Gender-specific Risk Preferences and Fertilizer Use in Kenyan Farming Households

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Abstract

The adoption of new technologies, such as fertilizer, plays an important role in improving agricultural production in Africa. 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 adoption. Typical empirical research ignores the family dynamics that affects household's agricultural choices. This paper uses 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. We find that empowered females who are more risk and loss averse use less fertilizer, than disempowered females in collective households. More loss averse male household heads opt for using more affordable type of fertilizer to avoid higher losses in the event of a negative shock. More risk averse and loss averse female household heads are also less likely to use riskier types of fertilizer.

Keywords: Collective household model, Loss aversion, New agricultural technology adoption, Non-linear probability weighting, Risk aversion, Women empowerment.

JEL Classifications: O13, O14, O33, O55

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1. Introduction

The adoption of new technologies by farmers in the developing world plays an important role in improving agricultural production leading to the reduction in malnutrition, poor future human capital, and, ultimately, reducing persistent poverty. Fertilizer can be considered such a technology. Applications of fertilizer paired with the use of improved seed varieties and other farming practices have proven to significantly increase agricultural yields in Asia. Nevertheless, fertilizer use by African farmers remains low. Despite having 15% of the world's population (Danzhen 2014), African countries account for less than 1% of global consumption of fertilizer (Morris 2007).

A number of experimental studies show that fertilizer use improves crop yields in Africa, making it a profitable investment (Duflo, Kremer, and Robinson 2008, Beaman et al. 2013), although, according to Suri (2011), high average returns to fertilizer conceal the heterogeneity of profits, as benefits and costs of new technology adoption differ greatly across farmers. Despite the evidence of positive effects of fertilizer use on agricultural productivity, fertilizer use remains low in Kenya. Maize is a country's major staple food crop. It accounts for about 40% of fertilizers applied to cereal crops. However, only about a third of total cultivated maize area is fertilized. As a result of underuse of fertilizer, the 37% gap exists between current and Comprehensive Africa Agriculture Development Program (CAADP) target maize production levels in Kenya (IFDC 2012).

Among the reasons of low fertilizer use often cited in the literature are price factors (prices of fertilizer and output prices), limited access to markets and information, credit constraints, and weather risk (Croppenstedt, Demeke, and Meschi 2003, Morris 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). Fertilizer is known to significantly improve crop yields under normal weather conditions. Unfavorable weather often leads to complete or partial crop damage. Fertilizer is an expensive input that needs to be purchased and applied prior to the occurrence of a negative shock. Weather risks may prevent farmers from using optimal levels of fertilizer. For risk-averse farmers, weather risk decreases the expected benefit of fertilizer use.

Economists have extensively studied the role of risk and risk preferences in fertilizer use (Dercon and Christiaensen (2011), Lamb (2003), McIntosh, Sarris, and Papadopoulos (2013) Simtowe et al. (2006)). The studies find that risk aversion negatively affects both the decision to purchase fertilizer and fertilizer demand. All of these studies, however, assume that a unitary (male) decision-maker decides whether or not to use fertilizer, whereas farming households in developing countries are predominately family enterprises involving both men and women. Also, these studies do not use experimental data on individual risk preferences in the analysis, but rather empirically estimate risk-premiums that are later used as proxies for risk aversion. In this paper we analyze how experimentally derived risk parameters of men and women from the same households affect their fertilizer use. We find that empowered more risk and loss averse females use less fertilizer than disempowered females in collective households. More loss averse male household heads opt for using more affordable type of fertilizer to avoid higher losses in the event of a negative shock. More risk averse and loss averse female household heads are also less likely to use riskier types of fertilizer.

The rest of the paper is organized as follows. Section 2 provides some background on the role of gender, bargaining power, and risk preferences. In Section 3, we present a collective model that shows how the amount of fertilizer application varies depending on gender specific risk preferences and intra-household dynamics in Kenyan households. In Section 4, we describe the experiment used to capture gender specific preferences, as well as survey and experimental data used in the analysis. In Section 5, we estimate the collective model using a log-normal hurdle (LNH) model. Section 6 concludes.

2. Background

In this section we provide background information on intra-household bargaining and gender specific experimentally derived risk preferences, and discuss how individual risk preferences combined with the bargaining power of spouses affect fertilizer use by farming households.

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, Bauer and Chytilová 2009, Croson and Gneezy 2009, Charness and Gneezy 2012). Men are generally more confident and competitive than women, which makes them more likely to exhibit risk-loving behavior (Croson and Gneezy 2009). Women traditionally perform the role of 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 a risky activity (Wik et al. 2004). Despite the differences, most studies on risk preferences and household behavior only consider the preferences of a single decision-maker, usually the household head. In this study we consider how the risk preferences of both men and women in the same household (husbands and wives, generally) affect household decisions.

Another important aspect in the household decision making process is relative bargaining power of the spouses. The degree of bargaining power of a woman in a household determines to what extent her risk preferences will affect household's agricultural choices. Under 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 by a single decision maker subject to a pooled resource constraint (Becker 1973). This approach completely ignores family dynamics in household consumption choices. Bargaining (collective household) models provide a richer framework for modeling household demand, as they allow preferences to vary among members of the same household. A typical bargaining model incorporates both husband's and wife's utility functions into the allocation and distribution of gains within a household (Manser and Brown 1980, Schultz 1990). Manser and Brown (1980) and McElroy and Horney (1981) developed a Nash bargaining model that clearly distinguishes bargained decision making from an individual decision by a dominant decision maker. Schultz (1990) used survey data of households in Thailand to empirically test restrictions implied by the neoclassical model. He finds that resource allocation within a household is primarily driven by self-interest of its members, rather than by a common set of preferences shared by all members of the household. Following Schultz (1990), several studies used a collective household model to analyze the allocation of resources in African farming households (Udry 1996, Andrews, Golan, and Lay 2014). These studies found that women controlled plots were much less intensively farmed than similar plots controlled by men in the same household, and that women were less productive than men in general. Udry (1996) also found that women used fewer farm inputs on their plots, and that most of fertilizer use was concentrated on the plots controlled by men. These studies show that spouses make distinct agricultural choices within the same household, suggesting that the unitary household model that ignores family dynamics may not be appropriate to analyze new technology choices of farming households.

Recognizing the role of women in agriculture, a number of studies used collective (bargaining) modeling approach in the analysis of new agricultural technology choices. Zepeda and Castillo (1997) and Fisher, Warner, and Masters (2000) investigated the effects of intra-household dynamics on new technology adoption. By incorporating indicators of household structure and wife's bargaining power, the studies showed that the adoption choices differ between women and men. In this study, we propose a collective household model that incorporates individual risk preferences of spouses paired with a bargaining power indicator into the estimation of fertilizer use by households.

A number of experimental studies use field experiments to elicit individual's risk preferences (Binswanger 1980, Holt and Laury 2002, List 2004, Wik et al. 2004, Tanaka, Camerer, and Nguyen 2010) and tie the results of these experiments to new technology adoption choices (Engle-Warnick, Escobal, and Laszlo 2007, Ross, Santos, and Capon 2010, Liu 2013, Liu and Huang 2013). Individual risk preferences are typically modeled under the expected utility (EU) framework. Based on EU theory, the concavity of the utility function alone characterizes risk preferences, where a single risk aversion parameter (σ) embodies the entire scope of individual attitudes toward risk. 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 for determination of individual attitudes toward risk. Under PT, the concavity of the utility function is jointly determined by risk aversion (σ), loss aversion (λ), and non-linear probability weighting (α). Loss aversion measures individual's sensitivity to loss vs. equal size gain. Loss aversion implies that disappointment from a loss is greater than the satisfaction from an equal size gain. Non-linear probability weighing implies overweighing small probabilities and underweighting large probabilities of uncertain outcomes and vice versa. If loss aversion and probability weighting are not present, PT collapses to EU. Fertilizer is a risky input. Using fertilizer can lead to a loss, and farmers may overweigh the probability of a negative shock such as drought or excessive rainfall. We therefore believe that risk aversion alone may not sufficiently explain why farmers limit fertilizer use.

Recent work by Tanaka, Camerer, and Nguyen (TCN) (2010) has opened the door for empirical estimation 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, as well as nonlinear probability weighing parameters from farmers in Vietnam. The TCN approach is more flexible, as it nests both EU and PT, allowing the authors to explicitly test the proper use of TP vs. EU framework. Liu (2013) and Liu and Huang (2013) applied TCN design to elicit risk preference parameters of Bt cotton farmers in China and showed that these parameters effect farmers' technology adoption decisions. Specifically, Liu (2013) found that more risk and loss averse farmers adopt Bt Cotton later, and farmers who overweigh small probabilities of bollworm infestation adopt it sooner. Liu and Huang (2013) also used TCN design to analyze the overuse of pesticides by cotton farmers in China. The authors find that risk aversion and loss aversion have significant effect on pesticide use. Similar to Liu and Huang (2013), we employ TCN design to estimate risk aversion, loss aversion, and nonlinear probability weighing among male and female farmers in Kenya. This study adds to the existing literature on risky technology investments by incorporating gender and bargaining power dynamics within a household into individuals' attitudes towards risk and evaluating how gender specific risk preferences paired with women's empowerment in a collective household affect fertilizer use.

3. Theoretical Model of Individual Risk Preferences and Fertilizer Use

Relying on the prospect theory results (Kahneman and Tversky 1979, Prelec 1998), similarly to Tanaka, Camerer, and Nguyen (2010) and Liu and Huang (2013), we define the utility function in the following form:

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

$$\text{where } v(z)=\begin{cases} z^{1-\sigma} & for\ z>0 \\ -\lambda(-z^{1-\sigma}) & for\ z<0 \end{cases},\ z=x,y, \text{ and } \ \pi(p)=\exp\left[-(-\ln p)^{\alpha}\right].$$

where 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 risk-neutral, and $\sigma<0$ for a risk-loving individual. The parameter λ is a measure of loss aversion, with a larger λ indicating more loss averse individual. $\pi(p)$ is the probability weighing function, derived by Prelec (1998), where the parameter α that represents nonlinear probability weighing. If $\alpha<1$, an individual overweighs low probabilities and underweighs high probabilities of uncertain events and vice versa when $\alpha>1$. The TP model reduces to EU model when $\alpha=1$ and $\lambda=1$.

Drought or excessive rainfall can severely damage crops. 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 the 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. $g(k, \varepsilon) > g(\varepsilon)$.

We now assume two possible states of the world: a state in which a negative shock 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:

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

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:

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

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:

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

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

FOC with respect to fertilizer is defined as follows:

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

We are interested in the effects of risk aversion, loss aversion, and unequal probability weighing 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 A 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 framers that underweight small probabilities of a negative shock will use more fertilizer (see Appendix A 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 weighing. We further expect that male and female risk preferences will differentially affect fertilizer use on male and female controlled plots, and potentially both affect fertilizer use on jointly controlled plots.

The degree to which differential effects of individual risk preferences affect household's agricultural decisions depends on intra-household 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. Therefore, household's optimal level of fertilizer application can be described as follows:

$$F^* = F_H + \mu F_W,$$

where F^* is the optimal level of fertilizer use by a household, F_H and F_W are husband's and wife's respective levels of fertilizer application, 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 a wife has greater bargaining power, her risk preferences will play a greater role in how the household uses fertilizer on female and jointly controlled plots. If she has no bargaining power, then her husband acts as a sole decision maker in a household, and his risk preferences alone determine the household's agricultural choices. If the spouses have different preferences, the amount of wife's bargaining power will determine to what extent her preferences come through in the household decisions. We account for intra-household bargaining dynamics in the collective household framework by incorporating the interactions of individual risk preferences with a women empowerment index (the index is based on the Women Empowerment in Agriculture Index (WEAI) discussed in detail in Section 4) in the empirical model.

Empirical Collective Model of Fertilizer Use

The empirical model is specifies as follows:

$$F_{jhr} = R_{hr}^{H}{}'\theta^{H} + R_{hr}^{W}{}'\theta_{emp}^{W} + R_{hr}^{W}{}'\theta_{disemp}^{W} + \gamma E_{hr} + H_{jhr}{}'\varphi + X_{jhr}{}'\delta + \eta_{r} + \varepsilon_{jhr},$$

where 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}^{H} is a vector of husband's risk preference variables $(\sigma, \lambda, \alpha)$; E_{hr} is a women's empowerment indicator in a household; R_{hr}^{W} is a vector of wife's risk preference variables and their interactions with the empowerment indicator; H_{jhr} is a vector of indicator variables that equal 1 if high yield (HY) (stress tolerant (ST)) hybrid maize is planted and 0 if non-hybrid (NH) maize is planted; X_{jhr} is a vector of individual, household, and plot characteristics, such as age, education, income, access to credit, access to extension services, previous drought/disease severity indicators, land holdings, soil type, as well as quantity of manure owned by a household; and η_{r} are region fixed effects.

The individual risk preferences are derived from the experiments, and empowerment indicator, as well as individual, household, and plot level controls are obtained from the household and individual surveys (the detailed information about surveys and experiments is provided in Section 4). The main coefficients of interest are θ^{H}, θ_{emp}^{W}, and θ_{disemp}^{W}. θ^{H} is a vector of husband's risk preference parameters, and θ_{emp}^{W} and θ_{disemp}^{W} are vectors of risk preference coefficients for empowered and disempowered women, respectively. We expect that greater degree of women empowerment paired with greater risk aversion by women will result in lower fertilizer use by the household.

In the empirical model specified above, 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 agricultural decisions, and the same traditional households may also choose not to use fertilizer and maintain traditional agricultural practices. Since we are primarily interested in the effect of the interaction of risk preferences and women's empowerment on fertilizer use, the endogeneity of empowerment index itself is not of a great concern here. With the interaction between a potentially endogenous and exogenous variable, the endogeneity problem is more nuanced. While one can think of a number of factors that may affect both fertilizer use and women's empowerment itself, it is very difficult to think of a factor that would affect risk preferences interacted with women' empowerment conditional on women's empowerment and fertilizer adoption. Therefore, conditional on women's empowerment, the interaction terms can be treated as exogenous. Incorporating women's empowerment paired with individual risk preferences into the analysis of fertilizer use by Kenyan households is important, as it is expected that women who have a greater bargaining power in a household are more likely to influence the head of the household's agricultural decisions. Since women are generally more risk averse than man, higher degree of female risk aversion paired with women's empowerment may result in lower use of risky inputs, such as fertilizer.

The estimation of fertilizer demand in developing countries is complicated by the fact that a large percentage of farmers do not use fertilizer. 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. 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 models allow different factors influence the participation and the consumption decisions. The estimation of Cragg's models 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 (or log-normal) model is used to estimate demand for fertilizer. The choice of log-normal hurdle model (Wooldridge 2010), also referred in the literature as the Wooldridge hurdle model, specification is more appropriate for our data, since the distribution of fertilizer use is very highly skewed, with mean fertilizer use greatly exceeding median use. We expect log-normal distribution to provide a better fit for highly skewed fertilizer use data in our sample (Figures 1 and 2).

4. Data

Survey and Experiment Sample Description

As a part of the Adoption Pathways Project (AP)[1], survey data were collected between September and November 2013 in Eastern and Western parts of Kenya. The respondents of the household survey were selected based on a three-stage sampling procedure from the purposefully chosen five districts (Embu, Meru, and Tharaka Nithi in the East, and Bungoma and Siaya in the West) that represent market differences and accessibility. Administrative divisions were randomly selected in each district, and then villages were randomly selected in a manner proportional to the each division's size. Finally, households were randomly selected within each village. In the initial round of data collection, 613 households completed the survey.

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[1] 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 2013).

This study uses the household-level and individual-level data on 540 households (802 individuals) from the second round of survey that was conducted in 2013. In each household, both male and a female with most decision making power were asked to identify the head of the household. In single decision-maker households, the sole respondent was asked to identify the gender of household head. All multiple decision-maker households in the sample were male-headed with female spouses identified as “wife of male-head,” suggesting that while a wife has some decision-making power, a husband is the primary decision maker. The degree of female spouse empowerment within male-headed household (MHH) will most likely affect the agricultural decisions that this household undertakes. Single decision-maker households were all identified as having a female head. Women in female-headed households (FHH) were singles, divorcées, widows, or separated from their spouses.

The household survey was conducted with the head of the household and focused on questions related to on-farm production, input use, soil fertility, yields, technology choices, stress occurrence and severity, and household demographics. All agricultural information was collected at the subplot level. Plot tenure was identified within the household. In our sample, 21% and 20% of subplots were identified as male and female controlled plots, respectively, and 59% were identified as jointly controlled. Household surveys were followed by the individual surveys where male household head and his wife were separately interviewed to prevent spousal interference and to encourage honesty in the responses. In female headed households, female head answered both surveys. The individual survey questions included inquiries into individual savings, decision-making within the household, asset ownership, group membership, and leadership in the community. In this study, data from both surveys were used to estimate the effect of experimentally derived male and female risk preferences on fertilizer use by the household.

A field experiment was performed in December 2013 in order to elicit risk preferences from the respondents who completed the individual surveys prior to the experiments. Only households where both husband and wife completed the individual survey were allowed to participate in the experiments to ensure matching between survey and experimental data. Women from female headed households also were allowed to participate in the experiments.

Attrition was common in the data with only 304 individuals from 172 households participating in the experiments. One possibility for such 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. Pair-wise t-tests for mean differences in age, education, household size, income, and farm income of the individuals that attrited and participating individuals were performed to assess the possibility of attrition bias (Table 1). The non-returning individuals are significantly different from returning individuals in age, household size, and income. Although the differences in age and 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.

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 KSH3 (about 2USD), which is close to a daily wage in Kenya, 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. The respondents were asked to make pair-wise choices on 27 different lotteries. Appendix B contains the risk preference series. In Series 1 Task 1 example, 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, the only thing that changes is the payout in Option B that gradually increases as one moves down the table, thus increasing the expected value of Option B, which eventually surpasses the expected value of Option A. More risk-averse individuals switch from Option A to Option B further down the table. The rationality of subjects was insured by enforcing monotonic switching from Option A to Option B, as well as permitting respondents to never switch to Option B or always choose Option B. Loss aversion parameters were elicited from the series containing both gains and losses. The series' payouts were designed such that the potential losses did not exceed the 200 KSH respondents received for participating in the experiments. More loss-averse respondents switch from Option A to Option B later in the table.

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. Similarly to TCN approach, three switching points were identified for each respondent, one in each series. The switching points from the first two series were used to identify risk aversion and non-linear probability weighing parameters. Then the range of values of the loss aversion parameter was identified for specific values of risk aversion for each individual.

Empowerment Index

Depending on the strength of the bargaining power of women in farming households, the amount of farm inputs used by the household may differ significantly. Several recent studies have considered the importance of women's empowerment in agriculture on the improvement in household's health and nutrition (Sraboni et al. 2014, Malapit and Quisumbing 2015). These studies use newly introduced survey-based Women Empowerment in Agriculture Index (WEAI), developed by Alkire et al. (2013), to measure the level of empowerment of women in developing countries.

The WEAI uses individual level data obtained from both female and male respondents within a household. The WEAI consists of two indexes: five domains of women empowerment (5DE) score and gender parity index (GPI). The 5DE 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. 5DE index is calculated for both spouses in a household. GPI is the difference between female and male 5DE scores. It measures gender parity gap or the relative women empowerment level in a household. When gender parity (GP) gap is greater than or equal to 0, gender parity exists between spouses, implying that a woman is empowered. Otherwise, a woman has less bargaining power than her husband, and the magnitude of the GP gap measures how disempowered she is compared to him.

In this study, we focus on the relative bargaining power of women in male-headed households, and we use GPI to measure the gender parity gap. We first obtain empowerment scores for both spouses (5DEs). Each 5DE score is based on four domains of empowerment (see Appendix C for details). Each domain consists of several indicators of empowerment. The resulting empowerment index is a weighted average of the eight indicators in the selected four domains, where each domain is assigned an equal weight. The index is bounded between 0 and 1, where 1 indicates that an individual is empowered and 0 means she has no say in the decision making within the household.

In our sample, women are least empowered in the decisions concerning household resources, such as assets and credit, and use of income, followed closely by decisions in agricultural production (Table 2). Women are most empowered in areas of leadership in the community, as most women in the sample belong to at least one social group. However, when we consider the contribution of each indicator to women empowerment index, it appears that women are least empowered in access and decisions on credit, even women in female-headed households (Table 3). Also, women have less power over the agricultural production decisions in a household. 62% of women in MHH participate in agricultural decisions in a household, compared to 78% in FHH. Even if women have different risk preferences, when it comes to agricultural decisions, their preferences may not matter as much, since they do not possess enough bargaining power to affect these decisions. Women in MHH are generally less empowered, particularly in the decisions of agricultural production, as well as the use of income.

Finally, 60% of women in MHH are relatively empowered, i.e. have equal or greater bargaining power in making household decisions relative to the household head.

Fertilizer Type Data

Fertilizers provide nutrients necessary for plant development, including phosphorous, potassium, and nitrogen. Two types of fertilizer, DAP and Urea, are used by farmers in this study. DAP is a multiple nutrient fertilizer that is the 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. Since DAP is more risky due to the timing of its application and more expensive than Urea, we expect farmers attitudes towards risk matter more in DAP application decisions, as opposed to use of Urea. 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, 58% of survey households applied Urea and 87% applied DAP on at least one subplot in 2013. Fertilizer use by region and household type is presented in Table 4. Households with male head use more of both kinds of fertilizer on their plots, compared to households with single female head. This can be expected, as females in female headed households 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.

About 85% of households in both regions use DAP on at least one subplot. 20% more households in the East use Urea.

5. Results

We now proceed with the estimation of the collective model of fertilizer use by Kenyan farming households discussed in Section 4. First, we provide the calibration of individual risk preferences using the experimental data described in the previous section. Next, we provide the results from the estimation of the collective model with the experimentally derived gender specific risk preferences interacted with relative empowerment indicator as independent variables of interest.

Risk Experiments

Following TCN (2010), three series of switching points are used to elicit individual risk preferences. The first two series results are used to obtain risk aversion (σ) and nonlinear probability weighing (α) parameters. Two switching points are obtained from the two series, one from each series, for every respondent. 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 nonlinear probability weighing (α) parameters. Series 3 is used to estimate loss aversion (λ). For a given value of risk aversion parameter, using the switching points in the last series, one can obtain a range of values for λ. The median of the range of loss aversion values is used as loss aversion parameter for each individual.

Contrary to TCN (2010) and Liu (2013) results, the distributions of the three risk preference parameters do not appear normally distributed, as many respondents in this sample exhibit extremely high levels of risk aversion ($\sigma > 0.15$) and are either extremely loss averse ($\lambda > 10$) or barely loss-averse ($\lambda < 0.15$). The average values of σ and λ are 0.50 and 0.86, respectively. The results are similar to those in TCN (2010) and Liu (2013). TCN find average values of 0.59 and 0.74, and Liu finds 0.48 and 0.69 for σ and λ, respectively. The average value of α is 3.17, compared to TCN's 2.63 and Liu's 3.47.

Table 5 contains summary statistics of the three risk preference parameters by gender and type of the household. Two sample t-tests are used to test significant differences between subsample means. No significant differences in risk preferences exist between males and females within the same household, as well as males and all females in a sample. 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.

Risk Preferences, Women Empowerment, and Fertilizer Use

Typical adoption models only consider the household head's preferences. In this study, however, we specifically incorporate both husband's and wife's risk preferences paired with the degree of relative women's empowerment to account for collective agricultural decisions within a household. We then estimate models with only female preferences and other covariates in FHH (Tables 10 and 11) as a comparison to the results of collective choices in MHH.

Table 6 contains summary statistics of independent variables used in the model estimation. The explanatory variables 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).[2] The individual characteristics include age, education, level of empowerment, access to credit, and access to agricultural extension services. Females in FHH are 10 years older on average than males in MHH and almost 20 years older than females in MHH. Males have more education than females in MHH, and twice the level of education of females in FHH. Females in MHH are less empowered than males in FHH. Males have more agricultural credit than females in MHH. Females in FHH have least access to credit, as only 13% received an agricultural loan in 2013. Females in FHH have the same level of access to the extension services as males in MHH, and more excess than females in MHH.

The household and subplot-level characteristics are presented in the last two sections of Table 6. MHH are bigger in size, have more income and savings than FHH. They also own more land and use more manure on their plots than FHH households in the sample. MHH have adopted hybrid seeds on more than 75% of their subplots, whereas FHH have adopted hybrids on just over 50%. FHH in this sample use ST hybrids and HY hybrids 30% and 23% of their subplots, respectively. MHH use both HY and ST on 38% of their maize subplots. We expect that farmers who adopt hybrid maize varieties will also use more fertilizer on their subplots.

Summary statistics of the dependent variables are in Table 7. MHH on average apply much more fertilizer on their subplots compared to FHH, suggesting again that income and credit constrained FHH tend to use less if any amount of risky inputs, such as fertilizer.

As suggested in the Section 4, DAP is riskier input compared to Urea due to the timing of its application. DAP is also associated with greater losses in the event of a negative shock, since it is more expensive than Urea. Therefore, we expect farmer's attitudes toward risk to affect

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

DAP use to a greater extent, as opposed to the use of Urea fertilizer. We proceed with the estimation of the LNH model, discussed in Section 3, by separately estimating the effects of risk preferences paired with relative women's empowerment index (GPI) on Urea and DAP use. Tables 8 and 9 contain average partial effects (APEs) of purchase (participation) and amount (consumption) decisions in MHH for Urea and DAP fertilizers, respectively. For each fertilizer type, we first estimate models with only male risk preferences and female risk preferences interacted with GPI (the first two columns), and then we add additional controls in the estimation (the last two columns). Of particular interest are APEs of female risk preferences interacted with GPI on each type of fertilizer use.

In the second column of Table 8, more risk averse, both empowered and disempowered, females use less Urea, given that they purchase it in the first place. After controls are incorporated in the estimation, disempowered more risk averse and loss averse women will be more likely to purchase Urea, but those who purchase it, will use less of this fertilizer. More importantly, more loss averse empowered women will be less likely to buy Urea, than equally loss averse disempowered women. Male risk preferences are not significant, with the only exception being non-linear probability coefficient, which is positive and significant in the participation equation in column 3. This suggests that males who underweight small probabilities of a negative shock, will be more likely to purchase Urea fertilizer. In FHH in Table 10, the risk aversion coefficient is negative and significant in the participation equation, suggesting that more risk averse farmers are less likely to purchase Urea fertilizer. The effect becomes insignificant once we control for other independent variables. After we incorporate controls in the estimation, in the consumption equation in column 4, female risk aversion is negative and significant, suggesting that more risk averse female household heads use less Urea, given that they decide to purchase it. Also, the coefficient of loss aversion is positive and significant in the consumption equation, which is not a strange result, considering that Urea is less expensive input. More loss averse female farmers choose to use more affordable Urea instead of DAP, which is associated with greater losses if a negative shock occurs. Non-linear probability weighing is positive and becomes significant after the addition of controls in both purchase and amount equations. This result suggests that females in FHH who underweight small probabilities of a negative shock will be more likely to purchase Urea fertilizer, and those who purchase, will use more of it.

With respect to DAP fertilizer estimation in Table 9, male loss aversion parameter is negative and becomes significant in the consumption equation, when controls are added into the model. This suggests that more loss averse males who buy DAP will use less of it, which is expected given that DAP is riskier input than Urea. Also, female risk aversion coefficient for disempowered females is positive and becomes significant in the participation equation when controls are included in the estimation. This suggests that more risk averse females who are not empowered will be more likely to purchase DAP, than empowered females. Also, in the consumption decision in column 4, risk aversion coefficient for empowered women is negative and significant, suggesting that empowered females who are more risk averse will use less DAP, than disempowered females, given that they buy it. As expected, empowerment of risk averse women may lead to even lower fertilizer use. Finally, not empowered females who underweight small probabilities of a negative shock, will be more likely to purchase this fertilizer, and those who purchase will also be more likely to use more of it. In FHH in Table 11, risk aversion coefficients are negative and significant without controls in both hurdles, suggesting that risk averse females are less likely to purchase DAP, and those who purchase it, use less of this fertilizer on their plots. When we include controls, only purchase decision result remains significant, suggesting that more risk averse female household heads are less likely to use riskier DAP fertilizer. Also, loss aversion coefficient is negative and becomes significant with the inclusion of controls in the participation equation, suggesting that more loss averse females will be less likely to purchase DAP fertilizer.

6. Conclusions

The adoption of new technologies by farmers in the developing world plays an important role in improving agricultural production leading to the reduction in malnutrition, poor future human capital, and, ultimately, reducing persistent poverty. Fertilizer can be considered such a technology. Applications of fertilizer paired with the use of improved seed varieties and other farming practices can significantly increase agricultural yields.

Despite relatively well known benefits of fertilizer application, Kenyan farmers underuse fertilizer on their plots. Fertilizer is a risky and expensive input, and farmers' attitudes towards risk can result in suboptimal use of different types of fertilizer. Male and female farmers are known to have distinct risk preferences, with women being generally more risk and loss averse than men. Therefore, it is important to incorporate both male and female risk preferences in the analysis of fertilizer use by farming households.

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 household's choices, resulting in a lower use of riskier inputs. We proposed 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 use of fertilizers. We also analyze how women’s attitudes towards risk affect fertilizer use in FHH.

In Kenya, drought and sever fungus disease are two major threats to agricultural production. In this study, we considered two main types of fertilizer: Urea and DAP, with DAP being considered a riskier input due to its higher cost and early timing of application. We find that male loss aversion in MHH decreases DAP, but not Urea application, suggesting that more loss averse household heads opt for using more affordable fertilizer to avoid higher losses in the event of a negative shock. Empowered females who are more risk and loss averse use less fertilizer, than disempowered females in MHH. Also, males and disempowered females in MHH, as well as females in FHH, who underweight small probabilities of a negative shock are more likely to purchase fertilizer. In FHH, we find that more risk and loss averse females are less likely to purchase DAP fertilizer. Being the only bread winners in their households, female household heads seem to avoid using riskier inputs.

To be continued…

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Figures

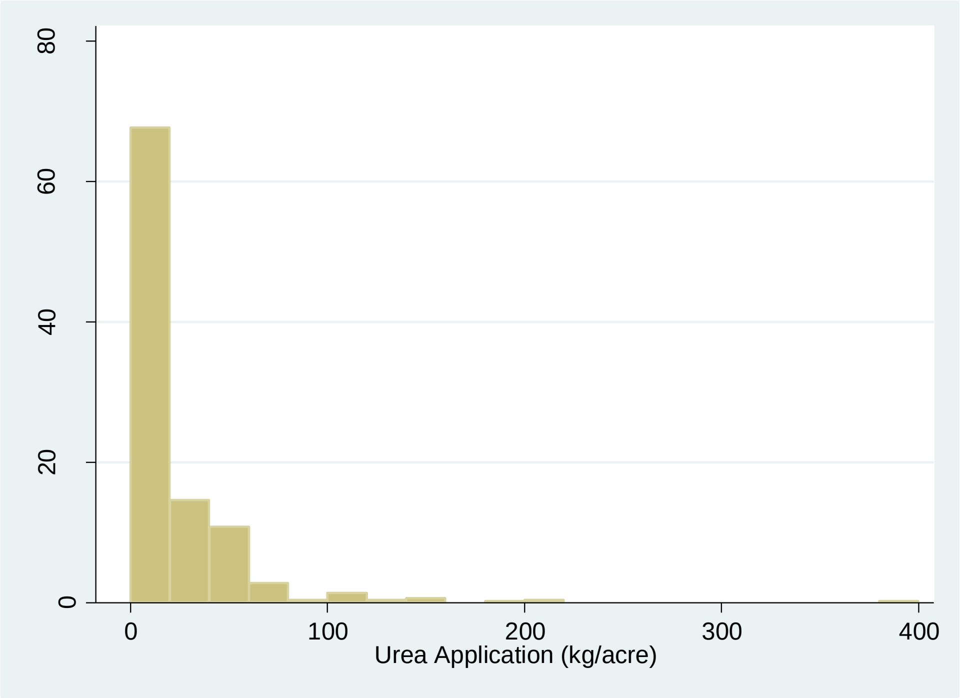

Figure 1. The Rate of Urea Application at a Subplot Level

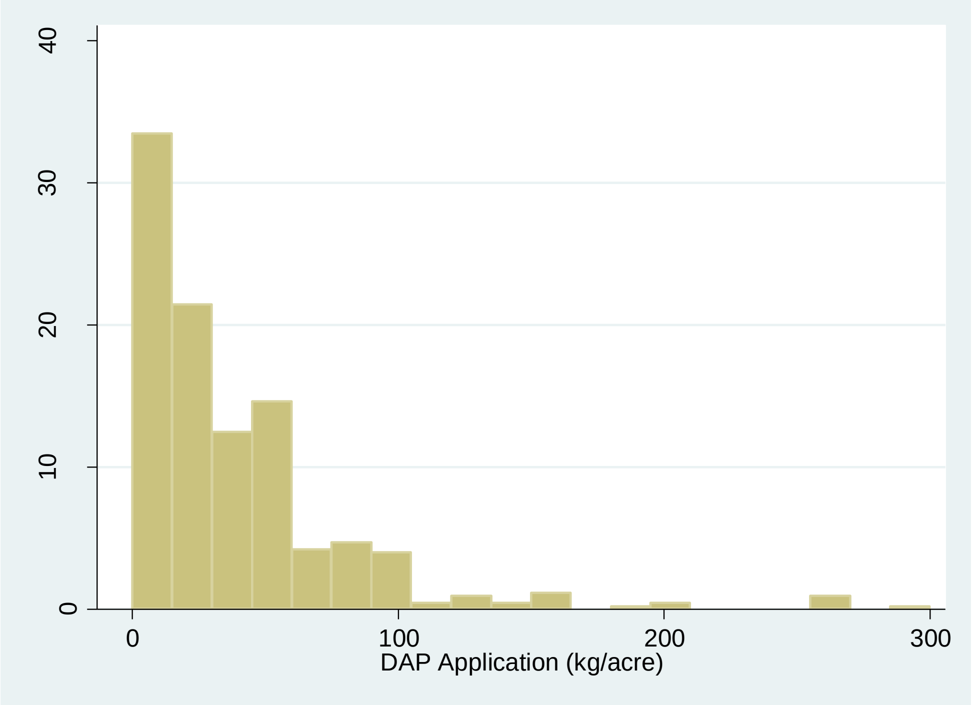

Figure 2. The Rate of DAP Application at a Subplot Level

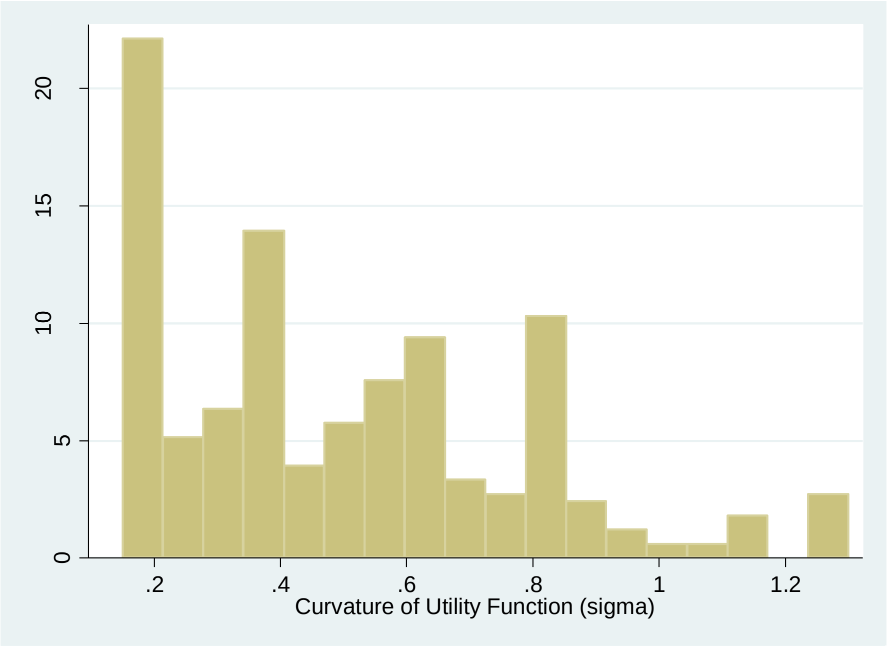

Figure 3. Distribution of Risk Aversion Parameter

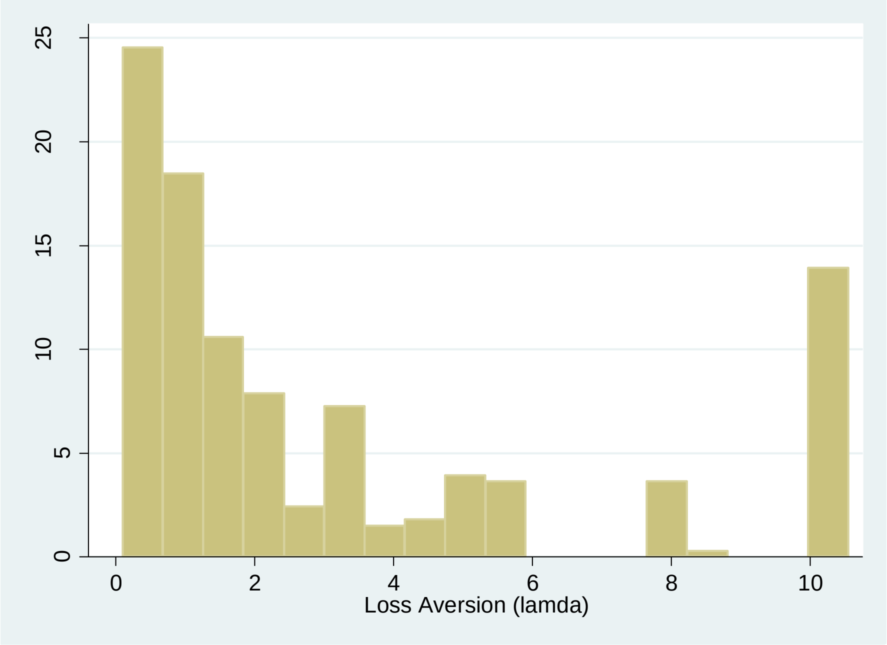

Figure 4. Distribution of Loss Aversion Parameter

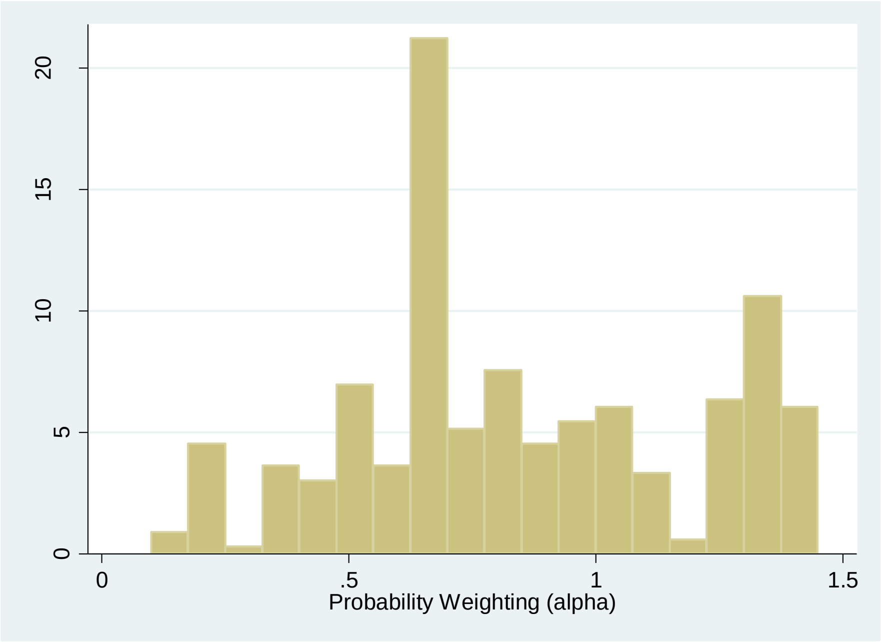

Figure 5. Distribution of Non-Linear Probability Weighting Parameter

Tables

Table 1. Mean Comparison for Attrited and Returning Individuals

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

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

Table 2. Contribution of Domains to Women Empowerment

Domain	Proportion
Production	0.20
Resources	0.17
Income	0.19
Leadership	0.23

Table 3. Contribution of Domain Indicators to Women Empowerment by Household Type and Relative Women Empowerment

Indicator	Women in MHH		FHH	
Input in productive decisions	0.62	(0.49)	0.78	(0.42)
Autonomy in production	0.94	(0.24)	0.90	(0.30)
Ownership of assets	0.97	(0.17)	0.93	(0.27)
Purchase, sale, or transfer of assets	0.87	(0.34)	0.90	(0.30)
Access and decisions on credit	0.18	(0.39)	0.07	(0.27)
Control over use of income	0.74	(0.44)	0.88	(0.33)
Group member	0.91	(0.29)	0.88	(0.33)
Speaking in public	0.93	(0.25)	0.88	(0.33)
Relative Women's Empowerment Indicator (1 if GPI $\geq$ 0)	0.62	(0.49)	1.00	(0.00)

Note: mean coefficients; standard deviations are in parentheses.

Table 4. Fertilizer Use by Region

Fertilizer Type	MHH		FHH		Total	
			West			
Urea	0.551	(0.501)	0.259	(0.447)	0.476	(0.502)
DAP	0.897	(0.305)	0.741	(0.447)	0.857	(0.352)
			East			
Urea	0.704	(0.461)	0.538	(0.519)	0.672	(0.473)
DAP	0.870	(0.339)	0.769	(0.439)	0.851	(0.359)

Note: mean coefficients; standard deviations are in parentheses.

Table 5. Risk Preferences Summary Statistics

Variables	Full Sample		Males in MHH		Females in MHH		Females in FHH		All Females	
N	304		132		132		40		172	
Sigma	0.50	(0.29)	0.50	(0.27)	0.48	(0.31) [0.65][a]	0.55	(0.31) [0.25][b]	0.50	(0.31) [0.97][c]
Lambda	3.16	(3.55)	2.85	(3.37)	3.16	(3.69) [0.48]	4.30	(4.08) [0.10]*	3.43	(3.80) [0.17]
Alpha	0.86	(0.34)	0.87	(0.34)	0.87	(0.34) [0.99]	0.78	(0.35) [0.17]	0.85	(0.34) [0.62]

Note: Mean coefficients; std deviations 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%.

Table 6. Summary Statistics of Explanatory Variables

Variables	Males in MHH		Females in MHH		Females in FHH	
Individual Characteristics						
N	132		132		40	
Age	52.89	(13.54)	44.51	(12.18)	62.63	(13.18)
Education (years)	8.28	(3.08)	7.09	(3.14)	4.13	(3.45)
Empowerment Score (5DE)	0.51	(0.10)	0.49	(0.10)	1.00	(0.02)
Any agricultural credit (1=yes)	0.21	(0.41)	0.19	(0.39)	0.13	(0.33)
Agricultural Extension Service (1=yes)	0.73	(0.44)	0.68	(0.47)	0.72	(0.45)
Household Characteristics						
N	132		132		40	
GPI (1=empowered)	0.62	(0.49)	0.62	(0.49)		
Household size	6.56	(2.88)	6.56	(2.88)	4.88	(3.45)
Household saves (1=yes)	0.80	(0.40)	0.80	(0.40)	0.75	(0.44)
Non-farm Income (10,000KSH)	5.62	(9.53)	5.62	(9.53)	2.92	(3.65)
Region (West=1)	0.59	(0.49)	0.59	(0.49)	0.68	(0.47)
Subplot Characteristics						
N	317		317		107	
HY Corn Variety (1=yes)	0.38	(0.49)	0.38	(0.49)	0.23	(0.43)

ST Corn Variety (1=yes)	0.38	(0.49)	0.38	(0.49)	0.30	(0.46)
Traditional Corn Variety (1=yes)	0.24	(0.43)	0.24	(0.43)	0.47	(0.50)
Land area owned (hectares)	0.78	(0.86)	0.78	(0.86)	0.53	(0.64)
Fertile soil (1=yes)	0.18	(0.38)	0.18	(0.38)	0.14	(0.35)
Manure Use (1=yes)	0.44	(0.50)	0.44	(0.50)	0.34	(0.47)
Drought Severity (0-3 scale)	0.28	(0.68)	0.28	(0.68)	0.16	(0.48)
Disease Severity (0-3 scale)	0.50	(0.84)	0.50	(0.84)	0.40	(0.85)

Note: Mean coefficients; standard deviations are in parentheses.

Table 7. Fertilizer Application

Fertilizer Application Rate (kg/acre)	MHH Plots		FHH Plots	
Urea	19.22	(34.51)	0.411	(0.494)
DAP	39.87	(44.89)	0.794	(0.406)
N	317		107	

Note: Mean coefficients; standard deviations are in parentheses.

Table 8. LNH Model Estimation of Urea Use in MHH

	(1)	(2)	(3)	(4)
Urea	Hurdle 1	Hurdle 2	Hurdle 1	Hurdle 2
Male sigma	0.164	-0.897	0.173	-0.753
	(0.163)	(0.563)	(0.128)	(0.481)
Male lambda	0.010	0.061	0.015	0.050
	(0.013)	(0.038)	(0.012)	(0.033)
Male alpha	0.159	-0.131	0.154*	0.044
	(0.127)	(0.348)	(0.093)	(0.322)
GPI	-0.097	0.371	-0.133**	0.344
	(0.090)	(0.304)	(0.063)	(0.290)
Female sigma				
Not Empowered	0.263	-1.344**	0.243*	-1.110*
	(0.167)	(0.566)	(0.139)	(0.607)
Empowered	0.020	-0.611*	0.164	-0.206
	(0.167)	(0.362)	(0.122)	(0.334)
Female lambda				
Not Empowered	0.020	-0.189***	0.024**	-0.155***
	(0.015)	(0.061)	(0.011)	(0.053)
Empowered	-0.019	0.023	-0.024*	0.031
	(0.014)	(0.036)	(0.012)	(0.035)
Female alpha				
Not Empowered	0.127	-0.681	0.168	-0.639
	(0.194)	(0.687)	(0.136)	(0.562)
Empowered	0.044	-0.428	0.082	-0.415

	(0.160)	(0.350)	(0.131)	(0.433)
Controls			Yes	Yes
Observations	317	172	317	172

Note: The coefficients are APEs of participation (Hurdle1) and amount (Hurdle 2) equations; Robust Std. Errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 9. LNH Model Estimation of DAP Use in MHH

	(1)	(2)	(3)	(4)
DAP	Hurdle 1	Hurdle 2	Hurdle 1	Hurdle 2
Male sigma	-0.097	0.163	0.052	0.254
	(0.126)	(0.251)	(0.110)	(0.213)
Male lambda	-0.011	-0.017	-0.003	-0.042**
	(0.010)	(0.027)	(0.008)	(0.020)
Male alpha	-0.122	0.148	-0.013	0.008
	(0.092)	(0.269)	(0.086)	(0.179)
GPI	0.043	-0.196	0.057	-0.214*
	(0.066)	(0.180)	(0.047)	(0.119)
Female sigma				
Not Empowered	0.232	0.029	0.376***	0.239
	(0.153)	(0.458)	(0.105)	(0.388)
Empowered	0.061	-0.266	-0.109	-0.486***
	(0.106)	(0.244)	(0.083)	(0.177)
Female lambda				
Not Empowered	-0.018	-0.002	-0.005	0.005
	(0.016)	(0.035)	(0.009)	(0.026)
Empowered	-0.012	-0.002	0.007	-0.009
	(0.010)	(0.026)	(0.007)	(0.020)
Female alpha				
Not Empowered	0.256**	0.246	0.207**	0.466*
	(0.123)	(0.307)	(0.103)	(0.263)
Empowered	-0.013	-0.153	-0.031	-0.068
	(0.112)	(0.256)	(0.097)	(0.216)
Controls			Yes	Yes
Observations	317	258	317	258

Note: The coefficients are APEs of participation (Hurdle1) and amount (Hurdle 2) equations; Robust Std. Errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 10. LNH Model Estimation of Urea Use in FHH

	(1)	(2)	(3)	(4)
Urea	Hurdle 1	Hurdle 2	Hurdle 1	Hurdle 2
Female sigma	-0.469*	1.346	-0.276	-13.111***
	(0.250)	(2.222)	(0.202)	(0.827)
Female lambda	-0.007	-0.173	-0.001	0.396***
	(0.020)	(0.176)	(0.015)	(0.050)
Female alpha	0.240	-0.998	0.381***	22.502***
	(0.206)	(1.540)	(0.140)	(1.378)
Controls			Yes	Yes
Observations	107	36	107	36

Note: The coefficients are APEs of participation (Hurdle1) and amount (Hurdle 2) equations; Robust Std. Errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Table 11. LNH Model Estimation of DAP Use in FHH

	(1)	(2)	(3)	(4)
DAP	Hurdle 1	Hurdle 2	Hurdle 1	Hurdle 2
Female sigma	-0.620***	-0.891*	-0.981***	0.090
	(0.171)	(0.466)	(0.217)	(0.865)
Female lambda	-0.020	-0.002	-0.049***	0.037
	(0.018)	(0.034)	(0.015)	(0.035)
Female alpha	0.033	0.032	-0.211	0.341
	(0.174)	(0.287)	(0.143)	(0.258)
Controls			Yes	Yes
Observations	107	75	107	75

Note: The coefficients are APEs of participation (Hurdle1) and amount (Hurdle 2) equations; Robust Std. Errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Appendix A Derivation of the Theoretical Model of Individual Fertilizer Use

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:

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

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

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

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

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:

$$\begin{aligned}\frac{\partial G'}{\partial k} &= \pi(p)\lambda w(wk)^{-\sigma}\sigma(k)^{-1} \\ &\quad + \pi(q)\left(\frac{\partial^2 g}{\partial k^2}(g(k) - wk - g)^{-\sigma} - \sigma(g(k) - wk - g)^{-\sigma-1}\left[\frac{\partial g}{\partial k} - w\right]^2\right) < 0,\end{aligned}$$

$$\begin{aligned}\frac{\partial G'}{\partial k} &= \pi(q)\left[\frac{\partial g}{\partial k} - w\right](g(k) - wk - g)^{-\sigma}\sigma(k)^{-1} \\ &\quad - \pi(q)\left(-\frac{\partial^2 g}{\partial k^2}(g(k) - wk - g)^{-\sigma} + \sigma(g(k) - wk - g)^{-\sigma-1}\left[\frac{\partial g}{\partial k} - w\right]^2\right) < 0,\end{aligned}$$

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

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

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

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

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

Unless k is absolutely miniscule then $\frac{\partial G'}{\partial k} < 0$. 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 B Prospect Theory Experiments

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	If **Option A** is chosen, move **DOWN** the table. If **Option B** is chosen, move **UP** the table.
2		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 1030 if 10	
3		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 1175 if 10	
4		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 1380 if 10	
5		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 1655 if 10	
6		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 2020 if 10	
7		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 2425 if 10	
8		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 3310 if 10	
9		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 4410 if 10	
10		110 if 1 2 3 4 5 6 7 440 if 8 9 10	55 if 1 2 3 4 5 6 7 8 9 6620 if 10	

Prospect Theory Series 2 (KSH)

Task	Starting Point	Option A	Option B	**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	

Prospect Theory Loss Aversion Series 3

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
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	**DOWN** the table. If **Option B** is chosen, move **UP** the table.
4		5 if 1 2 3 4 5 -30 if 6 7 8 9 10	220 if 1 2 3 4 5 -120 if 6 7 8 9 10	
5		5 if 1 2 3 4 5 -60 if 6 7 8 9 10	220 if 1 2 3 4 5 -120 if 6 7 8 9 10	
6		5 if 1 2 3 4 5 -60 if 6 7 8 9 10	220 if 1 2 3 4 5 -100 if 6 7 8 9 10	
7		5 if 1 2 3 4 5 -60 if 6 7 8 9 10	220 if 1 2 3 4 5 -80 if 6 7 8 9 10	

Appendix C The Four Domains of Empowerment Index

Domain	Indicator	Indicator Description	Weight
Production	Input in productive decisions	Sole or joint decision making over food and cash-crop farming, livestock, and fisheries	1/8
	Autonomy in production	Autonomy in agricultural production (e.g., what inputs to buy, crops to grow, what livestock to raise, etc.). Reflects the extent to which the respondent's motivation for decision making reflects his/her values rather than a desire to please others or avoid harm	1/8
Resources	Ownership of assets	Sole or joint ownership of major household assets	1/12
	Purchase, sale, or transfer of assets	Whether respondent participates in decision to buy, sell, or transfer his/her owned assets	1/12
	Access to and decisions on credit	Access to and participation in decision making concerning credit	1/12
Income	Control over use of income	Sole or joint control over income and expenditures	1/4
Leadership	Group member	Whether respondent is an active member in at least one economic or social group (e.g., agricultural marketing, credit, water users' groups)	1/8
	Speaking in public	Whether the respondent is comfortable speaking in public concerning various issues such as intervening in a family dispute, ensure proper payment of wages for public work programs, etc.	1/8

Source: Alkire et al. (2013)