probability p; and no stress (no drought or GLS), which occurs with probability q, where $p + q = 1$. In each state of the world there are associated yields depending on the variety chosen. In a non-stress ("good") environment, HY hybrids yield more than ST hybrids which yield more than or equal to NH ($Y_{HY,good} > Y_{ST,good} \geq Y_{NH,good}$). In a stress ("bad") environment, however, ST hybrids will give the highest yield (*Y*), followed by HY and NH ($Y_{ST,bad} > Y_{HY,bad} \geq Y_{NH,bad}$). All else equal, we expect that $Y_{HY,good} > Y_{ST,good} \geq Y_{NH,good} > Y_{ST,bad} > Y_{HY,bad} \geq Y_{NH,bad}$. Using these inequalities we can deduce possible gains and losses in each state of the world.

The payoff a farmer receives from a varietal choice in these two states of the world depends on her reference point, i.e., her status quo. We assume farmers use the profit acquired from the NH yield minus the cost of NH seeds and inputs in stress conditions ($\pi_{NH,bad} = Y_{NH,bad} - C_{NH}$) and non-stress conditions ($\pi_{NH,good} = Y_{NH,good} - C_{NH}$) as their reference points. If a farmer decides to adopt a HY hybrid, she has stress ($\pi_{HY,bad} = Y_{HY,bad} - C_{HY}$) and non-stress $\left(\pi_{HY,good} = Y_{HY,good} - C_{HY}\right)$ outcomes as well. Finally, if she adopts a ST hybrid instead of NH or HY, she also has stress and non-stress outcomes: ($\pi_{ST,bad} = Y_{ST,bad} - C_{ST}$) and ($\pi_{ST,good} = Y_{ST,good} - C_{ST}$), respectively. Using the inequalities from above, and using NH profit as the reference point, we examine possible outcomes in the good and bad states of the world associated with each choice.

First, we assume a farmer chooses a HY hybrid. In the case of a stress occurring, outcome x is the profit from adopting HY less the status quo profit from using NH seeds:

(1) $$x = \left(\pi_{HY,bad} - \pi_{NH,bad}\right) < 0,$$

because $C_{NH} - C_{HY} < 0$ and $|C_{NH} - C_{HY}| > |Y_{HY,bad} - Y_{NH,bad}|$. Alternatively, in the case with no stress, outcome y becomes:

(2) $$y = \left(\pi_{HY,good} - \pi_{NH,good}\right) > 0.$$

We assume $Y_{HY,good}$ is higher than $Y_{NH,good}$ by enough to make up for the cost of inputs $\left(|C_{NH} - C_{HY}| < |Y_{HY,good} - Y_{NH,good}|\right)$, otherwise no one would adopt HY. Thus, the farmer sees y as a gain and x as a loss.

Next, assume a farmer chooses a ST hybrid. In the case of a stress occurring, outcome x is the profit from adopting ST less the status quo profit from using NH seeds:

(3) $$x = \left(\pi_{ST,bad} - \pi_{NH,bad}\right) > 0,$$

because the ST seed resists the stress and $Y_{ST,bad} > Y_{NH,bad}$. Alternatively, in the case with no stress, possible outcome y becomes:

(4) $$y = \left(\pi_{ST,good} - \pi_{NH,good}\right) < 0.$$

We assume that even though $Y_{ST,good} \geq Y_{NH,good}$ the costs of C_{ST} are higher than C_{NH} such that $|C_{NH} - C_{ST}| > |Y_{ST,good} - Y_{NH,good}|$, otherwise everyone would choose ST. Thus, the farmer sees x as a gain and y as a loss.

In these two scenarios, if a farmer adopts a HY hybrid or a ST hybrid instead of a traditional, NH seed there are possible gains and losses depending on the stress level. Figure 2 gives a visual representation of the above scenario. In the presence of gains and losses ($x < 0 < y$) the PT utility function takes the following form:

$$(5) \qquad U(x,p;y,q) = \pi(p)v(x) + \pi(q)v(y)$$

Plugging in for $\pi(p), v(x)$ and $v(y)$ yields the following:

$$(6) \qquad U(x,p;y,q) = \exp[-(-\ln p)^{\alpha}] * [-\lambda(-x)^{\sigma}] + \exp[-(-\ln q)^{\alpha}]\,(y)^{\sigma},$$

where $x = (\pi_{HY,bad} - \pi_{NH,bad} | \, stress) < 0$ and $y = (\pi_{HY,good} - \pi_{NH,good} | \, no\ stress) > 0$ for HY. The opposite is true for ST ($x > 0 > y$).

Next, we take partial derivatives with respect to $\sigma, \lambda,$ and α to determine how risk aversion, loss aversion and nonlinear probability weighting are expected to affect the utility gained from hybrid adoption. Full derivations are in Appendix A.

$\frac{\partial U}{\partial \sigma}$ depends on the values of x and y as well as $p, q, \alpha,$ and λ. Thus, its sign is ambiguous. However, due to the risky nature of HY hybrids, we expect the sign to be positive indicating that more risk-loving individuals are more likely to adopt HY. We expect the sign for ST hybrid adoption to be less than zero. $\frac{\partial U}{\partial \lambda} < 0$ due to the value function for x and y in the presence of losses in the HY and ST specifications, respectively. As loss aversion increases, an individual is less likely to adopt HY or ST over NH. $\frac{\partial U}{\partial \alpha}$ also depends on the values of x and y as well as $p, q, \alpha,$ and λ. Using experimental risk preference data and data on household production and decision-making we can empirically test these analytical findings for both men and women.

4. Study site and data collection

Household and individual survey

Enumerators collected household data between September and November 2013 in five districts in Kenya as a part of the Adoption Pathways Project (AP). AP is a collaboration between the

International Maize and Wheat Improvement Center (CIMMYT), Australian Center for International Agricultural Research (ACIAR), and researchers in Kenya, Tanzania, Malawi, Mozambique, and Ethiopia with the purpose of "[accelerating] demand-driven research, delivery and adoption of innovations to improve food security" (CIMMYT 2013). In 2009, a CIMMYT led initiative, the Sustainable Intensification of Maize-Legume Systems for Food Security in Eastern and Southern Africa (SIMLESA), performed a baseline survey in to understand the production environment of thousands of rural farmers in these five countries, their socioeconomic statuses, and technology choices.

For this survey, AP chose respondents from a three-stage sampling procedure. In Kenya, the project purposefully chose five districts (Embu, Meru, and Tharaka Nithi in the East, and Bungoma and Siaya in the West) to represent market differences and accessibility. Within these districts, AP randomly selected administrative divisions; then, AP randomly selected villages proportional to the size of the division; finally, they randomly selected households within villages. 613 households answered the household survey in the first round of data collection.

For this study, we use data from Kenya collected in the second round of this survey in 2013. 540 households (802 individuals) participated in this round. We combine data from the household and individual surveys with data from a field experiment conducted several weeks after the household survey, discussed in detail below.

The second round of the survey collected individual- and household-level data. In each household, enumerators identified the male and female most responsible for making decisions and asked both respondents to identify the household head. In single decision-maker households, the enumerators asked the sole respondent whether the household head was male or female. In our sample, all multiple decision-maker households are male-headed with female spouses that identified themselves as “wife of male-head.”[1] This does not mean she has no decision-making power, but implies that the male is the primary decision maker. Female-headed households in the sample identified no other principle decision-maker in their households. These females are either widows, divorcées, single, or living without their spouses. We provide a breakdown of marital status and house headship in Table 1.

The household survey included questions related to on-farm production, input use, yields, technology choices, as well as household demographics. The survey asked detained questions about seed and other input use at the plot level, and also about who managed the plots within the household. Following the household survey, conducted with the head of household, enumerators performed the individual surveys separately with the male household and head and his wife after concurrently and separately to prevent interference and encourage honest responses. For single-headed households, the household head answered both surveys. The individual survey contained questions related to savings, group membership, leadership, decision-making within the household, as well as asset ownership. We use data from both surveys to estimate the effect of male and female risk preferences on maize technology adoption at the plot level.

Maize technology data

We break the hybrids in this study into two groups based on the prominent quality of the seed advertised. Hybrids are higher yielding than OPVs if grown under optimal conditions, but some hybrids have other qualities that may attract Kenyan farmers. We aggregate the hybrids into two groups: high yielding (HY), those that are advertised for their yield potential, and stress tolerant (ST), those that are advertised for their tolerance to drought or Gray Leaf Spot (GLS). Hereafter we will refer to these groups as HY and ST. Table 2 contains the HY varieties that are mainly

[1] See Appendix C for relevant survey questions.

supplied by Kenya Seed Company Ltd., their principle traits, and adopters in our sample by region.

We aggregate hybrids that are either drought tolerant or GLS tolerant because farmers' reactions towards adopting them should be similar. Farmers are faced with an uncertain probability that a stress (drought or GLS) will occur, and must decide whether or not to adopt the stress-tolerant hybrid as a form of insurance against the shock. In addition, we aggregate due to small sample sizes of strictly GLS or drought tolerant seeds. Therefore, Table 3 contains the four stress-tolerant varieties in this study. DUMA 43 is the most popular ST variety in the East, possibly due to its tolerance to drought, GLS, leaf blight, and cob disease. WS 505 is the ST variety of choice in the West. We explore these varieties and factors related to their adoption in the following sections.

Risk preference data

In December 2013, enumerators experimentally elicited risk preference parameters from the same respondents who completed the individual surveys. To ensure matching between datasets, we only allowed households where both male and female decision-makers completed the individual survey to participate in the experiments. In addition, we included households with sole decision-makers—i.e., married but spouse lives away, widowed, divorced, or never married—in the experiments. Attrition was common: only 304 individuals from 172 households.[2] We use data from these households for our analysis. Figure 1 shows the households' locations.

In order to check for attrition bias, we conducted *t*-tests for mean differences in age, education, household size, income, and farm income of the individuals that did and did not return for the experiments (Table 4). We find significant differences in mean age and household size,

[2] The household and individual surveys were lengthy (4-5 hours) and tedious, possibly deterring respondents from returning to perform the experiments.

but non-returning individuals are only slightly younger on average and have slightly smaller households. Returning individuals have less income, which could possibly be attributed to the financial incentive of attending the experiments. These caveats to the sample should be kept in mind when extrapolating results to the general population.

Enumerators performed the experiments in a public place such as a schoolroom or government office and males and females attended different sessions in the same day to reduce co-influence. Sessions took about 3 hours to complete all preference experiments. Respondents received 200 KSH[3] (about 2USD), comparable to a daily wage, for attending the experiments and obtained further payments based on their choices in the experiments.

Respondents played two different types of risk preference games: one modeled after Holt and Laury (2002) and the other after Tanaka, Camerer, and Nguyen (2010). This study only considers the TCN results. We asked respondents to make pair-wise choices on 27 different lotteries. Appendix B contains the three risk preference series and Figure contains an example of the choices. In this example, Option A has a 70% probability of receiving 110 KSH and 30% probability of receiving 440 KSH; Option B has a 90% probability of receiving 55 KSH or 10% probability of receiving 920 KSH.

As respondents move down the table, the only thing that changes is the value of Option B's 10% probability payout. Thus, the expected value of Option B increases and eventually surpasses the expected value of Option A. More risk-averse individuals switch from choosing Option A to choosing Option B further down the table. We ensured rationality of subjects by enforcing monotonic switching from Option A to Option B but also permitted respondents to never switch to Option B or always choose Option B. To estimate loss aversion we used a series that contains both gains and losses (available upon request from the authors). We ensured that

[3] Mean daily income is 245 KSH for male-headed households and 160 KSH for female-headed households.

the potential losses in the lottery did not exceed the 200 KSH respondents received for participating in the experiments. More loss-averse respondents switch from choosing Option A to choosing Option B later in the table. In this series we also did not permit respondents to switch.

Due to possible illiteracy or innumeracy, the lead enumerator used 10 balls in a bag to explain the concept of probabilities. The lead enumerator gave a 10-minute introduction to each type of series to ensure understanding and homogeneous explanations. The lead enumerator then drew one ball from the bag to determine a random starting point for the series in order to reduce starting point bias. After the introduction, enumerators worked independently with 1-2 respondents to ensure understanding of the choices. After a switch point was identified, enumerators stopped respondents for that series. The lead enumerator drew the next random starting point once all respondents completed a series.

We paid respondents 200 KSH with certainty and they won additional money based on their responses to the other series. At the end of each session, one respondent chose a random ball from the bag to see which of the non-loss aversion series was used for payment. Then, a different respondent randomly chose a ball to determine which task (i.e. which row in the winning series) was used for payment. Next, depending on whether an individual chose Option A or Option B in that task, a third respondent randomly chose another ball to determine the amount given to respondents. For example, in Figure 3, if respondents picked Option A and ball 4 was chosen by randomly selection, they received 110 KSH. Alternatively, if they picked Option B, they received 55 KSH. Following the same procedure as above, respondents randomly chose a task for the loss aversion series. Depending on each individual's choice, and the random ball chosen for payment, respondents either gained or lost money.

4. Results

Risk experiments

Following TCN (2010) and Liu (2013), we use results from the first two series to estimate each respondent's utility function curvature (σ) and nonlinear probability weighting parameter (α). Based on each respondent's switching point in these series, we estimate a range of reasonable values of these parameters. For example, if in Series 1 a respondent switches from Option A to Option B at Task 4, we know that at Task 3, the respondent preferred Option A to Option B. At Task 4, however, she prefers Option B to Option A. Two inequalities result from this switching point. We estimate σ and α using a combination of switching points from Series 1 and Series 2. A range of reasonable values results from this combination and we use the interval midpoints for analysis. We estimate the loss aversion parameter using the results from σ and the switching points in Series 3. Again, we use the median of the interval for analysis.[4]

Figures 4, 5, and 6 contain the distributions of σ, λ, and α, respectively. Compared to TCN and Liu, whose distributions look relatively normally distributed, many respondents in this sample exhibit extremely high levels of risk aversion ($\sigma \to 0.15$) and are either extremely loss-averse ($\lambda > 10$) or barely loss-averse ($\lambda < 0.15$). The average values of σ and α are 0.50 and 0.86, respectively. TCN find average values of 0.59 and 0.74 and Liu finds 0.48 and 0.69 for σ and α, respectively. These are relatively close to my findings. The average of λ is 3.17 whereas TCN and Liu find 2.63 and 3.47, respectively.

Table 5 contains more experiment result details. We use sample mean *t*-tests to test significant differences between subsamples. Females and males within the same household have no significant differences in their risk preferences. In addition, all males and females in the

[4] See Tanaka, Camerer, and Nguyen (2010) and Liu (2013) for a more thorough explanation of parameter estimation.

sample have no statistically significant differences in preferences, although females are more loss averse on average. Females in FHH, however, are significantly more loss averse than females in MHH at the 10% level. One hypothesis for this finding is that FHH face resource constraints and therefore react differently to potential losses than females in MHH who have the security of another income generator in the household.

Risk preferences and technology adoption

Respondents are either adopting non-hybrid maize varieties, high yielding hybrids, or stress tolerant hybrids. We use a multinomial logistic model because the dependent variable takes the value of {0,1,2} for NH, HY, and ST, respectively. The multinomial logistic model specification taken from Wooldridge (2002) is as follows:

(9)
$$(y = j|x) = \left(\exp(X\beta_j) \Big/ \left[1 + \sum_{h=1}^{J} \exp(X\beta_h)\right] \right), j = 1, \ldots, J,$$

where P is the response probability and $j = 1{,}2$ in this study. P $(y = 0|x)$ is calculated once the other two probabilities are known, since the probabilities must sum to unity. X is a vector of explanatory variables including control variables specific to males and females within the same households including age, education, and number of extension contacts in a year. In addition, we control for subplot-level characteristics—soil fertility, slope, and land ownership—and household characteristics—region, household size, non-farm income, wealth index, and proportion of maize harvest consumed in the household. Finally, we include the risk preference parameters in the models. Table 6 contains summary statistics of independent variables used in the regressions.

The individual characteristics differ for each subset of respondents, i.e., males in male-headed households (MHH), females in MHH, and females in female-headed households (FHH).

Males have more education than females in MHH and especially more than females in FHH. Females in FHH are roughly 10 years older on average than males in MHH and have more extension contact each year. We expect positive coefficients on age, education, and extension contact.

The household and subplot-level characteristics are the same for males and females within MHH households.[5] MHH own more land than FHH households in the sample. The proportion of maize consumed within the household variable reveals which farmers produce maize for home consumption (subsistence farmers) or are more commercial producers. FHH and MHH consume 67% and 65% of their maize at home, respectively. Subsistence farmers (those consuming nearly all that they produce) may prefer local seeds due to taste preferences or ST hybrids as a form of insurance. We expect subsistence farmers to be less likely to adopt HY hybrids due to the risky nature of the hybrid and possible preference for the taste of traditional varieties.

If the coefficients on the female risk preference parameters in MHH are insignificant, then the unitary household model, i.e. models only considering household head preferences and covariates, may be sufficient to explain how risk preferences affect adoption. However, if female risk aversion, loss aversion, or nonlinear probability weighting significantly affect MHH's maize technology decision, then we must consider her preferences when modeling household technology adoption.

Summary statistics of the dependent variables are in Table 7. MHH have adopted hybrid seeds on more than 75% of their subplots, whereas FHH have adopted hybrids on just over 50%.

[5] A plot refers to piece of land that is physically separated from another. A subplot, the unit of measurement used in this analysis, refers to a subunit of a plot. Households may have more than one subplot on a plot. Only subplots that contain maize are considered.

FHH in this sample use ST hybrids and HY hybrids 30% and 24% of their subplots, respectively. MHH use both HY and ST on 38% of their maize subplots.

As previously stated, typical adoption models only consider the household head's preferences. In order to investigate the validity of this method and to see if and how regression results change when we include female preferences the model, we start with just male risk preferences and covariates. Subsequently, we examine female information on household maize adoption to provide a baseline for her preferences towards maize varieties.

Table 8 contains regression results from these models on all 317 household subplots[6]. The non-hybrid varieties are the reference group in the multinomial logit regressions. Columns 1 and 2 compare HY and ST adoption to non-hybrid adoption when we regress adoption on male risk preferences only. In this specification, risk parameters do not significantly impact the likelihood of adopting HY or ST over NH. We add male-specific, household-level, and subplot-level covariates to the regression in columns 3 and 4 and find risk preferences insignificantly correlated with HY adoption over NH adoption. Male risk lovingness, however, is positively correlated with ST adoption, and suggests that risk-loving males are more likely to adopt ST over NH. While ST hybrids are a form of insurance, adopting them is a change from the status quo and may cause farmers to perceive them as a risky investment. Next, we examine female-specific parameters and maize adoption.

Columns 5 through 8 detail the relationship between female preferences and hybrid adoption. In column 5, more loss-averse women are less likely to adopt HY hybrids over NH. Once we control for other covariates in column 7, however, the correlation between lambda and

[6] Males and females in MHH solely manage 64 and 26 maize subplots, respectively. The male household head and his spouse jointly manage 223 (70%) subplots. Thus, males either partially or fully manage 287 (91%) of the MHH maize subplots. See Appendix C for survey question related to subplot management.

HY adoption is no longer statistically significant. The insignificant risk preference parameters in columns 6 and 8 suggest that female risk preferences are not important when describing why households choose ST hybrids over NH. Other covariates including wealth and subplot slope are significantly correlated with ST adoption.

In the male- and female-specific regressions we see a positive affect of male sigma on ST adoption and a negative effect of female lambda on HY adoption when we eliminate other covariates. Next, we combine male and female preferences to see how the joint household model behaves. The subsequent full household models are the main interest of the paper.

Table 9 contains regression results for adoption as a function of both male and female risk parameters, with and without controlling for covariates. We initially regress without additional explanatory variables to investigate the combined effect of male and female preferences on adoption. Female loss aversion is negatively correlated with household adoption of HY over NH, as seen in Table 8, column 5. Neither male nor female risk preferences significantly affect ST adoption.

Columns 3 and 4 show that once we control for other covariates, male and female risk preferences in MHH are not significant factors in the household maize choice. The sign on female loss aversion in the HY regression remains negative and is likely connected to the proportion consumed at home variable, which also has a negative sign; her main concern may be feeding her household and therefore she is more averse to loss than her spouse. Another explanation for the negative sign on proportion consumed at home is taste preferences; a household chooses non-hybrids over HY as they consume more at home because it tastes better.

Households in the west are more likely to adopt HY hybrids over NH and less likely to adopt ST over NH.

Columns 5 through 8 in Table 9 investigate female-headed households' risk preferences and associated effects on FHH maize adoption. There are 40 FHH with a total of 108 maize subplots, about 1/3 the sample size of the MHH. Columns 5 and 7 show loss aversion significantly decreasing the likelihood of HY hybrids adoption over NH. Due to possible constraints faced by single-headed households, it is not surprising that females in FHH are averse to losses (Doss and Morris 2000). Once we add other explanatory variables to the model (column 7), the coefficient on sigma becomes significant which suggests risk-loving females are more likely to adopt HY over NH. Other covariates such as age, education, household size, and savings all positively affect the likelihood of FHH adoption HY hybrids over NH.

In column 6, the results indicate that risk-loving females in FHH are less likely to adopt ST hybrids over NH, or put another way, risk-averse women are more likely to adopt ST. We expect this sign, since ST hybrids should be risk-reducing. Once we add covariates, the sign on sigma remains negative and the nonlinear probability weighting parameter, α, becomes positively significant. This suggests that as females place excessive weight on small probabilities they are less likely to adopt ST. The alpha results aren't easily interpretable because respondents may be overweighting a variety of things that affect adoption such as weather, seed quality, etc.

Regional differences

The eastern and western parts of Kenya face different climatic conditions. Households in the East live in a semi-arid region whereas western households receive adequate rainfall (see Figure 1). Enumerators asked respondents to rank drought stress on a scale from 0 to 3, with 0 indicating no stress and 3 indicating catastrophic stress. Of the 172 households, 60% and 97% of households responded no stress in the East and West, respectively. Disaggregating the regions may shed light on the types of risks faced in the East and West. In addition, there may be differences in gender dynamics in the two regions due to ethnic group traditions and social norms[7]. The possible climatic and social differences could cloud the effects of risk preferences on maize adoption in the combined regressions.

Due to small sample sizes in region-disaggregated models, we regress MHH adoption on risk preferences, age, and education only. FHH have too few observations to run region-disaggregate regressions. Table 10 contains the average marginal effects and associated standard errors for the full sample, eastern, and western regions.

Male preferences are insignificant at the conventional levels in all three specifications. This finding is interesting because males solely or jointly manage over 90% of the plots and we anticipated their risk preferences to be correlated with household adoption. In column 4, however, male lambda is marginally insignificant at the 10% level (p=0.103) and suggests loss-averse males are more likely to adopt ST over NH.

In the full sample and eastern models, households with loss-averse females are less likely to adopt HY over NH. Due to a higher probability of drought in the East compared to the West, it is sensible that loss-averse females are less likely to engage in HY activity. The sign on sigma in column 3 signals that western households with risk-loving females are more likely to adopt HY than NH. In addition, the sign on alpha in columns 2 and 4 indicates that MHH with females who overweight small probabilities are more likely to adopt ST varieties. Because stress in the East is more likely to be drought, it's possible that females overweight the probability of a drought and are consequently more likely to adopt drought-tolerant hybrids as insurance. Neither male nor female risk preferences are significant in the western region regression.

[7] Data on household ethnic group was not available for this study.

The region-disaggregated results illuminate clear differences between the East and West. Enumeration teams differed in the two regions, so there is possible enumerator bias associated with these results. In addition, the risks and stresses prevalent in the regions differ. Regardless of the reason, the results invite further discussion and investigation into the causal differences of region-specific risk preferences and associated effects on maize adoption.

5. Conclusions

In this paper, we examine risk preferences of male and female farmers in Kenya. This includes mostly sets of husbands and wives, but also some FHH who are the lone decision-maker in their households. We find no difference in risk preferences between males and females living with MHHs, but do find female household heads to be more risk averse.

Our estimates of the reveal notable differences between MHH and FHH as well as regional variations. Both female and male risk preferences are insignificant in the MHH models, and suggest risk preferences do not significantly affect MHH adoption of HY or ST hybrids over non-hybrids. In FHH, however, risk preferences do significantly affect maize adoption decisions. Risk-loving females are more likely to adopt HY hybrids over NH and less likely to adopt ST hybrids over NH. FHH's risk preferences have expected signs with the exception of the alpha parameter in the full FHH, ST specification which suggests females who overweight small probabilities are less likely to adopt ST hybrids. Alpha is difficult to interpret and an interesting parameter because there are multiple possibilities for the types of probabilities an individual is overweighting.

In the region-specific regressions, female risk preferences are significant in the full sample and eastern region regressions. These regressions showed clear differences between the East and the West, which are possibly due to gender dynamics or social norms in the regions, climatic differences, or exposure to various varieties. Future research should explore the cause of the regional differences.

The MHH and FHH regression results do not support or reject the notion that the unitary household model is sufficient. Both male and female parameters in the MHH are insignificant in the full household model, but her loss aversion parameter is significant in both preference-only regressions in Table X and Table X. This information would have been lost if we only interviewed and performed experiments with the male head of household. In addition, the female parameters are significant in the reduced, region-disaggregated models in Table X. Therefore, female preferences provide information on household maize technology adoption that male preferences fail to reveal. The results do support the hypothesis that PT is more appropriate than EU in this context. The full MHH regressions reveal no significant differences with or without the other parameters, but both lambda and alpha are significant in the FHH regressions. In addition, alpha and lambda are both statistically different from 1 using an F-test, suggesting PT explains Kenyan farmers' decisions over maize better than EU.

To be continued….

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Figures and Tables

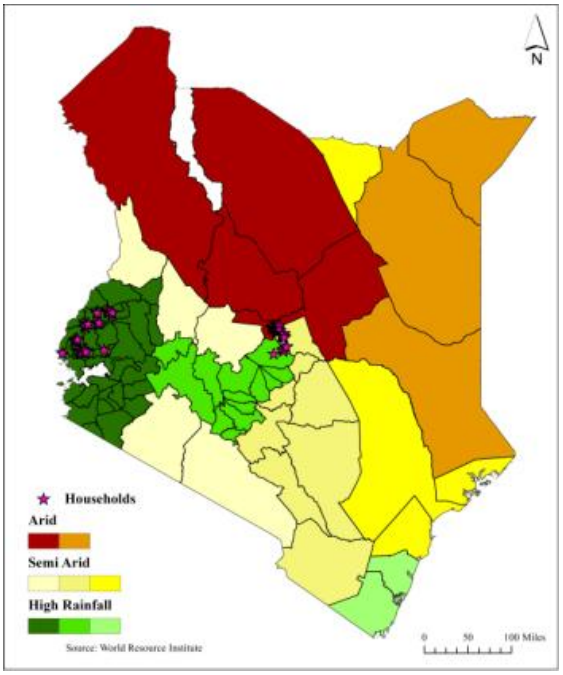

Figure 1: Map of Households in Sample

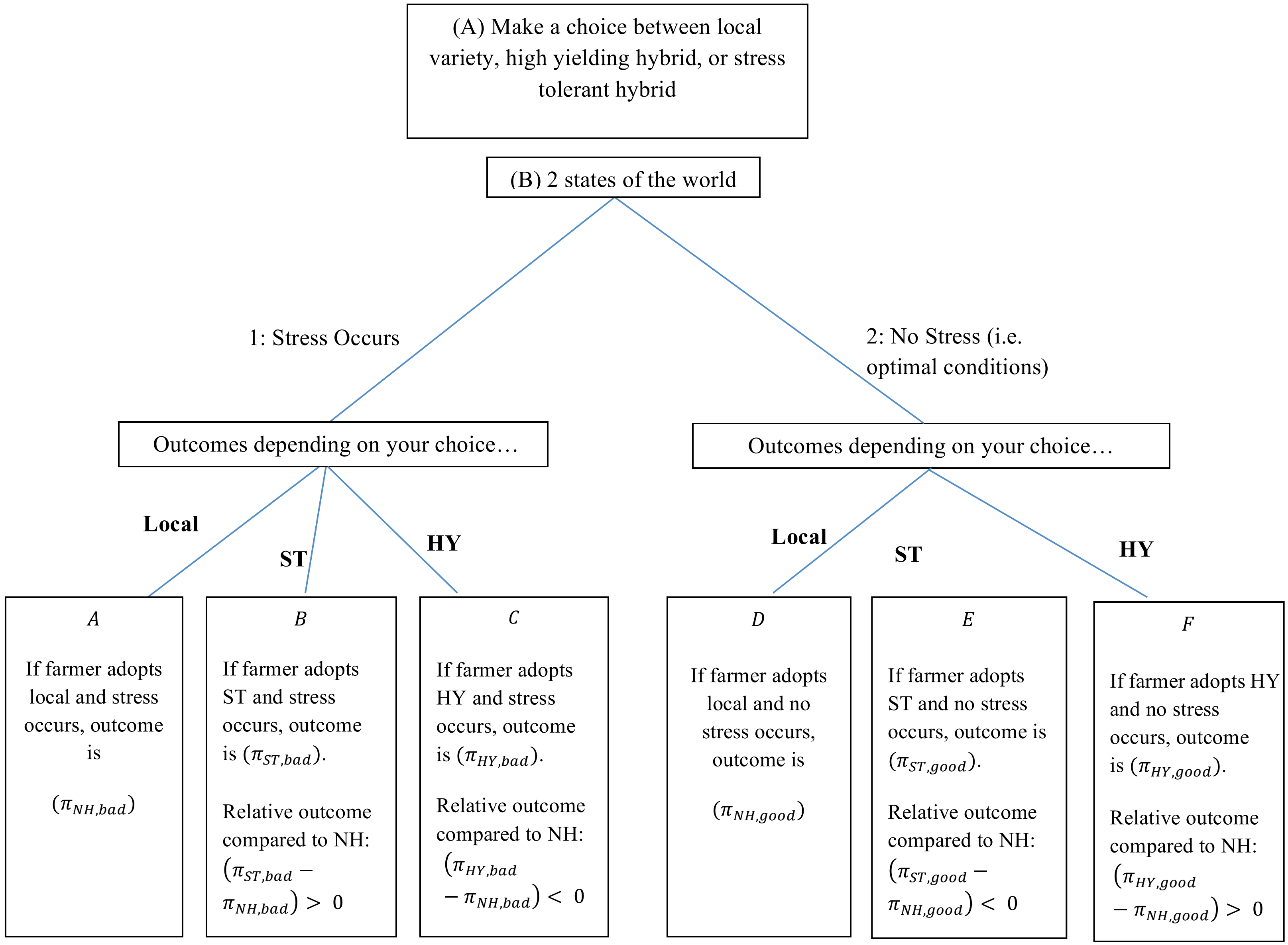

Figure 2: Maize Adoption Conceptual Map

Option A	Option B
110 if $\boxed{1}\boxed{2}\boxed{3}\boxed{4}\boxed{5}\boxed{6}\boxed{7}$	55 if $\boxed{1}\boxed{2}\boxed{3}\boxed{4}\boxed{5}\boxed{6}\boxed{7}\boxed{8}\boxed{9}$
440 if $\boxed{8}\boxed{9}\boxed{10}$	920 if $\boxed{10}$

Figure 3: Risk Preference Experiment Example

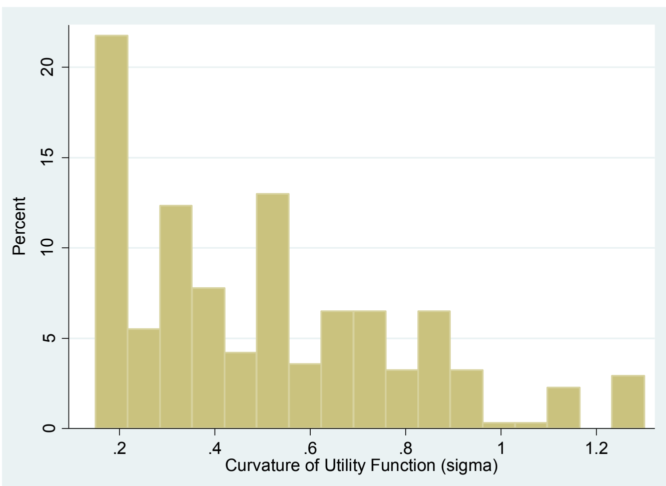

Figure 4: Sigma Distribution

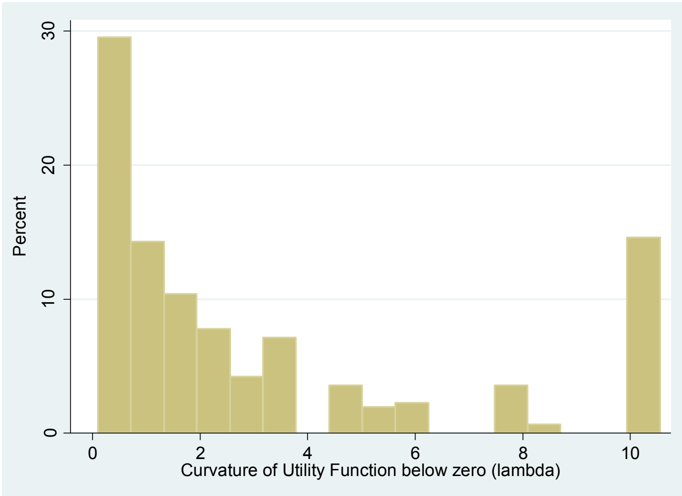

Figure 5: Lambda Distribution

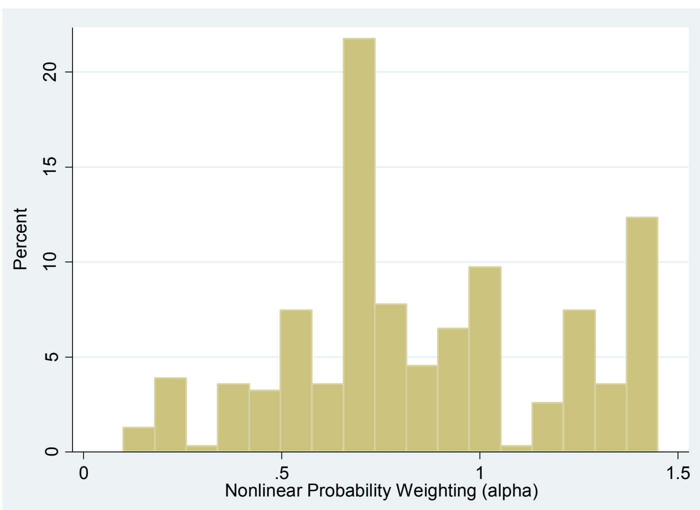

Figure 6: Alpha Distribution

Table 1: Marital Status and Household Headship

	Marital Status				
Gender and Headship	Married living with spouse	Married living without spouse	Widowed	Single/never married	*Total*
Females in MHH[a]	132	0	0	0	134
Males in MHH	132	0	0	0	134
Females in FHH[b]	0	4	35	1	40

Note: [a]MHH=Male headed household; [b]FHH=Female headed household

Table 2: High Yielding Varieties Used by Sample

Variety	Qualities Possessed	Supplier	Number of Adopters (subplot-level) (Western)	Number of Adopters (subplot-level) (Eastern)
DK 8031	High yield, good standability	Monsanto	23	9
H512	High yield, earlier maturity	Kenya Seed Company Ltd.	1	2
H513	High yield, good standability	Kenya Seed Company Ltd	15	20
H516	High yield	Kenya Seed Company Ltd	14	11
H624	High yield	Kenya Seed Company Ltd	1	0
H625	High yield	Kenya Seed Company Ltd	5	0
H614	High yield	Kenya Seed Company Ltd	18	3
H6210	High yield	Kenya Seed Company Ltd	1	0
H6213	High yield	Kenya Seed Company Ltd	21	0
PH B3253	High yield	Pioneer Hi-Bred	0	1
		Total HY hybrid adopters	99 (23.3%)[a]	43 (11.3%)[b]

[a]Proportion of all maize plots (East and West) under HY hybrid in West; [b]Proportion of all maize plots under HY hybrid in East

Table 2: Stress Tolerant Varieties Used by Sample

Variety	Qualities Possessed	Supplier	Number of Adopters (subplot-level) (Western)	Number of Adopters (subplot-level) (Eastern)
WS 505	GLS tolerant, Drought tolerant	Western Seed Co	29	0
DH 04	Drought tolerant	Kenya Seed Company Ltd	10	4
DUMA 41	Drought tolerant	Seed Co Ltd.	2	8
DUMA 43	Drought tolerant, GLS tolerant	Seed Co Ltd.	5	95
		Total ST adopters	46 (10.8%)[a]	107 (25.2%)[b]

[a]Proportion of all maize plots (East and West) under ST hybrid in West; [b]Proportion of all maize plots under ST hybrid in East

Table 4: Means Comparison for Returning and Attrited Individuals

Independent Variables	Returning Individuals	Attrited Individuals
Age in years	50.53	48.19 (2.23)*
Education in years	7.31	7.51 (0.76)
Household size	6.34	5.71 (3.21)**
Total Income	81711.76	119643.29 (3.56)***
Farm Income	29106.22	38200.14 (1.73)
Observations	304	498

Absolute value of t-statistics in parenthesis; Significant at *10%, ** 5%, and *** 1%.

Table 5: Risk Preference Parameters Summary Statistics

	Full Sample		Males in MHH		Females in MHH		Females in FHH		All females	
	Mean	sd	Mean	sd	Mean	sd	Mean	sd	Mean	sd
Sigma	0.50	(0.29)	0.50	(0.27)	0.48	(0.31)	0.55	(0.31)	0.50	(0.31)
						[0.65][a]		[0.25][b]		[0.97][c]
Lambda	3.18	(3.63)	2.86	(3.37)	3.16	(3.69)	4.30	(4.09)	3.43	(3.80)
						[0.48]		[0.10]*		[0.17]
Alpha	0.86	(0.34)	0.87	(0.34)	0.87	(0.34)	0.78	(0.35)	0.85	(0.34)
						[0.99]		[0.17]		[0.62]
N	*304*		*132*		*132*		*40*		*172*	

Note: Mean coefficients; Standard deviation in parenthesis. [a]*p*-value for mean differences between male and females in MHH in brackets. [b]*p*-value for mean differences between females in FHH and females in MHH in brackets. [c]*p*-value for mean differences between male and and all females in brackets. Significant at *10%, ** 5%, and *** 1%.

Table 6: Summary Statistics of Explanatory Variables

Independent Variables	Males in MHH		Females in MHH		Females in FHH	
Individual Characteristics						
N	132		*132*		*40*	
Age	52.89	(13.54)	44.51	(12.18)	62.63	(13.18)
Education (years)	8.28	(3.08)	7.09	(3.14)	4.13	(3.45)
Maize extension contact (# times/year)	4.02	(10.42)	3.88	(10.03)	4.50	(12.12)
Any agricultural credit (1=yes)	0.21	(0.41)	0.20	(0.39)	0.13	(0.33)
Household Characteristics						
N	*132*		*132*		*40*	
Household size	6.56	(2.88)	6.56	(2.88)	4.88	(3.45)
Nonfarm Income (10000 KSH)	5.62	(9.53)	5.62	(9.53)	2.92	(3.65)
Wealth Index	2.93	(1.31)	2.93	(1.31)	2.55	(1.47)
Household saves (1=yes)	0.80	(0.40)	0.80	(0.40)	0.75	(0.44)
Region (1=Western)	0.59	(0.49)	0.59	(0.49)	0.68	(0.47)
Proportion of harvest consumed at home	0.65	(0.35)	0.65	(0.35)	0.67	(0.26)
Subplot Characteristics						
N	*317*		*317*		*108*	
Fertile Soil (1=Yes)	0.18	(0.38)	0.18	(0.38)	0.14	(0.35)
Slope (1=Flat)	0.52	(0.50)	0.52	(0.50)	0.70	(0.46)
Own land area (hectares)	0.78	(0.86)	0.78	(0.86)	0.53	(0.63)

Mean coefficients; Standard deviations in parentheses

Table 7: Maize Variety Adoption

Variables	All MHH plots		All FHH plots	
Non-hybrid seeds	0.237	(0.426)	0.463	(0.501)
High Yield hybrids	0.382	(0.487)	0.241	(0.430)
Stress Tolerant hybrids	0.382	(0.487)	0.296	(0.459)
N	317		108	

Mean coefficients; Standard deviation in parentheses

Table 8: Separate Male and Female Preferences on Household Subplots

Independent Variables	(1) HY Males on HH plots	(2) ST Males on HH plots	(3) HY Males on HH plots (full)	(4) ST Males on HH plots (full)	(5) HY Females on HH plots	(6) ST Females on HH plots	(7) HY Females on HH plots (full)	(8) ST Females on HH plots (full)
Male sigma	-0.049	0.229	-0.021	0.229*				
	(0.16)	(0.17)	(0.15)	(0.13)				
Male lambda	0.007	0.005	0.001	0.010				
	(0.01)	(0.01)	(0.01)	(0.01)				
Male alpha	-0.112	0.041	-0.134	-0.055				
	(0.13)	(0.12)	(0.11)	(0.10)				
Male age			0.000	-0.003				
			(0.00)	(0.00)				
Male education (years)			0.025*	0.005				
			(0.01)	(0.01)				
Male extension contact			-0.001	-0.003				
			(0.00)	(0.00)				
Female sigma					0.101	-0.022	0.098	-0.004
					(0.13)	(0.14)	(0.13)	(0.11)
Female lambda					-0.020*	0.005	-0.008	-0.009
					(0.01)	(0.01)	(0.01)	(0.01)
Female alpha					-0.022	-0.148	-0.138	-0.094
					(0.13)	(0.13)	(0.13)	(0.12)
Female age							-0.000	-0.001
							(0.00)	(0.00)
Female education							-0.012	0.024
							(0.02)	(0.01)
Female extension contact							0.000	0.001
							(0.00)	(0.00)

Table 8: Separate Male and Female Preferences on Household Subplots (continued)

Independent Variables	(1) HY Males on HH plots	(2) ST Males on HH plots	(3) HY Males on HH plots (full)	(4) ST Males on HH plots (full)	(5) HY Females on HH plots	(6) ST Females on HH plots	(7) HY Females on HH plots (full)	(8) ST Females on HH plots (full)
Household size			-0.014	0.016			-0.008	0.012
			(0.02)	(0.01)			(0.02)	(0.01)
Wealth Index			0.039	-0.081***			0.073**	-0.090***
			(0.03)	(0.03)			(0.03)	(0.03)
Non-farm Income (10,000 KSH)			-0.006	0.008			-0.005	0.006
			(0.00)	(0.01)			(0.00)	(0.00)
Household saves (Yes=1)			0.141	-0.113			0.124	-0.087
			(0.09)	(0.08)			(0.10)	(0.08)
Land area - owned (ha)			0.052	-0.054			0.049	-0.055
			(0.04)	(0.04)			(0.04)	(0.05)
Proportion of harvest consumed at home			-0.260**	0.138			-0.243*	0.130
			(0.13)	(0.11)			(0.13)	(0.11)
Slope (Flat=1)			-0.138*	0.193***			-0.193***	0.177***
			(0.07)	(0.06)			(0.07)	(0.07)
Fertile soil (Yes=1)			0.196*	0.067			0.180	0.101
			(0.10)	(0.10)			(0.11)	(0.09)
Region (West=1)			0.320***	-0.468***			0.315***	-0.506***
			(0.10)	(0.08)			(0.10)	(0.07)
Observations	317	317	317	317	317	317	317	317
Log Likelihood	-336.18	-336.18	-271.81	-271.81	-332.44	-332.44	-278.19	-278.19
Pseudo R2	0.02	0.02	0.20	0.20	0.03	0.03	0.19	0.19
% Correctly Predicted[a]	62.45	65.93	70.1	72.2	62.2	61.8	70.35	75.5

Average marginal effects. Standard errors clustered at the household level in parenthesis. Significant at *10%, **5%, ***1%. [a]Percent correctly predicted calculated at a 50% cutoff.

Table 9: Male and Female-Headed Household Models

	(1) HY MHH on HH plots	(2) ST MHH on HH plots	(3) HY MHH on HH plots (full)	(4) ST MHH on HH plots (full)	(5) HY FHH	(6) ST FHH	(7) HY FHH (full)	(8) ST FHH (full)
Male sigma	-0.075	0.244	0.013	0.176				
	(0.16)	(0.16)	(0.15)	(0.14)				
Male lambda	0.006	0.007	0.001	0.012				
	(0.01)	(0.01)	(0.01)	(0.01)				
Male alpha	-0.086	0.056	-0.098	-0.036				
	(0.13)	(0.12)	(0.10)	(0.10)				
Male age			-0.002	0.000				
			(0.00)	(0.00)				
Male education (years)			0.035**	-0.003				
			(0.01)	(0.01)				
Male extension contact			-0.002	-0.003				
			(0.00)	(0.00)				
Female sigma	0.097	-0.025	0.013	-0.009	0.221	-0.696***	0.490**	-0.960***
	(0.12)	(0.13)	(0.14)	(0.12)	(0.19)	(0.23)	(0.25)	(0.37)
Female lambda	-0.019*	0.006	-0.010	-0.006	-0.034*	0.006	-0.026*	-0.003
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)
Female alpha	-0.016	-0.168	-0.122	-0.073	-0.026	-0.011	-0.026	0.349**
	(0.13)	(0.12)	(0.12)	(0.11)	(0.16)	(0.16)	(0.19)	(0.17)
Female education (years)			-0.026	0.027*			0.060***	0.045*
			(0.02)	(0.01)			(0.02)	(0.02)
Female age[a]							0.025***	-0.004
							(0.01)	(0.01)
Female extension contact			0.001	0.002			0.005	-0.005
			(0.00)	(0.00)			(0.01)	(0.00)

Table 9: Male and Female-Headed Household Models (continued)

	(1) HY MHH on HH plots	(2) ST MHH on HH plots	(3) HY MHH on HH plots (full)	(4) ST MHH on HH plots (full)	(5) HY FHH	(6) ST FHH	(7) HY FHH (full)	(8) ST FHH (full)
Household size			-0.013	0.018			0.059**	0.002
			(0.02)	(0.01)			(0.03)	(0.02)
Wealth Index			0.049	-0.100***			0.080**	0.055
			(0.03)	(0.03)			(0.04)	(0.05)
Non-farm Income (10,000KSH)			-0.006	0.008			0.109***	0.021
			(0.00)	(0.00)			(0.04)	(0.02)
Household saves (Yes=1)			0.109	-0.124			0.235**	0.094
			(0.09)	(0.08)			(0.10)	(0.09)
Land area - owned (ha)			0.065	-0.068			-0.475**	0.319**
			(0.04)	(0.05)			(0.20)	(0.15)
Proportion of harvest consumed at home			-0.244**	0.127			-0.345	0.178
			(0.12)	(0.11)			(0.43)	(0.27)
Slope (Flat=1)			-0.159**	0.175***			0.779***	-0.574***
			(0.08)	(0.06)			(0.28)	(0.21)
Fertile soil (Yes=1)[b]			0.177*	0.096				
			(0.10)	(0.09)				
Region (West=1)			0.330***	-0.502***			0.204**	-0.325***
			(0.09)	(0.08)			(0.10)	(0.08)
Observations	317	317	317	317	108	108	108	108
Log Likelihood	-327.43	-327.43	-259.73	-259.73	-99.36	-99.36	-38.70	-38.70
Pseudo R2	0.04	0.04	0.24	0.24	0.13	0.13	0.66	0.66
% Correctly Predicted[c]	60.3	63.1	72.2	75.4	76.9	74.1	86.1	90.7

Average marginal effects. Standard errors clustered at the household level in parenthesis. Significant at *10%, **5%, ***1%. [a]Female age removed from MHH regression due to strong correlation with male age. [b]Soil fertility removed from FHH regression due to small sample size. [c]Percent correctly predicted calculated at a 50% cutoff.

Table 10: Male-Headed Household Preferences on Adoption, by Region

Independent Variables	(1) HY MHH (Full sample)	(2) ST MHH (Full sample)	(3) HY MHH (Eastern region)	(4) ST MHH (Eastern region)	(5) HY MHH (Western region)	(6) ST MHH (Western region)
Male sigma	-0.022	0.215	-0.187	0.305	0.269	-0.102
	(0.16)	(0.16)	(0.18)	(0.21)	(0.21)	(0.19)
Male lambda	0.005	0.008	-0.010	0.027	0.026	-0.012
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Male alpha	-0.107	0.054	-0.220	0.278	-0.034	-0.163
	(0.12)	(0.11)	(0.20)	(0.20)	(0.14)	(0.12)
Female sigma	0.032	-0.014	0.324*	0.105	-0.269	0.092
	(0.14)	(0.14)	(0.19)	(0.35)	(0.19)	(0.16)
Female lambda	-0.021**	0.009	-0.028**	0.015	-0.011	-0.013
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Female alpha	-0.013	-0.204*	0.104	-0.662**	0.059	-0.080
	(0.13)	(0.12)	(0.20)	(0.28)	(0.14)	(0.12)
Male age[a]	-0.002	-0.001	0.001	-0.005	-0.003	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male education (years)	0.039***	-0.006	-0.021	-0.012	0.069***	-0.002
	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.02)
Female education (years)	-0.024	0.024	-0.024	0.054**	-0.019	0.013
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	317	317	147	147	170	170
Log Likelihood	-309.91	-309.91	-110.46	-110.46	-143.63	-143.63
Pseudo R2	0.09	0.09	0.23	0.23	0.20	0.20
% Correctly Predicted[b]	63.1	65.0	74.2	66.0	63.53	77.65

Average marginal effects. Standard errors clustered at the household level in parenthesis. Significant at *10%, **5%, ***1%. [a]Female age removed from regressions due to strong correlation with male age. [b]Percent correctly predicted calculated at a 50% cutoff.

Appendix A: Derivation of partial derivatives

(1) $\left(\frac{\partial U}{\partial \sigma}\right) = -\lambda\pi(p)(-x^{\sigma})\ln(x) + \pi(q)(y^{\sigma})\ln(y)$

(2) $\left(\frac{\partial U}{\partial \lambda}\right) = -\pi(p)(-x^{\sigma})$

(3) $\left(\frac{\partial U}{\partial \alpha}\right) =$
$\left(-\lambda x^{\sigma}[\ln(-\ln(p))\,(-\exp(-(-\ln(p))^{\alpha}))(-\ln(p))] + y^{\sigma}[\ln(-\ln(q))\,(-\exp(-(-\ln(q))^{\alpha}))(-\ln(q))]\right)$

Appendix B: Prospect theory series

Prospect Theory Series 1 (KSH)

Task	Starting Point	Option A	Option B
1		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 920 if 10
2		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 1030 if 10
3		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 1175 if 10
4		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 1380 if 10
5		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 1655 if 10
6		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 2020 if 10
7		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 2425 if 10
8		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 3310 if 10
9		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 4410 if 10
10		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 6620 if 10

Prospect theory series 2 (KSH)

Task	Starting Point	Option A	Option B
1		330 if 1 440 if 2 3 4 5 6 7 8 9 10	55 if 1 2 3 590 if 4 5 6 7 8 9 10
2		330 if 1 440 if 2 3 4 5 6 7 8 9 10	55 if 1 2 3 610 if 4 5 6 7 8 9 10
3		330 if 1 440 if 2 3 4 5 6 7 8 9 10	55 if 1 2 3 625 if 4 5 6 7 8 9 10
4		330 if 1 440 if 2 3 4 5 6 7 8 9 10	55 if 1 2 3 660 if 4 5 6 7 8 9 10
5		330 if 1 440 if 2 3 4 5 6 7 8 9 10	55 if 1 2 3 700 if 4 5 6 7 8 9 10
6		330 if 1 440 if 2 3 4 5 6 7 8 9 10	55 if 1 2 3 735 if 4 5 6 7 8 9 10
7		330 if 1 440 if 2 3 4 5 6 7 8 9 10	55 if 1 2 3 810 if 4 5 6 7 8 9 10
8		330 if 1 440 if 2 3 4 5 6 7 8 9 10	55 if 1 2 3 880 if 4 5 6 7 8 9 10
9		330 if 1 440 if 2 3 4 5 6 7 8 9 10	55 if 1 2 3 995 if 4 5 6 7 8 9 10
10		330 if 1 440 if 2 3 4 5 6 7 8 9 10	55 if 1 2 3 1105 if 4 5 6 7 8 9 10

Prospect Theory Series 3 (KSH)

Task	Starting Point	Option A	Option B
1		185 if 1 2 3 4 5 -30 if 6 7 8 9 10	220 if 1 2 3 4 5 -150 if 6 7 8 9 10
2		30 if 1 2 3 4 5 -30 if 6 7 8 9 10	220 if 1 2 3 4 5 -150 if 6 7 8 9 10
3		5 if 1 2 3 4 5 -30 if 6 7 8 9 10	220 if 1 2 3 4 5 -150 if 6 7 8 9 10
4		5 if 1 2 3 4 5 -30 if 6 7 8 9 10	220 if 1 2 3 4 5 -120 if 6 7 8 9 10
5		5 if 1 2 3 4 5 -60 if 6 7 8 9 10	220 if 1 2 3 4 5 -120 if 6 7 8 9 10
6		5 if 1 2 3 4 5 -60 if 6 7 8 9 10	220 if 1 2 3 4 5 -100 if 6 7 8 9 10
7		5 if 1 2 3 4 5 -60 if 6 7 8 9 10	220 if 1 2 3 4 5 -80 if 6 7 8 9 10