Risk Aversion and Adoption of Conservation Agriculture Practices in Eastern Uganda

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ABSTRACT

Many poor farmers, especially in Africa, have not adopted recent farming innovations to improve their yields. One theory is that poor farmers are risk averse and therefore do not invest in high risk high return innovations and that risk averse farmers will only adopt larger innovations if they experience success with small ones. Risk preferences were measured in two districts in Uganda (Tororo and Kapchorwa) where adoption of agricultural innovations has been slow, and where a program is underway to encourage use of conservation agriculture practices (CAPs) to reduce soil erosion and sequester carbon. An ordered lottery selection was used to measure risk preferences and an ordered probit model was estimated. Thirty five percent of a random sample of 200 farmers in Tororo (and fifty three percent of 200 farmers in Kapchorwa) made lottery choices that implied severe or extreme risk aversion. However there was no indication that risk preferences correlate with willingness to adopt new technologies (such as CAPs). Neither wealth nor previous success with technology adoption were found to correlate with farmers' risk preferences.

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Chapter 1: Introduction

The Green Revolution increased agricultural productivity in numerous countries, especially in Asia and Latin America. However, not all countries were able to capitalize on the improved farming technologies. Uganda for example still has 66 percent of its labor force working on farms and yet remains a net food importer.[1] One theory as to why countries like Uganda have not capitalized on higher yield technologies is that the poor are too risk averse to invest in high-risk, high-return investments. Poor farmers continue to farm with their old proven techniques and do not capitalize on farming innovations in order to avoid production risk.

Conservation agriculture practices (CAPs) may help increase food production, decrease labor needs, and provide environmental benefits such as soil retention and carbon sequestration. Practices such as minimum tillage, cover crops, and beneficial crop rotations have the potential to increase soil fertility and slow soil erosion. These CAPs also sequester carbon by increasing the organic matter in the soil. Many farming techniques can deplete the soil's quality over years of use, lowering future yields. The development and spread of CAPs, especially in developed countries and on larger farms in developing nations, have demonstrated their potential benefits in recent years.[2]

Unfortunately, adoption of CAPs has been slow among limited-resource farms in developing countries. These farms are the majority of farms in the world. The importance of improving agricultural productivity to raise incomes of low-income farmers, and of sequestering carbon to help mitigate climate change has created pressures to design and disseminate CAPs for small farms. A conservation agriculture program called the Sustainable Agriculture and Natural Resource Management Innovation Lab (SANREM IL) was formed with a goal to design CAPs

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[1] Most recent year available:2010 from www.data.un.org/CountryProfile.aspx?crName=Uganda (1/2014)
[2] www.icarda.org

that will increase or at least maintain soil productivity on small farms in developing counties, improve food security for the farmers, and provide global environmental services such as sequestering carbon. Uganda is one of the countries in which the SANREM IL research is focused.[3] The research is aimed at increasing yields reducing labor and other input costs, while improving the soil quality.

Even if SANREM IL research develops a farming system that meets these goals, there is no guarantee that Ugandan farmers will adopt the system. The CAPs techniques in Uganda are tailored to overcome barriers to adoption such as high investment and labor costs. However, fear of an unknown technique may cause people not to adopt the CAPs. Although CAPs may increase yields in the future, they seldom result in dramatic first-year effects on yields or profits. Only after a few years of nitrogen-fixing rotations and leaving cover crops on the field will larger yield benefits begin to accrue. Therefore, the incentives to adopt a completely new farming system may not be immediate enough to overcome people's aversion to trying something new.

Partial adoption of the CAPs will most likely not benefit the farmer since it is the interaction of the techniques that yields the greatest benefit. Therefore CAPs require an adopter to learn an entirely new system with many unknowns. It might be easy to convince a risk-neutral farmer to give it a try, but a risk-averse farmer may require more convincing to change farming techniques they learned from their fathers and mothers. Risk aversion may be a substantial barrier to the adoption of CAPs even when other barriers to adoption are addressed. Therefore, it is important to assess the degree of risk aversion of Ugandan farmers in the area where the SANREM IL project is focused.

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[3] http://www.oired.vt.edu/sanremcrsp/ (03/2013).

Objective

The objective of this thesis is to assess the degree of risk aversion of farmers in eastern Uganda.

Hypotheses

1. Increased wealth decreases risk aversion of farmers in eastern Uganda
2. Previous success with new technologies (i.e. improved seed varieties or fertilizers) decreases the farmers' risk aversion, and failures with new technologies increase risk aversion

Previous research on measuring risk aversion is reviewed in Chapter 2. Chapter 3 discusses the conceptual framework for measuring risk aversion. Chapter 4 presents the methods used for collecting the data. Chapter 5 gives the empirical model and presents the descriptive statistics. In Chapter 6 the results are discussed and conclusions given.

Chapter 2: Background

Are subsistence farmers risk averse? In the 1960s there was debate in the field of economic development whether or not subsistence farmers optimized by equating their marginal value product across all inputs. Shultz (1964) argued "there are comparatively few significant inefficiencies in the allocation of the factors of productions in traditional agriculture" (p.37). One of Shultz's key arguments came from W. David Hopper who collected detailed production data in Senapur India. Hopper (1965) estimated marginal values of some inputs of production (land, bullock time, labor, and irrigation water) across four different crops (barley, wheat, pea, and gram). Hopper and Shultz both agreed that these subsistence farmers were equating marginal values of their farming inputs across their crops.

Michael Lipton (1968) on the other side of the debate pointed out that Hopper did not include dung, a key input in his marginal value estimates. Lipton goes on to argue that when the model is expanded to include dong reallocation of inputs in Senapur India could increase production ten percent (Lipton, 1968). Hence, while farmers may be rational, they are not simply profit maximizers. Lipton argued that farmers were not optimizing their marginal value product of inputs because they were risk averse and made decisions based on a safety-first algorithm. While researching in India, Lipton witnessed the volatility of weather, especially rainfall, and hypothesized that people cannot adequately guess the probability of high or low rainfall. He argued they have learned which techniques will protect them from the greatest catastrophe, and rather than try to optimize their profits, they use the technique that will protect them from the failures that will cause irreparable harm. Lipton assumed people living close to starvation and without explicit safety nets will be forced to do things like sell their land and other valuable assets or hire themselves out as indentured servants if a catastrophe strikes. Lipton

concluded that poor farmers in less-developed countries are risk averse and the policies and interventions in agriculture need to take that into account. He gave an example of what might happen if a policy were poorly implemented that convinced farmers in a low rainfall area that they would benefit greatly from fertilizer. The application of fertilizer would increase the expected yield as well as increase the variance. If a farmer tried the fertilizer and due to the lack of rainfall lost his/her investment, he/she would lose faith in all innovations. Lipton's policy advice was not just to consider if an innovation on average has greater gains than costs, but to consider its risk. He claimed that if it fails, risk-averse farmers will harden their stance on using traditional methods and will more vehemently reject other innovations.

Lipton's theory that poorer farmers are more risk averse was well accepted in the late 1960s and early 1970s; the argument that people living meagerly are more averse to taking risk than others made a lot of sense. It seemed rational that people would not take a risk that might starve them even though it had the potential to increase their wealth and pull them out of poverty. Development organizations were concerned that risk might be stopping subsistence farmers from realizing the gains of the Green Revolution. In 1977, the Research and Training Network of the Agricultural Development Council invited a group of researchers to discuss risk and risk preferences. The conference did not reach a consensus, but it did spur research in the area of risk, adoption, and policy possibilities for addressing risk barriers to adoption (Roumasset & Research in Agriculture, 1979).

One of those attending the conference was Hans Binswanger. Binswanger noticed the lack of empirical work on measuring risk preferences and went to India to conduct an experiment to test risk preferences of poor farmers. Binswanger played a lottery game with farmers that offered a list of lotteries that increased risk as expected payout increased (Binswanger, 1980).

He reported that wealth was not an indicator of a person's risk aversion. Binswanger concluded that risk aversion is not what keeps poor farmers from adopting new technologies and pointed to other constraints such as lack of credit, market access, and extension information. Binswanger's use of an experiment to measure risk preferences allowed people to make risky decisions without being constrained by a lack of liquidity, credit, labor, and other market failures that subsistence farmers often face in less-developed countries. When risk preferences are measured from observing people's daily choices, these constraints confound the data. It is hard to say if a person does not choose a particular new farming technique because of risk preference or because of a limiting constraint like lack of credit or information.

Binswanger offered eight lotteries ranging from risk neutral to severely risk averse for the respondents to choose from. Binswanger wanted to know if there was a demographic or observable situation that caused farmers to be more risk averse than their neighbors. He did not find a significant attribute of poorer farmers that correlated with greater risk aversion. The theory that those close to a subsistence level are more risk averse was not supported by his empirical work. In his seminal paper, Binswanger (1980) concluded "it is not the innate or acquired taste that hold the poor back but external constraints" (p.406).

Since Binswanger's time, a few economists have replicated his research with similar studies in less-developed countries; some have found similar results, some have found that poorer farmers are more risk averse than wealthier farmers. Binswanger (1980), Mosley & Verschoor (2005), and Cook (2011) have not found a significant correlation between risk preferences and wealth. However, Wik et al. (2004) and Yesuf & Bluffstone (2004) found a significant negative correlation between risk aversion and wealth, concluding that poorer farmers are more risk averse.

The problem with risk aversion and wealth being negatively correlated is that poor risk-averse farmers might not invest in innovations that yield higher returns due to higher risk. Risk aversion might create a vicious cycle of poverty in which people stay in poverty due to their choices to avoid high-risk, high-return investments. Mosley & Verschoor (2005) diagramed the vicious cycle of poverty simply; if poverty leads to increased risk aversion and risk-averse people invest in low return investments then their asset levels remain low, trapping them in poverty. Like Binswanger, they found no significant evidence that the poorer are more risk averse than others, thus the vicious cycle of poverty should not trap them. If poorer farmers are not risk averse, they should be willing to make high risk/return investments. On average taking higher risk and getting higher return will allow poorer farmers to accumulate assets for consumption smoothing and increase their food security, ultimately escaping poverty. Also like Binswanger, Mosley and Verschoor concluded that risk aversion is not innate in the poor but market constraints like lack of insurance and credit are the problem.

Yesuf & Bluffstone (2004) using data from the highlands of Ethiopia found that one to two thirds of the respondents were severely or extremely risk averse. They also found that small amounts of accumulated wealth reduced people's risk aversion. Their result suggests that the poor are caught in a vicious cycle of poverty, and that a little wealth accumulation may decrease their risk aversion, enabling them to make high risk/return investments to escape poverty. This finding is in stark contrast to Binswanger, Mosley and Verschoor. Yesuf and Bluffstone also found that previous success reduced a respondent's risk aversion. These findings suggest that escaping poverty may require or at least be greatly helped by intervention in risk mitigation. They concluded that poor farmers are path dependent since their risk aversion will decrease with small successes. Yesuf & Bluffstone (2004) concluded with a hopeful policy suggestion: "the

possibility of path dependence due to prior success and changes in wealth indicates that rural development efforts do well to assure initial successes that can serve to demonstrate the conditions under which investments are viable" (p.1034)

The past decades governments and non-governmental organizations have attempted to remove some of the constraints facing farmers by setting up micro-credit organizations and combining agricultural research with extension. Programs such as SANREM IL and organizations such as IFPRI have strategically focused their research on key agricultural products to have the maximum impact on food security. However, relatively little has been done to assess the risk attitudes of farmers in many of the poorest developing countries. If risk aversion is not a barrier to adoption, then no *special* attention needs to be devoted to it and research to cope with actual risk should get priority. However, if Lipton's argument is valid, policies and extension programs need to consider the risk attitudes of the stakeholders as well as the risk portfolio of their innovations. This paper adds to the body of knowledge by measuring risk aversion in two rural districts in eastern Uganda to see if risk aversion is a barrier to adopting CAPs.

Chapter 3: Conceptual Framework

People's attitudes toward risk are relative to the options available to them. People could be averse to risk at all levels but must still choose a portfolio of options that has a fair amount of risk in it because they do not have the option to sustain their life with a risk-free portfolio. Since everyone has to make decisions in a world of risky options, they will make those decisions based on the knowledge, experience, and options available to them.

When considering the risk of adopting a new farming technique like the CAPs being studied by SANMREM IL a farmer cannot simply look at the expected yields and variations of harvests because it has not been exhibited for years by all his/her neighbors. The first adopters of a new technique have to make their risk decisions with a lot of uncertainty about the actual risk portfolio of the technique. How people make risky decisions under uncertainty is beyond the scope of this paper. This paper follows the convention of the authors eliciting risk preferences cited earlier in this paper by offering an experiment were respondents choose an option from differing risks and payouts.

There is no direct and tractable way to pin-point what level of risk aversion is an ultimate barrier to adoption; it would be nice to know at what precise risk measure is a barrier to adoption. In the absence of this level of research many economists have used ranges to stratify people's risk aversion into different classifications (Binswanger, 1980; Miyata, 2003; Wik, Kebede, Bergland, & Holden, 2004; Yesuf & Bluffstone, 2009). These researchers have assumed those with greater measured risk aversion will be slower to take the risk of adopting a new farming technique and those with lower risk aversion will be quicker to take the risk of a new farming technique. Similarly, the adoption of CAPs can be estimated by hypothesizing that farmers in certain risk aversion ranges are too risk averse to adopt.

Chemical fertilizer can increase yields and variations due to rainfall. In years of good rainfall fertilizer will increase yields. However, when rainfall is especially low some fertilizers can harm crop production. Therefore, an investment in an innovation like fertilizer increases expected yield and increases variability. CAPs are unique in that they are expected to decrease variability without decreasing yields. There are two distinct ways of thinking about the risk of adopting CAPs: the actual variation of yields and the uncertainty of an unproven technique. If CAPs reduces variation without any cost as expected, it will benefit everyone regardless of their level of risk aversion. However, the actual yield variation of CAPs in eastern Uganda is unknown, making the adoption of CAPs risky in that there is little data to make an informed decision.

Risk Measures

The three main ways to elicit risk preferences that are common in economic analysis are: Multiple Price List, Ordered Lottery Selection, and Certainty Equivalence (Anderson et al. & Agriculture Organization of the United Nations, 1992). Each of these methods has different strengths and weaknesses. The ordered lottery selection was used for this research because it offers the ability to narrow the scope of risk options to ones that are close to those currently experienced, and it is the easiest to understand for people with low education. The ordered lottery gives the respondent a list of gambles from which he/she chooses to play one. Economists often favor the convention of giving all gambles a 50/50 probability of winning or losing the correlated amounts in less-developed countries where many people have low education. This is the elicitation tool that Binswanger utilized in India. He argued that in developing countries with lower educated respondents, the equal chance lottery is relatively easy

math, and it is more likely that the respondent will understand the game. The ordered lottery selection maintains the same probability through all options but varies the amount won or lost.

There are two ways to measure risk attitudes using an ordered lottery selection and each has its strengths and weaknesses. One way is in yield/variance space with the risk-measure Z. Z is calculated by the change in expected yield divided by the change in variance and is the slope of the line segment between the choices. Looking at Figure 1, we can see that a person who chooses lottery C prefers it to all others or at least is indifferent between C and B or indifferent between C and D. There are two indifference curves drawn on Figure 1, one that has tangencies to the line segment between B and C and one indifference curve that is tangent to the line segment between C and D. The slopes between the points that represent the different lotteries will give a range of how much risk the respondent prefers. We know the most risk-averse person who chose lottery C is indifferent between B and C and least risk-averse person whose chose lottery C is indifferent between C and D. The last column in Table 1 and Table 2 gives these ranges for each lottery choice. For example, the respondent who chose C in Tororo (which along with Kapchorwa are the two districts examined in this study) is in the range between the two indifference curves which have the slopes of .5 (indifferent between B and C) and .33 (indifferent between C and D).

Figure 1: Tororo Lottery Risk Frontier

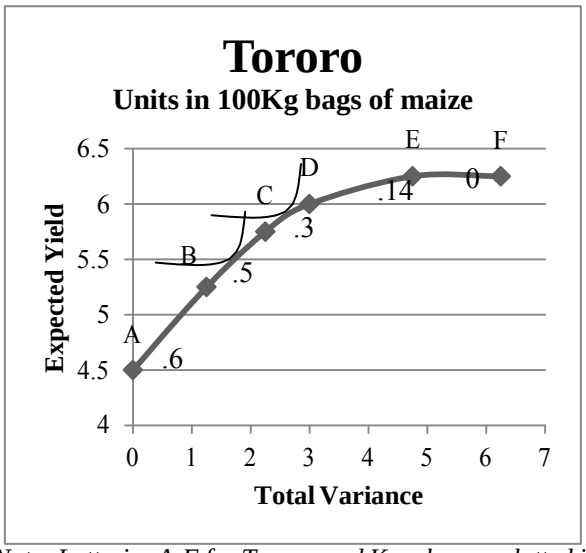
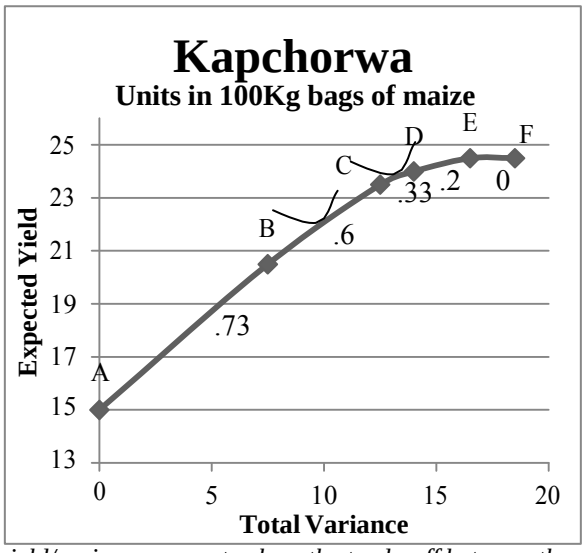


Figure 2: Kapchorwa Lottery Risk Frontier



Note: Lotteries A-F for Tororo and Kapchorwa plotted in yield/variance space to show the trade-off between the lottery options, two indifference curves are drawn to represent how an individual who chose lottery option C could be indifferent between B and C or C and D . See footnote 4 for information on units and the methods section for why yields are different in the two regions.

Table 1: Tororo Lottery Risk Measures

Lottery Option	Number of 100 Kg bags of maize, bad harvest	Number of 100 Kg bags of maize, good harvest	Risk Aversion Classification	r=risk coefficient	$Z=\frac{\Delta E(Yield)}{\Delta SD}$
A	4.5	4.5	Extreme	∞ to 6.244	1 to .6
B	4	6.5	Severe	6.244 to 1.674	.6 to .5
C	3.5	8	Intermediate	1.674 to .720	.5 to .33
D	3	9	Moderate	.720 to .190	.33 to .14
E	1.5	11	Slight to Neutral	.190 to 0	.14 to 0
F	0	12.5	Neutral to Negative	0 to -∞	0 to -∞

Table 2: Kapchorwa Lottery Risk Measures

Lottery Option	Number of 100 Kg bags of maize, bad harvest	Number of 100 Kg bags of maize, good harvest	Risk Aversion Classification	r=risk coefficient	$Z=\frac{\Delta E(Yield)}{\Delta SD}$
A	15	15	Extreme	∞ to 5.649	1 to .73
B	13	28	Severe	5.649 to 1.419	.73 to .6
C	11	36	Intermediate	1.419 to .55	.6 to .33
D	10	38	Moderate	.55 to .274	.33 to .2
E	8	41	Slight to Neutral	.274 to 0	.2 to 0
F	6	43	Neutral to Negative	0 to -∞	0 to -∞

One strength of analyzing risk preferences in expected yield/variation space is the straight forward way in which it can be analyzed. The slope of the line segments can be interpreted as the 'price' in increased yield that a farmer needs to receive to take on more risk. When the expected yield and variation of the new CAPs are known, they can be compared to the 'price' captured by Z. Taking current yields and variations into account, adoption rates could be estimated using Z as a price to take on or discard risk. Since the respondent is seeing all six lottery choices at once, and only those six, there is no precise or final exchange for mean yield and variation. There are only the exchanges between the given choices, but the actual mean and variance of CAPs should lie within the range of this risk-frontier. Mean/variance analysis makes it possible to discuss the substitution rate of expected mean and variation.

The second way this ordered lottery selection was analyzed was with a Von Neumann-Morgenstern risk coefficient in Expected Utility Theory (EUT). The advantage of EUT analysis is the mathematical tractability of the risk measures, and the risk coefficient is unit free and therefore can be compared to other studies based on different pay amounts and different currencies. Arrow and Pratt derived risk coefficients from EUT that can reflect absolute risk aversion and relative risk aversion (Pratt, 1964). Building on Pratt and Arrow, Menezes and Hanson (1970) defined a third coefficient: partial risk aversion:

$$1) \quad P(W_0, \pi) = -\pi \frac{U''(W_0+\pi)}{U'(W_0+\pi)}$$

where W_0 denotes initial wealth, π is stochastic income, and $U' and\ U''$ indicate the first and second derivative of the expected utility function.

Absolute risk aversion describes situations where income is fixed and the initial wealth is variable. Relative risk aversion is a good measure for situations where income and initial wealth change proportionately. When initial wealth is fixed and income varies, partial risk aversion is

the most appropriate measure (Wik et al., 2004). Partial risk aversion (PRA) was most appropriate in this study because the survey questions varied the yield of the next harvest; which affects the farmer's yearly income through the stochastic harvest. The utility function used in this paper is the same as others cited earlier (Binswanger, 1980; Humphrey & Verschoor, 2004; Mosley & Verschoor, 2005; Wik et al., 2004; Yesuf & Bluffstone, 2009):

$$2) \quad U = (1-r)^{(1-r)}$$

where U is the utility, Y is the certainty equivalent, and r is the risk coefficient. Solving for the person who is indifferent between each consecutive lottery choice bounds the risk aversion coefficient for each lottery option. In Tables 1 and 2, the column labeled "r= risk coefficient" gives the risk coefficient ranges. For example a person choosing lottery B in Tororo could be indifferent between lotteries A and B (r=6.244) or indifferent between lotteries B and C (r=1.674). This specific range of possible risk coefficients is obtained by solving for r in the following two equations for r.

$$3) \quad (1-r)4.5^{(1-r)} + (1-r)4.5^{(1-r)} = (1-r)4^{(1-r)} + (1-r)6.5^{(1-r)} \quad \text{r=6.244}$$

$$4) \quad (1-r)4^{(1-r)} + (1-r)6.5^{(1-r)} = (1-r)3.5^{(1-r)} + (1-r)8^{(1-r)} \quad \text{r=1.674}$$

By solving equations 3 and 4, we know that a person who chooses lottery B in Tororo has a PRA coefficient between 6.244 and 1.674. By solving each lottery option this way there are six ranges for the risk aversion coefficients that correlate with the lottery choices in each district. These ranges are listed in the fourth column of Table 1 for Tororo and Table 2 for Kapchorwa.

Hypothetical vs. Paid Lotteries

People are likely to more accurately present their risk preferences when there are real stakes then when there is a hypothetical choice set. For this reason, many researchers have

played lotteries in which the respondents gamble real money. For ethical reasons when playing lotteries in less-developed countries, most researchers only offer a win/win lottery with no chance of the person losing their own money. The researcher using a lottery with real money has little doubt that the respondent is answering the same question the researcher is asking on the survey due to the power of the financial incentives. The ordered lottery selection with actual payouts is a theoretically precise way of measuring risk preferences based on risk attitudes toward money. However, the final analysis needs to translate this experiment into how farmers make farming decisions under uncertainty in their fields.

When farmers make decisions in their fields, there may not be a direct correlation between their stated degree of risk preference for monetary lottery games and their actions in real life. When a farmer makes a choice from the list of lotteries, he/she does not have to consider any of their real constraints, and the decision is based on how they think about risks and payoffs at that time and place and at those amounts. The environment of a monetary gamble is different from the field and the payout timelines are different too. Also since it is a win/win game, they do not have to think about negative consequences of losing money from their normal budget. When making a farming decision however, a farmer must think about the consequences of a failed crop or very low yield. The farmer invests money in farming inputs which he/she hopes will return a profit at harvest time. There is usually a family counting on the harvest for their food and livelihood. This conundrum exists between precise experimental measurement of risk aversion and the interpretation in the reality in which farmers make their farming decisions.

The weakness of the paid lottery becomes apparent when the findings are translated into the farmers' risk preferences for their livelihood across an entire growing season. A hypothetical choice set based as closely as possible on farming reality combined with a well-constructed

script may even be a more accurate measure of farmers making their farming decisions than an experiment with real money. This study used a hypothetical game anchored in the production realities that farmers face. The game was anchored so that the respondents would view the game as realistic and make their decisions to accept risk the same way they would at planting time. In their decision process, they will include their loss aversion in that if they have a very poor crop they will lose their investment and they may not be able to adequately feed their family. A person who loses when gambling for real money in a win/win scenario, as has been the custom in many risk-preference elicitation studies, does not have to worry about how it will affect his/her budget since it is not part of their budget.

A hypothetical lottery is not part of their real budget either, but it can be anchored on crop yields for an entire growing season. To payout real money at the level of a single harvest would be too costly and paying people in produce a logistical nightmare. The unit used in this hypothetical research is 100 kilogram bags of maize, which provided many benefits: it allowed for the use of pictures since some respondents were illiterate, they sell their maize harvest in 100 kilogram bags, and maize is the most important crop.[4]

Since the benefits of CAPs are expected to be small incremental yield increases over a few years, it is relevant to test the farmers' preferences for risk at and around their current combination of yields and variances. Anchoring the choice set around current yields not only makes its hypothetical aspects more believable, it also means the measurement of risk aversion may be relevant for a farmer making a decision about CAPs. Conservation agriculture is an entirely new system of farming for most farmers, and it requires full commitment to accrue benefits. Therefore, the perceived risk of the CAPs may be greater than the actual risk. This

[4] The 100 KG bags are a standard size bag they fill with maize still on the cob; Ugandans do not weigh the bags or take the kernels off the cob.

research does not elicit farmers' perception of the riskiness of CAPs, but the hypothetical lottery spans a large enough range of believable crop harvest yields so as to catch a relevant range of risk measures. Hypothetical bias is no small matter, but it can be minimized by how the choices are presented; so much effort was given in training the enumerators to make sure the respondents understood the survey and grounded the hypothetical choices in the respondents' reality.

Chapter 4: Methods

This study was administered in two districts in eastern Uganda: Tororo and Kapchorwa. These districts were chosen because they are where SANREM IL is conducting its research and demonstrations, both on-station and in the fields of participating farmers. SANREM IL is researching CAPs based around maize because maize is the primary crop grown in eastern Uganda.

It is assumed that adoption will start close to the fields of participating farmers and spread out from there (Lamb, 2011). The two districts have very different climates, farming techniques, and expected yields. Therefore, to properly anchor the lottery choice sets and control for differences between the districts, different lotteries were designed for each district. It would have been nice to design one lottery and administer it to 400 people, but to minimize hypothetical bias and control for other differences Tororo respondents received a lottery set based on their typical yields and Kapchorwa received a lottery set based on their typical yields. These two sets provided the study with two separate groups of 200 respondents in each region.

Both districts are in eastern Uganda, but Tororo is lower, flatter, and more arid than Kapchorwa. Tororo depends entirely on rainfall to water the fields and receives less rain than Kapchorwa. Kaptchorwa not only receives more rain, but there are springs and streams that provide some water when there are no rains. The soil quality in Kapchorwa is much better than the sandy soil in Tororo.[5] "Kapchorwa is one of the most productive districts in Uganda".[6] The two districts have very different yields due to water availability, soil quality, and differences in the use of fertilizer. Kapchorwa farmers use fertilizer and do not plant anything between their rows of maize. Very few people in Tororo use fertilizer and most of them plant beans between

[5] http://www.oired.vt.edu/sanremcrsp/professionals/research-activities/phase4/ltra10/

[6] A quoted from Grace Tino (director of Appropriate Technologies Uganda).

their rows of maize. The people interviewed in Kapchorwa reported that historically they also planted beans between their rows of maize, but as the use of chemical fertilizer increased, they found mono-cropping maize to be more profitable.

Due to their differences, CAPs are important to these two regions for different reasons. Due to Kapchorwa's steepness, soil erosion causes farmers to lose valuable land during heavy rains. The minimal disturbance of the soil and leaving on cover crops of CAPs will help slow erosion by keeping valuable topsoil in place. In Tororo, the soil is sandy and lacks nutrients to produce high yields. By leaving the cover crop on the land, Tororo farmers can increase the organic matter in their soil, which over time can increase yields. There may also be a benefit of retained moisture in the soil since cover crops provide shade.

Because an accurate anchor is crucial in minimizing hypothetical bias, information about the current mean and variation experienced in each region was obtained. Five experts/extension agents and nine farmers were interviewed in Tororo and asked: "what is the average yield, the yield for a typical bad harvest, and the yield for a typical good harvest? In Kapchorwa, three experts/extension agents and nineteen farmers were interviewed. Within each district, people's answers were relatively homogenous, with the exception of two farmers in Tororo and three farmers in Kapchorwa who indicated lower expected yields than the rest. Also, one farmer in Tororo utilized advanced techniques compared to his neighbors and realized higher yields. That farmer was running a test farm for SANREM IL and reported that the CAPs were working well. He also used fertilizer along with the conservation farming techniques. The homogeneity of farming techniques and the consistency of expected yield in each region made it feasible for the lottery set to be anchored on a common experience. In Tororo, the average yield reported was 8-10 bags, the bad harvest was complete crop loss, and the typical good harvest was 10-12 bags.

For Kapchorwa, respondents reported an average of 20 bags, a bad harvest was 10 bags, and a good harvest was 40 bags.

Data Collection

The data for this paper were collected in June and July of 2013. The survey questionnaire was designed to collect data for this study and another study that analyzed a choice model experiment.[7] To administer the survey, ten enumerators were recruited in Tororo and nine enumerators in Kapchorwa. The farmers in these two regions spoke different languages and needed different enumerators. One full day was spent in each district training the enumerators on the survey. The first part of the survey included basic demographic questions; therefore, significant time was spent during enumerator training to make sure everyone understood the risk-preference elicitation game and the choice-model experiment.[8]

Two hundred farmers were randomly selected in each region by first randomly selecting twenty villages from a list of all villages in each region. Ten people were then randomly selected from each of the selected villages. The names of the villagers were obtained from the county district office that had information from a 2007 census. Since the census was not recent, three extra names were randomly selected from each village as a reserve in case some of the selected farmers had died or moved away. The village randomization in Tororo was done by taking every fourth village from an alphabetical list. The rest of the randomization was done with an Excel random number generator. The surveys were administered by interview on the respondent's farm or wherever the respondent could be located. Researchers who invited farmers in to a

[7] Kate Vaiknoras of Virginia Tech collected data for a choice experiment to ascertain the importance of environmental services to the Ugandan stakeholders. The survey form can be seen in the appendix
[8] The choice-model experiment was the part of the survey relevant to Kate Vaiknoras.

central location i.e. (Binswanger, 1980; Cook, Chatterjee, Sur, & Whittington, 2013; Harrison, Humphrey, & Verschoor, 2010; Mosley & Verschoor, 2005; Yesuf & Bluffstone, 2009) remove farmers from their homes. This survey controlled for location influence by meeting most of the respondents where they live and made farming decisions.

Risk Aversion Measurement

The respondents' risk preferences were measured with a hypothetical game of six lottery choices laid out on a concave risk frontier in the style of Binswanger. The first option was a completely safe one with the same payout for winning or losing. The next four options had higher expected yields and higher variances. Farmers 'pay' for the higher expected yield by taking on more risk. The sixth and final choice increased the variance while keeping the expected yield equal to the fifth choice; this option added the 'cost' of more risk without a higher payout. Tororo's risk frontier is shown in Figure 1 and Kapchorwa's is shown in Figure 2. Each lottery option consisted of a bad outcome of lower yield and a good outcome of higher yield with a 50/50 chance of good or bad. See Figure 3 for an example of the three lottery options used as a practice game. If the first lottery (A) was chosen, it paid out 5 bags of maize if the person lost and 10 bags if the person won. If the second lottery (B) was chosen, it paid out 3 bags if the person lost and 15 bags if the person won. Lottery choice C paid out nothing if the person lost and 20 bags if the person won.

To make sure each respondent understood the equal chances of good or bad outcomes for each lottery, a practice game was played first that consisted of three lottery options that covered a large range of yields (see Figure 3). The respondent chose one of the lotteries and the enumerator asked why they chose that lottery to make sure they understood they had an equal

chance of the good and the bad outcomes. The enumerators were trained to ask the respondents to explain why they made their choices. The enumerators listened to the person's explanation to be sure the respondent understood there was an equal chance of a bad or good harvest. If the enumerator did not feel the respondent understood, he/she would explain again how the game was played. When a respondent told a story of what would happen in their home if they received the bad harvest and what would happen if they received the good harvest that correlated with their particular lottery choice, it showed they understood their choice.

Figure 3: Lottery Choice Practice Game

Practice Game		
Equal Chance	Bad Harvest	Good Harvest
A	x5	x10
B	x3	x15
C	x0	x20

A local game was used that everyone had played as a child and understood well. The enumerator would show the person an object and hide it in a hand behind his/her back. The enumerator would then show the respondent both closed fists and ask the person to pick a hand. If the person picked the hand containing the object, they received a good harvest, but if the person picked the empty hand they received a bad harvest. This game was very familiar to all respondents because they had played it as children. The enumerator asked the respondent to talk through the outcome. Playing the game once and discussing the outcome helped ground the hypothetical aspect of the game in the farmer's reality. To further ground the games before moving on to the next two games, the enumerators asked the respondents to think of their budget, family responsibilities, all the crops they grow, and how their decisions for planting maize on one acre of land with the expected outcomes shown would affect their lives. Only the practice game was played and discussed. For the actual risk elicitation game, the enumerators where trained to only read through the options and record the person's choose.

Farmers were told the actual risk elicitation game would not be played. They were told to imagine the enumerator standing in the field at harvest time with two closed fists and whether they won or lost the game at that time dictated the size of their harvest. This was done to place the hypothetical game in the same time frame as farming decisions. Not finding out if they won or lost immediately allowed them to make their decisions without being motivated by the immediate emotion of playing the 50/50 game, and it helped control for hypothetical bias.

When the enumerator asked questions and interacted with the respondent during the practice game, they were able to know if the person understood the task from the face-to-face intimacy of the interview. Any coaching that might have gone on during the practice game was disconnected from the actual risk-elicitation tool in two ways. First, the expected means and

variances of the practice game were different from the lottery options in the actual ordered lottery list. That way, if the enumerator had coached them toward a certain lottery in the practice game, that coaching would not easily transfer to a lottery in the actual elicitation tool. Second, once the enumerators introduced the actual elicitation tool, they did not talk anymore about grounding the lotteries in reality or how the game was played. They did that in the practice game, but for the elicitation tool they only read the options to the farmer and recorded their selections.

After the practice game was completed, each respondent made choices from two lottery sets. The first choice set was a list of six lotteries (A-F) of bad and good yield expectations designed to elicit a risk preference. The second choice was designed to test if Lipton's theory that subsistence farmers make decisions based on a safety-first algorithm has any validity and to test for misunderstanding by including a risk-loving choice. The second game is discussed in greater detail in the next section and appendix A (Safety-First).

Validation of Respondents' Comprehension

Researchers want to know if the respondents understood the survey and answered the same questions the researchers were asking. To determine whether or not respondents understood his ordered lottery list, Binswanger (1980) included two inefficient choices. His two choices offered the same expected payout as another lottery but with greater variance. Binswanger placed these two options in the middle of the ordered lottery game so that the other lottery choices had stochastic dominance over these inefficient choices. By doing this, Binswanger offered six lottery choices on the risk frontier and two inefficient lotteries inside the risk frontier. If a respondent did not understand the game and chose randomly, Binswanger's verification method

would catch them two out of eight times or 25%, suggesting there could be more people misunderstanding then 'caught' making a mistake. Binswanger (1980) had two hundred and eighty-six people complete nine games each and found that 33% of them chose an inefficient lottery at least once.

A multiple price list offers a list of choices between a safer and a riskier lottery. The risk coefficient is measured where the person switches from the riskier to the safer lottery or vice versa. Researchers using this method of eliciting risk preference can hypothesize that people switching more than one time misunderstood the exercise or were inconsistent. Cook et al. (2013) found that of the 404 respondents they surveyed, 238 or 59% of them made mistakes. It is likely that Binswanger had as many people misunderstanding the exercise as Cook et al. did, but the ordered lottery selection does not allow for mistakes as readily as a multiple price list.

Due to the difficulty in knowing whether a respondent understood the game based on the data, this researcher primarily counted on the enumerator to ascertain if the person understood the task during the practice game. The enumerators shared the same culture and language as the respondents and had face-to-face interviews in which they tried to make sure the respondents understood the task. Also a risk loving option was included in the second ordered lottery to catch people making mistakes. This option (F*) gave lower expected yield and higher variance than lotteries D and E.

One model is estimated in this paper in which the respondents who chose lottery F* in the second game are left in and risk-loving behavior is allowed. A second model is estimated in which respondents who chose lottery F* are removed and assumes Ugandan farmers are not risk loving in terms of their yearly harvest but they made a mistake. Similar to Binswager's inefficient options, this risk loving option (F* in the second game) will only 'catch' one out of

six or 17% of the people making random choices. Therefore removing these respondents does not guarantee that there are not mistakes in the data, but the reliability of the data is based on the competency of the enumerator performing face-to-face interviews.

Conceptual Model

As stated earlier there are two assumptions about how risk aversion will effect adoption of CAPs. We can assume those who are less risk averse will be quicker to try a new unproven farming technique. This assumes that first adopters are generally not going to be the most risk-averse people of a given population. Alternatively we can assume that since CAPs are expected to decrease variability, farmers who are more risk averse will be equally quick to adopt them. The author of this paper thinks that the unknown outcomes of CAPs are a greater barrier to adoption than the unproven assumption that CAPs will decrease variation in eastern Uganda. Knowing what observable characteristics correlate with decreased risk aversion will help estimate adoption of CAPs. Also, once more is known about the CAPs, knowing what observable characteristics are correlated with decreased risk aversion will aid extension agents by highlighting the farmers more willing to try a new technique with the unique attributes of CAPs.

The primary characteristic of interest is the wealth of the farmers. As Lipton argued, the poor lack tools to cope with loss and therefore will be more risk averse. If Lipton's argument is accurate it would be beneficial for extension agents to focus first on wealthier farmers since they would be more likely to adopt a new technique. To test Yesuf and Bluffstone's theory that the poor are path dependent and need small guaranteed successes to gain the confidence to adopt innovations on their own, this study asked respondents about previous successful and unsuccessful innovations. If those with more previous successful innovations are less risk averse

and/or if those who felt their innovations have been unsuccessful are more risk averse, then this study will support Yesuf and Bluffstone's path dependency theory.

Chapter 5: Empirical Model

An ordered probit model was used to analyze if household attributes correlate with risk aversion levels. Ordered probit was chosen because the dependent variable in the model (lottery chosen) is a discrete ordinal variable including six integers (A-F/6-1). Risk aversion is continuous, but we can only observe if it falls within one of the six ranges on the survey. The six ranges are decreasing in risk aversion from extremely risk averse to slight risk averse/risk neutral. We are interested in knowing if any of the independent variables increase the probability of a person moving from a higher risk aversion level to a lower risk aversion level or vice-versa.

Summary of Descriptive Statistics

Table 3 lists the variables utilized with short descriptions, the ranges of answers in the data set, and the expected effects on the dependent variable, where a negative sign means a higher probability of moving toward a less risk-averse level and a positive sign means a higher probability of moving toward a more risk-averse level.

Table 3: Variables in the Model

Variable	Description	Range	Expected effect on risk aversion
Lottery Option	Lottery option chosen	A-F/6-1	
Gender		Male=1 female=0	+/-
Age		18-93	+/-
Education	Level of education completed	0=no formal education 1=some primary 1-6yrs 2=completed primary 7yrs 3= some secondary 8-12yrs 4=completed secondary 13yrs 5=post-secondary >13yrs	+/-
Over Half Income	Nonfarm income is over half your income	No=0 Yes=1	-
Crop Failure	Number of complete crop failures divided by years farming	0-1	+
Successful	Successful farm innovations divided by years farming	0-1	-
Unsuccessful	Unsuccessful farm innovations divided by years farming	0-1	+
Roof	Type of roof as a measure of wealth	Thatched=0 Corrugated Steel=1	-

A person who obtains more than half of their income from non-farming activities can afford to take more risk on their farm because they are less dependent on their harvest for income. A person who has tried new farming techniques and has had success might be more willing to take on another risky innovation due to their increased confidence from previous success. Conversely, a farmer who has been unsuccessful with new technologies may be more risk averse due to being let down by other risky innovations. The coefficient on corrugated roof as a proxy for wealth is expected to be negative because greater wealth allows a person to smooth consumption during low yields. If the coefficient on wealth is negative, then as people

increase their assets their risk aversion of investing in high-risk, high-return decreases. If the effects of previous successful and unsuccessful innovations have the expected effects on risk aversion, and if risk aversion decreases with increased wealth, then there may be a place for policy intervention. A policy that insured small investments and provided a way for farmers to experience success and accumulate assets might decrease risk aversion and enable farmers to invest in higher risk/return investments. However, policies to insure success can have moral hazard issues, so implementing them must be done cautiously and have substantial benefits.

Assessing wealth in developing countries can be difficult. This paper chose type of roof as the variable to stratify wealth classes because the roof type represents a large investment that people are generally anxious to make when they can afford it. The thatching for a traditional roof is low cost but it does not last very long. People with thatched roofs must replace them often and risk damage to their house due to frequent leaks. Corrugated steel roofing is costly up front but has a long expected lifetime, protecting the house from rain damage better than thatch. Therefore, the thatched roofs have smaller but more frequent costs (especially labor costs) than corrugated steel, and in the long-run the corrugated steel will be the better investment most of the time. The extension agents and farmers that helped pilot the survey all agreed that corrugated steel was a good indicator of wealth. They claimed that a corrugated steel roof is also a status symbol.

This study attempted to use other measures of wealth. The other measures of wealth used were animal units, land ownership, and an investment expenditure combining animals and land ownership. Market prices were used to combine land and animals into a monetary value. None of these alternate measures of wealth gave any further insight, therefore roof type was ultimately used as an indicator of wealth because it is easily observable and there is no calculation error due

to volatile market prices. The price of land in eastern Uganda varies according to land quality and distance from main roads and markets. These attributes are hard to observe and furthermore the market for land is not very active in the area, which meant there were few observation on land price.

The variables "successful" and "unsuccessful" speak to the pathways out of poverty as described by Yesuf and Bluffstone. If the coefficient on success is found to be negative, then a person can escape the poverty trap of investing in low risk/return investments through small successes. A negative correlation suggests that risk aversion becomes less of a barrier to adoption as people experience success. Likewise, if the coefficient on unsuccessful is found to be positively correlated with risk aversion, then farmers who experience success rather than of failures will have lower risk aversion and thereby escape a poverty trap. However, if no correlation is found, Yesuf and Bluffstone's conclusion that policies to insure small successes can reduce farmers' risk aversion and help them escape the poverty trap may be incorrect, and attempting policy initiatives such as those that they suggest might do more harm than good.

Tables 4 and 5 give the mean and standard deviation of the independent variables. The median, minimum, and maximum are included to give the reader an idea of the distribution in the sample.

Table 4: Descriptive Statistics in Tororo

Variable	Mean	Standard Deviation	Median	Minimum	Maximum
Gender	.49	.50	0	0	1
Age	47.02	16.1	46	20	93
Education	1.5	1.2	1	0	5
Over half income	.179	.384	0	0	1
Crop fail	.114	.126	.076	0	1
Success	.05	.112	.019	0	1
Unsuccessful	.034	.091	0	0	1
Roof	.833	.374	1	0	1

Note: Statistics are based on removing risk-loving respondents from the sample

Table 5: Summary of Descriptive Statistics in Kapchorwa

Variable	Mean	Standard Deviation	Median	Minimum	Maximum
Gender	.527	.501	1	0	1
Age	39.95	14.85	37.5	18	88
Education	1.77	1.16	2	0	5
Over half income	.067	.25	0	0	1
Crop fail	.164	.208	.1	0	1
Success	.103	.176	.05	0	1
Unsuccessful	.079	.129	0	0	.667
Roof	.52	.501	1	0	1

Note: Statistics are based on removing risk-loving respondents from the sample

Models

Two full models were estimated for each district as described in the validity section. The first model identified as 'All Complete Surveys' estimated an ordered probit using all surveys that

were completed successfully. In Tororo, six observations lack crucial data. In Kapchorwa, there were eleven surveys missing a response to a question, primarily gender did not get recorded. The second model removed observations with respondents who chose the risk-loving lottery (F*) in the second game and is titled 'Risk-Loving Respondents Removed'.

The model regressed the risk aversion level on a vector of household attributes thought to affect a person's degree of risk aversion:

5) $$Lottery\ Option = \beta_1 gender + \beta_2 age + \beta_3 agesquared + \beta_4 education + \beta_5 overhalfincome + \beta_6 cropfail + \beta_7 successful + \beta_8 unsuccessful + \beta_9 roof$$

where *Lottery Option* is the lottery option chosen and is regressed on *gender, age, education* (categorically defined), , *over half income* (if more than half their income is nonfarm income), *successful, unsuccessful* (number of time they tried something new and found it to be successful or unsuccessful), *roof* (corrugated steel roof as a proxy for wealth).

In addition to the full models, restricted models were estimated as well; none of which provided additional insight. Gender, age, and education along with the different wealth indicators were included. Also the variable of previous success and crop loss were included in restricted models.

Chapter 6: Results

The distribution of lotteries chosen in Tororo was centered on lottery C which has a PRA coefficient range of 1.674 to .72, which implies an intermediate level of risk aversion. The choices of lotteries resembled a normal distribution; except for the risk neutral lottery F which was chosen more than the more efficient lottery E (see Figure 4). In Kapchorwa, Lottery B with a PRA coefficient range of 5.649 to 1.419 was chosen 61 times, far more frequently than the other lotteries (see Figure 5). Lottery B is classified as severely risk averse.

Figures 4 and 5 indicate that the two districts have different distributions of lotteries chosen, with Kapchorwa being more risk averse. Due to differences in anchoring for the two regions, the lotteries are not precisely capturing the same ranges of PRA coefficients, making econometric comparison inappropriate. However, they are close (Tables 1 and 2). Although it appears that Kapchorwa is on average more risk averse than Tororo, their PRA ranges overlap (1.674 to 1.419). If 20 people in Kaptchorwa have a PRA coefficient in the overlapping range, the regions would have similar distributions.

Figure 4: Lotteries Chosen Tororo

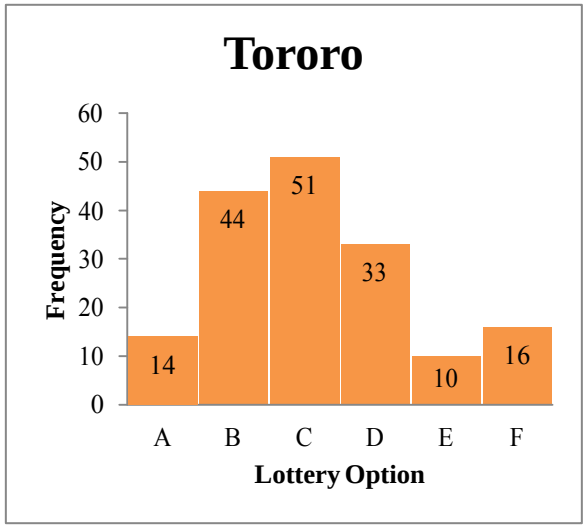
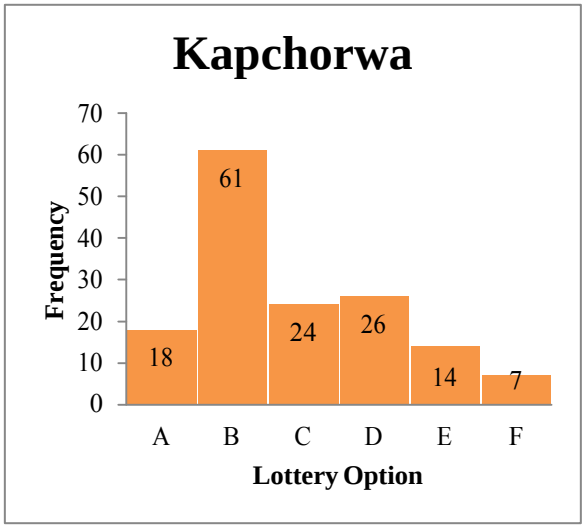


Figure 5: Lotteries Chosen Kapchorwa



Note: See Tables 1&2 for full description of lotteries A-F

Estimation Results

In neither region were any of the estimated coefficients on the included attributes statistically different than zero at a 10% significance level (Table 6). The first model has 194 respondents; the second model drops 26 risk-loving respondents and retains 168 respondents. In Kapchorwa, the first model has 189 respondents; the second model drops 39 observations by removing those who chose the risk-loving lottery F*, leaving the second model with 150 observations.

Table 6: Tororo Ordered Probit Coefficient Estimates

Variable	**All Complete Surveys**		**Risk-Loving Respondents Removed**	
	Coefficient	**P value**	**Coefficient**	**P value**
Gender	-.031	.846	-.04	.812
Age	.009	.736	.021	.46
Age Squared	0	.854	0	.593
Education	.003	.963	.015	.841
Over Half Income	.285	.156	.296	.17
Crop Fail	-.217	.777	.535	.518
Successful	.465	.632	.513	.609
Unsuccessful	-.767	.538	-2	.126
Roof	-.035	.862	-.184	.416
Log Likelihood	-326.282		-271.026	
Pseudo R^2	.005		.011	
Observations	194		168	

Table 7: Kapchorwa Ordered Probit Coefficient Estimates

Variable	All Complete Surveys		Risk-Loving Respondents Removed	
	Coefficient	**P value**	**Coefficient**	**P value**
Gender	.072	.661	.147	.440
Age	.015	.637	.03	.420
Age Squared	0	.556	0	.330
Education	.059	.433	-.065	.458
Over Half Income	-.307	.252	-.174	.626
Crop Fail	-.926	.149	-.646	.392
Success	.302	.667	.402	.609
Unsuccessful	.082	.932	.146	.890
Roof	-.006	.970	.17	.370
Log Likelihood	-319.018		-234.619	
Pseudo R^2	.01		.011	
Observations	189		150	

*Note: * significant at 10% level; ** significant at 5% level*

When estimating an ordered probit, the marginal effects give more useful information than coefficient estimates. The coefficient estimates are calculated at the mean for the given independent variable across all risk classifications. The marginal effects give the effects that the independent variables have on risk aversion at each risk aversion classification. This way we can see the effect at a particularly interesting risk aversion level. For example, we can see the effect that a given variable has at the risk free (extremely risk averse) level. Following Binswanger (1980), each lottery option was given a qualitative name that classified the range of the PRA (see fourth column of Tables 1 and 2). The marginal effects of some of the variables are shown for these classifications in Table 8 for Tororo and for Kapchorwa in Table 9.

Table 8: Tororo Marginal Effects

Model	Variable	Extreme	Severe	Intermediate	Moderate	Slight/Neutral	Neutral
All Complete Surveys	Over Half Income	.046 (.215)	.059 (.145)	.002 (.83)	-.029 (.204)	-.025 (.168)	-.053 (.117)
	Crop Fail	-.031 (.777)	-.046 (.777)	-.007 (.783)	.02 (.778)	.019 (.778)	.045 (.777)
	Success	.066 (.634)	.1 (.633)	.014 (.654)	-.043 (.634)	-.04 (.635)	-.096 (.633)
	Unsuccessful	-.109 (.54)	-.164 (.54)	-.023 (.576)	.07 (.542)	.067 (.542)	.159 (.54)
	Roof	-.005 (.864)	-.008 (.862)	-.001 (.846)	.003 (.864)	.003 (.862)	.007 (.86)
Risk-Loving Respondents Removed	Over Half Income	.05 (.231)	.062 (.155)	-.001 (.581)	-.042 (.195)	-.02 (.181)	-.043 (.128)
	Crop Fail	.079 (.519)	.118 (.521)	.001 (.928)	-.073 (.519)	-.037 (.525)	-.088 (.521)
	Success	.076 (.610)	.113 (.609)	.001 (.929)	-.07 (.611)	-.035 (.613)	-.084 (.609)
	Unsuccessful	-.294 (.138)	-.437 (.136)	-.005 (.928)	.271 (.141)	.138 (.164)	.327 (.137)
	Roof	-.03 (.456)	-.04 (.405)	.003 (.746)	.026 (.433)	.012 (.417)	.028 (.379)

Note: Marginal effects of five variables are given for each risk-aversion classification with p value in parenthesis.

Table 9: Kapchorwa Marginal Effects

Model	Variable	Extreme	Severe	Intermediate	Moderate	Slight/Neutral	Neutral
All Complete Surveys	Over Half Income	-.054 (.182)	-.065 (.286)	-.002 (.834)	.021 (.149)	.033 (.243)	.066 (.317)
	Crop Fail	-.188 (.154)	-.179 (.16)	.013 (.397)	.08 (.169)	.102 (.17)	.171 (.155)
	Success	.061 (.668)	.058 (.668)	-.004 (.69)	-.026 (.669)	-.033 (.669)	-.056 (668)
	Unsuccessful	.017 (.932)	.016 (.932)	-.001 (.932)	-.007 (.932)	-.009 (.932)	-.015 (.932)
	Roof	-.001 (.97)	-.001 (.97)	0 (.97)	.001 (.97)	.001 (.97)	.001 (.97)
Risk-Loving Respondents Removed	Over Half Income	-.031 (.591)	-.038 (.649)	.006 (.478)	.022 (.607)	.023 (.639)	.018 (.667)
	Crop Fail	-.126 (.394)	-.131 (.397)	.029 (.415)	.087 (.398)	.082 (.403)	.059 (.403)
	Success	.078 (.609)	.082 (.61)	-.018 (.615)	-.054 (.61)	-.051 (.612)	-.037 (.612)
	Unsuccessful	.029 (.89)	.03 (.89)	-.007 (.89)	-.02 (.89)	-.018 (.89)	-.013 (.89)
	Roof	.033 (.372)	.035 (.376)	-.008 (.389)	-.023 (.376)	-.021 (.382)	-.016 (.386)

Note: Marginal effects of five variables are given for each risk-aversion classification with p value in parenthesis.

Discussion

Farmers who chose lotteries A or B are of most interest since they are classified as extremely and severely risk averse. These ranges are the most interesting because of their high PRA coefficients and they are the ones expected to be least likely to adopt CAPs if we assume farmers are more resistant to adopting new technology the higher their risk aversion. In Tororo, 58 people or 35% of the sample chose a lottery with less risk than lottery C, which is classified as intermediate risk averse. Of those, 14 or 8% chose lottery A, which has no risk at all. In Kapchorwa, 79 or 53% chose lottery A or B and 18 or 12% chose lottery A, the risk free lottery. Those revealing a high level of risk aversion are a substantial percentage of the population and their risk aversion could slow their adoption of new farming techniques.

If however we assume that CAPs will be adopted by the more risk averse due to their presumed benefit of decreasing yield variability, then the story of adoption could be switched. The more risk averse would adopt CAPs for the benefit of reducing production risk. All farmers would be happy to reduce risk if it does not cost them anything, so if CAPs reduce variability then all groups will be quick to adopt them based on yield/variation calculations. These two assumptions prescribe very different estimates for CAPs adoption as it pertains to risk preference.

The hypothesis that the wealthier are less risk averse is not born out in this data from eastern Uganda. The models do not find that wealth as represented by roof type has any correlation with a farmer's tolerance for risk. These findings agree with most previous studies (Binswanger, 1980; Cook et al., 2013; Humphrey & Verschoor, 2004) but does not find any evidence to support the findings of Wik et al. (2004) or Yesuf and Bluffstone (2009). The range

of wealth for this data set is limited by wealth differences among the randomly selected Ugandan farmers. By Ugandan standards, there was a large variation of wealth in the data set, but by international standards the range was relatively small. The models therefore do not claim that large amounts of wealth do not have an effect, but that wealth as represented by current wealth stratification represented by those with improved roofing, animals, or land does not significantly affect risk aversion. The wealth variable in this study does not capture the entirety of a farmer's wealth; future studies might be able to calculate a more complete wealth index. With a more precise wealth calculation, empirical modeling might find wealth to influence risk aversion. Also, a more complete wealth calculation could allow for calculation of absolute and relative risk aversion.

The data estimated here do not support the hypothesis that previous success with adoption is correlated with decreased risk aversion. This is in contrast to Yesuf and Bluffstone (2009) who suggest that the poor are path dependent and become more confident and less risk averse as they experience small successes. This does not mean that if the CAPs being studied in Uganda are successful that people will not adopt them. What the lack of correlation between success and risk aversion suggests is that each innovation a farmer tries is judged on its own merits and the farmer maintains his/her risk aversion level no matter how successful each innovation turns out to be. Also, this lack of correlation means that an adopter of successful CAPs will not necessarily be more willing to adopt an unrelated innovation and vise-versa.

There are benefits to CAPs other than yield and variation that are important to adopters. For farmers in Kapchorwa who are farming on very steep land, soil retention is paramount. Even if the yield and risk-reducing benefits of CAPs are not proven, farmers who have watched their soil flow down the hill during heavy rains may be anxious to try something that offers any

promise of retaining their soil. It may be a hard to convince farmers in Tororo the benefits most appropriate to them are that minimal soil disturbance and cover crops shade the soil from the sun and therefore increase the soils ability to retain moisture. It is likely that risk preference as it pertains to trying something new will be a significant factor in adoption in Tororo but may be less of a factor to farmers in Kapchorwa.

Conclusions

Will aversion to risk limit the adoption of CAPs in eastern Uganda if SANREM IL researchers discover that CAPSs are beneficial? 35% of farmers in Tororo and 53% of farmers in Kapchorwa selected either an extreme or severe risk-averse lottery from the ordered lottery selection used to measure risk aversion and of those 32, or 14% chose a risk free option. There is no threshold PRA coefficient that can be used to decipher who will adopt. However, the Z score provides a 'price' of variation in terms of increased yield that can be used to compare current practice to the mean yield and variation of the new CAPs. This study does not claim to completely capture how farmers make uncertain decisions, and the risk measurement only captures mean/variance substitution and misses other real or perceived externalities of CAPs. Risk aversion may be a barrier to adoption of CAPs and limit the spread of CAPs. However, this research does not find any the poor view risk differently than their wealthier neighbors. Risk is a factor all farmers deal with and can be addressed in Uganda based on institutions, laws and politics present there realizing their poor are not more risk averse than the rest.

No correlation was found between risk preference and any of the demographics collected from the farmers of eastern Uganda. This hypothetical risk measurement tool obtained similar findings to Binswager's results over three decades ago. Higher wealth as measured here did not

correlate with a reduced risk aversion. This study agrees with Binswanger that risk aversion is not innate to poverty. This study used self-reported previous successful and unsuccessful innovations and found that people are not more willing to take on risk when they have had previous success, as suggested by Yesuf and Bluffstone. These findings suggest that the poverty trap identified for the poor, due to their inherent risk aversion, is not evident.

Lipton's argument that the poor living in fear of a catastrophe that will cause irreparable harm are inherently more risk averse seems logical, but the research here does not support it. The risk preferences of the two groups, stratified by roof type, do not have significantly different distributions. That is not to say that risk is not a major issue for low-income farmers just as it is for people all over the world. Many people in many places have developed tools to mitigate or distribute risk, but many of these explicit tools have not found their way into all parts of the world. The farming decisions of low-income farmers may make it appear that they are more risk averse, but it is the lack of market structures like those accessible to farmers in developed countries that make them handle risk differently. When asked how they coped with crop failure, 40% said they obtained a loan from friends or family. Ugandans have informal tools for dealing with risks that are ex-post rather than ex-ante. One man summed up what many farmers said while talking about how they smooth their consumption after a catastrophic crop failure: "we have ways of dealing with crop loss; it's ok". Even though farmers in eastern Uganda lack strong market structures to manage risk, they still are anxious to try new things that may be promising in spite of risk. This survey of eastern Uganda found many people anxious to learn about CAPs that might help maintain quality soil, reduce erosion, and minimize weeds and labor costs; they did not seem fearful of trying something new.

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Appendix A

Safety First

Introduction

People may not make risky decisions based on maximizing expected utility. As Lipton argued, they may make decisions based on a minimum required survival yield and will only maximize expected yield after they are confident the farming practice will give them their minimum requirements with a high enough probability. (cite) defines this survival algorithm as:

a) $Max\ (y)$

b) $s.t.\ \Pr[y > d*] > Pr*$

where y is the yield, d* is minimum acceptable yield and Pr* is minimum acceptable probably. This simple form of the model assumes risk neutrality after achieving a yield greater than a d* threshold. This simple model is easy to test since it assumes risk neutrality beyond the threshold and is not complicated by other risk preferences. This model is most likely not an accurate representation as to how someone would make a safety-first decision. More likely a person would make a risk preference weighted decision subject to the probability of exceeding a minimum yield requirement is greater than some critical probability. The testing of both of these hypotheses of the more complex model confounds each other making empirical results beyond the scope of this paper.

However, if as in equations a and b, risk neutrality is assumed, then by repeating a risk-preference elicitation game designed correctly one can see if there is a pattern of choosing the option that provides the greatest yield with a specific minimum. Knowing a person's minimum threshold could be a useful guide to what level of risk is too great for a farmer to adopt a risky practice

Methods[9]

To test Lipton's theory that people make decisions based on a survival algorithm; two games were presented to each respondent. The first game gave six options with increasing expected yield and variance, forming a risk frontier from no risk to risk neutral. The second game was designed to give the respondent a chance to pick the same bad yield and receive a higher good yield than in the first game. This way if a person was choosing the highest expected yield given a minimum requirement, there would be a lottery designed to capture that form of decision making. By designing the two games this way, it was possible to see if there was a bad yield option chosen in both games. This choice would coincide with Lipton's survival algorithm. For example, a person might have chosen the option that has 3 bags as the bad outcome in both games because their decision making process was described by a survival model based on picking the highest expected yield given a minimum threshold of 3 bags of maize.

Although we cannot ever be certain why someone chose a specific lottery from the choice set or how their decision process changed from the first game to the second, it seems reasonable that people would making their decisions based on a safety-first process would be consistent in back-to-back games. After making each choice, respondents were asked to explain it. This was done primarily to see if the respondent understood the game. However, while explaining their reasoning, many respondents said they could make do with the number of bags in the case of a bad outcome on their chosen option but would love to get the higher yield. A story like this not only shows they understood the game, but that they might be making their decision based on a safety-first algorithm.

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[9] To learn more about the methods of data collection see the methods section from the main body of the thesis. This appendix just adds what is relevant for the testing of the safety-first model.

A respondent choosing in the second game the lottery positioned one letter higher than the lottery they chose in the first game is consistent with the safety-first model. Table A1 shows the two games side by side for each region. A person who chose options A through D had an option one letter higher in the second game that they can still be guaranteed to same bad outcome but get a higher expected outcome. For example, a respondent in Tororo who chose lottery option B in the first game could still receive a minimum of 4 bags of maize by choosing lottery C in the second game but get a greater E(y). A respondent who chose lottery options E or F in the first game did not have a safety-first choice in the second game because option F* in the second game was being used to conduct a validity test as explained above in the validity section. Notice that a person in Tororo who has a minimum required yield of 1.5 bags and chooses E in the first game is not maximizing their E(y) by choosing option F* in the second game.

Table A1: Tororo Lottery Game 1 and 2 side by side

Lottery Options Game 1	Bad Yield	Good Yield	E(y)	Variance	Lottery Options Game 2	Bad Yield	Good Yield	E(y)	Variance
A	4.5	4.5	4.5	0	A	5.25	5.25	5.25	0
B	4	6.5	5.25	1.25	B	4.5	7	5.75	1.25
C	3.5	8	5.75	2.25	C	4	8	6	2
D	3	9	6	3	D	3.5	9	6.25	2.75
E	1.5	11	6.25	4.75	E	3	9.5	6.25	3.25
F	0	12.5	6.25	6.25	F*	1.5	10	5.75	4.25

Note: all yield units are in 100 Kg bags of maize.

Table A2: Kapchorwa Lottery Game 1 and 2 side by side

Lottery Options Game 1	Bad	Good	E(y)	Variance	Lottery Options Game 2	Bad	Good	E(y)	Variance
A	15	15	15	0	A	20.5	20.5	20.5	0
B	13	28	20.5	7.5	B	15	32	23.5	8.5
C	11	36	23.5	12.5	C	13	35	24	11
D	10	38	24	14	D	11	38	24.5	13.5
E	8	41	24.5	16.5	E	10	39	24.5	14.5
F	6	43	24.5	18.5	F*	8	40	24	16

Note: all yield units are in 100 Kg bags of maize.

In the context of the lottery list, the probability of a bad or good outcome was always 50%; therefore the critical probability (Pr*) of the safety-first model was fixed and d* was the only variable in the constraint. Since the objective of the safety-first model assumes risk neutrality subject to meeting a minimum requirement, and the curvature of the game assumes risk aversion, the safety first model suggests a person will choose the highest yielding and subsequently riskiest lottery they can as long as the bad outcome does not drop lower than their d*.

The assumption that people are risk neutral after satisfying a safety-first constraint is unlikely. It is more likely that people balance their risk preferences and minimum requirements simultaneously. It is difficult to test a safety-first constraint while relaxing the risk neutrality assumption and allowing for risk preferences in the objective. Testing the decision making process and risk preferences confound each other. Therefore, as an alternative, these two aspects of choice under uncertainty were analyzed by taking the EUT risk preference in game 1 and examining the results of the respondents who chose a lottery in game 2 that was consistent with the safety-first model. This meant that respondents choosing lottery A in the first game then B in

the second game or first B then C or first C then D or first D then E were included and considered to be following a safety-first algorithm.

It could be argued that people following the pattern identified as safety-first decision process are actually exemplifying decreasing PRA. Decreasing PRA means the people will take more risk when the stakes are higher. In this context, the second game has slightly higher yields so a person who's PRA decreases will take a higher risk higher return lottery in the second game than they did in the first game. However, decreasing PRA is unlikely it is more likely people become more risk averse as the stakes increase. Miyata (2003) tested the hypothesis that PRA is non-decreasing with 400 respondents in Indonesia and found that risk aversion did increase with higher stake (Miyata, 2003). This study assumes that PRA is non-decreasing.

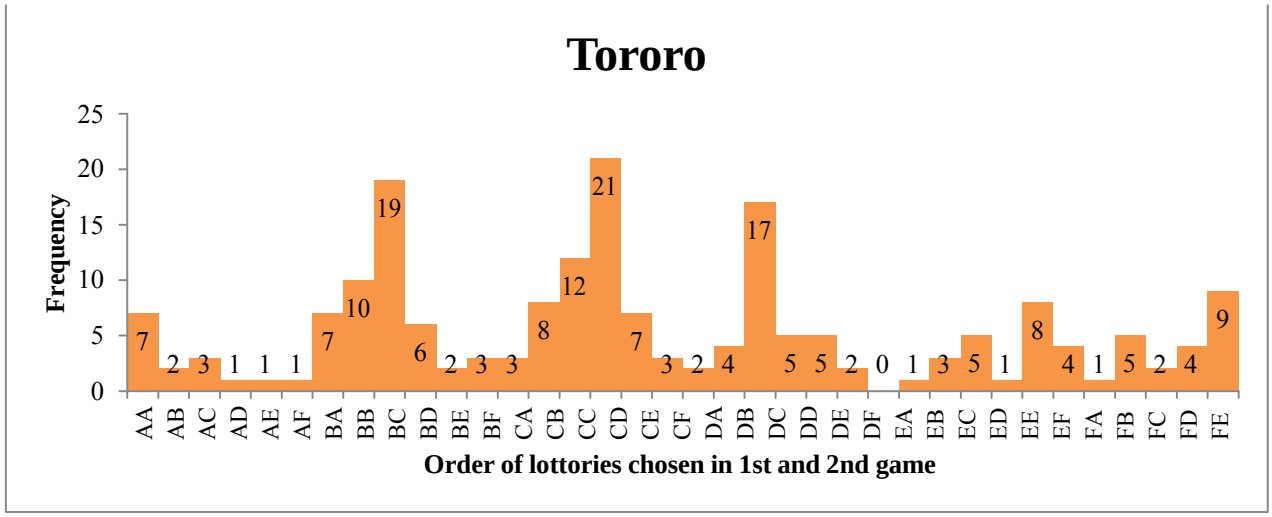
Results

The histograms in Figures A1 and A2 show the frequencies of occurrences for all choice combinations. The two digit letters across the X axis stand for the combination of lottery options chosen in games 1 and 2. For example, a person who chose lottery A in the first game and lottery B in the second game is coded as AB; likewise a person who chose lottery C in the first game and lottery D in the second game is CD. Coded this way the people whose choices are consistent with the safety-first model are: AB, BC, CD, and DE.

Tororo has 194 respondents in the sample and of these 55 people or 28% chose lottery combinations that are consistent with the safety-first model. Two people chose AB which has a d* of 4.5 bags, nineteen people chose BC with a d* of 4 bags, twenty-one people chose CD with a d* of 3.5 bags, and five people chose DE with a d* of 3.

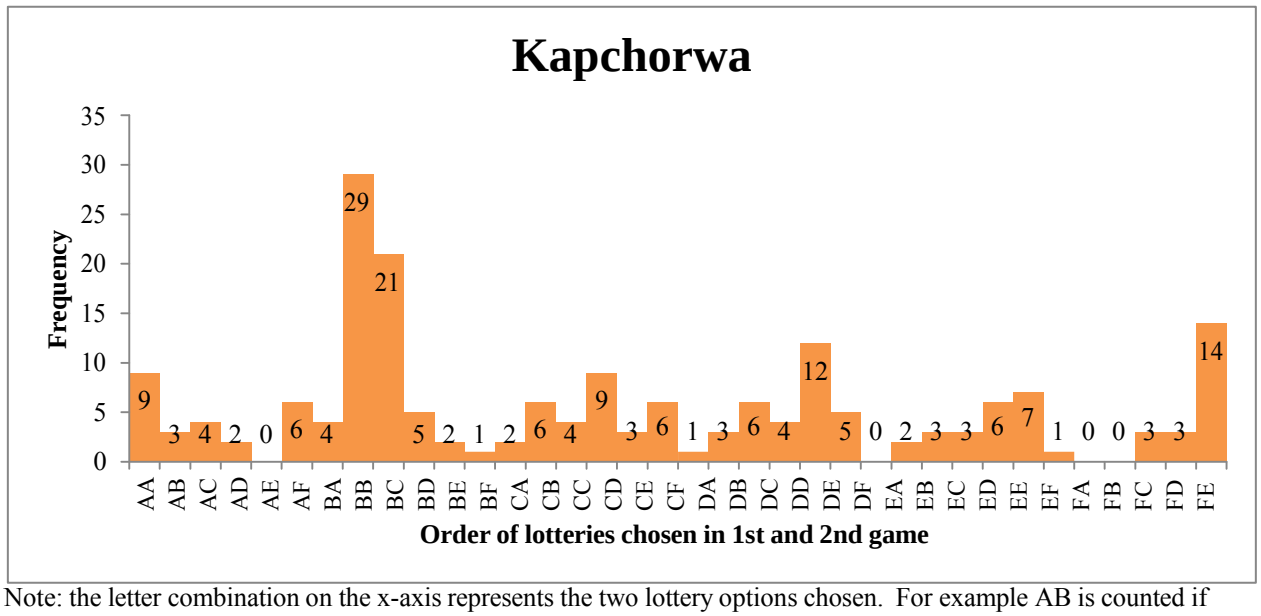
In Kapchorwa there were 189 respondents in the sample and of these 45 people or 23% chose lottery combinations that are consistent with the safety first model. Three people chose AB which has a d* of 15 bags, twenty-one people chose BC with a d* of 13 bags, nine people chose CD with a d* of 11 bags, and twelve people chose DE with a d* of 10.

Figure A1: Combination of lotteries chosen from both games in Tororo



Note: the letter combination on the x-axis represents the two lottery options chosen. For example AB is counted if the respondent chose lottery option A in the first game and Lottery B in the second game.

Figure A2: Combination of lottery chosen from both games in Kapchorwa



Note: the letter combination on the x-axis represents the two lottery options chosen. For example AB is counted if the respondent chose lottery option A in the first game and Lottery B in the second game.

Discussion

Two other patterns that appear on these histograms that are interesting are the ends (AA and FF*) and the bunching around consistent choices. The people who chose lottery option A each time can be definitively labeled extremely risk averse. These seven people in Tororo and nine people in Kapchorwa chose the risk-free option in both games and received the lowest expected yield of all choices. The nine people in Tororo and fourteen people in Kapchorwa who chose lottery F in both games are interesting but more difficult to say something about. Lottery option F in the first game is risk neutral, but lottery option F* in the second game is risk loving. These options were included in the study for validity testing[10] since all respondents are assumed to be risk averse at some level. If however, we allow for risk loving behavior, then 6% of the total sample exemplifies this behavior. For this paper, people choosing option F* in the second game are assumed not to be making a decision that maximizes their EUT. This paper assumes that people choosing lottery F* are mistaken in not realizing its inefficiency or are not worried about their choice due to the hypothetical aspect of the game.

The other pattern evident in the histogram is the clustering around consistent choices between games. For example, a person who chose lottery C in the first game was expected to choose a lottery close to C in the second game: B, C, or D. Since the curvature of the two games are not the same and since increasing and decreasing PRA are not measured, the consistency of choices cannot be definitively measured. This being said, it is arguable that people who chose

[10] See the section on validation for more in-depth discussion on risk neutrality and risk loving and how these options are used for validation.

the risk-free lottery in the first game (A) and the risk-loving option (F*) in the second game are not presenting a stable risk preference.

Conclusion

There were approximately a quarter of the respondents whose choices from the two risk-elicitation games were consistent with the safety-first model. These people can be assumed to be making their decision based on a safety-first algorithm if a strict non-decreasing PRA is adhered to. However, the lottery in the second game that corresponds to a safety-first decision is not very different from the lottery in the first game and could be interpreted as a consistent EUT choice. Realizing that the same choice sets that are consistent with safety-first model are almost consistent with a stable EUT choice decision makes it difficult to say much about their decision making process. Even when strict non-decreasing EUT is assumed there are still only a quarter of the people who exemplify safety-first algorithm and their d* is as diverse as possible given the lottery choices.

There does not appear to be much evidence that eastern Ugandan farmers make their uncertain decisions based on the specified safety-first model. Considering those that did make safety-first lottery choices, the minimum threshold (d*) they exemplified is not homogeneous enough to be useful in suggesting what minimum yield CAPs must attain to satisfy the safety-first constraint. The EUT analysis of this paper agreed with Binswanger's empirical findings from three decades ago that risk aversion is not innate in poverty and this appendix does not find much evidence to support Lipton's theory either. Therefore, agricultural development agencies in less-developed countries should not think of farmers' risk aversion any different than any farmer living with constraints and market structures in place. There is no increased risk aversion

innate in poverty; subsistence farmers are mitigating risk the best they can with the information, resource, and institutions in place where they live.

This was put in an appendix due to the difficulty of empirically testing if people make decisions based on a safety-first algorithm. There could be a great amount of work done using behavior economics that could parcel out risk aversion and minimum threshold as well as real compared to perceived risk. Another difficulty of this research that could be tested is how an empirically tested risk aversion correlated to the adoption of higher-risk higher-return investments.

Appendix B

Uganda Survey

Uganda Survey Respondent ID: _____

District :_____Sub-County:_____Village:_____

Name of Interviewers: _____Date: _____

Gender of respondent: **Male** **Female**

Hello, my name is_____, and this is_____and_____. We are conducting research for the SANREM Project, which has many institutions involved, including Makerere University, Appropriate Technology, and universities in the United States. We would like to ask you questions about your household farming decisions. Would you be willing to participate in this survey? Participation in this survey is voluntary and the answers that you provide will be anonymous and confidential.

This survey will take about 1 hour. Do you agree to participate in this survey? **YES** **NO**

1) Do you make farming decisions for your household? **YES** **NO**
    - ***(If there is no person to make farming decision go on to the next farm)***
2) What is your age?_____
3) How many years of school have you completed? _____
4) How many people in total are in your household?_____
5) How many people in your household work on your farm?_____
6) How many people in your household are under 13 years old?_____
7) How many years have you worked on a farm? _____

8) How many acres are you farming this season? _____

9) Of these acres that you are farming this season, how many acres do you own? _____

10) Do you borrow money to buy inputs for your farm? **YES NO**

If yes, what type? Mark all that apply.

- o Banks
- o Get money from family and/or friends
- o SACCO/Group Savings Schemes
- o Other _____

11) In this season was more than half of your land preparation done by hired labor? **YES NO**

12) In this season was more than half of your weeding done by hired labor? **YES NO**

13) Do you have any nonfarm source of income? **YES NO**

- o If yes is it greater than your farm income? **YES NO**

14) How many of each of the following animal do you own?

Type	Cattle	Goat	Donkey	Sheep	Oxen	Pig
# Head						

15) In the last five years, how many complete crop failures have you had? (Circle the correct answer)

0 1 2 3 4 5 6 7

16) How did you cope with these crop failures? Mark all that apply.

- o Spent savings
- o Sold assets

- Reduced consumption
- Bank Loan
- Got help from family and/or friends
- Other _____

17) In the last five years, how many times have you tried something new on your farm that you considered to be successful? For example, a new crop variety, a new fertilizer, a new piece of equipment. _____

18) In the last five years, how many times have you tried something new on your farm that did not meet your expectations? For example, a new crop variety, a new fertilizer, a new piece of equipment. _____

19) Which of these crops did you plant on your farm this season? Circle all that apply.

MAIZE BEANS CASSAVA GROUNDNUTS IRISH POTATOES

SWEET POTATOES VEGETABLES FRUIT

20) Have you ever practiced minimum tillage? **YES NO**

- If yes, do you still practice minimum tillage? **YES NO**

21) Have you ever grown a cover crop? **YES NO**

- If yes, do you still grow a cover crop? **YES NO**

22) Have you ever practiced crop rotations? **YES NO**

- If yes, do you still practice crop rotations? **YES NO**

23) Do you view soil erosion as a problem on your land? **YES NO**

24) Are you doing something to manage erosion? **YES NO**

25) Type of roof on house:

THATCHED TIN IRON SHEET TILE OTHER_____

26) Type of floor in house:

MUD FLOOR CEMENT TILE OTHER_____

27) Number of rooms in house: _____

Choice Survey # 1: Risk

As you know, maize production is risky. When you plant maize you cannot be certain how much maize you will eventually harvest. For this question we will show you 6 different possibilities for maize yields on one acre. Assume you have a 50/50 (or equal) chance of a good harvest or bad harvest. We are interested in which yield possibility sounds best to you.

**Do the practice game with three options. Have respondent play the game, using a coin/object in one hand and have them choose a hand.*

Practice Game

Which option did the person pick? **A B C**

Did the person win the game ? **YES NO**

**Once you feel confident that the person understands the way the game is played explain that we want them to think about what it means for them to live with the outcome of the different choices.*

We will now show you a paper with 6 choices of different yield outcomes. When making this decision we would like you consider the consequences your choice would have on your family and make this decision the same way you would make a planting decision. When picking an option please consider how your life would be if the harvest is good and if the harvest is bad.

What option did the respondent choose for **Game 1?**_____(A-F)

What option did the respondent choose for **Game 2**?_____(A-F)

Figure B1: Ordered Lottery Selection used to elicit risk preference in Tororo

Game 1		
	Bad Harvest On 1 Acre	Good Harvest On 1 Acre
A	x4.5	x4.5
B	x4	x6.5
C	x3.5	x8
D	x3	x9
E	x1.5	x11
F	x0	x12.5

Figure B2: Ordered Lottery Selection used to test safety-first in Tororo

Game 2		
	Bad Harvest On 1 Acre	Good Harvest On 1 Acre
A	x5.25	x5.25
B	x4.5	x7
C	x4	x8
D	x3.5	x9
E	x3	x9.5
F	x1.5	x10

Figure B3: Ordered Lottery Selection used to elicit risk preference in Kapchorwa

Game 1		
	Bad Harvest On 1 Acre	Good Harvest On 1 Acre
1	x15	x15
2	x13	x28
3	x11	x36
4	x10	x38
5	x8	x41
6	x6	x43

Figure B4: Ordered Lottery Selection used to test safety-first in Tororo

Game 2		
	Bad Harvest On 1 Acre	Good Harvest On 1 Acre
1	x20.5	x20.5
2	x15	x32
3	x13	x35
4	x11	x38
5	x10	x39
6	x8	x40