MALE AND FEMALE RISK PREFERENCES AND MAIZE TECHNOLOGY ADOPTION IN KENYA

By

Abby Dean Moore

(Under the direction of Nicholas Magnan)

ABSTRACT

This thesis uses experimental techniques to elicit risk aversion, loss aversion, and nonlinear probability weighting parameters from Kenyan farmers. Enumerators interviewed primary male and female decision-makers within the same household about their maize cultivation practices and performed risk experiments with these same respondents. I use risk preference parameters to explain household maize variety adoption decisions at the subplot level and find that all three Prospect Theory parameters are significant in different model specifications. This suggests that Prospect Theory is more appropriate than Expected Utility Theory. Risk preferences affect adoption differently for men and women in the same households, and also differently in the eastern and western regions.

INDEX WORDS: Gender-Disaggregated Risk Preferences, Technology Adoption, Kenya, Agriculture, Maize Hybrids, Prospect Theory, Risk Preference Experiments

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DEDICATION

To KC, Mom, Pop, Shelley, and the Wischerths. I wouldn’t be here without each of you, your continual support, and belief in me when I didn’t believe in myself. Also, to the folks in Bungu who don’t have the chance to pursue higher education: this one’s for you. Tuko pamoja.

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CHAPTER 1

INTRODUCTION

1.1 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 preferences have been identified as key variables in the technology adoption process (Feder, Just, and Zilberman 1985; Sunding and Zilberman 1999).

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.

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.

This study uses experimental techniques to elicit risk preferences from both males and females in Kenyan farming households in order to analyze the following issues: 1) test whether Expected Utility Theory (EU) or Prospect Theory (PT) is more appropriate when defining a Kenyan farmer's utility function; 2) explore intra-household differences in male and female risk preferences to; 3) determine if the unitary household model is sufficient to explain Kenyan household technology decisions with respect to risk preferences.

1.2 Hypotheses

There are three main hypotheses in this study:

i. Prospect Theory and its three independent parameters—risk aversion (σ), loss aversion (λ), and non-linear probability weighing (α)—will explain farmers' utility over technology adoption better than Expected Utility Theory and its single parameter (σ).
ii. Males and females will exhibit significant differences in the curvature of the utility function (σ) and are likely to have differing loss aversion and nonlinear probability weighting parameters.
iii. Female preferences in male-headed households will be significant in the explanation of maize technology adoption in Kenyan households, i.e. the unitary household model will be insufficient.

1.3 Motivation

Three fields of literature intersect in this study: experimental elicitation of risk preferences, gender differences in preferences, and technology adoption. This is one of the first studies to combine experimentally elicited, gender-disaggregated preferences in the same household and test the impact of these preferences on agricultural technology adoption.

The technology adoption literature generally assumes a unitary household model. However, due to empirical evidence that male and female household members at times have divergent preferences and objectives, it is important to test whether or not the unitary household model applies. If researchers assume unitary preferences in all contexts, they may overlook the complete household decision-making 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 may also be significant determinants of adoption. 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 policy makers in choosing the most effective technology interventions. If the issue is loss aversion, providing farmers with crop insurance may facilitate adoption; if risk aversion inhibits adoption, demonstration plots or money-back guarantees may increase adoption rates. However, without knowing which of these parameters affects the adoption process, interventions may not target the core issue.

1.4 Organization of the Thesis

Chapter 2 contains background information on risk preferences. This includes a literature review, experiment design and protocol, as well as results from the experiments. Chapter 3 uses the risk experiment data, in addition to household, individual, and subplot-level data, to examine maize technology adoption in Kenya. Chapter 4 concludes the thesis.

CHAPTER 2

EXPERIMENTALLY ELICITED RISK PREFERENCES

2.1 Introduction

This chapter provides background on risk preference theory and parameter estimation techniques. Various studies have employed experimental elicitation methods throughout the developing and developed world (see Cardenas and Carpenter (2008) for a review). Recently Tanaka, Camerer, and Nguyen (2010) developed a technique to elicit Prospect Theory (PT) parameters including risk aversion, loss aversion, and probability weighting. This is the technique used for this study.

The rest of this chapter is as follows: (2.2) literature review of risk preference experiments; (2.3) literature review of gender differences in preferences; (2.4) methodology; (2.5) data and experiment protocol; (2.6) results and discussion.

2.2 Previous Literature on Risk Preference 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) developed a method to measure PT's risk aversion, loss aversion, and nonlinear probability weighting parameters. 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. I employ a similar approach in this study.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.

2.3 Previous Literature on gender differences in risk preferences

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. This study explores whether or not Kenyan females are more risk-averse than males.

The following sections detail the methods with which I elicit, estimate, and analyze gender-disaggregated risk preference parameters.

2.4 Methodology

Risk is commonly modeled using EU theory where the concavity of the utility function alone characterizes risk preferences. 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 (Tanaka, Camerer, and Nguyen 2010). The model allows empirical results to determine if PT or EU fit the data better. TCN use 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. In both the TCN and Liu (2013) studies, loss aversion and probability weighting parameters are significantly different than one, suggesting concavity of the utility function is insufficient in defining risk preferences.

Following TCN and Liu, the utility function is of the following form:

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

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

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 Liu and TCN. 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. I use experimental techniques to estimate each of these parameters and test whether EU is sufficient to explain individuals' utility functions.

2.5 Field Experiment Design and Data Collection

2.5.1. Household Characteristics Data

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 Kenya to understand the production environment of thousands of rural farmers in these five countries, their socioeconomic statuses, and technology choices. The most recent round of data collection is the second in this panel data set. I use data from the most recently collected household and individual surveys for individuals that attended the experiments.

Enumerators gave two separate surveys to respondents: a household survey and an individual survey. The household head answered both surveys. The spouse, or secondary decision maker in the household, answered only the individual survey. Enumerators performed the individual surveys concurrently and separately for respondents in the same household. For single-headed households, the household head answered both surveys.

AP chose respondents from a three-stage sampling procedure. 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. 540 households (802 individuals) participated in the most recent round, and I use 172 households (304 individuals) in the present study. Figure 1 represents the households' locations. I consider only 304 individuals in this study because individuals had to be present at both the December survey and the experiments to be included; a number of individuals attended the experiments but were not at the survey and vice versa. The household and individual surveys were lengthy (4-5 hours) and tedious, possibly deterring respondents from returning to perform the experiments shortly after the surveys concluded.

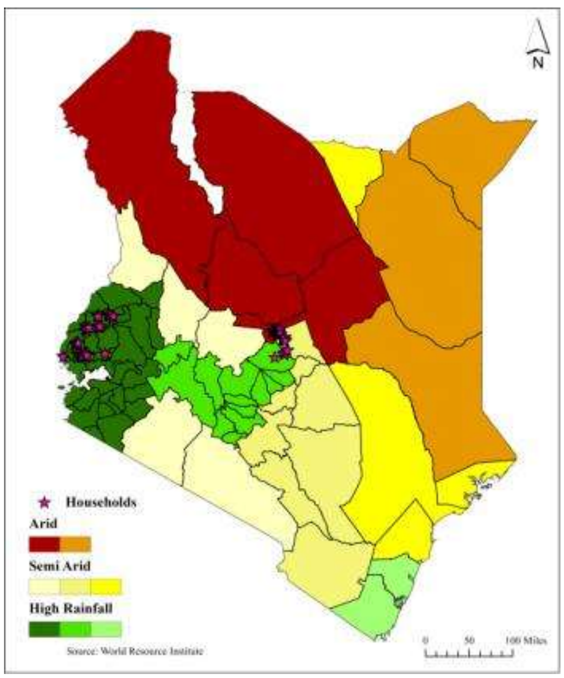

Figure 1: Map of Households in Sample

The household survey included questions related to on-farm production, input use, yields, technology choices, as well as household demographics. The individual survey, modeled after the International Food Policy Research Institute's (IFPRI) Women's Empowerment in

Agricultural Index (WEAI), contained questions related to savings, group membership, leadership, decision-making within the household, as well as asset ownership. The technology adoption regressions in the subsequent chapter use information from both surveys.

In order to ensure that there was no attrition bias, *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 are presented in Table 1. There are significant differences in the means of age and household size, 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.

Table 1: Means Comparison for Attrition and Non-Attrition Sample

Independent Variables	Returning Individuals	Attrition 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%.

In the subsequent chapter I use an asset-based wealth index constructed from household assets and home characteristics. Due to a lack of reliable income data, I created an asset-based wealth index as an alternative measure of wealth following the Demographic and Health Survey (DHS) Wealth Index protocol (Rutstein and Johnson 2004). I use Principal Components Analysis

(PCA), a statistical technique that measures variability among a set of variables, to create the index. After obtaining the factor predictions, I categorize them into five quintiles in order to meaningfully analyze the data. Table 2 contains the index broken into quintiles. Quintile 1 and Quintile 5 represent the least wealthy and most wealthy quintiles, respectively.

Table 2: Asset-based Wealth Index

Factor	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
Watch	0.48	0.56	0.43	0.52	0.54
Silver	0.11	0.02	0.07	0.03	0.1
Bicycle	0.72	0.45	0.51	0.56	0.59
CD Player	0.04	0.07	0.45	0.43	0.78
Phone	0.49	0.51	0.48	0.66	0.78
Car	0.08	0.05	0.06	0.11	0.09
Fridge	0.06	0.05	0.09	0.11	0.17
Cement Exterior Walls	0.00	0.00	0.00	0.05	0.54
Brick Exterior Walls	0.04	0.06	0.07	0.31	0.15
Mud Floors	1.00	0.99	0.81	0.28	0.02
Number of Rooms in House	1.85	2.57	2.89	3.77	4.9
Electricity	0.00	0.00	0.00	0.01	0.41
Piped Water	0.01	0.04	0.12	0.42	0.56
Flush toilet	0.00	0.00	0.00	0.00	0.09
Shared pit latrine	0.37	0.15	0.17	0.16	0.06

*Note: Numbers represent percentage of respondents in a particular quintile who own the asset (factor) in the leftmost column, or the average number for that quintile.

With the exception of number of rooms, the values in the table represent the percentage of respondents in a particular quintile who own the asset (factor) in the leftmost column. Because enumerators asked for asset information individually, males and females within a household do not always fall in the same quintile. To ease analysis, I take the average quintile value of males and females in the same household for use in the adoption regressions in Chapter 3.

The household and individual survey data make up a portion of the data needed to analyze technology adoption. The explanatory variables of interest in this study, however, are the individual risk preferences. Section 2.5.2 discusses the experiments.

2.5.2 Risk Preference Field Experiments

In December 2013, enumerators experimentally elicited risk preference parameters from Kenyan households. After the AP team completed the household and individual surveys in Fall of 2013, enumeration teams returned to the same households to perform the experiments with head males and females within each household. 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. In total, we consider 304 individuals from five districts, 72 villages, and 172 households in this study. I provide a breakdown of marital status and house headship in Table 3.

Both respondents in multiple decision-maker households identified household headship. In single decision-maker households, the sole respondent identified whether the household head was male or female. In this 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.

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[2] (about 2USD), comparable to a daily wage, for attending the experiments and obtained further payments based on their choices in the experiments.

[1] See Appendix C for relevant survey questions.
[2] Mean daily income is 245 KSH for male-headed households and 160 KSH for female-headed households.

Table 3: 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

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 A contains the three risk preference series and Figure 2 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. I 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. I estimate loss aversion using a series that contains both gains and losses (see Table 14 in Appendix A for full series). I ensured that 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 I also permitted respondents to never switch.

Option A	Option B
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]

Figure 2: Risk Preference Experiment Example

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. Then, 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 2, 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.

2.6 Experiment Results and Discussion

Following TCN and Liu, I 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, I 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, I 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. I 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 I use the interval midpoints for analysis. I estimate the loss aversion parameter using the results from σ and the switching points in Series 3. Again, I use the median of the interval for analysis.[3]

Figures 3, 4, and 5 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 ($\sigma \rightarrow 0.15$) 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.

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

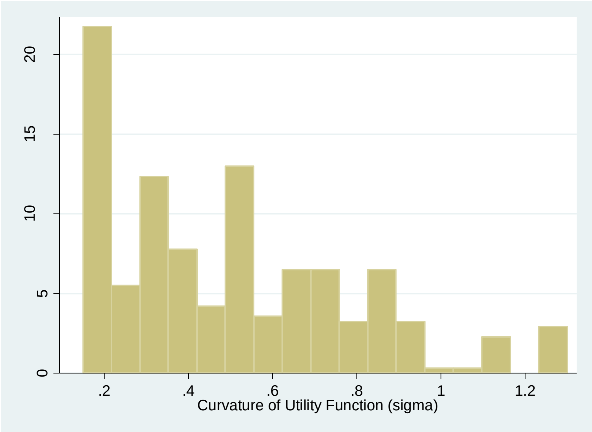

Figure 3: Sigma Distribution

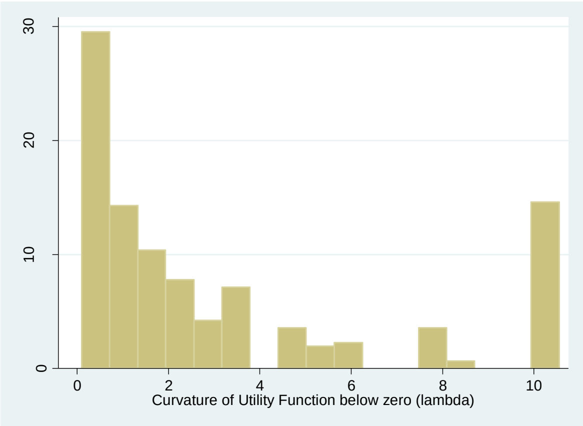

Figure 4: Lambda Distribution

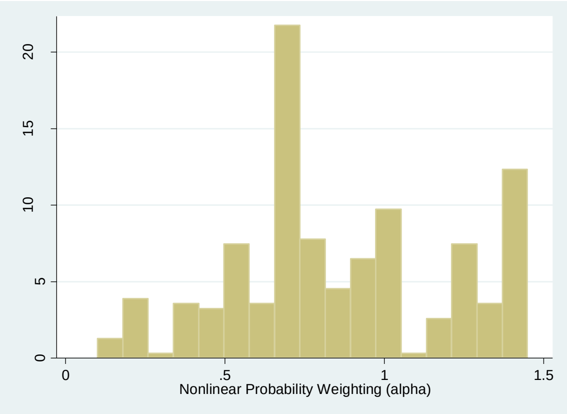

Figure 5: Alpha Distribution

Table 4 contains more experiment result details. I 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 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 FHH 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.

Table 4: 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) [0.65][a]	0.55	(0.31) [0.25][b]	0.50	(0.31) [0.97][c]
Lambda	3.18	(3.63)	2.86	(3.37)	3.16	(3.69) [0.48]	4.30	(4.09) [0.10]*	3.43	(3.80) [0.17]
Alpha	0.86	(0.34)	0.87	(0.34)	0.87	(0.34) [0.99]	0.78	(0.35) [0.17]	0.85	(0.34) [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%.

In the following chapter, I use the estimated parameters as explanatory variables in maize technology regressions. Differentiating the effects of risk aversion and loss aversion on adoption enables policy makers to create more appropriate targeting schemes. If loss aversion is significant, an insurance or safety net program may incentivize adoption; if risk aversion is significant, information and extension may reduce risk associated with adopting new technologies.

CHAPTER 3

TECHNOLOGY ADOPTION IN KENYA

3.1 Introduction

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 (IRRI 2009). In addition, hybrid seeds must be purchased new each season to maintain their vigor.

I 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. I 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 I will refer to these groups as HY and ST.

HY maize hybrids are known for their yield potential but may also contain other traits such as good standability, early maturity, or stress tolerance. Table 5 contains the HY varieties, which are mainly supplied by Kenya Seed Company Ltd.

Table 5: 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

The other hybrids in this study are ST. 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.

I 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, I aggregate due to small sample sizes of strictly GLS or drought tolerant seeds. Therefore, Table 6 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. I explore these varieties and factors related to their adoption in the following sections.

Table 6: 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

The rest of this chapter is as follows: (3.2) review of the technology adoption literature; (3.3) review of the intra-household bargaining power literature (3.4) methodology and empirical specification; (3.5) results and discussion.

3.2 Literature Review of Technology Adoption

Technology adoption has been extensively studied. Researchers have identified observable factors including wealth, income, education, credit constraints, and access to information as key variables in the technology adoption process (Feder, Just, and Zilberman 1985; Sunding and Zilberman 1999). In addition, multiple studies cite the importance of risk preferences in the technology adoption decision (Feder 1980; Feder, Just, and Zilberman 1985; Liu 2008; Engle-Warnick, Escobal D'Angelo, and Laszlo 2007; Liu 2013). Liu (2013) models Bt cotton adoption rates in China and includes loss aversion, risk aversion, and nonlinear probability weighting in her model. She determines that farmers with higher risk aversion and higher loss aversion adopt Bt cotton later. In addition, farmers that overweight small probabilities adopt Bt cotton sooner.

I have one pertinent body of literature left to discuss: gender differences in preferences over technologies. Doss and Morris (2000) examine factors affecting modern variety (MV) maize technology adoption decisions at the plot level in Ghana and find that gender is not statistically significant, i.e., females in male-headed households (MHH) make the same technology decisions as males. However, when they look at whether a male or a female heads the household, gender does significantly impact the adoption decision, a result likely attributable to resource constraints faced by women in female-headed households (FHH) (Doss and Morris 2000). Tanellari, Kostandini, and Bonabana (2013) explore peanut technology adoption in

Uganda and find that using the individual farmer as the unit of observation yields a positive and significant coefficient on the male dummy variable. Heterogeneous access to extension, education, and land may affect this technology adoption choice.

The studies just reviewed examine gender-specific technology adoption choices but do not explore the role of preferences and intra-household bargaining behind these choices. The next section summarizes this literature.

3.3 Literature Review of Intra-household Bargaining Power

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.

The empirical evidence discussed in 3.2 and 3.3 provides a basis for the empirical analysis to follow. I include gender-specific risk preferences and covariates in the models to capture intra-household dynamics and investigate the validity of the unitary household model in Kenya. Before the empirical analysis, however, I provide a conceptual framework.

3.4 Methodology

3.4.1. Conceptual Framework: Utility function for high yielding and stress tolerant varieties

It is important to examine a conceptual model to understand how risk preference parameters influence HY and ST maize hybrid adoption in Kenya. The source of uncertainty in this model is the probability of a drought or GLS infestation occurring. For simplicity, I will call 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 is a better function. Refer to Section 2.4, Equation 1 for the PT utility function and its parameters.

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 are targeting 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 this sample, seed and input costs for HY seeds are greater than ST and NH seeds. In addition, ST costs are higher than NH, i.e., $C_{NH} < C_{ST} < C_{HY}$. 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 yield the most, followed by HY and NH ($Y_{ST,bad} > Y_{HY,bad} \geq Y_{NH,bad}$). All else equal, I 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 I 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. I 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, I examine possible outcomes in the good and bad states of the world associated with each choice.

First, 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:

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

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:

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

I assume $Y_{HY,good}$ is higher than $Y_{NH,good}$ by enough to make up for the cost of inputs $(|C_{NH} - C_{HY}| < |Y_{HY,good} - Y_{NH,good}|)$, 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:

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

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:

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

I 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 6 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:

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

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

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

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, I 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 B.

(6) $\left(\frac{\partial U}{\partial \sigma}\right)$ depends on the values of x and y as well as $p, q, \alpha,$ and λ. Thus, its sign is ambiguous and I will test it empirically. However, due to the risky nature of HY hybrids, I expect the sign to be positive indicating that more risk-loving individuals are more likely to adopt HY. I expect the sign for ST hybrid adoption to be less than zero.

(7) $\left(\frac{\partial U}{\partial \lambda}\right) < 0$ 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.

(8) $\left(\frac{\partial U}{\partial \alpha}\right)$ also depends on the values of x and y as well as $p, q, \alpha,$ and λ.

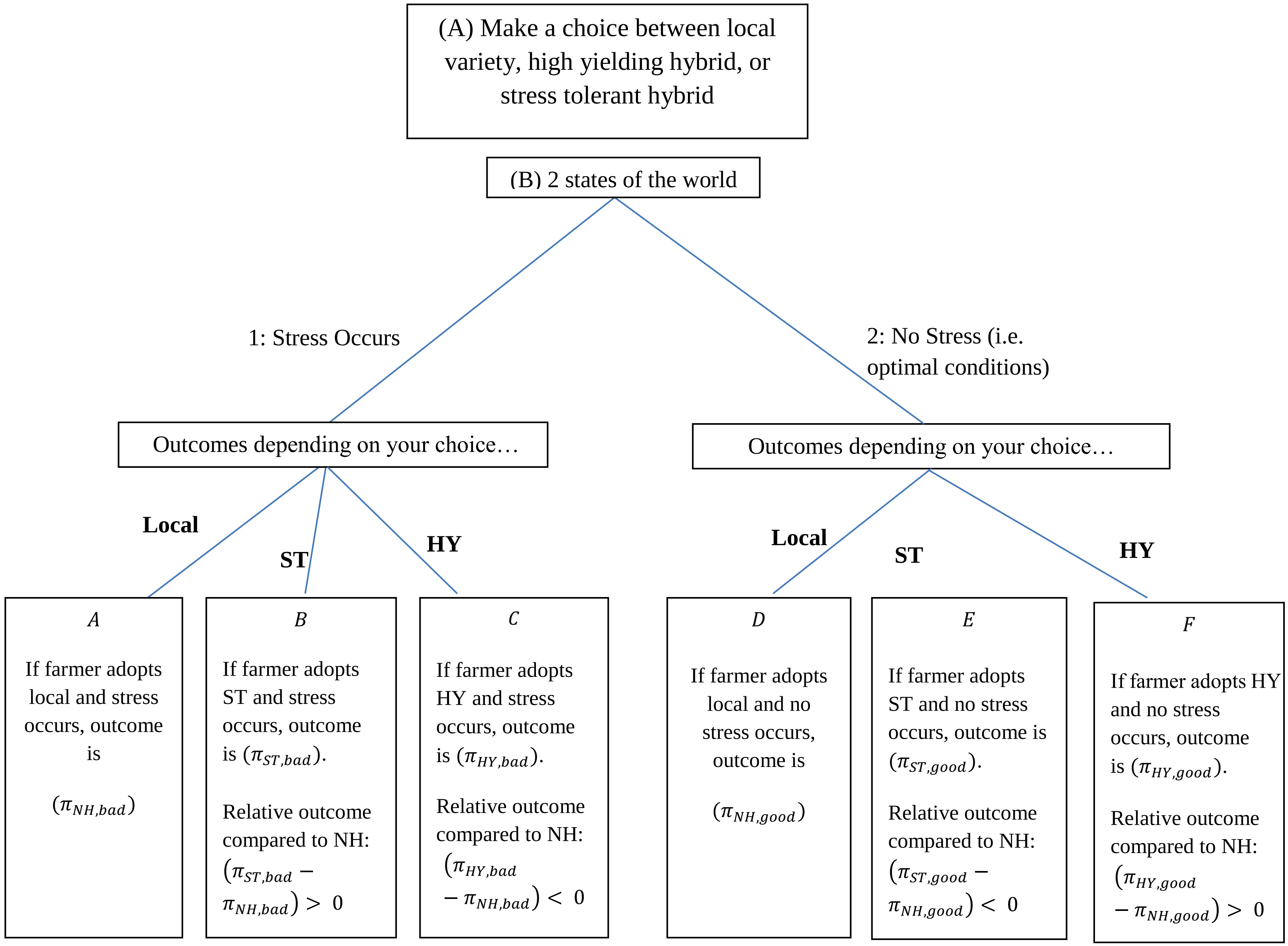

Figure 6: Maize Adoption Conceptual Map

3.4.2. Empirical Model Specification

Respondents are either adopting non-hybrid maize varieties, high yielding hybrids, or stress tolerant hybrids. I 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:

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

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, I 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, I include the risk preference parameters in the models. Table 7 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. I expect positive coefficients on age, education, and extension contact.

Table 7: 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

The household and subplot[4] level characteristics are the same for males and females within MHH households. 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. I 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

[4] 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.

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 8. MHH have adopted hybrid seeds on more than 75% of their subplots, whereas FHH have adopted hybrids on just over 50%. 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.

Table 8: 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

In the following analyses I consider various models. The first models look at male and female preferences separately and regress household maize adoption on these preferences. Next, I considered full MHH and FHH model. Finally, I run models specific to the eastern and western regions.

3.5 Results

3.5.1. Male and female risk preferences and household maize technology adoption

As I 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 I include female preferences the model, I start with just male risk preferences and covariates. Subsequently, I examine female information on household maize adoption to provide a baseline for her preferences towards maize varieties.

Table 9 contains regression results from these models on all 317 household subplots[5]. The non-hybrid varieties are the reference group in the multinomial logistic regressions. Columns 1 and 2 compare HY and ST adoption to non-hybrid adoption when I 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. I 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, I 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 I control for other covariates in column 7, however, the correlation between lambda and 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.

[5] 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.

Table 9: 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)
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.

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 I eliminate other covariates. Next, I 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 10 contains regression results for adoption as a function of both male and female risk parameters, with and without controlling for covariates. I 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 9, column 5. Neither male nor female risk preferences significantly affect ST adoption.

Columns 3 and 4 show that once I 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. Due to strong regional significance and divergent risk threats in the two regions, region-disaggregated regressions are examined in Table 11.

Columns 5 through 8 in Table 10 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 I 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. I expect this sign, since ST hybrids should be risk-reducing. Once I 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.

Appendix D contains regression results for MHH and FHH regressions with the removal of lambda and alpha from the regressions. I do this to measure significant changes or differences in the regressions without these parameters. In the MHH, none of the risk parameters are significant in the various specifications. When I add FHH lambda and alpha parameters to the model they are significant and suggest PT is more appropriate than EU in this context.

Due to the continual significance of the region explanatory variable, the next section explores differences in preferences between the East and West regions.

Table 10: 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)
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.

3.5.2. Regional differences in preferences over maize technologies

As discussed in the introduction of Chapter 3, 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[6]. 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, I regress MHH adoption on risk preferences, age, and education only. FHH have too few observations to run region-disaggregate regressions. Table 11 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 I 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

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

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.

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.

Table 11: 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.

CHAPTER 4

CONCLUSIONS

This chapter discusses results from the experimentally elicited risk preferences and their effects on household maize adoption in Kenya. I examine general conclusions, limitations, and further research.

The risk preference experiment results revealed no significant differences between male and female risk aversion, loss aversion, or nonlinear probability weighting parameters. Between females in MHH and females in FHH, however, the latter group is significantly more loss-averse than the former. I hypothesize that FHH face resource constraints and therefore react differently to potential losses than females in MHH who have more assets, non-farm income, and the security of another income generator in the household. The experiments also reveal that the sample is extremely risk-averse on average.

Experimental results enable researchers to observe real behavior towards risk and loss. There are limitations, however, to these results. A few limitations include enumeration bias, language barriers, and respondent understanding. Distinct enumeration teams performed the experiments in the East and the West, causing potential concern if respondents in the different regions received heterogeneous explanations. We trained both enumeration teams together, however, in an effort to minimize bias. There are also language differences among respondents. We taught enumerators how to perform the experiments in English but they had to translate them into Swahili or other local languages. Some words do not easily translate to other languages (e.g.

risk, probability, etc.) which possibly resulted in heterogeneous explanations to respondents. Finally, respondent understanding undoubtedly differed based on education levels. Probabilities and lotteries are not simple concepts so it is possible that respondents did not fully understand their choices. Future experiment implementers should consider these issues.

In Chapter 3, the maize adoption regression results 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 (Table 10, column 8) 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. I examine the MHH results further by regional disaggregation.

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 9 and Table 10. 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 11. Therefore, female preferences provide information on household maize technology adoption that male preferences fail to reveal.

The results do support the hypothesis that Prospect Theory is more appropriate than Expected Utility Theory 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.

In conclusion, much can be gleaned from this study. First, researchers should perform risk experiments with every effort to ensure homogeneous explanations and understanding among respondents. Secondly, male and female risk preferences are not significantly different in this study, but females in FHH are significantly more loss-averse than females in MHH. Third, MHH risk preferences are insignificant in these model specifications but caution should be taken in extrapolating this result to the general population. Fourth, results from the FHH regressions show significant effects of risk preferences on maize adoption. Finally, there are clear regional differences between the East and the West that should be explored in greater detail. Replicating these experiments in other parts of Kenya or East Africa could illuminate why MHH risk preferences are insignificant, reasons for regional differences, and the importance and meaning of the alpha parameter.

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APPENDIX A

A.1 Risk Preference Experiment Tables

Table 12: Prospect Theory Series 1

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

Table 13: Prospect Theory Series 2

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

Table 14: Prospect Theory Series 3

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

APPENDIX B

B.1 Partial Effects Derivations

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

APPENDIX C

C. 1 Experiment Module

Module A: Respondent characteristics

	Question	Code	Response
A.1	Enumerator name (last name first)	n/a	
A.2	Household ID number	n/a	
A.3	Village	n/a	
A.4	Name of respondent (last name first)	n/a	
A.5	Date	(DDMMYYYY)	

A.6	Does respondent want to participate? (Respondent consent)	1=Yes; 0=No (if no, they are allowed to leave)	

A.7	Sex	1=M; 2=F	
A.8	Position of respondent in household	1=male head, 2=wife of male head, 3=female head, 4=husband of female head	
A.9	Does Respondent have MPesa?	1=Yes; 0=No (if yes go to A.11; if no, put 0 in A.10 and A.11 and go to A.12)	
A.10	(If **YES** in A.10) What is your phone number?	n/a	

C.2 Household Survey

MODULE 1. HOUSEHOLD AND VILLAGE IDENTIFICATION

Household Identification	**Code**
1. Region	
2. County	
3. Sub-county	
4. Location	
5. Sub-location	
6. Village	
7.New village name (Write N/A if same as in 6 above)	
8. Name of household head:	
9. Sex of household head 1=Male	
10. Name of the respondent (include grandfather name):	
11. Sex of respondent 1=Male	
12. Name of respondent's spouse	

MODULE 2: HOUSEHOLD COMPOSITION AND CHARACTERISTICS AND HOUSING CONDITIONS

PART A: HOUSEHOLD COMPOSITION AND CHARACTERISTICS (Household members=Persons who live together and eat together from the same pot (share food), including wokers, students/pupils and spouse living and working in another location but excluding visitors)

ID CODE	Name of household member [Start with respondent]	Sex 1 = M 0 = F	Relationship to the household head **CODE 1**	Age (complete years)	Marital status? **CODE 2**	Education (years) **CODE 3**	Primary occupation **CODE 4**	How many months in the past 12 months was [NAME] present in the household?	Labor contribution to farms cultivated by household in 2012/2013 **CODE 5**
	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**
1									
2									
3									
4									
5									
6									
7									

CODE 1		**CODE 2**	**CODE 3**	**CODE 4**	**CODE5**
1.Household head 2.Spouse 3.Son/daughter 4.Son/daughter-in-law 5.Grandson/granddaughter 6.Mother/Father 7.Brother/sister 8. Nephew/niece	9.Cousin 10.Brother/sister-in-law 11.Mother/father-in-law 12.Domestic worker 13. Other relationship (specify) …………..	1.Married living with spouse 2.Married living without spouse 3.Single/never married 4.Divorced/separated 5.Widowed	0. None/Illiterate 100. Religious education 1. Adult education or 1 year of education * Give other education in years	1. Agriculture self employed 2. Agriculture wage labour 3. Non-agricultural self-employment 4. Non-agricultural wage labour 5. Salaried worker 6. Domestic work 7. Student 8. Unemployed 9. Retired 10. Too young (under 5 years) 11. Other, (specify)……………	1. Full time 2. Part time 3. Not a worker

MODULE 2: HOUSEHOLD COMPOSITION AND CHARACTERISTICS AND HOUSING CONDITIONS

PART B: HOUSING CONDITIONS

Variable code	**Questions**	**Code**	**Response**
B1	Does the household own the main house they stay in?	0=No 1=Yes	
B2	Major material of the exterior walls of the main house the respondent stays in: **ENUMERATOR TO OBSERVE/ASK**	1=Wood and Mud 2=Wood/timber 3=Reed and Bamboo 4=Mud and Stones 5=Mud/soil 6=Cement and Stones 7= Iron sheets 8=Bricks (baked) 9=Bricks (unbaked) 10=Blocks (cement+sand) 11=Other (specify)……….	
B3	Major material of the floor of the main house the respondent stays in: **ENUMERATOR TO OBSERVE/ASK**	1=Earth/Mud 2=Wood 3=Cement 4=Ceramics/Tiles 5=Other (specify)……………	
B4	Major roofing material of the main house the respondent stays in: **ENUMERATOR TO OBSERVE**	1=Corrugated Iron Sheet 2=Thatch and Grass 3= Reed and Bamboo 4= Clay 5= Tiles 7= Other (specify)………	
B5	Total number of rooms in the main house the respondent stays in		
B6	Does this <u>main</u> house has electricity?	0=No 1=Yes	
B7	Does this household has piped water?	0=No 1=Yes	
B8	Total number of buildings including kitchens, but not including toilets		
B9	Type of toilet facility this household uses	1=Pit latrine (Private) 2=Pit latrine (Shared) 3=Flush toilet (Private) 4=Flush toilet (Shared) 5=Field/Forest 6=Other (specify)……………	

MODULE 3: CROP PRODUCTION FOR ALL CROPS GROWN BY THE HOUSEHOLD DURING THE 2012/13 PRODUCTION YEAR

PART A: Plot Information: Agricultural practices, crops and varieties cultivated and cropping area (Definitions: A plot is a piece of land physically separated from others; a sub-plot is a sub-unit of a plot; Include rented/borrowed in/out plots, plots occupied by homestead, grazing and fallow land) **Note for Season column:** ***Long rains (March/April 2013 rains) and Short rains (Oct/Nov 2012 rains)***

A0: What is the total household land holding? (Acres) ……………………………….

Serial No	Season **1. Long rains** **2.Short rains**	Plot ID (start with one next to residence)	Sub plot ID	Sub-plot area **acres**	Sub-plot distance to residence (walking minutes)	Sub-plot tenure [A] **CODE 1**	Who in the hhld owns this sub-plot? **CODE 2**	Who in the hhld makes decisions on crops to be planted, input use, and timing of cropping activities on this [Sub-PLOT]?**CODE 2**	Inter-cropping on this plot? 0=No 1=Yes	Main crops grown on [Sub-PLOT] (if intercrop list up to 3 with primary crop first) **If not applicable put NA** **ANNEX 1 CODE**			Varieties grown on [Sub-PLOT]? **(In same order as in A12a-A12c)** **ANNEX 2 CODE**			Fruit trees in the plot **ANNEX CODE 1**	How fertile is the soil of this [sub-plot]? **CODE 3**	What is the soil slope of this [sub-plot]? **CODE 4**
A1	**A2**	**A3**	**A4**	**A6**	**A7**	**A8**	**A9**	**A10**	**A11**	**A12 a**	**A12 b**	**A12 c**	**A1 6**	**A1 7**	**A13 c**	**A14**	**A16**	**A17**

A/ for rented out/shared out and borrowed out plots, please fill up to COLUMN A8 ; for homestead, fallow land and grazing land, fill up to A9

CODE 1	**CODE 2**	**Code 3**	**Code 4**
1. Owned 2. Rented/shared in 3. Rented/shared out 4. Borrowed in 5. Borrowed out 6. Other, specify…..	1. Self 2. Mainly spouse 3. Self and spouse jointly 4. Other household member 5. Other (specify)………………..	1. Good 2. Medium 6. Poor	1. Gently slope (flat) 2. Medium slope 7. Steep slope

MODULE 3: CROP PRODUCTION FOR ALL CROPS GROWN BY THE HOUSEHOLD DURING THE 2012/13 PRODUCTION YEAR (CONTINUED)

PART A: Plot information: Decisions on production, production costs, production stress, and crops harvested

Serial No	Season **1. Long rains** **2.Short rains**	Plot ID [**same order as in above**]	Subplot ID [**same order as in above**]	Who decides when to harvest the crop in [sub-plot]? (separate by comma for intercrops) CODE1	total cost of hired oxen (Ksh)	total cost of hired tractor (Ksh)	total cost of hired labor (Ksh)	Stresses: Stress incidence on [sub-PLOT]? 1.Yes 0.NO	Stresses: Two major stresses CODE 2		Stresses: Level of stress; CODE 3	Total harvested per sub-plot **[same crop order as inA11a-A11c)**: Fresh or green (kg) (dry equivalent, except for vegetables)			Total harvested per sub-plot: Dry (kg)		
A1	**A2**	**A3**	**A4**	**A53**	**A54**	**A55**	**A56**	**A57a**	**A57b**	**A57c**	**A57d**	**A58a**	**A58b**	**A58c**	**A59a**	**A59b**	**A59c**

CODE 1	CODE 2		CODE 3
1.Self 2.Spouse 3.Self and spouse jointly 4.Other household member 5.Self and other household member(s) 6.Spouse and other household member(s)	1.insects/pests 2.Disease 3.WaterLogging 4.Drought 5.Frost	6.Hailstorm 7.Animal trampling 8. Other, specify…………….	1.Moderate 2.Severe 3.catastrophic

MODULE 4: UTILIZATION OF CROPS HARVESTED IN THE 2012/2013 SHORT RAINS SEASON AND PLANNED UTILIZATION FOR THE 2013 LONG RAINS SEASON HARVEST

Crop **(aggregate seasons production per crop; start with short rains season)** **ANNEX 1 CODE**	Season **1. Long rains** **2.Short rains**	Stock before season harvest (kg)	Season production (kg)	Total available stock after season harvest (kg)	From the total available stock after season harvest….						Average village price during the season (Ksh/kg)	Ending stock (Stock before next season's harvest) (kg)	Amount (to be) bought (kg)	Food aid/gifts (to be) received (kg)
					Quantity sold/planned sales after season harvest (kg)	In-kind payments/planned payments (labour, land & others) after season harvest(kg)	Quantity used/planned use as seed after season harvest (kg)	Gift, tithe, donations given/planned give out after season harvest (kg)	Quantity consumed/ planned consumption after season harvest (kg)	Post-harvest losses				
A1	**A2**	**A3**	**A4**	**A5 =A3+A4**	**A6**	**A7**	**A8**	**A9**	**A10**	**A9**		**A10=A5-A6-A7-A8-A9-A10**	**A11**	**A13**

ANNEX 1: CROP CODES

SIMLESA Crops	**Other cereals**	**Other Pulses (legumes)**	**Oil Crops**	**Root crops/tubers/ Vegetables/fruits**		**Perennial crops/fruit trees**	**Fodder legumes**
1. Maize	9. Wheat	24. Chickpea	28. Sunflower	33. Cassava	42. Kales (*sukuma wiki*)	50. Coffee	62. Lablab
2. Common bean	10. Barley	25. Field pea	29.Sesame	34. Irish potato	43. Carrot	51. Banana	63. Clover
3. Soybean	11. Sorghum	26.	30.Linseed	35. Sweet potato	44. Watermelon	52. Orange	64. Vetch
4. Pigeon pea	12. Finger Millet	27.	31.Rapeseed	36. Onion	45. Cucumber	53.Mango	65. Alfalfa
5. Groundnut	13. Pearl millet		32.Lupin	37. Garlic	46. Capsicum	54. Sugar cane	66. Sesbania
6. Cowpea	14. Rice			38. Pepper	47. Local vegetables	55. Eucalyptus	
7.	15.			39. Tomato	48.	56. Avocado	67. Grazing land
8.	16.			40. Ginger	49.	57. Macadamia	68. Fallow
	17.			41. Cabbage		58. Castor apple	
	18.					59. Napier grass	100. Other crops (specify).........
	19.					60.	
	20.					61.	
	22.						
	23.						

ANNEX 2: CROP VARIETY CODES

Maize		**Common bean**	**Soybean**	**Pigeonpea**	**Groundnut**	**Cowpea**	**Other crops**
1. DK8031	13. WS 505	31. Wairimu	51.Gazelle	61. 00040-**LD *(Agric.mrefu)***	76. Homa Bay local	86. M-66	96. Improved
2. H513	14. PH B3253	32. Mwitemania	52.SB 11	62. 00777-**LD**	77. Nyauyoma red	87.K-80	97. Local
3. H512	15. DH O4	33. Roscoco	53.SB 29	63. 00554 -**MD**	78. Virginia	88. K7-1	
4. H511	16. DUMA 41	34. Nyayo	54………..	64. 00557-**MD**	79. Mani Pinta	89. IT82C	
5. H624	17. DUMA 43	35. Gacera	55………..	65. 00068-**MD *(Syombonge)***	80. White Valencia/Uganda stripes/teso local	90. Kunde 1	
6. H629	18. PIONEER 3250	36. Katheri	56………..	66. 60/8-**MD** *(Mbaazi I)*	81.Nyahela/Uganda red	91. Black eye	
7. H625	19. Makueni	37. Gacugu		67. 87091-**SD *(Keritu/mwezi moja)***	82.Small red/kabonge	92 ……………	
8. H614	20. Katumani	38. KK8		68. Local-**LD**	83………………….	93. ……………	
9. H627	21……………	39Mama Safi		69. 00932-**LD**	84..…………………		
10.H6210	22……………	40………..		70. 00835-**MD**	85………………….		
11. H6213	23……………	41……………		71. ……………..			
12.WS 502	24……………	42……………		72…….................			
		43……………		73. …….................			
		44……………					

C.3 Individual Survey

MODULE 4: CAPITAL, CONTINUED

PART B: Household Savings, *Enumerator,* ***put 1 source of savings per row.***

B1. Did household save money in the last two years? ....0. No 1. Yes **if yes, answer questions below; if no go to module 4 part C**

Savings ID	Where did you save money? CODE 2	Who made the decision to save money? CODE 1	Who made the saving? CODE 1	What was the total amount you saved during 2012/13? (Ksh)	Who makes decisions about what to do with savings? CODE 1
	B1	**B2**	**B3**	**B4**	**B5**
1					
2					
3					
4					
5					

CODE 1		**CODE 2**
1=Self 2=Spouse 3=Self and spouse jointly 4=Other household member 5=Self and other household member(s) 6=Spouse and other household member(s) 7=Someone outside the household	8=Self and other outside people 9=Spouse and other outside people 10=Self, spouse and other outside people 11= Other (specify)…………	1=Saving at home (personal) 2=Commercial or other banks 3=Rural micro-finance 4=Saving by lending to money lender 5=SACCOs 6=Mobile phone accounts (e.g *Mpesa; M-shwari*) 7= ROSCAS/Merry-go-round 8=Other (specify)…………

MODULE 4: HOUSEHOLD ASSETS, ACCESS TO CAPITAL AND INFORMATION
PART D: Production equipment and major household furniture

Asset Category	*Asset type*	Does the household own [...]: 1= Yes 0=No
	D1	**D2**
Farm implements	Sickle	
	Hoe/Jembe	
	Spade or shovel	
	Axe	
	Knapsack sprayer	
	Slasher	
	Panga knife	
	Wheelbarrow	
	Ox-plough	
	Water pump	
	Tractor	
Transport	Push cart	
	Bicycle	
	Motorbike	
	Donkey/oxen cart	
	Car	
Household Furniture	Improved charcoal/wood stove	
	Kerosene stove	
	Water carrier	
	Fridge,	
	Table, sofas, chairs, and beds	
Communication	Radio	
	Mobile phone	
	Cassette or CD player	
	TV	
Jewelry	Gold,	
	Silver,	
	Wristwatch	
Trees	Fruit trees	
	Other trees (e.g. eucalyptus)	
Land	Land owned (acres)	
House	House	

MODULE 6: HOUSEHOLD INCOME ACTIVITIES DURING 2012/13 CROPPING YEAR

PART A: What was your household's income from the following sources during the past 12 months? (***Include the income of all household members listed***)

Income source	Who earned income? **Use NA if none** Code 1	Income for the past 12 months		
		Cash (Ksh)	In-kind (cash equivalent in Ksh)	Total
Income from salaried employment				
Income from machinery services for other farms (plowing etc.)				
Income from casual labor (on-farm)				
Income from casual labor (off-farm)				
Income from own **non-agricultural** businesses (shops, saloons etc)				
Income from non-farm agribusiness (grain milling, grain trading etc)				
Selling charcoal, brick making, selling firewood etc				
Pensions				
Remittances from family members/friends who do not live in the household				
Revenues from leasing/renting out land				
Other sources (specify)…………				

CODE 1
1=Self 2=Spouse 3=Self and spouse jointly 4=Other household member 5=Self and other household ember(s) 6=Spouse and other household member(s)

APPENDIX D

Table 15: Female-Headed Households with Different Risk Parameters

	(1) HY (full)	(2) ST (full)	(3) HY (no alpha)	(4) ST (no alpha)	(5) HY (no alpha or lambda)	(6) ST (no alpha or lambda)
Female sigma	0.490**	-0.960***	0.463**	-0.785**	0.503***	-0.833***
	(0.25)	(0.37)	(0.22)	(0.32)	(0.19)	(0.29)
Female lambda	-0.026*	-0.003	-0.018	0.003		
	(0.02)	(0.01)	(0.01)	(0.01)		
Female alpha	-0.026	0.349**				
	(0.19)	(0.17)				
Female education (years)	0.060***	0.045*	0.048***	0.023*	0.048***	0.029**
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)
Female age	0.025***	-0.004	0.017***	-0.001	0.018***	-0.000
	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Female extension contact	0.005	-0.005	0.001	-0.002	0.002	-0.004
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Household size	0.059**	0.002	0.036**	0.010	0.036**	0.012
	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
Wealth Index	0.080**	0.055	0.055*	0.027	0.060**	0.032
	(0.04)	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)
Non-farm Income	0.109***	0.021	0.076***	0.024	0.077***	0.023
(10,000KSH)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Household saves (Yes=1)	0.235**	0.094	0.210**	0.138	0.267**	0.125
	(0.10)	(0.09)	(0.09)	(0.10)	(0.13)	(0.11)
Land area - owned (ha)	-0.475**	0.319**	-0.278*	0.206*	-0.276**	0.173**
	(0.20)	(0.15)	(0.15)	(0.11)	(0.12)	(0.08)
Proportion of harvest	-0.345	0.178	-0.264	0.126	-0.239	0.083
consumed at home	(0.43)	(0.27)	(0.21)	(0.12)	(0.18)	(0.11)
Slope (Yes=1)	0.779***	-0.574***	0.589***	-0.362***	0.575***	-0.328***
	(0.28)	(0.21)	(0.13)	(0.09)	(0.14)	(0.12)
Region (West=1)	0.204**	-0.325***	0.167*	-0.351***	0.189**	-0.311***
	(0.10)	(0.08)	(0.09)	(0.10)	(0.09)	(0.08)
Observations	108	108	108	108	108	108
Log Likelihood	-38.70	-38.70	-41.96	-41.96	-43.08	-43.08
Pseudo R2	0.66	0.66	0.63	0.63	0.62	0.62

Average marginal effects. Standard errors clustered at the household level in parenthesis. Significant at *10%, **5%, ***1%.

Table 16: Male-Headed Households with Different Risk Parameters

	(1) HY (full)	(2) ST (full)	(3) HY (no alpha)	(4) ST (no alpha)	(5) HY (no alpha or lambda)	(6) ST (no alpha or lambda)
Male sigma	0.013	0.176	-0.027	0.165	-0.029	0.144
	(0.15)	(0.14)	(0.16)	(0.13)	(0.15)	(0.13)
Male lambda	0.001	0.012	0.001	0.012		
	(0.01)	(0.01)	(0.01)	(0.01)		
Male alpha	-0.098	-0.036				
	(0.10)	(0.10)				
Female sigma	0.013	-0.009	-0.044	-0.052	0.016	-0.022
	(0.14)	(0.12)	(0.14)	(0.12)	(0.13)	(0.12)
Female lambda	-0.010	-0.006	-0.014	-0.009		
	(0.01)	(0.01)	(0.01)	(0.01)		
Female alpha	-0.122	-0.073				
	(0.12)	(0.11)				
Male age[a]	-0.002	0.000	-0.002	0.001	-0.002	0.000
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Male education (years)	0.035**	-0.003	0.037**	-0.001	0.034**	-0.000
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Male extension contact	-0.002	-0.003	-0.003	-0.003	-0.003	-0.004
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Female education (years)	-0.026	0.027*	-0.028*	0.026*	-0.025	0.024*
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Female extension contact	0.001	0.002	0.002	0.003	0.001	0.002
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Household size	-0.013	0.018	-0.009	0.019	-0.011	0.011
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Wealth Index	0.049	-0.100***	0.038	-0.106***	0.045	-0.089***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Non-farm Income (10,000KSH)	-0.006	0.008	-0.006	0.007	-0.006	0.005
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)
Household saves (Yes=1)	0.109	-0.124	0.084	-0.120	0.106	-0.102
	(0.09)	(0.08)	(0.10)	(0.08)	(0.10)	(0.08)
Land area - owned (ha)	0.065	-0.068	0.061	-0.067	0.059	-0.057
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Proportion of harvest consumed	-0.244**	0.127	-0.207	0.145	-0.231*	0.143
at home	(0.12)	(0.11)	(0.13)	(0.11)	(0.13)	(0.11)
Slope (Flat=1)	-0.159**	0.175***	-0.153**	0.172**	-0.135*	0.173***
	(0.08)	(0.06)	(0.08)	(0.07)	(0.07)	(0.07)
Fertile soil (Yes=1)	0.177*	0.096	0.148	0.088	0.148	0.094
	(0.10)	(0.09)	(0.11)	(0.09)	(0.11)	(0.09)
Region (West=1)	0.330***	-0.502***	0.290***	-0.519***	0.322***	-0.466***
	(0.09)	(0.08)	(0.10)	(0.08)	(0.09)	(0.07)
Observations	317	317	317	317	317	317
Log Likelihood	-259.73	-259.73	-265.33	-265.33	-273.14	-273.14
Pseudo R2	0.24	0.24	0.22	0.22	0.20	0.20

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.