GENDER SPECIFIC RISK PREFERENCES, FEMALE EMPOWERMENT, AND HOUSEHOLDS' AGRICULTURAL INPUT CHOICES

by

GANNA SHEREMENKO

(Under the Direction of Nicholas Magnan)

ABSTRACT

The adoption of agricultural technologies, such as improved maize varieties and fertilizers, plays an important role in improving agricultural production in Africa. Hybrid seeds and fertilizers are risky inputs, and their adoption by farmers is often very low. Farmers' risk attitudes are often considered to be the reason behind low use of these technologies. Typical empirical research ignores the family dynamics that affects household's agricultural choices. This dissertation project consists of two essays, where we use a collective household model to estimate the effects of experimentally derived risk preferences of both spouses in farming households interacted with relative women's bargaining power on agricultural technology adoption by farmers in Tanzania and Kenya. We use a unique dataset that combines risk preference experiment with household and individual survey data to examine how spousal attitudes towards risk affect improved maize adoption in Tanzania and fertilizer use in Kenya. The first essay examines how spousal attitudes towards risk affect improved maize adoption in Tanzania. Our results show that male loss aversion decreases the use of hybrid seeds. Households where males underweigh small probabilities are more likely to purchase improved seeds. Female risk preferences do not seem to have an effect on household seed choice when we consider all households. However, when we focus on households with empowered women, we find that female risk aversion and overweighing of small probabilities decrease households' use of hybrids. In the second essay, we investigate the effects of individual risk preferences on households' fertilizer use in Kenya. We find that male and female risk/loss aversion reduces the use of fertilizers in male-headed households (MHH). Loss aversion of empowered females reduces the use of fertilizer in households that invest in fertilizers. In female-headed households (FHH), we find that more loss averse females are less likely to purchase fertilizers and that more risk and loss averse females in fertilizer adopting FHH use less fertilizers.

INDEX WORDS: Agricultural Input Choice, Collective household model, Female Empowerment, Loss aversion, New technology adoption, Non-linear probability weighting, Risk aversion.

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GANNA SHEREMENKO

BS, VH Kyiv National Economic University, Ukraine, 2007

MS, The University of Georgia, 2011

MS, The University of Georgia, 2015

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GANNA SHEREMENKO

Major Professor:	Nicholas Magnan
Committee:	Gregory J. Colson
	Genti Kostandini

Electronic Version Approved:

Suzanne Barbour
Dean of the Graduate School
The University of Georgia
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CHAPTER 1

INTRODUCTION AND BACKGROUND

1.1 Introduction

The use of agricultural inputs by farmers in the developing world plays an important role in improving agricultural production leading to improved nutrition, human capital formation, and, ultimately, a reduction in persistent poverty. Improved maize varieties and fertilizers can be considered examples of such inputs. Applications of fertilizer paired with the use of improved seed varieties and other farming practices have proven to significantly increase agricultural yields in Asia (Byerlee et al. 2007; Smale, Byerlee, and Jayne 2013). Nevertheless, their use by African farmers remains low. Despite having 15 percent of the world's population (Danzhen 2014), African countries account for less than 1% of global consumption of fertilizer (Byerlee et al. 2007). Only 44% of total maize area is planted using improved seeds, including both improved OPVs and hybrids, in Eastern and Southern Africa, excluding South Africa (Smale, Byerlee, and Jayne 2013).

Among the factors thought to impede agricultural technology adoption in African countries are low levels of education, liquidity and credit constraints, limited information, lack of access to formal insurance, and risk aversion (Feder, Just, and Zilberman 1985; Sunding and Zilberman 2001; Croppenstedt, Demeke, and Meschi 2003; Byerlee et al. 2007; Duflo, Kremer, and Robinson 2008, 2011; Ricker-Gilbert, Jayne, and Chirwa 2011;

Suri 2011; Dar et al. 2013; McIntosh, Sarris, and Papadopoulos 2013; Karlan et al. 2014). Uncertain returns on technological investments make these choices very risky for farmers, particularly in the absence of a safety net in the form of crop insurance or savings. Risk generally manifests itself in two ways. First, new technologies, such as improved seeds, present new and unknown distributions of returns for farmers, and therefore even risk-reducing technologies may be received as risky (Liu 2013). Second, adoption of agricultural technologies is often associated with high costs compared with traditional low-input practices. In predominantly rain fed agricultural systems, the possibility of negative environmental shocks makes the adoption of any technology that imposes costs before rainfall outcomes are revealed, such as seed and fertilizer, risky.

A number of studies have examined the role of risk and risk preferences in agricultural technology adoption (Binswanger 1980; Feder, Just, and Zilberman 1985; Saha, Shumway, and Talpaz 1994; Marra, Pannell, and Ghadim 2003; Lybbert 2006; Dercon and Christiaensen 2011; Liu 2013; Liu and Huang 2013; McIntosh, Sarris, and Papadopoulos 2013) and broadly find that risk aversion negatively affects the decision to use agricultural technologies. However, these studies assume that a unitary (male) decision-maker decides whether or not to invest in agricultural inputs based on his personal set of preferences and constraints, whereas farming households in developing countries are predominately family enterprises involving both men and women. In this study, we analyze how risk preferences of spouses affect a household's maize seed choices and fertilizer use.

1.2 Gender and Risk Preferences

In the risk preference literature most studies find that men are less risk averse than women (Holt and Laury 2002; Wik et al. 2004; Eckel and Grossman 2008; Croson and Gneezy 2009; Charness and Gneezy 2012; Bauer and Chytilová 2013). One possibility for this difference is that men are generally more confident and competitive than women, which makes them more likely to exhibit risk loving behavior (Croson and Gneezy 2009). Another is that women traditionally perform a role of a caregiver in a household by providing and preparing food and taking care of children. As such, they tend to be more protective of the family's future well-being, making them less likely to engage in risky activities (Wik et al. 2004). Despite these differences, a single set of risk preferences—overwhelmingly from the male household head—is typically used to explain household level decisions.

1.3 Intrahousehold Bargaining Power

The influence of individuals' preferences on household outcomes depends on how much bargaining power they have within a household. In the context of this study, the degree of women's bargaining power in a household determines to what extent her risk preferences will affect the household's choices. Under a standard Neoclassical model (also referred to in the literature as a unitary household model), consumption choices of a household are typically modeled as a constrained utility maximization problem of a single decision maker subject to a pooled resource constraint (Becker 1973). Thus, resource allocation within a household is always Pareto efficient. Collective models allow preferences to vary among members of the same household by incorporating distinct utility functions and constraint sets for individuals within a household (Manser and Brown 1980; McElroy and Horney 1981; Schultz 1990).

Several studies have used collective household models to analyze the allocation of resources in African farming households (Udry 1996; Andrews, Golan, and Lay 2014). These studies found that female controlled plots were much less intensively farmed than similar plots controlled by men in the same household, casting doubt on the use of the unitary household model.

Recognizing the role of women in agriculture, some studies have taken a more collective approach to analyze agricultural technology choices. Zepeda and Castillo (1997) and Fisher, Warner, and Masters (2000) investigated how intrahousehold dynamics affect technology adoption. These studies incorporate proxies for women's bargaining power such as number of children, wage, group membership, and self-reported decision making power as independent variables into somewhat standard "determinants of adoption" models. They do not consider specific preferences of men and women in the household, and how these preferences interact with bargaining power, to shape adoption decisions.

1.4 Risk Preference Experiments

Starting with Binswanger (1980), a host of papers use field experiments to elicit individuals' risk preferences and test the effects of these preferences on agricultural technology adoption (Ross, Santos, and Capon 2010; Liu 2013; Liu and Huang 2013). Individual risk preferences are typically modeled under the Expected Utility (EU) framework, where the concavity of the utility function alone characterizes risk preferences, and elicited using a Holt-Laury type experiment (Holt and Laury 2002). With risk aversion as a single indicator of risk preferences, EU theory is very restrictive and often times unrealistic for modeling individuals' behavior under uncertainly. In contrast, Prospect Theory (PT), developed by Kahneman and Tversky (1979), provides a richer and more flexible framework to describe individual attitudes toward risk. Under PT, the utility function includes risk aversion, loss aversion, and non-linear probability weighting. Loss aversion measures sensitivity to loss, allowing for the possibility that disappointment from a loss is greater than the satisfaction from an equal size gain. Non-linear probability weighting allows for the possibility that individuals overweigh small probabilities and underweigh large probabilities of uncertain outcomes.

Using agricultural inputs, such as new improved seeds or fertilizers, can lead to a loss. This could be negative returns or positive returns that are lower than some reference point, e.g., the expected returns under the status quo. Non-linear probability weighting could affect technology adoption in two ways. Farmers may overweigh the probability of an unlikely negative shock, such as drought or excessive rainfall, or, alternatively, overweigh the probability of a new technology not working. We therefore believe that risk aversion alone may not sufficiently explain how risk preferences affect technology adoption.

Under PT (Kahneman and Tversky 1979; Prelec 1998) the utility function can be defined in the following form:

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

$$\text{where } v(z) = \begin{cases} z^{1-\sigma} & for\ z > 0 \\ -\lambda(-z^{1-\sigma}) & for\ z < 0 \end{cases},\ z = x, y,$$

$$\text{and } \pi(p) = \exp\left[-(-\ln p)^{\alpha}\right].$$

In the equation (1) above, x and y represent possible outcomes and p and q are their respective probabilities. The parameter σ measures risk aversion, with $\sigma > 0$ for a risk averse individual, $\sigma = 0$ for a risk neutral individual, and $\sigma < 0$ for a risk loving individual. The parameter λ is a measure of loss aversion, with $\lambda > 0$ for a loss averse individual. $\pi(p)$ is the probability weighting function, derived by Prelec (1998), where the parameter α represents non-linear probability weighting. If $\alpha < 1$, an individual overweighs low probabilities and underweighs high probabilities of uncertain events and vice versa when $\alpha > 1$. The PT model collapses to EU when $\alpha = 1$ and $\lambda = 1$.

Recent work by Tanaka, Camerer, and Nguyen (TCN) (2010) has opened the door for experimental generation of PT risk preferences. TCN (2010) first proposed an experiment comprising of 35 pair-wise lottery choices, with seven choices containing both gains and losses, to elicit risk aversion, loss aversion, and non-linear probability weighting parameters. Because EU is nested in PT, the TCN approach is flexible, and allows users to test whether the PT model better fits the data than the EU model[1].

Liu (2013) and Liu and Huang (2013) applied the TCN design to elicit risk preference parameters of *Bt* cotton farmers in China and showed that employing PT did help explain farmers' technology adoption and pesticide use decisions. Specifically, Liu (2013) found that more risk and loss averse farmers adopt *Bt* cotton later, and farmers who overweigh small probabilities (presumably of pest infestation) adopt it sooner. These findings indicate that risk aversion can inhibit adoption of risk reducing technologies because the risk of new technology not working as well as the status quo technology is a

[1] In Chapter 2 we perform likelihood ratio tests to check whether PT model can be reduced to EU model.

more salient risk than the environmental one. Liu and Huang (2013) found that risk aversion and loss aversion affect pesticide use differently. More risk averse farmers use more pesticides, whereas more loss averse farmers use less pesticides. According to the authors, these results show that farmers weigh poor health over the loss of money, resulting in a negative effect of loss aversion on pesticide use.

In this study, we employ the TCN experiment to estimate risk aversion, loss aversion, and non-linear probability weighting among spouses in Tanzanian and Kenyan households. We combine these parameters with data on bargaining power to examine how individual risk preferences affect maize seed adoption and fertilizer use. To our knowledge this is the first study of how risk preferences of men and women in the same household (husbands and wives, generally) affect household decisions.

1.5 Dissertation Organization

The rest of the dissertation is organized as follows. In Chapter 2, we describe data collection process and discuss types of data used in the analysis and risk experiment used to capture gender-specific preferences. In Chapter 3, we investigate how gender specific risk preferences affect improved maize seed adoption by farming households in Tanzania. We propose a collective model that shows how seed choice varies depending on risk preferences of spouses and intrahousehold dynamics, estimate this model as a two-step process using a sequential logit modeling approach, and discuss the results. In Chapter 4, we describe how individual risk preferences affect fertilizer use in farming households in Kenya. We present a collective model that shows how fertilizer application varies depending on gender specific risk preferences and female empowerment, estimate this model using a double hurdle model, and discuss the findings. Chapter 5 concludes.

CHAPTER 2

DATA

2.1 Data Collection

Data comes from three different sources: a household survey, an individual survey, and an experiment. Data collection was a part of a broader research effort, the Adoption Pathways Project (AP). AP is a result of 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. The purpose of the project is "demand-driven research, delivery and adoption of innovations to improve food security" (CIMMYT 2012). This study uses data from two countries: Tanzania and Kenya.

The respondents of the two surveys and, ultimately, the experiment were selected based on a three-stage sampling procedure from five districts (Karatu and Mbulu in the Northern part of the country, and Mvomero, Kilosa, and Gairo in the Eastern part) in Tanzania and five districts (Embu, Meru, and Tharaka Nithi in the East, and Bungoma and Siaya in the West) in Kenya. In each country, administrative divisions were randomly selected in each district, and then villages were randomly selected in proportion to the each division's size. Finally, households were randomly selected within each village. Two individuals, a husband and a wife, were identified within each household to participate in the surveys and the experiment. In all sample households with both a husband and a wife present, female spouses self-identified as "wife of a male head," suggesting that while wives have some decision making power, husbands are the primary decision makers. Single decision maker households (FHH) all had a female head that was either single, divorced, widowed, or separated.

2.2 Survey Sample Description

Household surveys were conducted between September and November 2013 with the head of the household and focused on questions related to on-farm production, input use, soil fertility, yields, technology choices at a subplot level[2], along with questions regarding stress occurrence/severity and household demographics at a household level. In Tanzania, out of 532 households (both male and female-headed) that participated at this stage, 4 households did not provide any crop information and were removed from the sample. The remaining 528 households provided agricultural information for 2075 subplots. In Kenya, 540 households provided agricultural information on 4299 subplots.

Individual surveys were conducted immediately following the household survey. The male household head and his wife were separately interviewed to prevent spousal interference and encourage honesty. For female-headed households, only the household head completed the individual survey. The individual survey questions covered individual savings, individual decision making, asset ownership, group membership, and community leadership. A total of 996 and 819 individuals were interviewed at this stage in Tanzania and Kenya, respectively.

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[2] A plot refers to piece of land that is physically separated from another. A subplot, a unit of measurement used in the analysis, is a subunit of a plot. A plot usually contains several subplots.

Individual level data on decision making within the household were used to generate a female empowerment indicator. In improved maize adoption essay that uses Tanzanian data, the female empowerment indicator was obtained using indicators for being empowered in decision making across three agricultural dimensions: food crop farming, cash crop farming, and seed purchase decisions.[3] In our sample, 24.1% of households sell at least half of their maize harvest, whereas about 67.7% consume at least half. Since sampled households grow maize both for sale and consumption, we incorporate cash crop and food crop farming decisions into the calculation of the empowerment indicator.

Table 1. The Composition of Female Empowerment Indicator

Some Input in Agricultural Production Area	Mean	Std. Dev.
Food crop farming	0.85	(0.36)
Cash crop farming	0.57	(0.50)
Seed purchase	0.63	(0.49)

Table 1 above provides the contribution of each production decisions' indicator to the resulting women's empowerment indicator. In Tanzanian farming households 57%, 63%, and 85% of women have at least some input in cash crop farming, seed purchase, and food crop farming decisions, respectively, suggesting that women are least empowered in cash crop farming decisions. The resulting female empowerment indicator is a dichotomous variable, where 1 indicates that a woman has some input in all three

[3] The indicators come from the "Input in Productive Decisions" section of the Women Empowerment in Agriculture Index (WEAI) survey module (Alkire et al. 2013). The WEAI uses individual level data obtained from both female and male respondents within a household. The index is designed to measure the degree of women's empowerment in the following five domains: agricultural production, control over assets and use of credit, control over use of income, leadership in the community, and use of time.

maize production decisions in a household. In our sample, 44% of women were empowered by this criterion.

In fertilizer adoption essay that uses Kenyan data, a female empowerment over fertilizer decisions indicator was defined based on whether a woman had input in most decisions regarding fertilizer purchase. In our sample, 38% of women in MHH were empowered by this criterion (see Table 11). Females in FHH were assumed to be 100% empowered in fertilizer use decisions.

2.3 Experimental Data Description

Following the surveys, we conducted TCN risk preference experiments in December 2013 and January 2014. Only households from which both a husband and a wife, or a female head of a female-headed household, completed the individual survey were allowed to participate in the experiments.

In Tanzania, only 305 individuals (274 spouses and 31 female heads) from 168 households, who own a total of 658 subplots, returned to participate in the experiments. Individuals from 5 returning households, including 2 female-headed households, did not plant any maize on any of their subplots, further reducing the sample to 297 individuals. Also, 233 subplots where no maize was planted were removed from the sample. Remaining 29 female-headed households and 43 subplots were not included in the estimation due to sample size limitations. The final dataset in Tanzania consists of 134 male-headed households or 268 individuals, husbands and wives, who operate on 382 subplots. In Kenya, 321 individuals from 178 households operating on 972 subplots, including 35 FHH with 154 subplots, participated in the experiments.

Attrition was common in the data. One possibility for high attrition lies in the survey design. The surveys that preceded the experiments were rather lengthy (took 4-5 hours to complete), potentially deterring respondents to return and complete the experiments. Another reason lies in the need to have both spouses participating in the experiments. For a significant part of our data, only one member of the household completed the experiment.

Table 2. Mean Comparison for Attrited and Returning Individuals in Tanzania

Variable	Returning Individuals	Attrited Individuals
Age, years	45.00	45.87
		(0.88)
Education, years	5.74	5.08
		(3.07)**
Household size	6.29	5.89
		(2.34)*
Total income, TSH	1,322,291.99	980,361.84
		(1.83)
Farm income, TSH	226,197.73	221,798.70
		(0.09)
Observations	297	699

Note: Absolute value of t-statistics in parenthesis; Significant at *10%. **5%, and *** 1%.
Exchange rate was 1,606 TSH to 1 USD during the study period (US Department of Treasury, 2016).

Table 3. Mean Comparison for Attrited and Returning Individuals in Kenya

Variable	Returning Individuals	Attrited Individuals
Age, years	50.09	48.30
		(1.72)
Education, years	7.28	7.41
		(0.50)
Household size	6.39	5.66
		(3.74)***
Total income, KSH	86,977.03	118,134.14
		(2.93)**
Farm income, KSH	29,403.10	38,308.84
		(1.72)
Observations	321	464

Note: Absolute value of t-statistics in parenthesis; Significant at *10%. **5%, and *** 1%.
Exchange rate was 86.6 KSH to 1 USD during the study period (US Department of Treasury, 2016).

We conducted pair-wise t-tests for mean differences in age, education, household size, income, and farm income between attrited and participating individuals to assess the possibility of attrition bias. In the Tanzanian sample, Table 2 above shows that the non-returning individuals are slightly more educated and live in somewhat larger households, but the differences in education and household size are relatively minor between the two groups (0.66 years of education and 0.4 household members). In the Kenyan sample, the non-returning individuals are significantly different from returning individuals in household size and income (see Table 3). Although the differences in household size are very minor between the two groups, participating individuals have significantly less income. This finding suggests that individuals who participated in the experiments were more motivated by the financial incentives, since individuals were paid to participate in the experiments. Therefore, one must be very careful in extrapolating the results obtained in the analysis to the general population.

2.4 Experimental Design

The experiments were performed in a public place, typically in a school or government office. Husbands and wives attended different sessions in the same day to reduce co-influence. Sessions lasted for about 3 hours. Respondents received 200 KSH and 4,000 TSH (about 2USD), which is close to a daily wage in Kenya and Tanzania, respectively, for attending the experiments and obtained further payments based on the choices they made in the experiments. Respondents played two different types of risk preference games: one modeled after Holt and Laury (2002) and the other after Tanaka, Camerer, and Nguyen (2010). Only TCN results are used in this study.

During the experiment respondents were asked to make pair-wise choices on 27 different lotteries divided up into three series. The first two series contained only positive payments, whereas the third series included the possibility of negative payouts. Appendix A contains the risk preference series for each country. In the Tanzanian sample, in Series 1 Task 1 example, Option A pays 1,650 TSH with 70% chance of winning or 6,550 TSH with 30% chance of winning; Option B pays 800 TSH with 90% probability of winning or 10% probability of receiving 13,700 TSH. Similarly, in the Kenyan sample, Option A pays 110 KSH with 70% chance of winning or 440 KSH with 30% chance of winning; Option B pays 55 KSH with 90% probability of winning or 10% probability of receiving 920 KSH in Series 1 Task 1 example.

In Series 1 and 2, more risk averse individuals switch from Option A to Option B further down the table than less risk averse individuals. In Series 3, more loss averse individuals switch from A to B further down the table. To ensure parameter estimates could be derived from the respondents' choices, we enforced monotonic switching from Option A to Option B. Not switching was also a possibility. The series' payouts were designed such that the potential losses did not exceed the 4,000 TSH in Tanzania and 200 KSH in Kenya that respondents received for participating in the experiments.

Each series was given a 10 minute introduction by the enumerator to ensure understanding and homogeneous explanations. The lead enumerator used 10 balls in a bag to explain the concept of probabilities. A ball was then drawn from the bag to determine a random starting point for the series in order to reduce starting point bias. To ensure understanding of choices by the respondents, enumerators worked independently with 1-2 respondents after the initial introduction. Once a switching point was identified, enumerators stopped respondents for that series. The lead enumerator drew the next random starting point once all respondents completed a series.

Three switching points were identified for each respondent, one for each series. Suppose in Series 1 a respondent switches from Option A to Option B at Task 5, i.e. at Task 5 Option A is no longer the best choice. This suggests that at Task 4 he/she preferred Option A to Option B. One can obtain two inequalities from this switching point. Using a combination of switching points from Series 1 and 2, one can estimate risk aversion (σ) and non-linear probability weighting (α) parameters. Then for a given value of σ, using the switching points in Series 3, one can obtain a range of values for loss aversion (λ).

2.5 Risk Experiment Results

The distributions of experimentally derived risk preference parameters are presented in Figure 1 for the Tanzanian sample and Figure 2 for the Kenyan sample. Contrary to TCN (2010) and Liu (2013), the distributions do not appear normally distributed. Many respondents exhibit high levels of risk aversion (σ > 0.2 in Tanzania and σ > 0.15 in Kenya), as well as extreme loss aversion (λ > 7 in Tanzania and λ > 10 in Kenya) or almost no loss aversion (λ < 0.5 and λ < 0.15 in Tanzania and Kenya, respectively). The average values of σ and α are 0.62 and 0.94 in Tanzania and 0.46 and 0.86 in Kenya, respectively. TCN (2010) find $\bar{\sigma} = 0.59$ and $\bar{\alpha} = 0.74$ among farmers in Vietnam. Liu (2013) finds $\bar{\sigma} = 0.48$ and $\bar{\alpha} = 0.69$ among farmers in China. We find the average value of λ to be 3.84 in Tanzania and 3.33 in Kenya, compared to TCN's 2.63 and Liu's 3.47.

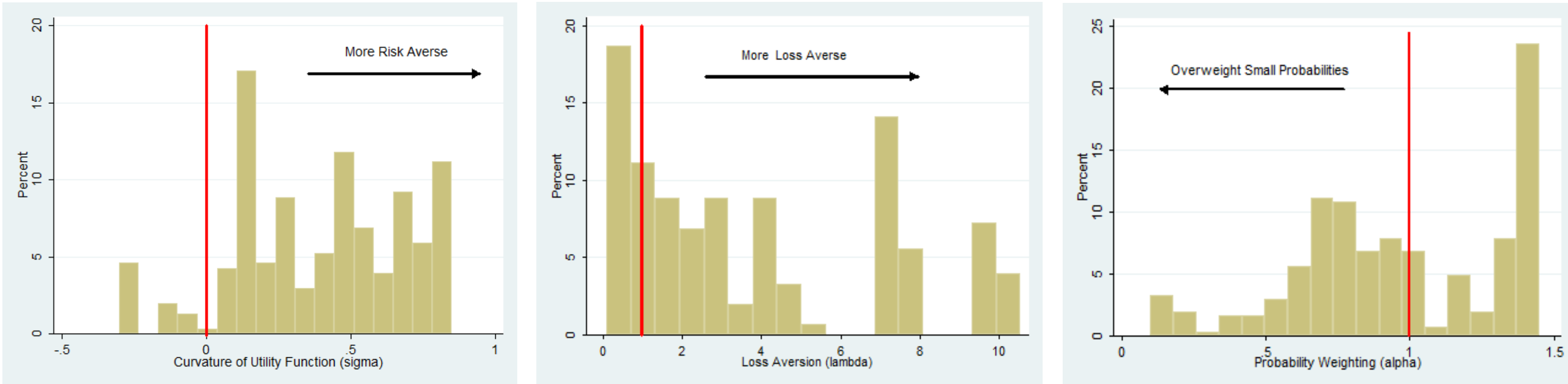

Figure 1. The Distributions of PT Risk Preferences Parameters in Tanzania

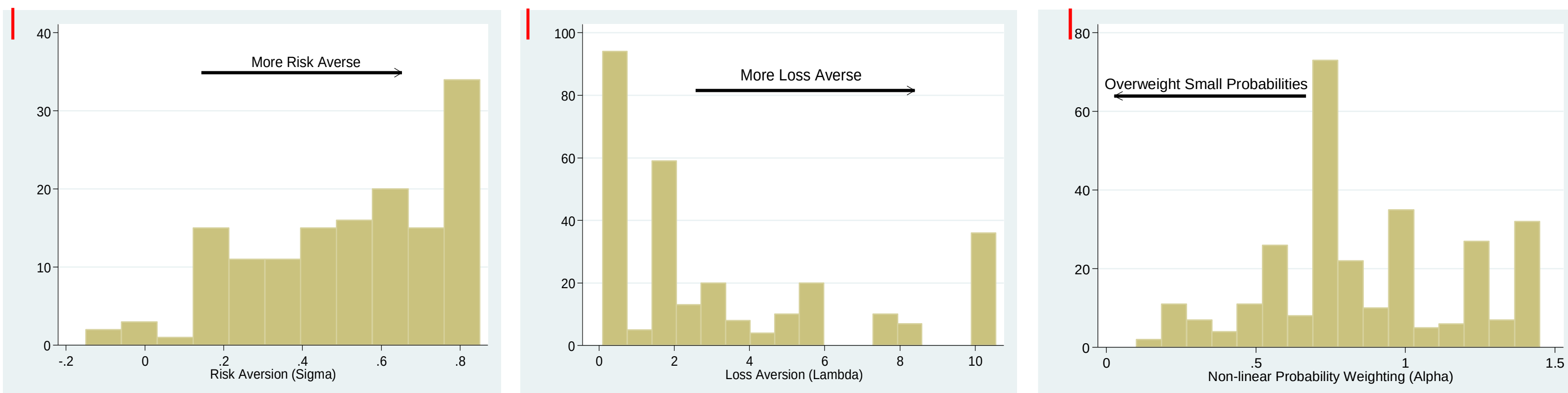

Figure 2. The Distributions of Risk Preference Parameters in Kenya

We first address the validity of PT approach used to elicit individuals' attitudes towards risk by testing whether PT model can be reduced to EU model. We perform Likelihood Ratio test with the null hypothesis that PT is valid, and we must incorporate all three risk preference parameters (σ, λ, and α) in the estimation of agricultural technology adoption. The test results are included at the bottom of Tables 9, 10, 13, 14 and 15. Using the Tanzanian sample, we find that PT is valid in all model specifications. Using the Kenyan sample, in Urea fertilizer adoption models we find that PT is valid in all model specifications with the exception of models with solely male risk preferences, Hurdle 1 of a model with both male and female risk preferences, and FHH models. In DAP fertilizer adoption models, we find that PT preferences are valid in all model specifications for both MHH and FHH. So, overall we believe that PT approach is justified in the analysis of improved maize adoption and fertilizer use detailed in Chapters 3 and 4.

Table 4. Tanzanian Spouses' Risk Preferences Summary Statistics

Variables	Male		Female	
σ	0.38	(0.30)	0.41	(0.30)
				[0.47][a]
λ	3.41	(3.22)	3.96	(3.42)
				[0.15]
α	0.95	(0.40)	0.98	(0.35)
				[0.44]
N	134		134	

Note: Mean coefficients; Standard deviations are in parentheses. [a] p-value for mean differences between a male and a female in a household in brackets. Significant at *10%, ** 5%, and *** 1%.

Table 4 above contains summary statistics of the three risk preference parameters by gender for the Tanzanian sample. Two sample t-tests are used to test significant differences between sub-sample means. It appears that no significant differences in risk preferences exist between males and females within the same households, suggesting that, on average, males and females have similar attitudes towards risk. However, we suspect that while on average spouses do not seem to have divergent preferences in our sample, there may be a significant portion of households where attitudes towards risk differ between a husband and a wife.

Table 5. Kenyan Farmers' Risk Preferences Summary Statistics

Variables	Males in MHH		Females in MHH		Females in FHH		All Females	
σ	0.53	(0.25)	0.55	(0.29) [0.55][a]	0.46	(0.29) [0.13][b]	0.53	(0.29) [0.94][c]
λ	3.11	(3.30)	3.56	(3.66) [0.26]	4.76	(3.91) [0.09]*	3.80	(3.73) [0.08]*
α	0.86	(0.33)	0.86	(0.32) [0.92]	0.80	(0.39) [0.35]	0.85	(0.34) [0.83]
N	143		143		35		178	

Note: σ, λ, α represent risk aversion, loss aversion, and non-linear probability weighting parameters, respectively; MHH stands for male-headed households; FHH stands for female-headed households; Mean coefficients; Standard deviations are in parentheses. [a] p-value for mean differences between males 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 males and all females in brackets. Significant at *10%, ** 5%, and *** 1%.

Summary statistics of the three risk preference parameters by gender and type of the household for the Kenyan sample are presented in Table 5 above. We find no significant differences in risk preferences between males and females in MHH, suggesting that, on average, males and females in the same household have similar attitudes towards risk. Females in FHH, however, are significantly more loss averse than females in MHH at the 10% level. Since FHH face income and credit constraints, they are more sensitive to potential losses, compared to females in MHH who have the security of another source of income in the household. Males are also significantly less loss averse than all the females in the Kenyan sample. This result is also driven by financially constrained FHH.

We also consider the correlation between male and female risk preferences in MHH (see Tables 22 and 23 in Appendix A3). The correlation coefficients for all three gender specific risk preference parameters (σ, λ, and α), do not exceed 0.13 in absolute value, suggesting that risk preferences of spouses are not highly correlated in both Tanzanian and Kenyan households. As such, male and female risk preferences can be reliably incorporated in the collective models discussed in Chapters 3 and 4.

To further explore the differences in preferences between males and females in the same household, we create relative risk preference variables by subtracting female preferences from male preferences. The histograms of these relative preferences are presented in Figures 3 and 4 for the Tanzanian and Kenyan samples, respectively. The figures show that while on average the difference is close to 0, the distributions have rather thick tails. This suggests that while on average there are no differences in preferences, there is a significant portion of households where spouses' preferences are very different.

To confirm this proposition, we further test whether the absolute differences between males and females in the same household are significantly different from 0. We find the absolute differences in risk preferences among spouses to be highly significant, suggesting that for many households in our sample, males and females have divergent preferences, even though on average they do not appear to be different. Therefore, it is important to account for these differences by specifying a collective model of agricultural technology adoption where female risk preferences are incorporated in the estimation.

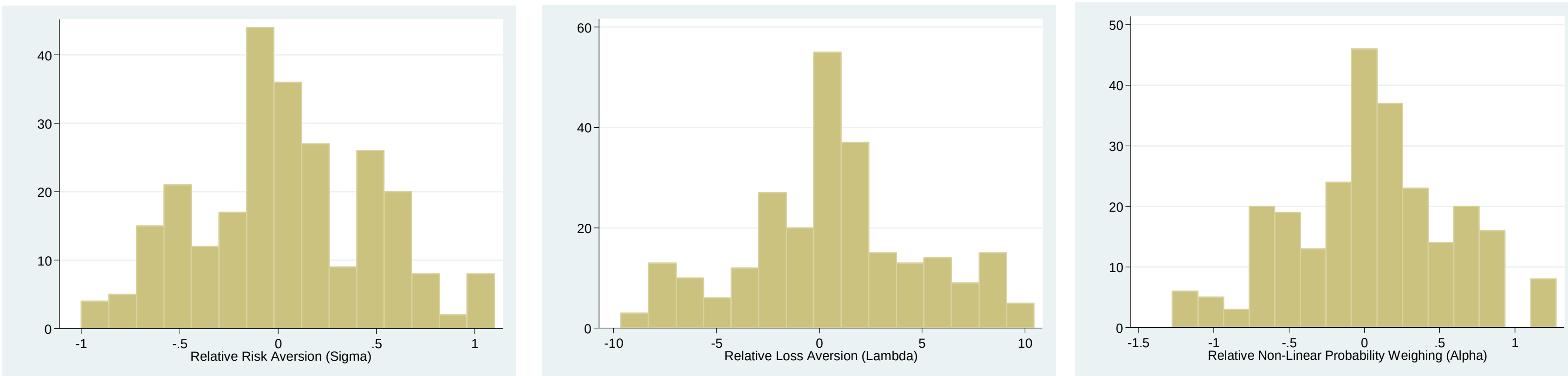

Figure 3. The Distributions of Relative Preferences in Tanzanian Couples

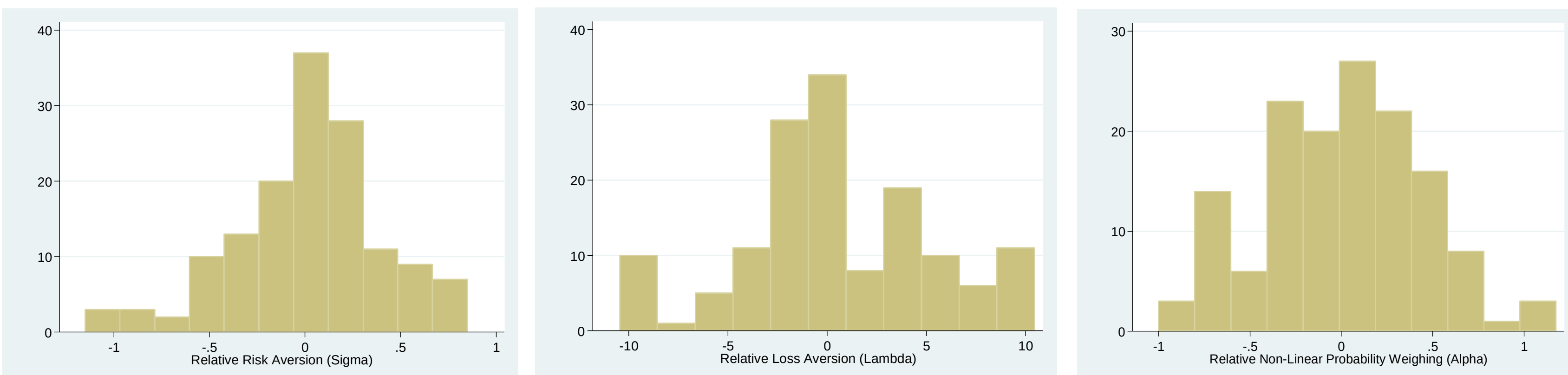

Figure 4. The Distributions of Relative Preferences in Kenyan Couples

CHAPTER 3

MAIZE ADOPTION IN TANZANIA

3.1 Introduction

New technology adoption is imperative in improving agricultural production in developing countries, such as Tanzania. Improved maize varieties are examples of these new technologies that farmers do not readily adopt due to high costs and risk associated with their use. Risk attitudes of farmers can explain low adoption. Husbands and wives can have different attitudes towards risk. Depending on how involved a female is in household's agricultural decisions, her risk preferences can have an effect on new technology adoption. As such, we believe that it is important to investigate how both male and female risk preferences influence household's technology adoption. We use a collective household model to estimate the effects of experimentally derived risk preferences of both spouses in farming households interacted with relative women's bargaining power on improved maize adoption in Tanzania.

3.2 Model of Individual Risk Preferences and Maize Adoption

Maize adoption is associated with two different kinds of risk: risk of new seeds not performing as expected and purely environmental risk (typically in the form of drought or severe plant disease) of using improved seeds. Improved maize varieties in our sample can be classified into two groups: hybrids and improved open pollinated varieties (IOPVs) (see Table 6). IOPVs are represented by such varieties as Situka M-1, Staha, Kito-ST, TMV-1 and Kilima that are planted on 124 subplots. Hybrids include such varieties as PAN67, SC627, DK8031, H513, H622, SC403 that are planted on 120 subplots. Traditional seeds are used on 126 subplots in the sample.

Table 6. Summary of Maize Varieties

Seed Variety	Seed Type	Plots
Situka M-1	IOPV	30
Staha	IOPV	48
Kito-ST	IOPV	2
TMV-1	IOPV	30
Kilima	IOPV	14
PAN 67	Hybrid	2
SC 627	Hybrid	58
DK 8031	Hybrid	38
H 513	Hybrid	8
H 622	Hybrid	4
SC 403	Hybrid	10
Improved	IOPV	12
Local	Traditional	126
N		382

Hybrid seeds are bred for their high yield quality, and some are also bred to be drought or disease resistant. IOPVs are improved seed varieties that, while do provide some yield improvements, are typically known for their disease tolerant properties. In our sample, all hybrids are considered high-yielding, and some are also disease/drought tolerant. In contrast, all IOPVs are stress tolerant and some are also believed to be high-yielding. If advertised qualities of new seeds are true, one would expect farmers to invest in improved seeds. However, farmers may be hesitant to do so because of fear that new largely unknown seeds may not work as advertised (Liu 2013). In fact, improved maize varieties are used on only 27% of total maize area in Tanzania (Lyimo, Mdurum, and De Groote 2014). The risk of new technology not working can force farmers to avoid adopting new maize varieties, hybrids or IOPVs, particularly since improved seeds are much more expensive than traditional seeds. In our sample, a 2 kg bag of hybrid seeds costs anywhere from 9,500 TSH to 12,500 TSH, whereas IOPVs can be purchased at 4,500 TSH to 5,000 TSH per 2 kg bag. Traditional seeds are mainly recycled and, if purchased, are typically bought from neighbors at a much lower price. As a result, even disease/drought tolerant and thus risk reducing new varieties may be perceived as very risky investments.

From a purely environmental perspective, unpredictable weather creates a significant amount of uncertainty in agricultural decision making for farmers in predominantly rain fed agricultural systems. In Tanzania, 94% (64%) of surveyed households experienced at least one drought (disease) event in the period from 2003 to 2013. Farmers who choose to plant improved maize varieties must decide what type of seed, hybrid or IOPV, to plant at the beginning of a season prior to the occurrence of a negative shock. In our sample, hybrid seeds are more expensive than IOPVs. Moreover, hybrid seeds cannot be recycled, unlike IOPVs. Therefore, conditional on choosing new seeds, planting hybrids is a much riskier investment than planting IOPVs, as it can amount to no yield improvements and result in a greater loss in a bad year.

Based on the nature of risks associated with maize production, the seed adoption choice can be modeled as a two step process. First, households decide whether they want to purchase improved seeds or continue to use traditional seeds instead. Second, households that choose to purchase new seeds have to choose between hybrids and IOPVs.

At every stage, we assume two possible states of the world: a state in which a negative shock, i.e. “a new seed does not work” in stage 1 or “drought/disease occurs” in stage 2, (bad outcome) with probability p and a state with no stress (good outcome) with probability q, s.t. $p + q = 1$. Each state of the world is associated with different yields depending on the chosen seed type. If improved seeds perform well, they will be higher yielding than traditional seeds, i.e. $Y_{imp,good} > Y_{tr,good}$. If improved seeds underperform, they will yield no better than locally used seeds, i.e. $Y_{imp,bad} = Y_{tr,bad}$. In the second stage, in a good season, hybrids will be better yielding than IOPVs, i.e. $Y_{hyb,good} > Y_{IOPV,good}$. In a bad season, IOPVs will be more resilient than hybrids: $Y_{IOPV,bad} > Y_{hyb,bad}$.

Cost wise, we have $C_{hyb} > C_{IOPV} > C_{tr}$. Using traditional seed choice under good weather conditions as a respective reference point, we can arrive at expected payoffs of choosing improved seeds in each state of the world: $\pi_{ij} = Y_{ij} - C_i$, where *i* is the choice of maize seed (*i* = improved or traditional seeds in stage 1 and hybrids or IOPVs in stage 2), and *j* is the state of the world, i.e., *j* = good, bad. Selling price of maize is normalized to 1. Given the expected payoffs, we now consider possible outcomes in each state.

In stage 1, if a farmer plants improved seeds and they work, the outcome is $y = \pi_{imp,good} - \pi_{tr,good} > 0$, since we assume that under good conditions the improvements in yield from improved seeds are sufficient to cover the additional input costs. In a bad year, however, $x = \pi_{imp,bad} - \pi_{tr,bad} < 0$, since improved seeds are more expensive and do not offer significant yield improvements if they do not perform well. In the second stage, if a farmer chooses to plant hybrids over IOPVs and the weather is good, the outcome is $y = \pi_{hyb,good} - \pi_{IOPV,good} > 0$, since hybrids are higher yielding than IOPVs even though they cost more s.t. $Y_{hyb,good} - Y_{IOPV,good} > C_{hyb,good} - C_{IOPV,good.}$ If a farmer chooses to plant hybrids and a negative environmental shock occurs, the outcome is $x = \pi_{hyb,bad} - \pi_{IOPV,bad} < 0$, since IOPVs will perform better than hybrids, as many of them are stress tolerant and more affordable than hybrids.

In the presence of both gains and losses in every stage, we can specify PT utility function in the following manner:

$$U(x, y, p, q) = \pi(p)(-\lambda)(-x)^{1-\sigma} + \pi(q)(y)^{1-\sigma}, \qquad (2)$$

where $\pi(w) = \exp[-(-\ln w)^{\alpha}]$, $w = p, q$ and $x < 0 < y$.

We are interested in the effects of risk aversion, loss aversion, and probability weighting on the utility gained from the adoption of improved seeds. We take partial derivatives of the utility function with respect to each parameter: $\frac{\partial U}{\partial \sigma}, \frac{\partial U}{\partial \lambda}$, and $\frac{\partial U}{\partial \alpha}$ (see derivation in Appendix B1). We expect $\frac{\partial U}{\partial \sigma} < 0$, i.e. households with more risk averse farmers will be less likely to prefer improved seeds in stage 1 or hybrids in stage 2. Similarly, we expect households with more loss averse farmers to be less likely to prefer improved seed or hybrids, i.e. $\frac{\partial U}{\partial \lambda} < 0$. Finally, we expect $\frac{\partial U}{\partial \alpha} > 0$, suggesting that households with farmers who underweigh small probabilities of a negative shock will be more likely to use non-traditional seeds (or hybrids) or, equivalently, farmers who overweigh small probabilities of a negative shock will be less likely to use these new technologies.

The degree to which differential effects of individual risk preferences affect household's agricultural decisions depends on intrahousehold dynamics. In our collective model, we assume that husband and wife's utilities separately enter a household utility function, where wife's utility is weighed by the degree of her bargaining power in a household.

$$U = U_M(\sigma_M, \lambda_M,\ \alpha_M) + \mu U_F(\sigma_F, \lambda_F,\ \alpha_F) \tag{3}$$

In equation (3) above, U is the household utility, U_M and U_F are husband and wife's respective utilities that are functions of their risk preferences, and μ is an indicator of bargaining power (empowerment) of a woman in a household. $0 \leq \mu \leq 1$, where $\mu = 0$ implies that a woman has no bargaining power in a household, and $\mu = 1$ implies that gender parity exists in household's choices. If spouses have different preferences, the amount of wife's bargaining power will determine to what extent her preferences come through in the household decisions.

3.3 Empirical Model of Maize Seed Choice

We have experimentally derived risk preferences of spouses in Chapter 2 and, based on the theoretical model specified in Section 3.2, we know how these preferences should affect seed choices. We can now test whether both male and female preferences matter in household seed choice decisions using the empirical model in equation (4) below. We account for intrahousehold bargaining dynamics by incorporating the interactions of female risk preferences with a female empowerment indicator in the empirical model.

$$S_{jh} = R_h^{M}{}'\theta^M + R_h^{F}{}'\theta^F + R_h^F E_h{}'\theta^{EMP} + \ \gamma E_h + X_{jh}{}'\delta + \varepsilon_{jh} \tag{4}$$

In equation (4) above, j stands for a subplot and h denotes a household; S_{jh} is the type of seed used on a subplot j; R_h^M is a vector of male risk preference variables $(\sigma, \lambda, \alpha)$; E_h is a women's empowerment indicator; R_h^F is a vector of female risk preference variables; X_{jh} is a vector of individual, household, and subplot characteristics, such as age, education, household size, income, land holdings, soil type and subplot tenure; and ε_{jh} is the error term.

Summary statistics for independent variables in X_{jh} are presented in Table 7. Males tend to be older and more educated than females in our sample. The average household consists of 6 people and owns 5 acres of land. 42% and 7% of subplots in our sample are identified as male and female managed plots, respectively, and 51% are identified as jointly controlled.

Table 7. Summary Statistics of Explanatory Variables

Variable Name	Mean	Std. Dev.
Male Age (years)	47.72	(13.11)
Female Age (years)	39.93	(11.27)
Male Education (years)	6.18	(2.98)
Female Education (years)	5.51	(3.00)
Female Empowerment (1=Empowered)	0.44	(0.49)
Household Size	6.34	(2.56)
Non-farm Income (10,000 TSH)	126.88	(291.29)
N (Individual & Household levels)	*134*	
Land Area - Owned (acres)	5.09	(5.62)
Fertile Soil (1=yes)	0.43	(0.50)
Male Managed Plot (1=yes)	0.42	(0 .49)
Female Managed Plot (1=yes)	0.07	(0.25)
N (Subplot level)		*382*

Summary statistics of the dependent variable seed choice, S_{jh}, are presented in Table 8 below. Households plant fewer hybrids and more IOPVs and traditional varieties on male managed plots than on female managed plots. More IOPVs than hybrids or traditional varieties are planted on jointly managed plots. Overall, improved seeds are planted on about two thirds of the sample subplots. It is possible that farmers possess at least some information about benefits of using these improved seed varieties. The agricultural technology adoption efforts of Sustainable Intensification of Maize and Legume Systems for Food Security in Eastern and Southern Africa (SIMLESA) program, developed by CIMMYT, can potentially explain such high adoption of improved seeds in Tanzania. SIMLESA performs field trials and field days designed to educate farmers about the benefits of using improved seeds and other technologies. In our sample, 11% of households claimed to have learnt about improved seed varieties from field trials, demos, or field days that were organized by SIMLESA research centers, suggesting potentially limited external validity of the results that follow.

Table 8. Maize Adoption by Plot Type

Variables	Male Managed Plots	Female Managed Plots	Jointly Managed Plots	All Plots
Hybrid	0.350	0.385	0.276	0.314
IOPV	0.313	0.308	0.439	0.377
Traditional	0.362	0.308	0.306	0.330
N	160	26	196	382

As shown in Table 8, about a third of plots are planted with either local seeds, IOPVs, or hybrids each. However, the evident diversification of seeds at a subplot level does not translate into seed diversification at a household level. Each household uses a certain type of seed (hybrid, IOPV or traditional seed), on all its subplots. In our sample, 36.5% of households plant either hybrid or IOPV varieties on their subplots and 27% of households continue to use traditional varieties on their subplots. As a result, the sample variation in the seed choice is present across households, not across subplots.

The main coefficients of interest are θ^M, θ^F, and θ^{EMP}. θ^M is a vector of male risk preference parameters, and θ^F and $\theta^F + \theta^{EMP}$ are vectors of risk preference coefficients for disempowered and empowered women, respectively. We expect to see negative coefficients for male and female risk and loss aversion, which would mean that households where males and females are more risk/loss averse will be less likely to adopt improved seeds. We also expect to see positive non-linear probability weighting coefficients of spouses, stating that households with males and females who tend to overweigh small probabilities of a negative shock are less likely to use improved seeds. For households, where a female has bargaining power, we expect to see a much more prominent negative effects of risk aversion, loss aversion, and overweighing of small probabilities on seed choice.

In the empirical model specified in equation (4), E_h is endogenous, as there are unobserved factors that can potentially affect both a woman's bargaining power and her seed choice. For example, women in more traditional households may not hold much power over household's agricultural decisions, and the same traditional households may also choose to avoid using improved seeds and maintain traditional agricultural practices. The coefficient estimate of E_h thus cannot be interpreted as causal. However, since we are primarily interested in the effect of the interaction of risk preferences and women's empowerment on the seed choice, the endogeneity of a female empowerment indicator itself is not of a great concern here. Conditional on E_h, we can still estimate the influence of risk preference parameters on seed choice without bias caused by the endogeneity of the female empowerment indicator.

We use a Sequential Logit model, proposed by Mare (1981) and Maddala (1983), to estimate the two step seed choice process detailed in Section 4. The dependent variable y is a dichotomous variable of seed choice that takes value of 1 if a household chooses any improved seeds (hybrids or IOPVs) over traditional seeds in stage 1 or chooses hybrids over IOPVs in stage 2. Under this model, we are able to sequentially estimate the probability of a farmer choosing improved vs. traditional seed types in the first stage (Transition 1) and the probability of a farmer choosing hybrids vs. IOPVs, conditional on farmers' choice of improved seeds, in the second stage (Transition 2). The decisions farmers face at each stage are assumed to be independent. Each transition is estimated with a logit regression on the appropriate sub-sample of data.

3.4 Results

We now proceed with the estimation of improved maize adoption models. Tables 9 and 10 contain average partial effects (APEs[4]) of individual risk preferences on improved vs. traditional seed choice (Transition 1) and on hybrid vs. IOPV choice, given that a farmer opts for improved seeds (Transition 2).[5]

In the first two columns of Table 9, we first estimate a unitary model with male risk preferences only. In column 1 of Table 9 (Transition 1), the sign of the APE of male non-linear probability weighting parameter (α) is positive and significant, suggesting that

[4] APE measures the average effect of risk aversion (loss aversion or non-linear probability weighting) on the probability of a household choosing improved seeds (Transition 1) or on the probability of a household choosing hybrids, conditional on the choice of improved seeds (Transition 2).

[5] Tables 24 and 25 in Appendix C1 contain APEs of controls described in Table 7.

Table 9. Unitary Models of Seed Choice

VARIABLES	(1) Transition 1	(2) Transition 2	(3) Transition 1	(4) Transition 2	(5) Transition 1	(6) Transition 2
Male σ	-0.067	0.217				
	(0.143)	(0.169)				
Male λ	-0.012	-0.032**				
	(0.012)	(0.015)				
Male α	0.219**	0.030				
	(0.098)	(0.138)				
Female σ			0.054	-0.199		
			(0.166)	(0.200)		
Not Empowered					-0.034	0.069
					(0.211)	(0.316)
Empowered					0.141	-0.538***
					(0.179)	(0.181)
Female λ			0.003	0.014		
			(0.013)	(0.016)		
Not Empowered					-0.001	0.015
					(0.017)	(0.023)
Empowered					0.011	0.014
					(0.020)	(0.017)
Female α			-0.083	0.230		
			(0.119)	(0.149)		
Not Empowered					-0.109	0.097
					(0.169)	(0.198)
Empowered					-0.041	0.254*
					(0.149)	(0.147)
Female Empowerment=1 if Empowered					0.234***	-0.118
					(0.080)	(0.084)
LR Chi Square Statistic Ho: PT is not valid	24.45***		12.09**		15.54**	
Observations	382	277	382	277	382	277

Note: σ, λ, α represent risk aversion, loss aversion, and non-linear probability weighting parameters, respectively; APEs and standard errors in parenthesis; Significant at *10%, **5%, ***1%; All models are estimated with controls listed in Table 7; APEs of controls are provided in Table 24 in Appendix C1.

households with male farmers who tend to overweigh a small probability of new seeds not working as expected will be less likely to purchase improved seeds. In column 2 of Table 9 (Transition 2), we find that male loss aversion (λ) has a significant negative effect on probability of planting hybrids, given that farmers opt for improved seeds. This result suggests that households with more loss averse males are less likely to adopt hybrid seeds, given that they choose to plant improved seed varieties.

We then consider a model with stand alone female risk preferences (columns 3-4) and a model where we incorporate female empowerment (columns 5-6) to see if female risk preferences on their own have any effect on households' seed choices. In columns 3 and 4 we see no significant results. Female loss aversion coefficient is ultimately 0 in either transition, irrespective of degree of female empowerment. However, when female empowerment is incorporated in column 6 (Transition 2), the coefficient of risk aversion for empowered females becomes negative and significant. This suggests that households with empowered more risk averse females will be less likely to invest in hybrids, conditional on the choice of improved seeds. Also, the coefficient of non-linear probability weighting is now positive and significant, suggesting that households where empowered females tend to overweigh a small probability of environmental shock will be less likely to purchase hybrids, given that they opt for improved varieties.

Table 10 below contains the results of the collective model estimation. In the first two columns we consider a collective model with both male and female risk preferences but do not account for the degree of female empowerment. With regard to male risk preferences, we obtain similar results as in columns 1 and 2 of Table 9. We see no significant results in female risk preferences in either transition, suggesting that while

Table 10. Collective Models of Seed Choice

VARIABLES	(1) Transition 1	(2) Transition 2	(3) Transition 1	(4) Transition 2
Male σ	-0.072	0.095	-0.115	0.003
	(0.149)	(0.180)	(0.153)	(0.164)
Male λ	-0.013	-0.031**	-0.013	-0.040***
	(0.012)	(0.014)	(0.012)	(0.014)
Male α	0.207**	-0.011	0.165*	-0.056
	(0.095)	(0.129)	(0.095)	(0.120)
Female σ	0.037	-0.135		
	(0.145)	(0.181)		
Not Empowered			-0.032	0.113
			(0.176)	(0.268)
Empowered			0.143	-0.492***
			(0.183)	(0.176)
Female λ	0.004	0.012		
	(0.013)	(0.016)		
Not Empowered			0.010	0.017
			(0.016)	(0.020)
Empowered			0.006	0.017
			(0.020)	(0.017)
Female α	-0.078	0.193		
	(0.111)	(0.155)		
Not Empowered			-0.146	-0.104
			(0.160)	(0.164)
Empowered			-0.015	0.366**
			(0.148)	(0.153)
Female Empowerment=1 if Empowered			0.234***	-0.064
			(0.078)	(0.072)
LR Chi Square Statistic Ho: PT is not valid	33.79***		44.45***	
Observations	382	277	382	277

Note: σ, λ, α represent risk aversion, loss aversion, and non-linear probability weighting parameters, respectively; APEs and standard errors in parenthesis; Significant at *10%, **5%, ***1%; All models are estimated with controls listed in Table 7; APEs of controls are provided in Table 25 in Appendix C1.

males and females may have different risk preferences, only male preferences seem to matter when it comes to seed choices.

Given the results in the last two columns of Table 9, we suspect that the degree of female empowerment may be a decisive factor in whether female risk preferences matter in household seed choices. Indeed, they may only have an effect if a female has bargaining power in maize production decisions. In columns 3 and 4 of Table 10 we incorporate female empowerment into the estimation.

In column 3 (Transition 1) we observe that only male probability weighting has a significant effect on improved seed adoption. Households with males that overweigh small probabilities of a negative shock, such as improved seed not working, are less likely to purchase improved seeds. In contrast, probability weighting coefficient for empowered females is not significant and close to 0 in magnitude. In column 4 (Transition 2), we find that male loss aversion has a negative effect on household's adoption of hybrids, whereas a loss aversion coefficient for empowered females is close to 0 in magnitude. Households with more loss averse males are less likely to purchase hybrids, conditional on the purchase of improved seeds. Similarly, empowered female risk aversion has a negative effect on household's use of hybrids, whereas male risk aversion coefficient is approximately zero.

The results confirm our proposition that households with empowered more risk averse females choose not to purchase risky inputs, such as hybrid seeds, given that they choose to invest in improved seeds. In Transition 2 it seems that, while male loss aversion matters much more than female loss aversion, female and not male risk aversion drives the choice of hybrids. We also find a positive significant coefficient of the APE of non-linear probability weighting for empowered females. The male coefficient is not significant and approximately 0 in magnitude. This result suggests that households with empowered females who tend to overweigh a small probability of a drought/disease are less likely to purchase hybrids, given that they choose improved seeds.

Overall, we find that, when it comes to seed choices, risk aversion does not matter for men at either stage, but it does for women. Loss aversion does not matter for women at either stage, but it does for men. Such prominent loss, but not risk, aversion result for men is interesting. It is possible that, as the head of a household, a husband carries a greater burden of responsibility for the consequences of his household purchasing a very expensive hybrid in the event of a negative environmental shock. Probability weighting matters for men and women (for men in the first stage and for women in the second stage). Men overweigh the probability of a seed not working, and women overweigh the probability of drought/disease occurrence. It may be that men are more suspicious of new unknown technology than women. As such, they care more about the possibility of new seeds not working, than they do about the possibility of an environmental shock. In contrast, empowered women are more open minded when it comes to trying new things, and for them, environmental shocks represent a far greater risk.

Our results show that female risk preferences do matter in maize adoption choices of Tanzanian farming households, when we consider how empowered these females are in the agricultural decisions of the household. Indeed, in terms of magnitude of the effects, risk aversion and non-linear probability weighing of empowered females matter to a much greater extent than respective preferences of men on the choice of hybrids in these households. Therefore, Tanzanian households do not act as unitary households where only men make agricultural production choices, but rather both spouses' attitudes towards risk affect these choices, depending on the degree of female empowerment.

CHAPTER 4

FERTILIZER USE IN KENYA

4.1 Introduction

The use of agricultural inputs, such as fertilizer, plays an important role in improving agricultural production in Kenya. Fertilizer is a risky input and its adoption by farmers is often very low. Farmers' risk attitudes are often considered to be the reason behind low fertilizer use. Men and women are known to have distinct attitudes towards risk. If a wife has input in fertilizer purchase decisions in a household, her risk preferences should influence household's use of fertilizers. We use a collective household model to estimate the effects of experimentally derived risk preferences of both spouses in farming households interacted with relative women's bargaining power on fertilizer use.

4.2 Model of Individual Risk Preferences and Fertilizer Use

Fertilizers provide nutrients necessary for plant development, including phosphorous, potassium, and nitrogen. Two types of fertilizer, Urea and DAP, are used by farmers in this study. DAP is a multiple nutrient fertilizer that is a source of phosphorous and nitrogen, whereas Urea is a single nutrient fertilizer that is a good source of nitrogen. Urea is also a more affordable fertilizer, compared to DAP. DAP is mostly used to support strong root development of the plant and usually applied at planting. Urea contributes significantly to leaf development and growth of a plant and is usually applied two months after planting at top dressing. DAP, therefore, is a riskier input due to the timing of its application. Significant improvements in yields are expected with the proper application of both fertilizers.

Drought is a major concern for Kenyan farmers in the Eastern semi-arid parts of the country. In the West, excessive rainfall creates favorable conditions for the spread of fungus disease in maize crop, causing the loss of crop and jeopardizing food security of poor households. Risks of drought in the East and excessive rainfall in the West may prevent farmers from using optimal levels of fertilizer. In our sample, 24% of MHH and 17% of FHH experienced at least one severe drought event in the past (see Table 11). Similarly, 49% of MHH and 29% of FHH experienced a severe crop disease event. Only 20% of MHH subplots and 13% of FHH subplots have fertile soil.[6] Urea was applied on 51% of subplots and DAP was applied on 73% of subplots.

Farmers decide on whether and how much fertilizer to use prior to the occurrence of a negative shock. Fertilizer is expensive, and farmers risk that all fertilizer they use will amount to nothing, resulting in a loss. We set up a simple utility maximization model to understand how risk preference parameters influence fertilizer adoption. At the beginning of a season, each farmer decides whether to use fertilizer and the amount of fertilizer needed (k), given that he/she decides to make a purchase. Fertilizer can be purchased at a price w. Fertilizer purchase is associated with total cost of $wk > 0$. The crop gross revenue $g(k, \varepsilon)$ is a function of both the amount of fertilizer used and a random shock. Gross revenue is generally higher when fertilizer is applied, i.e. $g(k, \varepsilon) > g(\varepsilon)$.

[6] Soil fertility has three levels: good, medium, and poor. Soil fertility indicator is a dummy variable that takes value of 1 if a farmer classified soil on a subplot to be of "good" fertility.

We now assume two possible states of the world: a state in which a negative shock (drought or plant disease) occurs (bad season) with probability p and a state with no stress (good season) with probability q, s.t. $p + q = 1$. In a good season, the application of fertilizer will increase yields, resulting in $g(k,\varepsilon)_{good} > g(\varepsilon)_{good}$, whereas in a bad season, fertilizer use will not make a difference, since regardless of whether fertilizer is used or not, the crop will be partly or entirely lost, i.e. $g(k,\varepsilon)_{bad} = g(\varepsilon)_{bad}$. We can now deduce farmers' payoffs from using fertilizer in each state. If a farmer decides to use fertilizer, his/her payoff in a bad season is $\underline{\pi}_F = g(k,\varepsilon)_{bad} - wk$ and in a normal season is $\overline{\pi}_F = g(k,\varepsilon)_{good} - wk$. If, however, a farmer decides not to use any fertilizer, his/her payoffs are $\underline{\pi}_0 = g(\varepsilon)_{bad} = g(k,\varepsilon)_{bad}$ and $\overline{\pi}_0 = g(\varepsilon)_{good}$ in a bad and a good season, respectively.

Now we consider possible outcomes in each state, conditional on the purchase of fertilizer. In a bad season, outcome x is the profit from using fertilizer less the status quo profit from choosing not to use fertilizer:

$$x = \underline{\pi}_F - \underline{\pi}_0 = g(k,\varepsilon)_{bad} - wk - g(\varepsilon)_{bad} = -wk < 0, \qquad (5)$$

indicating a loss in the amount of funds invested in fertilizer, since $g(\varepsilon)_{bad} = g(k,\varepsilon)_{bad}$ in a bad season.

Alternatively, in a good season, outcome y becomes:

$$y = \overline{\pi}_F - \overline{\pi}_0 = g(k,\varepsilon)_{good} - wk - g(\varepsilon)_{good} > 0, \qquad (6)$$

since improvements in crop yield from using fertilizer are assumed to be large enough to cover the costs of purchase, yet still exceed the payoffs when no fertilizer was applied on a plot.

We assume that a farmer's payoff increases (decreases) with the use of a fertilizer in a good (bad) year, i.e. $\frac{\partial y}{\partial k} = \frac{\partial g}{\partial k} - w > 0$ and $\frac{\partial x}{\partial k} = -w < 0$. The second derivatives of fertilizer use on outcomes are specified as follows: $\frac{\partial^2 x}{\partial k^2} = 0$, since the effect of fertilizer use is limited to a loss in the form of total costs of the input in a bad year. Continued use of fertilizer will have no effect on the outcome in a bad year. $\frac{\partial^2 y}{\partial k^2} = \frac{\partial^2 g}{\partial k^2} < 0$, suggesting that after a certain point, continued fertilizer application will result in crop damage, leading to a reduction in crop revenue.

In the presence of both losses and gains, the TCN utility function takes the following form:

$$U(k, \varepsilon) = \pi(p)(-\lambda)(wk)^{1-\sigma} + \pi(q)(g(k) - wk - g)^{1-\sigma}, \qquad (7)$$

where $\pi(w) = \exp[-(-\ln w)^{\alpha}],\ w = p, q$.

FOC with respect to fertilizer is defined as follows:

$$G' = \frac{\partial U}{\partial k} = -\pi(p)\lambda w(wk)^{-\sigma} + \pi(q)\left[\frac{\partial g}{\partial k} - w\right](g(k) - wk - g)^{-\sigma} = 0. \qquad (8)$$

We are interested in the effects of risk aversion, loss aversion, and non-linear probability weighting on fertilizer use. Using the implicit function theorem, we obtain $\frac{\partial k}{\partial \sigma}, \frac{\partial k}{\partial \lambda}$, and $\frac{\partial k}{\partial \alpha}$ (see Appendix B2 for details). With at least 50% chance of a good season in any given year and assuming that farmers use a non-trivial amount of fertilizer, the partial effect of risk aversion on fertilizer use is negative, $\frac{dk}{d\sigma} < 0$, suggesting that more risk averse farmers will use less fertilizer on their plots. Similarly, $\frac{dk}{d\lambda} < 0$ if the amount of fertilizer used is not absolutely miniscule. This result suggests that loss aversion will also lead to a reduction in fertilizer use. Finally, $\frac{\partial k}{\partial \alpha} > 0$, given that $p < q$, suggesting that farmers who underweigh small probabilities of a negative shock will use more fertilizer or, equivalently, farmers who overweigh small probability of drought/excessive rainfall will use less fertilizer (see Appendix B2 for the derivation of results). We therefore expect that fertilizer use will be decreasing in both risk aversion and loss aversion and increasing in non-linear probability weighting.

The degree to which differential effects of individual risk preferences affect household's agricultural decisions depends on intrahousehold dynamics. In our collective model, we assume that husband's and wife's utilities separately enter the household utility function, where wife's utility is discounted by the degree of her bargaining power in a household.

$$U = U_M(\sigma_M, \lambda_M,\ \alpha_M) + \mu U_F(\sigma_F, \lambda_F,\ \alpha_F) \quad (9)$$

In equation (9) above, U is the household utility, U_M and U_F are husband's and wife's respective utilities that are functions of their risk preferences, and μ is an indicator of bargaining power (empowerment) of a woman in a household. $0 \leq \mu \leq 1$, where $\mu = 0$ implies that a woman has no bargaining power in a household, and $\mu = 1$ implies that gender parity exists in a household's choices. If spouses have different preferences, the amount of wife's bargaining power will determine to what extent her preferences come through in the household decisions.

4.3 Empirical Model of Fertilizer Use

Using the theoretical model described in Section 4.2 and experimentally derived risk preferences of spouses from Chapter 2, we can now test whether both male and female preferences matter in household fertilizer use decisions using the empirical model in equation (10) below.

$$F_{jhr} = R_{hr}^{M}{}'\theta^{M} + R_{hr}^{F}{}'\theta^{F} + R_{hr}^{F} E_{hr}{}'\theta^{EMP} + \gamma E_{hr} + X_{jhr}{}'\delta + \eta_{r} + \varepsilon_{jhr} \qquad (10)$$

Here j stands for a plot, h denotes a household, and r denotes a region, respectively; F_{jhr} is the amount of fertilizer application in kg/acre used on a plot j; R_{hr}^{M} and R_{hr}^{F} are vectors of husband's and wife's risk preference variables $(\sigma, \lambda, \alpha)$, respectively; E_{hr} is a women's empowerment indicator over fertilizer purchase decisions in a household; X_{jhr} is a vector of individual, household, and plot characteristics, such as age, education, income, access to input markets and information indicator, previous drought/disease severity indicators, land holdings, soil type, crop type, subplot tenure, and quantity of manure owned by a household; η_{r} are region fixed effects; and ε_{jh} is the error term.

Table 11 contains summary statistics of independent variables (controls) in X_{jhr}. The controls include individual characteristics that differ for each subset of respondents (males in MHH, females in MHH, and females in FHH) and household and subplot level characteristics that only differ by household type (MHH vs. FHH). The individual characteristics include age and education. Females in FHH are 12 years older on average than males in MHH, and almost 15 years older than females in MHH. Males are more educated than females in MHH, and twice as educated as females in FHH. At a household level, MHH are bigger in size and have twice as much income as FHH. They also own more land and use more manure on their plots than FHH in the sample. FHH plant more field crops on their subplots. In terms of subplot tenure, 22% and 8% of subplots in our sample were identified as male and female controlled plots, respectively, and 70% were identified as jointly controlled.

Table 11. Summary Statistics of Explanatory Variables

Variables	Males in MHH		Females in MHH		Females in FHH	
N (Individual & Household Level)	143		143		35	
Age (years)	49.81	(13.56)	47.47	(13.02)	61.97	(13.08)
Education (years)	7.99	(3.25)	7.34	(3.27)	4.17	(3.75)
Household size	6.57	(2.82)	6.57	(2.82)	4.91	(3.45)
Non-farm Income (10,000 KSH)	6.10	(9.79)	6.10	(9.79)	2.95	(2.64)
No Input Market Access=1	0.30	(0.46)	0.30	(0.46)	0.40	(0.50)
Region (West=1)	0.60	(0.49)	0.60	(0.49)	0.74	(0.44)
Severe Drought Experience=1	0.24	(0.67)	0.24	(0.67)	0.17	(0.57)
Severe Crop Disease Experience=1	0.49	(0.82)	0.49	(0.82)	0.29	(0.71)
Female is Empowered = 1			0.38	(0.49)	1.00	(0.00)
N (Subplot Level)	818		818		154	
Land area - owned (hectares)	0.94	(1.01)	0.94	(1.01)	0.67	(0.72)
Fertile soil=1	0.20	(0.40)	0.20	(0.40)	0.13	(0.34)
Manure Use 1=Yes	0.34	(0.48)	0.34	(0.48)	0.23	(0.42)
Field Crop Subplot=1	0.47	(0.50)	0.47	(0.50)	0.62	(0.49)
Male Controlled Plot	0.22	(0.41)	0.22	(0.41)		
Female Controlled Plot	0.08	(0.28)	0.08	(0.28)	1.00	(0.00)
Jointly Controlled Plot	0.70	(0.46)	0.70	(0.46)		

Note: Mean coefficients; standard deviations are in parentheses.

Summary statistics of fertilizer use by subplot and household type are presented in Table 12. In MHH, more fertilizer was used on female controlled plots. The application rates of both types of fertilizers were similar on male and joint controlled subplots. More of DAP fertilizer was used on the subplots irrespective of subplot and household type. For comparison, Suri (2011) states that 60% of Kenyan farmers used fertilizers in 2004. Duflo (2008) provides a more conservative rate of 37% when analyzing fertilizer use by farming households in poor rural Busia district in Western Kenya. The application rates of either fertilizer type are well below recommended by Kenyan agricultural extension system 100 kg/acre rate (Ariga et al 2008). Households with male head used more of both kinds of fertilizer on their plots, compared to households with single female head. This can be expected, as females in FHH rely on one source of income, and therefore cannot afford to use as much or any fertilizer, compared to households where females are supported by the male head.

Table 12. Fertilizer Application by Subplot and Household Type

Fertilizer Application Rate/ Use	MHH					
	Male Controlled Plots	Female Controlled Plots	Jointly Managed Plots	All Plots	FHH	Total
Urea Use=1	0.49	0.55	0.55	0.54	0.33	0.51
	(0.50)	(0.50)	(0.50)	(0.50)	(0.47)	(0.50)
Urea Application Rate (kg/acre)	29.11	31.76	28.42	28.85	28.14	28.74
	(60.41)	(42.59)	(50.98)	(52.50)	(56.44)	(53.12)
DAP Use=1	0.78	0.80	0.74	0.75	0.62	0.73
	(0.42)	(0.41)	(0.44)	(0.43)	(0.49)	(0.44)
DAP Application Rate (kg/acre)	44.70	58.58	49.86	49.47	36.45	47.40
	(49.91)	(70.66)	(70.05)	(66.24)	(55.24)	(64.77)
Observations	179	69	570	818	154	972

Note: mean coefficients; sd in parentheses

The main coefficients of interest are θ^M, θ^F, and θ^{EMP}. θ^M is a vector of male risk preference parameters, and θ^F and $\theta^F + \theta^{EMP}$ are vectors of risk preference coefficients for disempowered and empowered women, respectively. We expect to see negative coefficients for male and female risk/loss aversion, stating that households with more risk/loss averse males and females will use less fertilizers. We also expect positive male and female non-linear probability weighting coefficients, meaning that households with males and females who tend to overweigh small probabilities of a negative shock will use less fertilizer. For households where a wife has bargaining power over fertilizer purchase decisions, we expect to see a much more prominent negative effects of risk aversion, loss aversion, and overweighing of small probabilities on fertilizer use.

In the empirical model in equation (7), E_{hr} is endogenous, as there are unobserved factors that can potentially affect both women bargaining power and fertilizer use. For example, women in more traditional households may not have much of bargaining power in a household's fertilizer choice decisions, and the same traditional households may also choose not to use fertilizer and maintain traditional agricultural practices. As such, E_h cannot have a causal interpretation. However, since we are primarily interested in the effect of the interaction of risk preferences and women's empowerment on fertilizer use, the endogeneity of the empowerment indicator itself is not of a great concern. Conditional on E_h, we can still estimate the influence of risk preference parameters on fertilizer use without bias caused by the endogeneity of the female empowerment indicator.

The estimation of fertilizer demand in developing countries is complicated by the fact that a large percentage of farmers do not use fertilizer (see Figures 5 and 6 below). The "excess zero" problem can be addressed with the estimation of a "two part" or "hurdle" models, proposed by Cragg (1971) that separate the participation decision from the amount (consumption) decision.

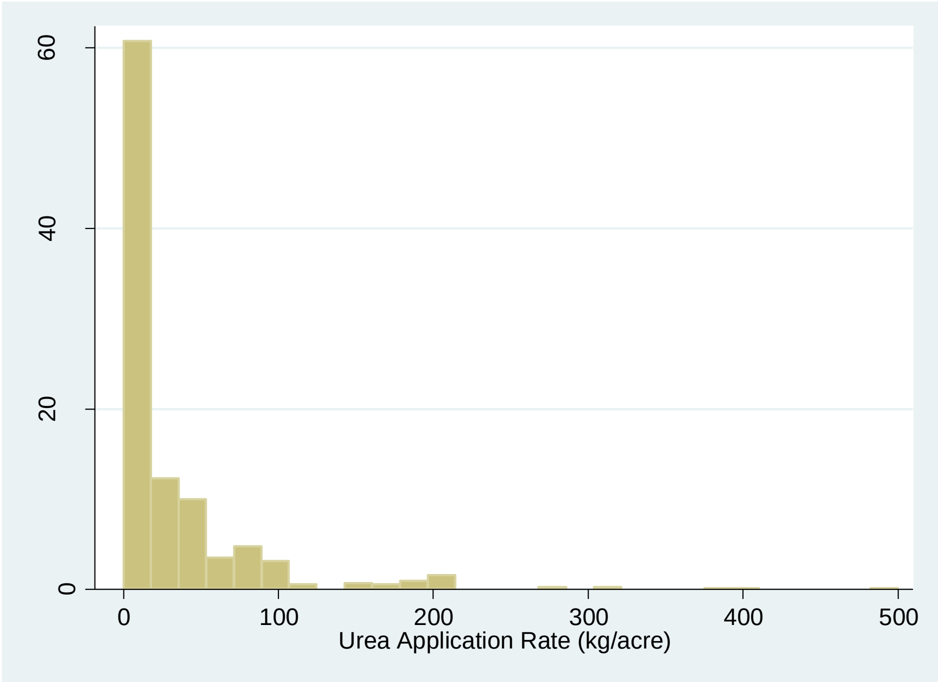

Figure 5. The Rate of Urea Application at a Subplot Level

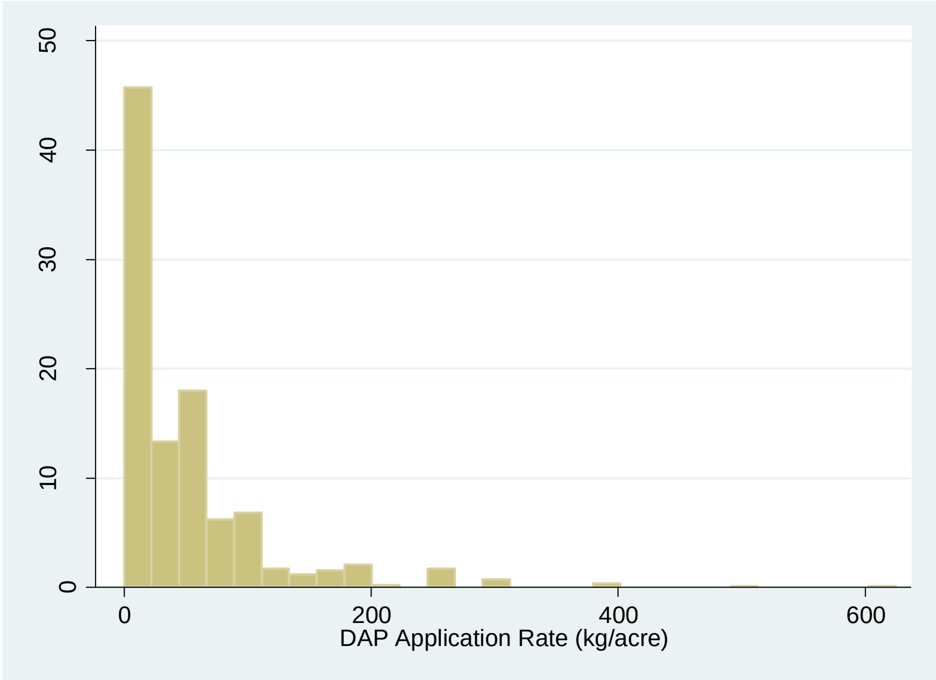

Figure 6. The Rate of DAP Application at a Subplot Level

Several studies have applied two-part model estimation in the analysis of fertilizer use (Coady 1995; Croppenstedt, Demeke, and Meschi 2003; Ricker-Gilbert, Jayne, and Chirwa 2011; McIntosh, Sarris, and Papadopoulos 2013; Yu and Nin-Pratt 2014).

Unlike the more restrictive Tobit Type I model, Cragg's model allows different factors to influence the participation and the consumption decisions. The estimation of Cragg's model proceeds in the following manner: first, a probit model is used to estimate the decision of farmers to buy fertilizer (participation decision), and then, the truncated normal model is used to estimate demand for fertilizer (Wooldridge 2010). In this study, we estimate a two part hurdle model such that the participation decision is a function of gender specific risk preferences, all the controls and the input market access constraint. While access to input market will affect households' choice to purchase fertilizer, it should have no effect on the amount of fertilizer applied on a plot by households that choose to purchase it. In our sample, 30% of MHH and 40% of FHH have no access to input market (see Table 11). The amount decision is therefore defined as a function of risk preferences and controls with the exception of input market constraint indicator.

4.4 Results

We now proceed with the estimation of the double hurdle model discussed above. We estimate the effects of risk preferences paired with female empowerment in fertilizer purchase decisions on Urea and DAP use. For each fertilizer type, we first estimate models with only male risk preferences (the first two columns), then male and female risk preferences (columns 3 and 4), and lastly male preferences and female risk preferences interacted with the female empowerment indicator (columns 5 and 6). Of particular interest are average partial effects (APEs[7]) of male risk preferences and female risk preferences interacted with empowerment indicator on each type of fertilizer use.[8] We then estimate models with only female preferences and other covariates in FHH as a comparison to the results of collective choices in MHH.

Tables 13 and 14 below contain the estimation of Hurdle 1 (purchase decision) and Hurdle 2 (amount or consumption decision) on Urea and DAP, respectively. In Table 13, the APE of male risk aversion coefficient (sigma) is negative and becomes significant in Hurdle 2, suggesting that households with more risk averse males use less Urea, given that they use fertilizers. When we incorporate female preferences in columns 3 and 4, we find that households with more risk averse females also use less Urea, given that they purchase it. However, the reduction in Urea use will be most likely driven by male risk aversion, as male risk aversion coefficient is twice larger in magnitude compared to a female coefficient. When we incorporate the female empowerment indicator in columns 5 and 6, we find that households with empowered more risk averse females are less likely to purchase Urea fertilizer. However, households with empowered more risk averse females will use more of Urea, given that they choose to purchase it. This result makes sense, since Urea is a less risky input compared to DAP, and one could expect households to use more of it if they decide to opt for using any fertilizer on their plots. Also, households, where more risk averse female is not empowered, use less Urea given that they choose to buy it. It may be that not empowered females use less fertilizer because they are less informed about its importance in improving yields and overall

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[7] APE measures the average effect of risk aversion (loss aversion or non-linear probability weighting) on the probability of a household choosing Urea (Dap) fertilizer (Hurdle 1) or on the amount of Urea (DAP) used by the household, given that the household chooses to purchase fertilizer (Hurdle 2).

[8] Tables 26, 27, and 28 in Appendix C2 contain APEs of controls listed in Table 11.

Table 13. Urea Use Models in MHH

	(1) Hurdle 1	(2) Hurdle 2	(3) Hurdle 1	(4) Hurdle 2	(5) Hurdle 1	(6) Hurdle 2
Male σ	-0.088	-0.822**	-0.088	-0.933**	-0.060	-0.877**
	(0.074)	(0.260)	(0.075)	(0.265)	(0.077)	(0.258)
Male λ	0.007	0.029	0.006	0.040**	0.007	0.020
	(0.006)	(0.018)	(0.006)	(0.020)	(0.006)	(0.020)
Male α	-0.031	0.104	-0.022	0.269	-0.022	-0.030
	(0.054)	(0.180)	(0.057)	(0.196)	(0.057)	(0.195)
No Input Market Access=1	0.058		0.051		0.049	
	(0.035)		(0.036)		(0.035)	
Female σ			0.028	-0.449**		
			(0.062)	(0.166)		
Female λ			-0.002	-0.054**		
			(0.005)	(0.018)		
Female α			-0.091*	-0.611**		
			(0.056)	(0.188)		
Empowered=1					0.389**	1.070**
					(0.142)	(0.398)
Emp. Female σ					-0.219**	0.706**
					(0.098)	(0.291)
Not Emp. Female σ					-0.103	-0.806**
					(0.072)	(0.237)
Emp. Female λ					-0.003	-0.143**
					(0.005)	(0.033)
Not Emp. Female λ					0.000	-0.039*
					(0.006)	(0.019)
Emp. Female α					-0.133**	-1.524**
					(0.040)	(0.299)
Not Emp. Female α					-0.018	-0.264
					(0.069)	(0.220)
LR Chi Square Statistic Ho: PT is not valid	2.12	3.79	4.76	14.63**	12.93*	33.11**
Observations	818	440	818	440	818	440

Note: σ, λ, α represent risk aversion, loss aversion, and non-linear probability weighting parameters, respectively; The coefficients are average partial effects (APEs); Bootstrapped standard errors in parentheses (1000 replications); Significant at *10%, **5%; All models include controls listed in Table 11; APEs of controls are provided in Table 26 in Appendix C2.

health of their crops. They might not believe that fertilizers work and thus avoid using more of them.

APE of male loss aversion coefficient is positive but close to 0 and significant when female risk preferences are included in the estimation in column 4, suggesting that households with more loss averse male farmers use more of Urea, assuming they choose to make the purchase. When we include female risk preferences in the estimation (columns 3 and 4), we find a negative and statistically significant APE of female loss aversion in Hurdle 2. This result suggests that fertilizer adopting households with more loss averse females will use less Urea to minimize potential loss of income if drought or disease damages their crops. Lastly, when we incorporate female empowerment into the model (columns 5 and 6), we find that households with both empowered and not empowered more loss averse females use less Urea. However, the size of the coefficient of not empowered females is close to 0 and is much smaller in magnitude, suggesting that households with empowered more loss averse females reduce their use of Urea fertilizer by a much greater extent.

Non-linear probability weighing coefficient is negative and significant for females in both hurdles, suggesting that households with females who tend to overweigh small probabilities of a negative shock are more likely to purchase Urea and use more of it. Similarly, the coefficient for empowered female alpha is negative and significant in both hurdles, suggesting that households with empowered females who tend to overweigh small probabilities of a negative shock will use more Urea. It is possible that households with females that overweigh small probabilities of drought buy Urea, as it is a safer input due to timing of its application later in the season.

Table 14. DAP Use Models in MHH

	(1) Hurdle 1	(2) Hurdle 2	(3) Hurdle 1	(4) Hurdle 2	(5) Hurdle 1	(6) Hurdle 2
Male σ	-0.026	-0.375**	-0.012	-0.383**	-0.035	-0.359**
	(0.067)	(0.156)	(0.066)	(0.152)	(0.072)	(0.150)
Male λ	-0.015**	-0.004	-0.015**	0.002	-0.016**	-0.005
	(0.005)	(0.013)	(0.006)	(0.013)	(0.006)	(0.013)
Male α	0.023	-0.154	0.019	-0.177	0.004	-0.234
	(0.051)	(0.121)	(0.053)	(0.127)	(0.056)	(0.124)
No Input Marker Access=1	-0.060**		-0.062*		-0.073**	
	(0.032)		(0.034)		(0.036)	
Female σ			0.017	-0.134		
			(0.056)	(0.114)		
Female λ			0.006	-0.003		
			(0.005)	(0.010)		
Female α			-0.101*	-0.046		
			(0.056)	(0.127)		
Empowered=1					0.174	1.023**
					(0.139)	(0.298)
Emp. Female σ					0.045	-0.144
					(0.146)	(0.216)
Not Emp. Female σ					0.036	-0.043
					(0.083)	(0.142)
Emp. Female λ					0.018	-0.029*
					(0.010)	(0.018)
Not Emp. Female λ					-0.001	0.004
					(0.006)	(0.013)
Emp. Female α					-0.149**	-0.563**
					(0.059)	(0.239)
Not Emp. Female α					-0.039	0.199
					(0.074)	(0.134)
LR Chi Square Statistic Ho: PT is not valid	8.61**	6.89**	12.87**	10.55**	19.46**	17.33**
Observations	818	613	818	613	818	613

Note: σ, λ, α represent risk aversion, loss aversion, and non-linear probability weighting parameters, respectively; The coefficients are average partial effects (APEs); Bootstrapped standard errors in parentheses (1000 replications); Significant at *10%, **5%; All models include controls listed in Table 11; APEs of controls are provided in Table 27 in Appendix C2.

In Table 14 above, the APE of male risk aversion coefficient is negative and significant in Hurdle 2 irrespective of the inclusion of female risk preferences, suggesting that households with more risk averse males will use less of DAP fertilizer, given that they choose to purchase it. Female risk aversion coefficient is close to 0 in Hurdle 1 and negative in Hurdle 2 but not significant irrespective of female empowerment. Male loss aversion parameter is negative and significant in Hurdle 1, implying that MHH with males that are more averse to loss are less likely to buy a riskier DAP fertilizer. When female preferences are included in columns 3 and 4, we get negative coefficient of male loss aversion, suggesting that households with more loss averse males are less likely to purchase DAP. Female coefficients are close to 0 and not significant in either hurdle. Finally, when we consider female empowerment in columns 5 and 6, the coefficient of male loss aversion is negative and significant in Hurdle 1 and female loss aversion is negative and significant in Hurdle 2, suggesting that MHH with more loss averse males are less likely to purchase DAP and households with empowered more loss averse females that buy DAP will use it less.

Similarly to results in Table 13, non-linear probability weighing coefficient is negative and significant for females irrespective of empowerment, suggesting that MHH with females that overweigh small probabilities of a negative shock will use more DAP. This is an unexpected result, given the riskier nature of DAP application.

The results of the hurdle model estimation for FHH are presented in Table 15 below. The APE of female risk aversion is negative and significant in Hurdle 2, suggesting that more risk averse female heads will use less of either type of fertilizer, if they choose to purchase it. The coefficient of loss aversion is negative and significant in both hurdles for Urea and DAP fertilizers. More loss averse females in FHH are less likely to buy either fertilizer and will use less of either type, if they choose to invest in these inputs. Finally, non-linear probability weighing coefficient is positive and significant in column 4, suggesting that FHH that tend to overweigh small probabilities of a negative shock will reduce DAP use, given that they decide to buy it. These results support our proposition that more income and credit constrained FHH will be less likely to invest in fertilizers.

Table 15. Fertilizer Use Models in FHH

	Urea		DAP	
	Hurdle 1	Hurdle 2	Hurdle 1	Hurdle 2
Female σ	0. 082	-6.061*	-0.655	-0.705**
	(0.54)	(3.51)	(1.03)	(0.02)
Female λ	-0.006*	-0.475**	-0.043**	-0.018**
	(0.00)	(0.16)	(0.02)	(0.00)
Female α	-0.035	-0.925	-0.112	0.058**
	(0.17)	(0.84)	(0.24)	(0.01)
No Input Market Access=1	-0.158		0.127	
	(0.16)		(0.29)	
LR Chi Square Statistics Ho: PT is not valid	0.34	1.40	9.27**	10.12**
Observations	154	51	154	96

Note: σ, λ, α represent risk aversion, loss aversion, and non-linear probability weighting parameters, respectively; The coefficients are average partial effects (APEs); Bootstrapped standard errors in parentheses (1000 replications); Significant at *10%, **5%; All models include controls listed in Table 11 with the exception of Subplot Control Type and Empowerment indicators; APEs of controls are provided in Table 28 in Appendix C2.

Overall, we find that while male risk preferences matter greatly in fertilizer purchase and amount decisions, the significance of female risk preferences cannot be ignored. In addition, we find that female attitudes towards risk matter greatly when a female is a household head. Our findings validate the use of the collective household model for the analysis of fertilizer use by farming households in Kenya.

CHAPTER 5

CONCLUSIONS

The use of agricultural technologies, such as improved maize varieties and fertilizers, by farmers in the developing world plays an important role in improving agricultural yields. African farmers tend to underuse these agricultural inputs on their plots. Improved seeds and fertilizers are risky and expensive inputs. Farmers' attitudes towards risk often interfere with the adoption of agricultural technologies. Male and female farmers are known to have distinct risk preferences. It is important to consider how male and female risk preferences shape households' agricultural production choices. In this dissertation project, we investigate how risk preferences of a husband and wife in a household affect the household's decision to use agricultural inputs.

Using experimental data, we elicit PT risk preferences - such as risk aversion, loss aversion, and non-linear probability weighting parameters - for both spouses in a collective household. Depending on the family dynamics, female risk preferences can play a greater role in households' choices, resulting in a lower use of risky inputs. We propose a collective household model to estimate the effects of gender-specific risk preferences accounting for women's relative bargaining power in a household on the seed choice in Tanzania and fertilizer use in Kenya. We show that risk attitudes of empowered females adversely affect households' use of hybrid seeds and fertilizers.

When investigating improved maize adoption by Tanzanian farming households, we find that male risk attitudes negatively affect the use of improved seeds due to both risk of new seeds not working and environmental risk, whereas female risk attitudes negatively affect use of hybrids mainly via environmental risk. Households with males who overweigh small probabilities of new improved seeds underperformance are less likely to purchase these seeds. In households that choose to invest in new technologies, male loss aversion decreases the use of hybrids. Households with more loss averse household heads opt for using more affordable types of seeds, such as IOPVs, to avoid higher losses in the event of a drought or severe plant disease. When we account for female empowerment in the estimation of seed choice, we find that households with empowered females who are more risk averse and prone to overweighing of a small probability of drought use less hybrids, given that they opt for improved seeds. Indeed, female risk aversion and non-linear probability weighting have a far greater effect on the use of hybrids than male risk aversion and non-linear probability weighting.

When investigating fertilizer use by farming households in Kenya, we find that fertilizer adopting households with more risk averse males use less of both DAP and Urea fertilizers. We also find that male loss aversion decreases DAP, but not Urea application, suggesting that households with more loss averse household heads opt for using more affordable fertilizer to avoid higher losses in the event of a negative environmental shock. Female risk/loss aversion reduces the use of Urea in households that use this fertilizer.

When we consider the degree of female empowerment over fertilizer purchase decisions in a household, we find that households with empowered females who are more risk averse will try to avoid using Urea. However, if they decide to invest in this input, these households will increase the amount of Urea application, as opposed to households where a wife has little input in these decisions. It is possible that empowered females have a better understanding of risk reducing properties of Urea, such as lower costs and later timing of application, than disempowered females. Loss aversion of empowered females will result in a lower use of either type of fertilizer in fertilizer adopting households, suggesting that fear of a potential loss of income overweighs the knowledge and understanding of benefits associated with using these inputs. In Kenyan FHH, we find that more loss averse female heads are less likely to purchase either fertilizer. Also, more risk and loss averse females in fertilizer adopting FHH will reduce their use of fertilizers. Being the only bread winners in their households, female heads seem to avoid using any risky inputs.

Our findings suggest that female preferences matter when it comes to agricultural input choices. Therefore, when promoting the use of agricultural technologies, the best strategy is to focus the extension and training services on both male and female farmers. Educating female farmers, and not only their spouses, about the benefits of the use of improved seeds and fertilizers is necessary to increase the use of these technologies by households in Tanzania and Kenya. Although our study is limited to the analysis of agricultural choices of spouses, we believe it is important to consider women's preferences in household's choices in general. This will be an interesting undertaking for future research with more context oriented experiments performed in a natural setting with real life outcomes at stake.

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APPENDICES

APPENDIX A: RISK EXPERIMENT SERIES

A1. Tanzania Risk Experiment Series

Table 16. Prospect Theory Series 1 (TSH)

Task	Starting Point	Option A	Option B	**How to search for switch point**
1		1650 if [1][2][3][4][5][6][7] 6550 if [8][9][10]	800 if [1][2][3][4][5][6][7][8][9] 13700 if [10]	
2		1650 if [1][2][3][4][5][6][7] 6550 if [8][9][10]	800 if [1][2][3][4][5][6][7][8][9] 15400 if [10]	
3		1650 if [1][2][3][4][5][6][7] 6550 if [8][9][10]	800 if [1][2][3][4][5][6][7][8][9] 17500 if [10]	If **Option A** is chosen, move **DOWN** the table. If **Option B** is chosen, move **UP** the table.
4		1650 if [1][2][3][4][5][6][7] 6550 if [8][9][10]	800 if [1][2][3][4][5][6][7][8][9] 20600 if [10]	
5		1650 if [1][2][3][4][5][6][7] 6550 if [8][9][10]	800 if [1][2][3][4][5][6][7][8][9] 24600 if [10]	
6		1650 if [1][2][3][4][5][6][7] 6550 if [8][9][10]	800 if [1][2][3][4][5][6][7][8][9] 30200 if [10]	
7		1650 if [1][2][3][4][5][6][7] 6550 if [8][9][10]	800 if [1][2][3][4][5][6][7][8][9] 36200 if [10]	
8		1650 if [1][2][3][4][5][6][7] 6550 if [8][9][10]	800 if [1][2][3][4][5][6][7][8][9] 49400 if [10]	
9		1650 if [1][2][3][4][5][6][7] 6550 if [8][9][10]	800 if [1][2][3][4][5][6][7][8][9] 65800 if [10]	
10		1650 if [1][2][3][4][5][6][7] 6550 if [8][9][10]	800 if [1][2][3][4][5][6][7][8][9] 98700 if [10]	

Table 17. Prospect Theory Series 2 (TSH)

Task	Starting Point	Option A	Option B	**How to search for switch point**
1		4950 if [1] 6550 if [2][3][4][5][6][7][8][9][10]	800 if [1][2][3] 8800 if [4][5][6][7][8][9][10]	
2		4950 if [1] 6550 if [2][3][4][5][6][7][8][9][10]	800 if [1][2][3] 9000 if [4][5][6][7][8][9][10]	
3		4950 if [1] 6550 if [2][3][4][5][6][7][8][9][10]	800 if [1][2][3] 9400 if [4][5][6][7][8][9][10]	If **Option A** is chosen, move **DOWN** the table. If **Option B** is chosen, move **UP** the table.
4		4950 if [1] 6550 if [2][3][4][5][6][7][8][9][10]	800 if [1][2][3] 9800 if [4][5][6][7][8][9][10]	
5		4950 if [1] 6550 if [2][3][4][5][6][7][8][9][10]	800 if [1][2][3] 10400 if [4][5][6][7][8][9][10]	
6		4950 if [1] 6550 if [2][3][4][5][6][7][8][9][10]	800 if [1][2][3] 11000 if [4][5][6][7][8][9][10]	
7		4950 if [1] 6550 if [2][3][4][5][6][7][8][9][10]	800 if [1][2][3] 12100 if [4][5][6][7][8][9][10]	
8		4950 if [1] 6550 if [2][3][4][5][6][7][8][9][10]	800 if [1][2][3] 13100 if [4][5][6][7][8][9][10]	
9		4950 if [1] 6550 if [2][3][4][5][6][7][8][9][10]	800 if [1][2][3] 14800 if [4][5][6][7][8][9][10]	
10		4950 if [1] 6550 if [2][3][4][5][6][7][8][9][10]	800 if [1][2][3] 16500 if [4][5][6][7][8][9][10]	

Table 18. Prospect Theory Series 3 (TSH)

Task	Starting Point	Option A	Option B	**How to search for switch point**
1		3400 if [1][2][3][4][5] -550 if [6][7][8][9][10]	4100 if [1][2][3][4][5] -2900 if [6][7][8][9][10]	
2		550 if [1][2][3][4][5] -550 if [6][7][8][9][10]	4100 if [1][2][3][4][5] -2900 if [6][7][8][9][10]	If **Option A** is chosen, move **DOWN** the table. If **Option B** is chosen, move **UP** the table.
3		150 if [1][2][3][4][5] -550 if [6][7][8][9][10]	4100 if [1][2][3][4][5] -2900 if [6][7][8][9][10]	
4		150 if [1][2][3][4][5] -550 if [6][7][8][9][10]	4100 if [1][2][3][4][5] -2200 if [6][7][8][9][10]	
5		150 if [1][2][3][4][5] -1100 if [6][7][8][9][10]	4100 if [1][2][3][4][5] -2200 if [6][7][8][9][10]	
6		150 if [1][2][3][4][5] -1100 if [6][7][8][9][10]	4100 if [1][2][3][4][5] -1900 if [6][7][8][9][10]	
7		150 if [1][2][3][4][5] -1100 if [6][7][8][9][10]	4100 if [1][2][3][4][5] -1500 if [6][7][8][9][10]	

A2. Kenya Risk Experiment Series

Table 19. Prospect Theory Series 1 (KSH)

Task	Starting Point	Option A	Option B	**How to search for switch point**
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	If **Option A** is chosen, move **DOWN** the table. If **Option B** is chosen, move **UP** the table.
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 20. Prospect Theory Series 2 (KSH)

Task	Starting Point	Option A	Option B	**How to search for switch point**
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]	If **Option A** is chosen, move **DOWN** the table. If **Option B** is chosen, move **UP** the table.
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 21. Prospect Theory Series 3 (KSH)

Task	Starting Point	Option A	Option B	**How to search for switch point**
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]	If **Option A** is chosen, move **DOWN** the table. If **Option B** is chosen, move **UP** the table.
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]	

A3. Correlation in Spousal Risk Preferences

Table 22. Correlation in Spousal Risk Preferences in Tanzanian Households

	Female σ	Female λ	Female α	Male σ	Male λ	Male α
Female σ	1					
Female λ	0.224	1				
Female α	-0.218	-0.056	1			
Male σ	-0.015	0.172	0.055	1		
Male λ	-0.069	0.125	0.048	0.067	1	
Male α	0.065	-0.038	0.015	-0.445	0.020	1

Table 23. Correlation in Spousal Risk Preferences in Kenyan Households

	Female σ	Female λ	Female α	Male σ	Male λ	Male α
Female σ	1					
Female λ	0.202	1				
Female α	-0.202	0.016	1			
Male σ	0.016	0.062	-0.111	1		
Male λ	0.103	0.079	-0.046	0.299	1	
Male α	-0.072	0.176	0.133	-0.222	-0.156	1

APPENDIX B: THEORETICAL MODEL DERIVATIONS

B1. Seed Choice Model Partial Effects Derivation

TCN Utility function:

$$U(k,\varepsilon) = \pi(p)(-\lambda)(wk)^{1-\sigma} + \pi(q)(g(k) - wk - g)^{1-\sigma}$$

1. Risk Aversion

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

where $x < 0$ and $y > 0, q > p > 0$, and $\pi(w) = \exp[-(-\ln w)^{\alpha}]$, $w = p, q$. In this case, the first part of the derivative is positive and the second part is negative. Therefore, to get $\frac{\partial U}{\partial \sigma} < 0,$ it must be that $\pi(q)(-(y^{1-\sigma}))lny > \lambda\pi(p)((-x)^{1-\sigma})\ln(-x)$. Assuming $\lambda = 1$, for an equal size gain and loss ($|x = y|$), we have that $|\pi(q) > \pi(p)|$, which is true, since the probability of new seeds not working as expected in stage 1 (or the probability of a bad season in stage 2) is much smaller than the probability that new seeds perform well in stage 1 (or the probability of a normal season in stage 2).

2. Loss Aversion

$$\frac{\partial U}{\partial \lambda} = -\pi(p)(-x)^{1-\sigma} < 0,$$

given that $x < 0$.

3. Non-linear Probability Weighting

$$\frac{\partial U}{\partial \alpha} = -\lambda(-x)^{1-\sigma}(\ln(-lnp))(-\exp(-(-lnp)^{\alpha}))(-lnp)^{\alpha} + y^{1-\sigma}(\ln(-lnq))(-\exp(-(-lnq)^{\alpha}))(-lnq)^{\alpha},$$

where $x < 0$ and $y > 0, q > p > 0$. In this case, both parts of the derivative are positive, given that a probability of new seeds not working (stage 1) or the probability of a bad season (stage 2), p, is much smaller than probability of seeds working well (stage 1) or probability of a good season (stage 2), $q,$ s.t. $(\ln(-lnq))(-\exp(-(-lnq)^{\alpha}))(-lnq)^{\alpha} > 0 > (\ln(-lnp))(-\exp(-(-lnp)^{\alpha}))(-lnp)^{\alpha}$. Therefore, $\frac{\partial U}{\partial \alpha} > 0$.

B2. Fertilizer Use Model Partial Effects Derivation

TCN Utility function:

$$U(k,\varepsilon) = \pi(p)(-\lambda)(wk)^{1-\sigma} + \pi(q)(g(k) - wk - g)^{1-\sigma}$$

Taking FOC w.r.t. fertilizer, we obtain:

$$G' = -\pi(p)\lambda w(wk)^{-\sigma} + \pi(q)\left[\frac{\partial g}{\partial k} - w\right](g(k) - wk - g)^{-\sigma} = 0,$$

Thus, $\pi(p)\lambda w(wk)^{-\sigma} = \pi(q)\left[\frac{\partial g}{\partial k} - w\right](g(k) - wk - g)^{-\sigma}$.

Using the implicit function theorem we can derive $\frac{dk}{dx} = -\frac{\frac{\partial G\prime}{\partial x}}{\frac{\partial G\prime}{\partial k}}$, where $x = \sigma, \lambda, \alpha$.

1. Derivation of $\frac{dk}{d\sigma}$:

$$\frac{\partial G'}{\partial \sigma} = -\pi(p)\lambda w[-(wk)^{-\sigma}\log(wk)] + \pi(q)\left[\frac{\partial g}{\partial k} - w\right][-(g(k) - wk - g)^{-\sigma}\log(g(k) - wk - g)],$$

$$\frac{\partial G'}{\partial \sigma} = \pi(p)\lambda w(wk)^{-\sigma}\log(wk) - \pi(q)\left[\frac{\partial g}{\partial k} - w\right](g(k) - wk - g)^{-\sigma}\log(g(k) - wk - g).$$

In the above expression, the first term is positive, while the second term is negative.

$$\frac{\partial G'}{\partial k} = \pi(p)\lambda\sigma w^2(wk)^{-\sigma-1} + \pi(q)\left(\frac{\partial^2 g}{\partial k^2}(g(k) - wk - g)^{-\sigma} - \sigma(g(k) - wk - g)^{-\sigma-1}\left[\frac{\partial g}{\partial k} - w\right]^2\right).$$

In the above expression, the first term is positive, while the second term is negative.

$$\frac{\partial k}{\partial \sigma} = -\frac{\pi(p)\lambda w(wk)^{-\sigma}\ln(wk) - \pi(q)\left[\frac{\partial g}{\partial k} - w\right](g(k) - wk - g)^{-\sigma}\ln(g(k) - wk - g)}{\pi(p)\lambda w(wk)^{-\sigma}\sigma(k)^{-1} + \pi(q)\left(\frac{\partial^2 g}{\partial k^2}(g(k) - wk - g)^{-\sigma} - \sigma(g(k) - wk - g)^{-\sigma-1}\left[\frac{\partial g}{\partial k} - w\right]^2\right)}.$$

2. Derivation of $\frac{dk}{d\lambda}$:

$$\frac{\partial G'}{\partial \lambda} = -\pi(p)w(wk)^{-\sigma} < 0,$$

$$\frac{\partial k}{\partial \lambda} = \frac{\pi(p)w(wk)^{-\sigma}}{\pi(p)\lambda w(wk)^{-\sigma}\sigma(k)^{-1} + \pi(q)\left(\frac{\partial^2 g}{\partial k^2}(g(k) - wk - g)^{-\sigma} - \sigma(g(k) - wk - g)^{-\sigma-1}\left[\frac{\partial g}{\partial k} - w\right]^2\right)}.$$

For $\frac{dk}{d\lambda} < 0$ it must be that:

$$\frac{\partial G'}{\partial k} = \pi(p)\lambda\sigma w^2(wk)^{-\sigma-1} + \pi(q)\left(\frac{\partial^2 g}{\partial k^2}(g(k) - wk - g)^{-\sigma} - \sigma(g(k) - wk - g)^{-\sigma-1}\left[\frac{\partial g}{\partial k} - w\right]^2\right)$$

$$< 0,$$

Which means that for $\frac{dk}{d\sigma} < 0$ it must be that:

$$\frac{\partial G'}{\partial \sigma} = \pi(p)\lambda w(wk)^{-\sigma}\log(wk) - \pi(q)\left[\frac{\partial g}{\partial k} - w\right](g(k) - wk - g)^{-\sigma}\log(g(k) - wk - g) < 0.$$

Using the equality condition from the FOC, we get:

$$\frac{\partial G'}{\partial \sigma} < 0 \; if \; \pi(p)\lambda w(wk)^{-\sigma}\log(wk) - \pi(p)\lambda w(wk)^{-\sigma}\log(g(k) - wk - g) < 0,$$

$$\frac{\partial G'}{\partial \sigma} < 0 \; if \; \log(wk) - \log(g(k) - wk - g) < 0,$$

$$\frac{\partial G'}{\partial \sigma} < 0 \; if \; g(k) - wk - g > wk,$$

$\frac{\partial G'}{\partial \sigma} < 0 \; if \; g(k) - g > 2wk$ or, equivalently, $\frac{\partial G'}{\partial \sigma} < 0 \; if \; \frac{1}{2}(g(k) - g) > wk.$

A risk averse farmer will use fertilizer if the expected value of fertilizer use is $EV(k) > 0$:

$$EV(k) = qy + px = q(g(k) - wk - g) + (1 - q)(-wk) = q(g(k) - g) - wk,$$

where $p + q = 1$ and $p = 1 - q$ is a probability of a negative shock.

Given that $EV(k) > 0$, it must be that $q(g(k) - g) > wk$. Since normal seasons are more prevalent than seasons of drought or excessive rainfall, one can expect $q > p$. As long as the probability of a good season is above 50%, i.e. $q > \frac{1}{2}$, then $\frac{\partial G'}{\partial \sigma} < 0$.

Using the equality condition from the FOC, we get:

$$\frac{\partial G'}{\partial k} = \pi(p)\lambda w(wk)^{-\sigma}\sigma(k)^{-1} + \pi(q)\left(\frac{\partial^2 g}{\partial k^2}(g(k) - wk - g)^{-\sigma} - \sigma(g(k) - wk - g)^{-\sigma-1}\left[\frac{\partial g}{\partial k} - w\right]^2\right)$$

$$< 0,$$

$$\frac{\partial G'}{\partial k} = \pi(q)\left[\frac{\partial g}{\partial k} - w\right](g(k) - wk - g)^{-\sigma}\sigma(k)^{-1}$$

$$- \pi(q)\left(-\frac{\partial^2 g}{\partial k^2}(g(k) - wk - g)^{-\sigma} + \sigma(g(k) - wk - g)^{-\sigma-1}\left[\frac{\partial g}{\partial k} - w\right]^2\right) < 0,$$

$$\frac{\partial G'}{\partial k} < 0 \; if \; \left[\frac{\partial g}{\partial k} - w\right](g(k) - wk)^{-\sigma}\sigma(k)^{-1}$$

$$-\left(-\frac{\partial^2 g}{\partial k^2}(g(k) - wk - g)^{-\sigma}\right.$$

$$\left. + \sigma(g(k) - wk - g)^{-1}\sigma(g(k) - wk - g)^{-\sigma}\left[\frac{\partial g}{\partial k} - w\right]^2\right) < 0,$$

$$\frac{\partial G'}{\partial k} < 0 \; if \; \left[\frac{\partial g}{\partial k} - w\right](g(k) - wk - g)^{-\sigma}\sigma(k)^{-1}$$

$$- (g(k) - wk - g)^{-\sigma}\left(-\frac{\partial^2 g}{\partial k^2} + \sigma(g(k) - wk - g)^{-1}\left[\frac{\partial g}{\partial k} - w\right]^2\right) < 0,$$

$$\frac{\partial G'}{\partial k} < 0 \; if \; \left[\frac{\partial g}{\partial k} - w\right]\sigma(k)^{-1} - \left(-\frac{\partial^2 g}{\partial k^2} + \sigma(g(k) - wk - g)^{-1}\left[\frac{\partial g}{\partial k} - w\right]^2\right) < 0,$$

$$\frac{\partial G'}{\partial k} < 0 \; if \; \left[\frac{\partial g}{\partial k} - w\right]\sigma(k)^{-1} - \left[\frac{\partial g}{\partial k} - w\right]\left(-\frac{\frac{\partial^2 g}{\partial k^2}}{\left[\frac{\partial g}{\partial k} - w\right]} + \sigma(g(k) - wk - g)^{-1}\left[\frac{\partial g}{\partial k} - w\right]\right) < 0,$$

$$\frac{\partial G'}{\partial k} < 0 \; if \; k^{-1} < \left(-\frac{\frac{\partial^2 g}{\partial k^2}}{\sigma\left[\frac{\partial g}{\partial k} - w\right]} + (g(k) - wk - g)^{-1}\left[\frac{\partial g}{\partial k} - w\right]\right).$$

Unless k is absolutely miniscule then $\frac{\partial G\prime}{\partial k} < 0$. Therefore, $\frac{dk}{d\sigma} < 0 |\ q > \frac{1}{2}, k$ is not tiny and $\frac{dk}{d\lambda} < 0 |\ k$ is not miniscule.

3. Derivation of $\frac{dk}{d\alpha}$:

$$\frac{\partial G'}{\partial \alpha} = \pi(p)\ln(-\ln(p))(-\ln(p))^{\alpha}\lambda w(wk)^{-\sigma}$$

$$- \pi(q)\ln(-\ln(q))(-\ln(q))^{\alpha}\left[\frac{\partial g}{\partial k} - w\right](g(k) - wk - g)^{-\sigma},$$

$$\frac{\partial k}{\partial \alpha} = -\frac{\pi(p)\ln(-\ln(p))(-\ln(p))^{\alpha}\lambda w(wk)^{-\sigma} - \pi(q)\ln(-\ln(q))(-\ln(q))^{\alpha}\left[\frac{\partial g}{\partial k} - w\right](g(k) - wk - g)^{-\sigma}}{\pi(p)\lambda w(wk)^{-\sigma}\sigma(k)^{-1} + \pi(q)\left(\frac{\partial^2 g}{\partial k^2}(g(k) - wk - g)^{-\sigma} - \sigma(g(k) - wk - g)^{-\sigma-1}\left[\frac{\partial g}{\partial k} - w\right]^2\right)}.$$

Using the equality condition from the FOC, we get:

$$\frac{\partial G'}{\partial \alpha} = \pi(q)\left[\frac{\partial g}{\partial k} - w\right](g(k) - wk - g)^{-\sigma}[\ln(-\ln(p))(-\ln(p))^{\alpha} - \ln(-\ln(q))(-\ln(q))^{\alpha}].$$

Given that $p < q$, $\frac{\partial G\prime}{\partial \alpha} > 0$, and thus $\frac{\partial k}{\partial \alpha} > 0$.

APPENDIX C: SUPPLIMENTAL MODEL ESTIMATION RESULTS

C1. Supplemental Seed Choice Modeling Results

Table 24. Seed Choice Unitary Model Estimation: Effects of Controls

VARIABLES	(1) Transition 1	(2) Transition 2	(3) Transition 1	(4) Transition 2	(5) Transition 1	(6) Transition 2
Male Age	0.002	-0.004				
	(0.003)	(0.004)				
Male Education	0.032**	0.016				
	(0.015)	(0.017)				
Female Age			0.004	-0.001	0.005	-0.003
			(0.004)	(0.005)	(0.004)	(0.005)
Female Education			0.019	0.005	0.015	0.001
			(0.016)	(0.022)	(0.016)	(0.021)
Household Size	-0.012	0.077***	-0.019	0.066***	-0.020	0.081***
	(0.014)	(0.017)	(0.017)	(0.018)	(0.015)	(0.017)
Non-Farm Income	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Land Holdings	0.002	-0.006	-0.003	-0.007	-0.003	-0.006
	(0.007)	(0.010)	(0.009)	(0.015)	(0.009)	(0.016)
Fertile Soil	0.065	0.010	0.045	-0.059	0.051	-0.062
	(0.074)	(0.087)	(0.080)	(0.085)	(0.077)	(0.084)
Male Controlled Plot	-0.029	0.029	0.015	0.054	0.056	0.002
	(0.088)	(0.099)	(0.084)	(0.102)	(0.086)	(0.093)
Female Controlled Plot	-0.056	0.048	-0.048	0.124	-0.013	0.151
	(0.154)	(0.219)	(0.188)	(0.193)	(0.169)	(0.184)
Observations	382	277	382	277	382	277

Note: APEs and standard errors in parenthesis; Significant at *10%, **5%, ***1%.

Table 25. Seed Choice Collective Model Estimation: Effects of Controls

VARIABLES	(1) Transition 1	(2) Transition 2	(3) Transition 1	(4) Transition 2
Male Age	-0.005	-0.017***	-0.007	-0.019***
	(0.006)	(0.006)	(0.006)	(0.006)
Male Education	0.030**	0.009	0.031**	0.012
	(0.015)	(0.017)	(0.015)	(0.015)
Female Age	0.010	0.017**	0.012*	0.017**
	(0.008)	(0.008)	(0.007)	(0.008)
Female Education	0.002	-0.001	-0.001	-0.002
	(0.017)	(0.022)	(0.017)	(0.020)
Household Size	-0.010	0.076***	-0.011	0.094***
	(0.015)	(0.017)	(0.015)	(0.015)
Non-Farm Income	0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Land Holdings	0.002	-0.004	0.001	-0.001
	(0.008)	(0.011)	(0.008)	(0.014)
Fertile Soil	0.075	-0.023	0.083	-0.030
	(0.074)	(0.084)	(0.071)	(0.076)
Male Controlled Plot	-0.034	0.009	0.015	-0.038
	(0.081)	(0.100)	(0.087)	(0.089)
Female Controlled Plot	-0.084	0.027	-0.038	0.036
	(0.150)	(0.196)	(0.133)	(0.178)
Observations	382	277	382	277

Note: APEs and standard errors in parenthesis; Significant at *10%, **5%, ***1%.

C2. Supplemental Fertilizer Use Modeling Results

Table 26. Urea Use Models in MHH: Effects of Controls

VARIABLES	(1) Hurdle 1	(2) Hurdle 2	(3) Hurdle 1	(4) Hurdle 2	(5) Hurdle 1	(6) Hurdle 2
Male Age	-0.003**	-0.007	-0.002	-0.010	-0.002	-0.011
	(0.001)	(0.006)	(0.002)	(0.008)	(0.002)	(0.008)
Male Education	0.016***	0.078***	0.018***	0.089***	0.016**	0.100***
	(0.006)	(0.022)	(0.007)	(0.026)	(0.007)	(0.026)
Female Age			-0.003	0.000	-0.002	0.004
			(0.002)	(0.008)	(0.002)	(0.008)
Female Education			-0.006	-0.029	-0.004	-0.036
			(0.006)	(0.025)	(0.007)	(0.025)
Household Size	0.002	0.017	-0.000	0.004	-0.000	0.006
	(0.007)	(0.027)	(0.007)	(0.028)	(0.007)	(0.027)
Non-farm Income	-0.004*	-0.020***	-0.003	-0.020***	-0.004**	-0.028***
	(0.002)	(0.007)	(0.002)	(0.008)	(0.002)	(0.008)
Land Area	0.007	0.025	0.017	0.039	0.014	0.036
	(0.017)	(0.067)	(0.018)	(0.070)	(0.018)	(0.070)
Fertile Soil	-0.092**	-0.296*	-0.095**	-0.359**	-0.096**	-0.362**
	(0.042)	(0.170)	(0.043)	(0.170)	(0.043)	(0.171)
Manure Use	-0.192***	-0.734***	-0.192***	-0.819***	-0.194***	-0.817***
	(0.036)	(0.147)	(0.037)	(0.150)	(0.037)	(0.148)
Drought Severity	-0.002	-0.025	0.001	0.007	-0.003	-0.011
	(0.029)	(0.113)	(0.029)	(0.113)	(0.029)	(0.113)
Disease Severity	-0.020	-0.062	-0.020	-0.057	-0.014	-0.047
	(0.023)	(0.089)	(0.022)	(0.088)	(0.022)	(0.088)
Region (West=1)	-0.144***	-0.419***	-0.138***	-0.419***	-0.145***	-0.447***
	(0.039)	(0.157)	(0.040)	(0.160)	(0.040)	(0.159)
Male Controlled Plot	-0.020	-0.073	-0.030	-0.088	-0.026	-0.048
	(0.041)	(0.163)	(0.042)	(0.165)	(0.042)	(0.165)
Female Controlled Plot	0.022	0.171	0.018	0.126	0.013	0.063
	(0.060)	(0.240)	(0.061)	(0.238)	(0.061)	(0.237)
Field Crop Subplot	0.165***	0.401***	0.167***	0.424***	0.164***	0.378***
	(0.033)	(0.133)	(0.033)	(0.132)	(0.032)	(0.131)
Observations	818	440	818	440	818	440

Note: APEs and standard errors in parenthesis; Significant at *10%, **5%, ***1%.

Table 27. DAP Use Models in MHH: Effects of Controls

VARIABLES	(1) Hurdle 1	(2) Hurdle 2	(3) Hurdle 1	(4) Hurdle 2	(5) Hurdle 1	(6) Hurdle 2
Male Age	-0.000	0.001	-0.001	-0.003	-0.002	-0.004
	(0.001)	(0.005)	(0.002)	(0.007)	(0.002)	(0.007)
Male Education	0.002	0.046**	0.003	0.039	0.005	0.058**
	(0.005)	(0.021)	(0.006)	(0.025)	(0.006)	(0.025)
Female Age			0.001	0.008	0.001	0.007
			(0.002)	(0.007)	(0.002)	(0.007)
Female Education			0.003	0.041*	0.002	0.026
			(0.006)	(0.024)	(0.006)	(0.024)
Household Size	0.013**	0.096***	0.009	0.079***	0.008	0.078***
	(0.006)	(0.025)	(0.007)	(0.026)	(0.007)	(0.026)
Non-farm Income	-0.005***	-0.035***	-0.006***	-0.039***	-0.006***	-0.040***
	(0.002)	(0.007)	(0.002)	(0.007)	(0.002)	(0.008)
Land Area	0.007	-0.072	0.011	-0.065	0.016	-0.052
	(0.015)	(0.063)	(0.016)	(0.066)	(0.016)	(0.066)
Fertile Soil	0.013	0.354**	0.018	0.362**	-0.000	0.302*
	(0.038)	(0.160)	(0.038)	(0.161)	(0.039)	(0.162)
Manure Use	-0.034	-0.324**	-0.031	-0.338**	-0.029	-0.321**
	(0.033)	(0.139)	(0.033)	(0.142)	(0.033)	(0.140)
Drought Severity	-0.012	-0.142	-0.018	-0.166	-0.012	-0.165
	(0.025)	(0.107)	(0.025)	(0.107)	(0.026)	(0.107)
Disease Severity	-0.002	-0.064	-0.002	-0.064	-0.002	-0.068
	(0.021)	(0.083)	(0.021)	(0.083)	(0.021)	(0.083)
Region (West=1)	-0.027	-0.658***	-0.014	-0.603***	-0.011	-0.624***
	(0.035)	(0.148)	(0.036)	(0.151)	(0.036)	(0.150)
Male Controlled Plot	0.069*	0.190	0.080*	0.254	0.084**	0.304*
	(0.037)	(0.153)	(0.038)	(0.157)	(0.038)	(0.156)
Female Controlled Plot	0.075	0.320	0.076	0.319	0.056	0.268
	(0.055)	(0.226)	(0.055)	(0.225)	(0.055)	(0.224)
Field Crop Subplot	0.221***	0.770***	0.217***	0.761***	0.210***	0.705***
	(0.028)	(0.125)	(0.028)	(0.125)	(0.028)	(0.124)
Observations	818	613	818	613	818	613

Note: APEs and standard errors in parenthesis; Significant at *10%, **5%, ***1%.

Table 28. Fertilizer Use Models in FHH: Effects of Controls

	Urea		DAP	
VARIABLES	Hurdle 1	Hurdle 2	Hurdle 1	Hurdle 2
Age	0.004	0.014	0.002	0.005
	(0.003)	(0.016)	(0.003)	(0.013)
Education	0.021**	0.084*	0.028***	0.132***
	(0.010)	(0.045)	(0.009)	(0.039)
Household Size	-0.021*	-0.052	-0.014	-0.072*
	(0.012)	(0.050)	(0.010)	(0.043)
Non-farm Income	-0.038**	-0.148**	0.022	0.156**
	(0.018)	(0.072)	(0.014)	(0.062)
Land Area	-0.110	-0.496**	-0.233**	-0.457**
	(0.075)	(0.240)	(0.109)	(0.207)
Fertile Soil	0.095	-0.200	0.056	-0.119
	(0.103)	(0.472)	(0.102)	(0.409)
Manure Use	0.222***	0.886**	0.211***	1.164***
	(0.080)	(0.403)	(0.073)	(0.348)
Drought Severity	-0.037	-0.294	-0.167***	-0.530**
	(0.065)	(0.284)	(0.060)	(0.246)
Disease Severity	0.003	-0.048	0.125**	0.479**
	(0.058)	(0.256)	(0.056)	(0.222)
Region (West=1)	-0.230**	-0.799**	-0.444***	-1.522***
	(0.090)	(0.399)	(0.084)	(0.345)
Field Crop Subplot	0.013	-0.206	0.127*	0.069
	(0.072)	(0.331)	(0.066)	(0.286)
Observations	154	51	154	96

Note: APEs and standard errors in parenthesis; Significant at *10%, **5%, ***1%.