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**REGIONAL VARIATION IN RISK AND TIME PREFERENCES:  
EVIDENCE FROM A LARGE-SCALE FIELD EXPERIMENT IN RURAL  
UGANDA**

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**REGIONAL VARIATION IN RISK AND TIME PREFERENCES: EVIDENCE  
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## Abstract

Experiments measuring risk and time preferences in developing countries have tended to have relatively small samples and geographically concentrated sampling. This large-scale field experiment uses a Holt-Laury mechanism to elicit the preferences of 1289 randomly selected subjects from 94 villages covering six out of seven agro-climatic zones across rural Uganda. As in previous studies we find evidence of risk aversion and loss aversion amongst most subjects. In addition we find significant heterogeneity in risk attitudes across agro-climatic zones. Especially, the farmers in the agro-climatically least favourable zone, the uni-modal rainfall zone, are the most risk averse, loss averse and impatient. We also find significant relationships between risk attitudes and village level predictors such as the distance to town and the road conditions. After controlling for the village level factors, we find that the level of schooling still positively correlates with the individual's level of loss tolerance and patience. The main results are not altered by allowing for probability weighting in subjects' choices. Overall the results provide clear evidence that within one country there may be significant regional variations in risk and time attitudes. We conjecture that the agro-climatic conditions that affect farmers' livelihoods may also affect their risk and time preferences and village level development in infrastructure could improve the household perception of investment related policies.

## **REGIONAL VARIATION IN RISK AND TIME PREFERENCES: EVIDENCE FROM A LARGE-SCALE FIELD EXPERIMENT IN RURAL UGANDA**

### **1. Introduction**

In a developing country, where formal financial services are still scarce, risk aversion and high discount rates remain possible obstacles to private investment in physical and human capital resulting in slow economic advancement (World Bank, 2008). While various external factors such as market conditions and quality of schools may affect household demand for investment, behavioural studies have pointed out that a better understanding of the risk and time preferences of rural households can provide insight into investment decisions (Yesuf, 2009; Bauer and Chytilová, 2010; Tanaka et al., 2010). Considering the different types and degree of uncertainties faced by rural households in different geographical regions, farmers' attitudes towards such risks or time preferences could also vary across the regions.

Risk attitudes and discount rates are not merely reflection of personal preferences but represent economic and other conditions of the individuals and households. For instance, in a Ugandan study, Bauer and Chytilová (2010) find a causal relationship between adult educational attainment and individual discount rates. In a broader context, risk and time preferences may also result from factors affecting villages and geographical regions in which the farmers live. At the macro level, countries with tropical climate have been found to experience slower economic growth than those with more temperate climate (Sachs and Warner, 1997). At the micro level, household studies find that in less favourable agro-climatic zones, farmers experience

lower level and/or higher variability of crop yields than those in more favourable zones, resulting in different risk-coping strategies across zones (Reardon and Taylor, 1996; Skees et al, 2001; Pender et al., 2004). While disadvantages in climatic conditions may be overcome by appropriate policies (Collier and Gunning, 1999), higher variability in agricultural production due to the exogenous factors may still lead to higher risk aversion or discount rate hindering efficient investment by farmers.

Despite the potentially important insight to be gained from analysing the regional variation in risk and time preferences, previous experimental studies have lacked such analyses due to limited sample sizes and geographical variation (Binswanger, 1980; Wik et al., 2004; Kirby et al., 2002; Yesuf, 2009; Harrison et al., 2010; Tanaka et al., 2010; Bauer and Chytilová, 2010).

This study, therefore, makes a unique contribution in that it covers almost the whole country geographically and six out of seven of its agro-climatic zones. Our large-scale field experiment uses a Holt and Laury (2002) mechanism to elicit the preferences of 1289 randomly selected subjects from 94 villages in the central, eastern and western regions of Uganda. Thus, it is the only paper to date from a developing country that can examine seriously issues of geographical variation.<sup>1</sup> If the variation in risky attitudes is found to be significant, this in turn implies that policies to induce household investment may require regional adjustment.

Our main result is that there is heterogeneity in preferences across agro-climatic zones possibly due to different types of crops produced in those areas. There are also other significant village level predictors such as the distances to town and the road

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<sup>1</sup> In a developed country context, Harrison et al, 2002, map preferences across Denmark, though their focus is not on geographical variation.

conditions. At the same time, after controlling for the regional and village-level factors, the individual level of education positively correlates with more patience and loss tolerance.

Any regional variation in measured risk attitudes, however, may be due to variation in background risk, variation in preference or even variations in risk and experience that have moulded preferences (Dercon, 2008; Ogden et al., 2004; Humphrey and Verschoor, 2004). Our data does not allow us to determine whether the measured risk attitudes represent preference or background risk (Gollier and Pratt, 1996). Decomposing the factors affecting the variation of the measured risk attitudes requires further research. Nonetheless, we have ruled out some obvious preference variables such as ethnicity and our main results are not altered by allowing for probability weighting in subjects' choices. Existing external data on agro-climatic conditions in Uganda does not show clear evidence of variations in background risk at the regional level.

In the next section, we discuss the conceptual framework on how the village characteristics affect the individual risk and time preferences. Section 3 presents the data, experimental design and estimation methodology. The results are presented in Section 4, followed by discussion in Section 5 and Section 6 concludes.

## **2. Literature Review**

### **2.1 Village Characteristics and Preferences**

The World Bank (2008) reports that weather related shocks are one of the biggest risks farmers face, and without adequate insurance or credit mechanism, it may take a long time for the rural households to recover from losses in times of crisis. In the

specific context of Uganda, the drought that especially hit the north-western region in March 2011 is the latest of the many recurrent droughts that have shortened the crop season, resulting in unstable farm income for farmers (EM-DAT, 2011). Pests and diseases also affect coffee production in various parts of Uganda (New Vision, April 5<sup>th</sup> 2010). Anticipating such shocks, farmers may be unwilling to invest their assets in new technology or schooling for their children since their future is highly uncertain and the commitment is long-term. Dercon (2008) points out that risk fundamental matters for behaviour because of such constraints as insurance market failure. People with fewer insurance options may also be those living further away from urban centres, where insurance and financial service agents are usually located. Subsequently, those having less access to such financial services may exhibit stronger aversion to risk, but this behaviour is not necessarily due to their preferences.

There may be other regional factors such as agricultural potential of the areas in which their farms are located that affect the observed risk attitudes and discount rates of the farmers. Reardon and Taylor (1996) in their study in Burkina Faso analyse the relationship between agro-ecological zones and poverty, and find that in the face of drought, the least favourable agro-ecological zone, where the rainfall is most erratic and the environmental degradation is most pronounced, experienced the highest increase in poverty. They further find that the poor households in the affected regions dispose of livestock possibly due to the lack of other income smoothing options, increasing the vulnerability of the poor farmers. Skees et al (2001) in Morocco also reports that the variation in cereal yield is mostly found in less favourable agro-climatic zones. Since rainfall patterns vary across agro-climatic zones, they suggest that weather insurance should be designed in such a way that account for the differences across the zones.

In rural Uganda, too, Pender et al. (2004) finds that observed development pathways in the 1990s differ across agro-climatic zones as mapped in Figure 1. Seven agro-climatic zones have been identified according to the agro-climatic potential based on rainfall pattern (bi-modal or uni-modal), lengths of growing period (LGP) and altitude: the high potential bi-modal rainfall zone (10-12 months LGP - mostly the Lake Victoria crescent), the medium potential bi-modal rainfall zone (8-9 months LGP – most of central and parts of western Uganda), the low potential bi-modal rainfall zone (6-7 months LGP - lower elevation parts of south-western Uganda), the high potential bi-modal rainfall south-western highlands (1500 metres above sea level and above), the high potential uni-modal rainfall eastern highlands (1500 metres above sea level and above), the medium potential uni-modal rainfall zone (6-7 months LGP—parts of northern and eastern Uganda), and the low potential uni-modal rainfall zone (less than six months LGP – much of north-eastern Uganda). They find, for instance, increased banana and coffee production to be the most common development pathway in the low and high potential bi-modal rainfall zones, while increased cereal production is most common in the medium potential bi-modal rainfall zone. While the former development results in positive outcomes such as better child nutrition and quality of drinking water, the latter results in not only better child nutrition, but also lower availability of energy sources (Pender et al., 2004). Another finding from a related work is that households in the uni-modal zone, with less rainfall than most other zones, are not necessarily poorer than households from other zones (Nkonya et al., 2004). Lower farm income is complemented by non-farm income where such activities are available and households have the necessary human and physical resources.

Agro-climatic conditions that thus affect the behaviour of farmers could also affect the farmers' risk and time preferences. For example, the experience of erratic rainfall or living in a uni-modal zone may result in less pro-investment preferences. Fearing high variability in farm income due to drought or shorter crop season, farmers in the less favourable areas may exhibit stronger impatience or aversion to risks than those in the more favourable areas. Alternatively, the relatively low level of welfare due to the unfavourable condition may result in higher risk aversion or higher discounting.

Other village level factors that may affect risk and time preference are population density, distance to towns and availability of local schools. First, Uganda's population growth rate is 3.1 per cent per annum and its decline is far slower than many other developing countries (Bremner et al., 2010). In a populous area, arable farm land per capita may be small and farmers may be less willing to take on risks on the types of crop to produce. Alternatively, a highly populous region may imply more cash income opportunities from non-farm activities such as taxi-driver or trading, resulting in less aversion to income risks. Second, shorter distance to urban centres and better road conditions generally increase farm income due to lower transport cost as witnessed among Kenyan farmers by Yamano and Kijima (2010). Proximity to town implies not only better access to financial services but also better access to assistance from local governments and non-governmental organisations in times of crisis, resulting in possibly more tolerant attitudes towards risks. Last, educational opportunity may affect farmers' preference. Bauer and Chytilová (2010) study uses the number of local schools as an instrumental variable for educational attainment, and find that the higher the educational attainment, the lower the discount rate. A possibility remains that the availability of schools in itself influences the risk and time preferences of the villagers.

With the knowledge that a local educational facility exists, one may be induced to exercise more patience in such endeavour as planning for children's schooling. There may also be externality through more educated villagers, such as school teachers, that may help transfer knowledge and information to other villagers. Information is crucial in making accurate investment decisions and may also reduce excessive aversion to risks (Humphrey and Verschoor, 2004).

One complexity in the analysis of correlation between environmental factors and farmers' preferences is the notion of 'background risk'. In the field experiment, individuals participate in a lottery game that involves risks that we may call 'foreground risk'. Gollier and Pratt (1996) establish theoretically that for the class of utility functions exhibiting decreasing absolute risk aversion, an addition of unfair 'background risk', such as variable current income, makes the individual more risk averse in such an independent risk experiment.<sup>2</sup> If farmers from certain agro-climatic zones exhibit higher risk aversion, for example, it may be due to differences in pure taste or differences in 'background risks' or both. Noting the 'risk vulnerability' of our measurement, the investigation into the relationship between preferences and the regional factors becomes even more important to investment policies in that it could reveal the potential role of 'background risks' in different regions in shaping the farmers' preferences.

Despite the potential insight gained from analysing the relationship between the risk/time preferences and the village level factors, no past study has done such an analysis probably due to the absence of the measurement of the preferences on a large

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<sup>2</sup> Constant relative risk aversion utility function that we use in our experiment is also in this class.

scale with geographical and regional variation. Insurance or credit take-up data that can be used to compute risk and time preferences are rare in low-income countries, especially in rural areas. Even when they are available, evidence from past studies show that, for example, the market interest rates are not necessarily the same as the individual's revealed discount rate (Coller and Williams, 1999). Therefore, incentivized experiments have become the norm to elicit the preferences, but such experiments are costly and require more controlled setting and designing than a survey (Holt and Laury, 2002; Carpenter et al., 2005). As a result, past empirical evidence from low-income countries has been based on a relatively small sample size with limited geographical variation: for example, 240 farmers in semi-arid tropical areas of India, 181 individuals in 9 villages from Southern and Northern Vietnam, 262 farming households in the State of Amhara, Ethiopia, 110 households in Northern Zambia and 205 farmers from two villages in East Uganda (Binswanger, 1981; Tanaka et al., 2010; Yesuf, 2009; Wik et al., 2004; Humphrey and Verschoor, 2004; respectively). Bauer and Chytilová (2010) experiment on discount rates was large in scale, but geographically limited to 10 villages in a single district in southern Uganda.

In addition, existing evidence on the determinants of preferences have been mixed. While some studies find a positive correlation between household wealth and risk aversion, others find a negative correlation (Yesuf, 2009; Wik et al., 2004; Binswanger, 1980). Schooling is generally associated with more patience, but the correlation between education and risk attitude is less clear (Bauer and Chytilová, 2010; Wik et al., 2004; Kirby et al., 2002; Tanaka et al., 2010; Binswanger, 1980). A possible reason for insignificant or mixed results is that variations in income or education of individuals and households are limited due to sample size. Such variation may also

depend on the village level characteristics. In fact, Tanaka et al. (2010) find that while the household income does not correlate with the farmers' risk aversion, the mean village income does. Could it be that conflicting results from past studies arise partly due to broader economic conditions that surround the subjects such as climates and other village characteristics?

In this paper, we analyse the village characteristics that may be correlating with farmers' risk aversion and subjective discount rates. By doing so, we identify certain aspects of the farmers' environment that may be hindering their potential investment activities.

## 2.2 Framework on Measuring Risk and Time Preferences

### *Risk Aversion*

The expected utility theory (EUT) states that a rational individual maximizes the expected utility of final wealth or  $\sum_{i=1}^n p_i u(W_i)$ , where  $u(W_i)$  is the level of utility derived from the final wealth  $W_i$  which occurs with probability  $p_i$  for each of the  $n$  possible states. When the utility function is concave, the individual is said to be risk-averse, preferring a sure income of  $W_i$  to a fair gamble with expected value of  $W_i$ . Using the Arrow-Pratt measure of risk aversion,  $r(W) = -u''(W)/u'(W)$ , the risk-averse individual is represented by  $r(W) > 0$ , the risk preferring individual by  $r(W) < 0$  and the risk neutral individuals by  $r(W) = 0$ . In risk experiments, the relative risk aversion parameter,  $r(M) = -M * u''(M)/u'(M)$ , is often estimated to represent the degree of risk aversion, where  $M$  is the change in wealth offered in the experiment

instead of the final wealth (Holt and Laury, 2002).<sup>3</sup> Assuming a constant relative risk aversion (CRRA) utility function,  $u(M) = \frac{M^{1-\sigma}}{1-\sigma}$ , where  $\sigma$  indicates the curvature of the utility function,  $r(M) = \sigma$ .<sup>4</sup>

In order to estimate the risk aversion parameter,  $\sigma$ , the risk experiment often takes the form of pair-wise choices or choices from a list of lotteries with varying probabilities  $p_i$  and payoffs  $M_i$  (Holt and Laury, 2002). The degree of risk aversion  $\sigma$  is computed by equating two lotteries that give the same level of expected utility  $\sum_{i=1}^n p_i \frac{M_i^{1-\sigma}}{1-\sigma}$  to the individual. Assuming EUT to be true, previous experimental studies have found individuals to be, on average, risk-averse (Binswanger, 1980; Wik and Holden, 1998 as cited in Cardenas and Carpenter, 2008; Yesuf, 2004). The estimated risk aversion coefficient ranged from between 0.68 and 0.97 in the USA, to 0.71 in India, and to between 0.81 and 2.0 in Zambia (Holt and Laury, 2002, Binswanger, 1980, and Wik and Holden, 1998 as cited in Cardenas and Carpenter, 2008). The significance of these findings was that, under the controlled experimental setting, the degrees of risk aversions as represented by the coefficients were not so different between the subjects in developed and developing countries.

### *Loss Aversion*

Besides risk aversion, loss aversion is also potentially an important aspect of risk

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<sup>3</sup> The rationale for measuring the risk aversion in terms of the change in wealth rather than the final wealth is that under the experimental setting, we are trying to measure the individual reaction to varying degrees of prospects given the wealth level. The psychology literature has usually followed this method as well (Binswanger, 1981).

<sup>4</sup> Another risk aversion coefficient typically used in the risk experiment is the Constant Partial Risk Aversion (CPRA) parameter with utility function,  $u(M) = (1 - \sigma)M^{1-\sigma}$  where  $M$  is the certainty equivalence of the (Binswanger, 1980; Yesuf, 2009). Assuming zero initial wealth, CRRA is equal to the CPRA parameter (Binswanger, 1981).

attitude among rural households in developing countries. Loss aversion is the concept from prospect theory (PT), the alternative theory to EUT, which states that a prospect of a loss tends to loom larger than that of a gain of the same magnitude, i.e.  $u(M) < -u(-M)$  (Kahneman and Tversky, 1979). Loss aversion has also been elicited using lottery games, but including negative amounts in some choices. Subjects typically chose relatively safer options when facing possible losses than in the gains-only games (Wik et al., 2004; Yesuf, 2009). For instance, for the same expected gain, the proportion of subjects preferring the sure income to the gamble doubled when the lower payoff in the gamble changed from a positive amount to a negative amount (Yesuf, 2009).<sup>5</sup>

The degree of loss aversion has also been estimated, using the value functions,  $u(M) = M^\sigma$  for gains  $M > 0$  and  $u(M) = -\lambda(-M)^\sigma$  for losses  $M < 0$  where  $\lambda$  is the loss aversion parameter. Tanaka et al. (2010) estimated the average loss aversion of Vietnamese subjects to be 2.63, close to the 2.25 estimated by Tversky and Kahneman (1992) for US university students. This suggests that the degrees of loss aversion are similar in developing and developed countries. Nonetheless, the regression analysis by Tanaka et al. (2010) revealed, within the Vietnamese sample, the loss aversion strongly correlated with lower village income (Tanaka et al., 2010).

### *Subjective Discount Rates*

The subjective discount rate is the rate at which individuals substitute future consumption with today's consumption. In an experimental setting, it is measured by

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<sup>5</sup> The first game was choosing between a sure income of 10 Birrs and a lottery with a 50-50 chance of winning 9 or 18 Birrs. The second game was choosing between a sure income of 0 Birrs and a lottery with a 50-50 chance of winning -1 or 8 Birrs. The risky options in both games have expected value of 3.5 Birrs higher than the sure income.

comparing the pair-wise choice of money at two different times. In past field experiments with real payoffs, the elicited annual discount rates have been: on average 28 per cent in Denmark (Harrison, Lau and Williams, 2002); and at the median, 43 per cent in highland Ethiopia (Yesuf, 2004); at the median, 30-60 per cent in India depending on the given time frame (Penders, 1996 as cited in Yesuf, 2004).

Present bias is the notion that the utility from the present consumption is weighted especially higher than the utilities derived from consumptions at future dates.<sup>6</sup> This notion of procrastination is also found by Duflo et al. (2009) in an agricultural experiment in Kenya, where farmers failed to adopt fertilizer not so much due to impatience but to present bias. In Vietnam, Tanaka et al. (2010) found that, estimating under a quasi-hyperbolic discounting function, their sample households in Vietnam weighted the utility from future earnings 0.64 less than the utility from the present earning.<sup>7</sup> Identification of such present bias helps us not only to accurately measure the discount rates, but also to find alternative policy measures.<sup>8</sup>

The second issue is the correlation between risk aversion and discount rates. When considering choices between a certain income today and an uncertain income at a future date, it is reasonable to assume that the decision is affected not only by time preferences but also by the risk attitude of the individual towards an uncertain future. Andersen et al. (2008), in their study in Denmark, estimate that the difference in the

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<sup>6</sup> There is also a discussion on the concept of hyperbolic discounting, which is that an individual's discount rate varies with the time horizon: the closer the timing of the payment to today, the higher the discounting. However, in empirical studies, the hyperbolic shape is often found not to be statistically significant (Coller, Harrison and Rutström, 2003; Tanaka et al, 2010). Rather, it is the existence of present bias that affected the shape of the discounting function.

<sup>7</sup> The quasi-hyperbolic discounting function used is  $u(y) = y\beta e^{-rt}$  where  $y$  is the reward,  $\beta$  is the present-bias and  $r$  is the discount rate at time  $t$ .

<sup>8</sup> Duflo et al. (2009), for example, suggest that a small timely subsidy can potentially increase the adoption of fertilizers among present-biased farmers, instead of having to provide heavy subsidies assuming high discount rates.

subjective discount rates assuming risk neutrality and moderate risk aversion is around 15 percentage points. In Ethiopia, too, more risk-averse subjects revealed higher discount rates (Yesuf, 2004). In developing countries, where the degree of risks and their impacts on people's attitudes are likely to be higher than in developed countries, it may be of even greater importance to take into account the risk attitudes in estimating discount rates.

### **2.3 Hypothesis**

Our main research purpose is to estimate the risk and time preferences of rural Ugandans and investigate whether they correlate with any of the village level characteristics. In estimating the risk aversion, the loss aversion and the discount rates of the rural Ugandan farmers, we expect to find highest risk/loss aversion and lowest patience among individuals located in the least favourable zone, namely the uni-modal zone. We also expect that the shorter the distance to town and the better the condition of the main road to town, the less risk/loss aversion or the more patience. While population density may affect the preferences positively or negatively, the number of schools in the village is expected to increase patience or risk/loss tolerance.

## **3. Data and experimental design and estimation method**

### **3.1 Data**

The data is collected in rural Uganda as part of a nation-wide project, Research on Poverty, Environment and Agricultural Technology (RePEAT).<sup>9</sup> Figure 1 shows the

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<sup>9</sup> RePEAT is a joint study by Makerere University (Uganda), Foundation for Advanced Studies on International Development (Japan) and National Graduate Institute for Policy Studies (Japan).

selected villages where the experiment took part. Following an earlier study on land management in Uganda (Pender et al., 2004) that is introduced in section 2, the villages (or Local Council 1, the lowest administrative unit in Uganda) were selected from a stratified random sample across six agro-climatic zones: the high potential bi-modal rainfall zone, the medium potential bi-modal rainfall zone, the low potential bi-modal rainfall zone, the uni-modal rainfall zone, the south-western highlands and the eastern highlands (Yamano et al., 2004).<sup>10</sup> Thus, our sample is not only large but also geographically representative of rural Uganda except for the northern region. The survey data had been collected from around 940 households in 94 villages in the three rounds of survey in 2003, 2005 and 2009. Because of the security concerns, the northern and north eastern parts of the country were excluded from the sampling. The risk and time preference experiments were then carried out in March 2009 targeting the same households and their neighbours.

The total number of respondents in the experiments is 1289 among which 787 are panel subjects for which we have household data for regression analysis. The sample statistics are shown in Table 1. The attrition rate between 2005 and 2009 for the panel subjects was 16.3 per cent.<sup>11</sup> The household characteristics of those subjects that participated in the experiments are not statistically significantly different from those that did not according to t-tests (Table 1), implying the representativeness of our sample still holds. The average household size of the respondent is 7.7 members. The mean dependency ratio, the ratio of the number of adults to that of children, is 1.2. Per capita

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<sup>10</sup> These zones correspond to the seven zones of Pender et al. (2004) introduced in section 2, except for the “uni-modal rainfall” zone which combines the low and medium potential uni-modal rainfall zones by Pender et al. (2004) which the original authors note to have relatively similar agricultural potentials.

<sup>11</sup>  $(= [940 - 787] / 940)$

income and the asset value of the respondents' household are on average 152.7 US dollars (USD) and 207.2 USD respectively.<sup>12</sup> Around 68 per cent of all the respondents are male with an average age of 45 years. While 66 per cent of them are literate, the average years of schooling is 5.7.

Table 2 shows the characteristics of the sampled villages. The average farm size is larger in the bi-modal rainfall zones than in other zones, but the trend does not necessarily translate to the differences in average per capita expenditure. The uni-modal zone has lower agricultural potential with shortest growing period, but the average wealth is similar to that in the high potential bi-modal rainfall zone with the same average land size. These statistics are consistent with the previous study in Uganda (Nkonya et al., 2004). In terms of crop production, while staple food crops such as maize and matooke are grown by the majority of households in any agro-climatic zone, other crops such as coffee, sweet potato and rice have more regional variation. The average distance to district town and the road condition for the road to district town are also different across region. In the low potential bi-modal rainfall zone, the distance to town is furthest, but the proportion of villages with all season tarmac road for the road to district town is the highest; in contrast, in the uni-modal rainfall zone, the average distance is shortest but in 75 per cent of the villages, the road condition is all season dirt. The effects of the distance to the town and the road conditions on the risk and time preferences may need to be analysed together. In terms of the population density, the high potential bi-modal rainfall zone is most populous, followed by the uni-modal rainfall zone. The number of primary and secondary schools seems to correlate with

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<sup>12</sup> The exchange rate used is 1730 Ugandan Shillings to 1 USD. Using the purchasing power parity conversion factor of 744.618, the average per capita income and the total asset value are 354.8 and 481.4 respectively. (source: [www.unstat.un.org](http://www.unstat.un.org))

population density: the more the people, the more schools there are. No single agro-climatic zone has extreme village characteristics in all of the above factors. In order to estimate the correlation between these characteristics and the preferences, we use the methodology as explained in the next section.

### 3.2 Experimental Design

The experimental design follows that of the pair-wise choice framework (Holt and Laury, 2002; Tanaka et al., 2010). We played eight games in total. The options within the four risk games and four time preference games are presented in Appendix Tables 1 and 2. Incentives were given for the risk games in order to elicit the subjects' true preferences (Holt and Laury, 2002). Thus, the respondents were told before the games begin that one of the risk games would be played for real and they would be paid cash according to their answers in the game. In all eight games, subjects were asked to choose between Column A and Column B. In the risk games 1, 2 and 3, involving gains (positive amounts), we asked the subjects to choose between column A, which offered a sure income of 4000 Ugandan Shillings (USh) and column B, which offered two different amounts with probabilities. Considering the level of education and illiteracy of some of our subjects, we simplified the notion of probabilities using four balls. The point is illustrated using Figure 2 which replicates one of the answer sheets, namely that of game 2, which the subjects filled out. The circled numbers below 'A' and 'B' indicate the number of each ball. We explained to the subjects that after completing the forms, one of the rows in the games would be played for real using a bingo. With four balls in a bingo cage, each participant draws a ball. Suppose row 2-3 is to be played for real. Whatever ball, 1, 2, 3 or 4, is drawn, if the subject has chosen A, he or she will

receive 4000 US\$. If the subject has chosen B and if ball 1, 2 or 3 is drawn, then the payoff will be 5000 US\$, whereas if ball 4 is drawn, it will be 2000 US\$. Thus, with a chance of three out of four times (or 75 per cent as indicated in Appendix Table 1), the payoff of column B will be 5000 US\$. If the participant chooses column A, four out of four times (or with 100 per cent certainty), he or she will receive 4000 US\$. Column B is progressively preferable as one goes down the list. The purpose of the games for the researcher is to identify the point at which the participant's preference changes from A to B, which in turn indicates the range of the subject's degree of risk aversion.<sup>13</sup>

The fourth risk game, which involved gains and losses and was used to measure the loss aversion, and the four time preference games were played similarly, though the time preference games were played hypothetically due to logistical constraints. It is known that hypothetical questions often result in relatively higher revealed discount rates (Coller and Williams, 1999). Yet, the future cash payment to each participant requires careful arrangement with village elders and the process may vary from village to village. Considering the number of sample villages in our study, a compromise has been made on estimating the accurate level of the time preference. The estimated discount rate is still relevant to the extent that one of the main purposes of the study is to compare the degree of patience and not to measure the absolute level of the preferences.

After all subjects had completed all eight answer sheets, the community leader drew a ball from a bingo cage containing 32 balls (eight balls for each of the rows in the

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<sup>13</sup> For example, if the subject chooses A in row 2-3, but chooses B in row 2-4, then mathematically, his or her risk preference can be represented as  $\frac{4000^{1-\sigma}}{1-\sigma} \geq 0.75 * \frac{5000^{1-\sigma}}{1-\sigma} + 0.25 * \frac{2000^{1-\sigma}}{1-\sigma}$  and  $\frac{4000^{1-\sigma}}{1-\sigma} \leq 0.75 * \frac{5500^{1-\sigma}}{1-\sigma} + 0.25 * \frac{2000^{1-\sigma}}{1-\sigma}$ . Solving the two equations simultaneously, the interval of the risk aversion parameter is  $0.92 < \sigma \leq 1.62$ .

four risk games). This ball determined the row number of the risk game to be played. Individuals then chose a ball from the four balls, 1, 2, 3 or 4, which identified the prize amount. Lastly, the payment was made according to the preferences revealed on the forms.<sup>14</sup>

### 3.3 Estimation Methodology

In terms of the estimation methodology, we apply the interval regression. This estimation approach is suited for data that are collected as parameter intervals. Unlike the ordered probit model or the multinomial logit model, the constant-only model allows us to estimate the average preference parameter. Furthermore, the regression coefficients for the explanatory variables can be interpreted as the marginal increase for the unit change of the variable in the same manner as OLS coefficients. The formula is as follows.

Let  $y_i^* = \beta'x_i + \varepsilon_i$  where  $y_i^*$  represents the unobserved degree of risk or time preference and  $x_i$  is a vector of individual, household and regional characteristics of subject  $i$ . I assume that  $\varepsilon_i$  is distributed normal with zero mean and the variance of  $\sigma^2$ . From our experiments, we can only observe  $y_1$  and  $y_2$ , not  $y_i^*$ . The unobserved  $y_i^*$  is greater than lower bound  $y_1$  (right-censored), smaller than or equal to upper bound  $y_2$  (left-censored) or lies between  $y_1$  and  $y_2$  (interval-censored). The likelihood function is:

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<sup>14</sup> The possibility of the actual prize being a loss remained. In order to address the ethical issue, we offered 5000 USh for completing the games as a transport fee, thus the net gain ranged from 1000 USh to 21,000 USh. (cf., the average per capita income of the sampled household is 152.7 USD as mentioned earlier, or around 1000 USh per day)

$$L = \prod_{\text{left-censored}} \Pr(y_i^* \leq y_2) \cdot \prod_{\text{right-censored}} \Pr(y_i^* > y_1) \cdot \prod_{\text{interval-censored}} \Pr(y_1 < y_i^* \leq y_2) ,$$

or

$$L = \prod_{\text{left-censored}} \Phi(y_2 - \beta' x_i) \cdot \prod_{\text{right-censored}} 1 - \Phi(y_1 - \beta' x_i) \cdot \prod_{\text{interval-censored}} \Phi(y_2 - \beta' x_i) - \Phi(y_1 - \beta' x_i).$$

Next, its log-likelihood is maximized:

$$\ln L = \sum_{\text{left-censored}} \ln[\Phi(y_2 - \beta' x_i)] + \sum_{\text{right-censored}} \ln[1 - \Phi(y_1 - \beta' x_i)] + \sum_{\text{interval-censored}} \ln[\Phi(y_2 - \beta' x_i) - \Phi(y_1 - \beta' x_i)].$$

The errors are assumed to be correlated across the games of the same individual.

Therefore, the clustering option is applied around individuals.

The level of loss aversion is estimated using the risk aversion parameter  $\sigma$  as elicited in game 1 and 3. Using the mean value of the estimated  $\sigma$  for each individual and together with the value function,  $u(M) = -\lambda * \frac{(-M)^{1-\sigma}}{1-\sigma}$  for losses, i.e.  $M < 0$ , we compute the range of loss aversion parameter  $\lambda$  for each switching point by equating the expected utilities in column A and B.<sup>15</sup>

For the time preference, we use the data from games 5 to 8 in order to identify the intervals of the discount rates. The value function is  $v(M_0) = \frac{1}{(1+r)^t} \cdot v(M_t)$  where  $M_0$  is the present value for the individual facing the payoff  $M_t$  offered at time  $t$  with discount rate  $r$ . Here, the assumption is that  $v(M_t) = M_t$ . By equating the switching point between two choices, we derive the subjective discount rate. For example, if the

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<sup>15</sup> We take the boundary values of  $\sigma$  for right censored and left censored data.

subject switches from Column A to B in row 6-4, then his or her time preference is represented by  $\frac{1}{(1+r)^4} \cdot (10,000) \leq \frac{1}{(1+r)^6} \cdot (18,000)$  or  $r \leq 0.3416$ .

In order to test the existence of present bias, we create a “present bias” dummy for games 5 and 7. Game 5 and 7, and 6 and 8 are exactly the same, except for the front-end delays: this means that the earlier date that participants can hypothetically receive the pay-off in game 5 and 7 is today whereas in game 6 and 8 it is delayed to four or five months later (Appendix Table 2). If the individuals show no sign of present bias, then the switch points or the discount rates should be exactly the same for game 5 and 6 (or for game 7 and 8).

Lastly, we test the correlation between the estimated risk aversion parameter and the estimated subjective discount rates by including the risk aversion parameter in the regression analysis for the discount rate.

There are other ways to model risk and time preference data. For instance, Andersen et al. (2008) use a structural approach where the degree of risk aversion and the subjective discount rate are modelled in a single equation that represents the net present value of total utility derived from the payoffs in the risk and time experiments.<sup>16</sup> Such structural models may be more tractable in relation to the theoretical framework and probably offer more accurate estimates of parameters, but the choice of model is partly dictated by the availability of data, and partly by the different focus of the research interest. In our case, we model the risk aversion and discount rates separately

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<sup>16</sup> They assume that the payoffs from the risk experiment are used for current consumption by the participants, while the payoffs from the time experiment are integrated with background consumption over a longer period.

due to the hypothetical nature of the latter that may lead to distorted results if integrated with the risk data.

The explanatory variables used in the regression analysis are as follows. Six agro-climatic zone dummy variables are created to categorize the villages, as explained in the data section. ‘South-western highlands’ is the base group. The “distance to town” variable measures the distance from a particular reference point in the village to the district town in miles. For the road condition variables, I use the ‘all tarmac’ dummy variable which takes one if the road to the district town is mainly a tarmac road throughout the year, and zero otherwise. Furthermore, an interaction term variable is created with the ‘all tarmac’ dummy and the distance to town to test whether the effect of distance is different for tarmac and non-tarmac roads. “Population density” is the number of people per square miles in the village. “Number of schools” is the number of primary and secondary schools in the village. We also include the log of the village mean asset value and the mean land size of the sample households to represent the wealth level of the villages.

In terms of game-related variables, we include the “expected value,” which is the average payoff in column B for each of the games 1 to 3. According to the increasing partial risk aversion hypothesis, we expect to find that the larger stakes in game 3 induce higher risk aversion. The “present bias” dummy is a dummy for games 5 and 7 which do not have front-end delays. The “risk aversion” and “loss aversion” variables are calculated as mid-points of the interval coded parameters  $\sigma$  and  $\lambda$  respectively as elicited in the experiment for each individual.

For household variables, the log of asset value and the log of land size are used as household wealth variables. Among other household characteristics is “household

size,” the number of household members that had lived in the household for more than 3 months in the past 12 months; and “dependency ratio,” calculated following Yesuf (2009): the ratio of household members below the age of 15 to household members aged 15 and over. We expect that members of smaller households with many children are relatively more risk-averse due to the lower ability to cope with financial risks. For basic individual characteristics, we include gender, age and schooling variables, the last of which is the number of years that the person attended school. We also include a “head” dummy which takes one if the individual is the head of the household and zero otherwise. The head of a household may have different preferences due to the financial responsibility they bear for the household members. We test whether the household and individual variables still correlate with the individual preferences after controlling for the village characteristics.

## **4. Results**

### **4.1 Experimental Results**

Tables 3.1 and 3.2 show the raw statistics from the experiments. The category names used in Table 3.1 correspond to the different rows at which the respondents switched from choosing column A to B, and are useful only to the extent that they label the direction of the attitude, which becomes more risk-averse as one goes down the list. Heterogeneity in the risk preferences is indicated by the wide spread of the respondents across the categories. It is noteworthy that significant numbers of respondents are on one of the extreme ends of the risk attitude categories. Figure 3 shows all the possible combinations of responses in game 1 and 2 on the floor surface and the frequency of responses are represented by the height of the columns. Here, we can visually see that

more than 100 respondents have chosen to switch at row 2 (risk loving or neutral) in both game 1 and 2 and around 140 respondents have chosen to switch at row 8 (very risk averse).

The descriptive statistics from Table 3.1 also suggest existence of loss aversion. For the gains-only games 1, 2 and 3, around 20 to 30 per cent of the respondents are “highly” or “very” risk-averse. For the gain-and-loss game 4, however, over 40 per cent of the respondents are “highly” or “very” risk-averse, 10 to 20 per cent higher than in the gains-only games, indicating that subjects choose safer option when the game involves losses.

As for the time preference, we can see from the first row of Table 3.2 that a large portion of the respondents show patience once the front-end delay is implemented. The portion of respondents choosing the later payments in the first row (switch-point 1, indicating strong patience) increases from 9.8 per cent in game 5 to 22.2 per cent in game 6. It increases from 20.2 per cent in game 7 to 31.2 per cent in game 8. At the same time, a substantial portion of the subjects exhibit high discount rates of more than 75 per cent. This may be due to the hypothetical nature of the question and/or the high degree of risk aversion among these individuals.

Note that around 6 to 8 per cent of the answers in each of the risk games and less than 5 per cent in time preference games are considered irrational.<sup>17</sup> The proportion of such irrational answers in our study is comparable to those in other studies, ranging from around 4 to 12 per cent (Holt and Laury, 2002; Harrison, Lau and Williams, 2002;

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<sup>17</sup> Some have chosen the sure income in column A over the lottery with a chance of winning the same amount as the sure income and another higher amount in column B (see Appendix Table 1). Similarly, some have chosen the risky option, column B, even where the same amount as the sure income and a smaller amount is offered. Others have switched from risky to sure income as the expected payoff of the gamble become higher. Finally, some others have switched multiple times in a game.

Yesuf, 2004). Nonetheless, when we put all the games together, both the discount rates and risk aversion, the total attrition becomes 18 per cent, which is larger than the average in the past. This could be due to the fact that we conducted a series of games and also combined both the time and risk experiment together, which is usually not the case. The test for the difference of means in the main characteristics of those respondents with irrational answers and rational answers shows that there are statistically differences (Appendix Table 3). The respondents with irrational answers have, on average, one year less schooling and are a few years older than those with rational answers. However, there is no statistically significant difference in the household characteristics between them. Due to the inability to estimate the parameters, we exclude those irrational answers from the analysis below.

The estimated parameters for risk aversion, loss aversion and discount rates using the constant-only interval regression are summarized in Table 4. The overall average degree of risk aversion is 1.32, which is comparable to that estimated between 0.81 and 2.0 in another African country, Zambia, (Wik and Holden, 1998 as cited in Cardenas and Carpenter, 2008). The estimated value of loss aversion  $\lambda$  is 3.93. This value of  $\lambda$  is substantially higher than the estimates from previous studies of around 2.63 or 2.25 (Tanaka et al., 2010; Tversky and Kahneman, 1992). This is partly due to the average being pulled upward by the many subjects that showed risk loving or risk neutral behaviour in the gains-only games and chose the safest options in the gains and losses game (13.9 per cent of total respondents).<sup>18</sup> The loss aversion seems to be an important characterization of risk attitude among our sample. Note that the loss aversion

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<sup>18</sup> Comparing the degrees of loss aversion across different degrees of risk aversion, we find that on average “risk-averse ( $0 < \sigma < 2$ )” people have  $\lambda=2.49$ , “very risk-averse ( $\sigma > 2$ )” people have  $\lambda=4.32$  and “risk neutral to risk loving ( $\sigma < 0$ )” have  $\lambda=6.35$  (regression results not shown).

parameter  $\lambda$  is estimated using a single risk aversion parameter or the utility curvature  $\sigma$  for each individual whether the person is risk loving, neutral or averse. Such a method is different from those applied by Tversky and Kahneman (1992) who allowed different utility curvatures for gain and loss frames or Tanaka et al. (2010) whose subjects only revealed risk aversion. Nonetheless, for the average person, who is a risk-averse person with  $\sigma=1.6$ , the estimated  $\lambda$  is 2.7 which is comparable to that found by past papers.

Lastly, the average discount rate is 47.5 per cent. Similar to the descriptive analysis, this monthly discount rate is substantially higher than those found in previous studies, which are usually measured in annual rates. A large part of the deviation probably comes from the hypothetical nature of the question. The focus, however, is not so much on the absolute values of the discount rates as on their relationship to other characteristics of time preference and variation across individuals.

One of our main objectives is to test heterogeneity in the preferences across agro-climatic zones. Table 4 shows that the average values of risk aversion, loss aversion and discount rate are all higher than the overall average in the uni-modal rainfall zone, while they are all lower than the overall average in the low potential bi-modal rainfall zone or in the south-western highlands. In the other zones, some of the parameters are higher than the overall average, while other parameters are lower. Such heterogeneity in the preferences may be due to the agro-climatic nature of the area or other village level factors. Further regression results are presented in the next section.

## **4.2 Determinants of risk aversion**

The regression results for the determinants of risk aversion are shown in Table 5. Column (A) is a result with agro-climatic zones only where the south-western highlands

is the base group. All zone dummies are significant and positive with the highest risk aversion seen among individuals in the uni-modal rainfall zone, followed by the eastern highlands area and the high potential bi-modal rainfall zone. These are the three areas where the high value crop, coffee, is produced by more than 40 per cent of the households (Table 2; Yamano et al., 2004). Risk aversion may be correlated with the high-risk high-return crop.

Column (B) shows the result including other village level variables. The ranking of the average risk aversion remains the same as in Column (A) but the statistical significance disappears for some zones partly due to the differences in the other variables representing village-level characteristics absorbing the differences across the agro-climatic zones. Villages with tarmac roads to the district town have on average higher risk aversion than those with non-tarmac roads. Furthermore, for those villages with tarmac roads, the further away from town, the less risk-averse people are. This is counter-intuitive in the sense that we would expect people in villages with tarmac road and that are closer to town have more access to information and generally better economic condition, resulting in the more pro-investment preferences. The log of average land size is also positively correlated with the farmers' risk aversion. People in villages with larger average land size and better road access may exhibit more risk aversion in the experiment if they already face considerable risk in investing in high-risk high-return crops, such as coffee, in real life. Alternatively, the direction of causality may be the opposite. Villages with people that are more risk-averse may attempt to buy more land or influence the local government to improve the road conditions to stabilize the transport of farm inputs and crops. On average, the household land size has increased two per cent between 2003 and 2009 (Yamano et al., 2004).

Further analysis on changes in individual land size and preference may reveal more insight. The causal relationship between the individual preferences and road construction is harder to test for the decision for the latter is more collective. Other variables including average asset value, population density and number of schools are not significantly correlated with the individuals' risk aversion.

Column (C) shows the result including household and individual characteristics as well as the expected value. None of the household variables are significant. Household wealth or household demography seems not to correlate with risk aversion. For individual variables, age or schooling does not correlate with risk aversion. Women, however, are more risk averse than men.

The coefficient on the expected value indicates that people reveal decreased partial risk aversion, which is contrary to our expectation. This may be due to the fact that in game 3, which has larger stakes than in game 1 or 2, the decisions were more influenced by the sheer size of the larger amounts in column B, namely "10,000," "13,000" and "16,000" than by the expected payoffs. The respondents may have been induced to be more risk-seeking by the sudden increase in the payoffs offered without considering the probabilities attached.

### **4.3 Determinants of loss aversion**

The predictors of loss aversion are presented in Table 6. In Column (A), we see that there is a wide difference in loss aversion across agro-climatic zones. Even controlling for village level factors in column (B), we find that individuals in the medium potential bi-modal rainfall zones and uni-modal rainfall zone are significantly more loss averse than those from other zones. While the two zones have rice production

as a common characteristic, it is not clear how rice production relates to higher aversion to losses unless the low rice harvest in 2008 due to poor weather affected the farmers' aversion to losses (New Vision, 30 June 2010). In column (B), we find that the villages with tarmac roads to district towns have on average lower loss aversion than those with dirt roads, and the log of average land size correlates negatively with loss aversion. These results are consistent with our expectation that those people in wealthier villages with better road access are less loss averse. Comparing the village-level covariates of the preferences between risk aversion and loss aversion, the effects of the road condition, the distance to the district town and the average wealth level are opposite: individuals in the villages with lower wealth or less favourable access to town are less risk averse but more loss averse. This indicates that loss aversion may be a more important characterization of poorer villages. Nonetheless, households in the uni-modal zone are more risk averse and loss averse than those in any other zone.

In terms of the individual and household characteristics, we find that higher household wealth level, more years of schooling and older age are associated with less loss aversion after controlling for the village level factors. Gender has no statistically significant effect on loss aversion.

#### **4.4 Determinants of discount rates**

The results on discount rates are shown in Table 7. In Column (A), we see that the uni-modal zone has the highest average discount rate and the eastern highlands has the second highest. In column (B), the tarmac road dummy is significantly correlated with a lower discount rate or more patience. For those with tarmac roads, the further away the village is from the district town, the less patient the people are. Individuals in

the villages with higher average asset value are more patient. The correlation between higher average wealth or better access to town and lower discount rate is as expected. Again, the causality may be not so much that the economically favourable environment of the villages induces patience but that the villagers' patience induces long-term investment in productive activities or drives infrastructure projects. In terms of the number of local schools, it is negatively correlated with patience, in contrast to our expectation.

In column (D), we see that while individuals with more schooling are more patient, household heads are more impatient than others. Age or gender does not have significant effect on patience. In terms of the game effects, present bias does exist, and the more risk-averse and loss averse people are, the more impatient they are.

## **5. Discussion**

In the above results, we have seen that risk aversion, loss aversion and patience are different across agro-climatic zones. In order to test the significance of the differences among all zones (not only against the south-western highlands), the same regression exercises are carried out with base dummies other than that of the south-western highlands. The significance of the zone dummies varies with different specification, but one result remains the same: all three preference parameters are highest for the uni-modal zone among all zones.

We suggested in the result section that the subjects in the uni-modal zone may be relatively more risk/loss averse or impatient due to the variability of crop yields due to erratic rainfalls. The situation may be exacerbated by the low soil quality. The FAO's categorization of agro-ecological zones that overlaps with that of Pender et al (2004)

shows that in the uni-modal zone, not only the rainfall season is relatively short, but also the soil fertility is lower than in other zones, resulting in the choice of crops that are drought tolerant (FAO, 1999).<sup>19</sup>

### 5.1 Extension - modelling probability weighting

We have estimated the risk aversion parameter assuming EUT to be true. In recent experiment studies, however, an alternative model of probability weighting has been modelled (Humphrey and Verschoor, 2004; Tanaka et al., 2010; Harrison et al., 2010). This concept from prospect theory states that individuals do not simply take the probabilities  $p_i$  given in the problem  $\sum_{i=1}^n p_i u(W_i)$  as they are, but subjectively weight them, i.e. maximizing  $\sum_{i=1}^n \pi_i u(W_i)$  where  $\pi_i = f(p_i)$  (Kahneman and Tversky, 1979). The evidence of probability weighting is ample, and may affect the magnitude of risk aversion in our analysis, too (Kahneman and Tversky, 1979; Tanaka et al., 2010; Humphrey and Verschoor, 2004). The initial evidence by Kahneman and Tversky (1979) is that probability weighting takes the inverse-S shape, implying overweighting of small probabilities and underweighting of large probabilities regardless of the relative sizes of the prospects to which the probabilities are attached. A recent study in rural Vietnam also supports this theory (Tanaka et al., 2010). The intuition given for the inverted-S shape probability function is that sensitivity increases around boundaries. However, the evidence from East Uganda given by Humphrey and Verschoor (2004) suggests the opposite; namely, S-shape probability weighting. The authors suggest that such an underweighting of small probabilities may possibly be due to highly volatile

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<sup>19</sup> The “Annual Cropping and Cattle Teso system” and “Annual cropping and Cattle Northern system” in the FAO (1999) zones cover the uni-modal zone in our sample.

environments. One may be induced to disregard the possibility of a certain amount of income if the chance is relatively small since the variability of income is too high anyway.

Therefore, we estimate the degree of risk aversion and the probability weighting simultaneously by constructing the random utility model following the maximum likelihood method by Harrison (2008). We assume the Tversky and Kahneman (1992) function,  $\pi = p^\gamma / [p^\gamma + (1 - p)^\gamma]^{1/\gamma}$  for  $\pi_i$  and CRRA utility function,  $u(M) = \frac{M^{1-\sigma}}{1-\sigma}$ .

The result is shown in Appendix Table 4. The result shows that the heterogeneity across agro-climatic zones still holds. The rankings of the degree of risk aversion are now different for many zones, except for the uni-modal rainfall zone being the most risk-averse. Thus, under the prospect theory of probability weighting, the result remains fairly stable. In terms of probability weighting, we find that most zones exhibit the inverse-S shape probability weighting function consistent with the results from most past studies, the uni-modal rainfall zone being an exception exhibiting an S-shape function. The uni-modal zone that is situated in the eastern region of Uganda, however, does not coincide with the village in the eastern highlands where Humphrey and Verschoor (2004) witnessed the S-shape probability weighting. Nonetheless, there may be some characteristics that are common in the sampled villages that are in the same region of the country.

## **5.2 Extension – including ethnic groups control**

Another robustness check is carried out using ethnic groups. As shown in Figure 4, some of the ethnic boundaries overlap with those of the agro-climatic zones. Our concern was that given a high correlation between the two categorizations, we may be

reporting differences in ethnicity-related preferences and not those affected by agro-climatic conditions. Studies from developed countries discuss the differences in consumer behaviours and attitudes towards risks across ethnic groups (Ogden et al., 2004; Yao et al., 2005). Therefore, we report the regression results including the ethnic group dummies in Appendix Table 5. Each of the three preference parameters is estimated using two different sets of ethnic groups. Column (A), (C) and (E) show the results using ethnic dummies that correspond to broad groups as seen in Figure 4. The base group is “other”. Column (B), (D) and (F) are the results with dummies representing ethnicity as reported by the household head. In all estimations we find that our main results regarding the uni-modal zone remain the same.

## **6. Conclusion**

Risks in agriculture continue to pose challenges to farmers in developing countries. In order to reduce such variability in agricultural income, research into disaster management and projects to improve agricultural technology are being conducted by the government of Uganda and the international development agencies (Government of Uganda, 2008; World Bank, 2010). Our goal in this study is to identify the potential role of regional factors as well as individual and household characteristics that may affect the investment-related preferences of the rural households in such efforts to improve their livelihoods. From the large-scale experiment eliciting the farmers’ risk and time preferences, we contribute several important findings.

First, we find that average risk aversion, loss aversion and discount rate differ across agro-climatic zones. These results may be driven by the types of crops produced in the areas. The highest risk aversion exhibited in the experiment is in the coffee

growing areas and may be due to the risks already taken in real-life investment. In rice producing areas, the temporal weather shocks in 2008 may have induced strong loss aversion. More importantly, we find a significant result that households in the uni-modal zone villages are on average more risk-averse, more loss-averse and less patient than the farmers from other zones. This suggests a correlation between the farmers' preferences and the relative low agro-climatic conditions. The single rainfall season with overall relatively short growing period and low soil fertility implies that any erratic rainfall may severely affect the farmers' crop yields and in turn their attitudes towards risks and subjective discount rates regarding future investments.

Stronger risk aversion could be attributed not to pure preferences but to background risks such as higher variability in income due to risky crop types or unfavourable rain conditions (Gollier and Pratt, 1996), but the evidence is difficult to obtain. Neither the previous literature (e.g. Pender et al., 2004), the external statistics (FAO, 1999), nor our study has clear evidence that uni-modal rainfall zone has a unique characteristic such as extremely erratic rainfall or variable crop yields. We have controlled for the ethnic groups that may correlate with the zone boundaries and found that the variation in the preferences still remain. In terms of external evidence on the variability of rainfall, most of the severest droughts are witnessed in the Karamoja regions in the north-west and floods occur in the bi-modal rainfall areas as well as the uni-modal areas (EM-DAT, 2011). Thus, we do not have independent measures of risks in different regions in order to differentiate between interpretations: risk preferences differ, background risks differ or differences in background risks cause the changes in risk preferences. This may be an area for further research.

Another limitation is that the one-time elicitation of preferences does not reveal the entire process by which the preferences and the agro-climatic conditions may correlate. Further research into the dynamic nature of investment related preferences and the farmers' environment may be important, especially in times where climate change is influencing the agricultural production in developing countries. Nonetheless, our evidence is the first of its kind, revealing a statistically significant relationship between climatic and topographical conditions and investment related preferences.

It is worthy of note that agro-ecological zones which are constructed by classifying villages and areas by "multivariate similarities" (Ruecker et al., 2003) do not have strict boundaries. Therefore, our result based on agro-ecological zones is useful only to the extent that it represents the average effect of the agro-ecological condition, and not the effect for the entire population within the artificial boundaries on the map. The individuals in the uni-modal zone may be on average more risk averse and impatient than those in other zones, but further investigation may reveal heterogeneous trends of preferences within the uni-modal zone.

Our second contribution is that we found that village level predictors are different for the risk aversion from those for loss aversion or the discount rate. While higher risk aversion correlates with wealthier villages with more land, higher loss aversion and discount rate correlate with poorer villages with lower asset values. Our results from a large sample confirm the result by Tanaka et al. (2010) that loss aversion, rather than risk aversion, is the characteristic of households in poorer villages in developing countries.

Third, we have shown that infrastructure, after controlling for the village wealth level, correlate with loss aversion and the discount rate. Such aspects of regional

variation can be improved or developed through policies, possibly resulting in more pro-investment preferences of the farmers. While improvements in road conditions may directly improve the economic welfare of the villagers through lower transaction cost, they may do so indirectly, too, through the impact on the perception of future economic opportunities by the people living in the areas.

Last, we have seen that after controlling for the village level factors, the level of schooling still correlates with both loss aversion and discount rates. The policy implication is that schooling not only increases individual income through increase in productivity but also possibly through inducing more pro-investment preferences.

In conclusion, our investigation into the determinants of the risk and time preferences has revealed that village and regional level factors affect the preferences. On one hand, the knowledge of agro-climatic conditions that affect the livelihood of the farmers may help shed light on the investment behaviour at the time of policy implementation. On the other hand, village level development, in infrastructure for instance, may improve the household perception on investment related policies that involves judgments on future uncertain income.

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**Table 1: Sampled Individuals**

	Respondent				Non-Respondent	
	All (a)	Panel (b)	Neighbour (c)	Diff. (b)-(c)	Panel (d)	Diff. (b)-(d)
<u>Individual Characteristics</u>	mean	mean	Mean		mean	
Gender (Male=1)	0.68 (0.47)	0.69 (0.46)	0.67 (0.47)	0.02		
Age	45.0 (14.7)	47.0 (15.0)	41.8 (13.74)	5.22***		
Literate (Yes=1)	0.66 (0.47)	0.64 (0.48)	0.69 (0.46)	-0.05*		
Schooling	5.70 (3.67)	5.44 (3.69)	6.09 (3.61)	-0.65***		
<u>Household Characteristics</u>						
Household Size		7.72 (3.82)			7.21 (4.15)	0.51
Dependency Ratio		1.19 (0.87)			1.08 (0.88)	0.11
Female Headed (=1)		0.12 (0.33)			0.12 (0.33)	0.0
Per capita income (US\$)		152.7 (240.1)			177.4 (271.5)	-24.7
Value of Assets (US\$)		207.2 (677.0)			160.6 (247.2)	46.6
Own Land Size (acre)		5.74 (23.65)			3.19 (3.80)	2.55
No. of Observations	1279	787	502		154	

Note: in parenthesis are standard deviations. \* indicates significance level at 10%, \*\* at 5%, \*\*\* at 1%. Dependency ratio is the ratio of the number of household members below age 15 to that of members above or equal to age 15. Per capita income and value of assets are valued at 2005 rate of 1US\$ = 1730 Ugandan Shillings.

**Table 2: Sampled Villages**

Agro-Climatic Zone <sup>1</sup>	Bi-Low	Bi-Med	Bi-High	Uni-	Eastern	SW
	Rainfall	Rainfall	Rainfall	Modal	Highlands	Highlands
Land size (acre)	8.6	10.5	5.6	5.6	3.5	4.2
Per capita expenditure (US\$)	295	221	271	244	209	320
<u>% Producer Households:</u>						
Maize	86.8	91.0	92.8	79.1	91.8	74.0
Matooke	90.0	41.2	62.1	69.6	72.4	60.7
Coffee	30.5	24.3	53.6	55.2	76.5	23.7
Sweet Potato	48.6	79.3	78.2	41.7	18.2	54.5
Cassava	49.7	78.8	79.0	82.0	45.9	28.6
Rice	0	14.8	2.6	4.5	0	0
Distance to town (miles)	22.7	13.0	15.4	6.1	10.5	7.5
<u>%Village with road condition:</u>						
All season tarmac	41.6	5.2	29.0	25.0	25.0	6.6
Seasonal dirt	16.7	5.3	6.5	0	25.0	26.7
All season dirt	41.7	89.5	64.5	75.0	50.0	66.7
Population density ( / km <sup>2</sup> ) <sup>2</sup>	100	100	371	480	98	154
No. of local schools <sup>3</sup>	1.2	0.8	1.9	0.6	0.4	0.6
No. of Villages	12	19	31	8	8	15

Note: All data from 2009, except for those stated otherwise. 1. The high potential bi-modal (Bi-High) rainfall zone covers mostly the Lake Victoria crescent, the medium potential bi-modal (Bi-Med) rainfall zone most of the central and parts of western Uganda, the low potential bi-modal (Bi-Low) rainfall zone the lower elevation parts of south-western Uganda. Other zones are the high potential bi-modal rainfall south-western (SW) highlands and the high potential uni-modal rainfall eastern (Eastern) Highlands at 1500 metres above sea level and above and the uni-modal (Uni-Modal) rainfall zone that covers part of eastern Uganda. 2. Population density data are from year 2003. 3. Number of local schools data are from year 2005.

**Table 3.1: Distribution of Risk Preferences among the Respondents**

Switch Point		Gains Only			Gain & Loss
		Game 1	Game 2	Game 3	Game 4
		%	%	%	%
2	Very Risk Loving	15.1	16.4	15.9	2.1
3	Risk Loving to Risk Neutral	11.9	11.6	14.1	15.7
4	Slightly Risk-Averse	9.6	9.2	8.7	11.7
5	Moderately Risk-Averse	9.8	14.9	9.9	12.2
6	Intermediate Risk-Averse	17.3	10.2	22.9	7.4
7	Highly Risk-Averse	9.5	14.1	7.7	11.5
8	Very Risk-Averse	19.8	16.4	14.6	31.5
	Irrational Answers	7.0	7.1	6.2	7.9
	All A	(2.4)	(2.7)	(1.7)	(3.3)
	All B	(0.9)	-	(1.2)	(0.5)
	Reversed choice	(0.1)	(3.4)	-	(0.1)
	Multiple Switching	(3.7)	(3.4)	(3.3)	(4.0)
	Total	100.0	100.0	100.0	100.0

**Table 3.2: Distribution of Time Preferences among the Respondents**

Switch point	Monthly Discount Rate (%)	No front –end delay	Front-end delay	Monthly Discount Rate (%)	No front –end delay	Front-end delay
		Game 5	Game 6		Game 7	Game 8
		%	%		%	%
1	0 – 9.54	9.8	22.2	0 – 10.00	20.2	31.2
2	9.54 – 18.32	5.2	6.7	10.00 – 20.00	9.6	5.8
3	18.32 – 26.49	9.8	13.3	20.00 – 30.00	13.5	11.9
4	26.49 – 34.16	13.1	15.7	30.00 – 40.00	16.8	11.2
5	34.16 – 50.00	26.5	18.9	40.00 – 55.56	20.1	22.4
6	50.00 – 73.21	8.5	4.3	55.56 – 75.00	4.4	3.7
7	73.21 – 112.13	6.6	3.8	75.00 – 100.00	3.4	1.6
8	112.13 – 200.00	5.7	2.7	100.00 – 180.00	1.9	3.6
	200.00 -	12.6	7.6	180.00 –	8.1	4.7
	Irrational	2.2	4.8	Irrational Answers	2.0	3.9
	Reversed choice	(0.8)	(2.3)	Reversed choice	(0.5)	(1.2)
	Multiple	(1.4)	(2.4)	Multiple	(1.6)	(2.7)
	Total	100.0	100.0	Total	100.0	100.0

**Table 4: Risk Aversion, Loss Aversion and Discount Rate by Agro-Climatic Zone**

Agro-Climatic Zone	Total	Bi-Low Rainfall	Bi-Med Rainfall	Bi-High Rainfall	Uni- Modal	Eastern Highlands	SW Highlands
Risk Aversion ( $\sigma$ )	1.32	1.18	1.14	1.41	2.22	1.56	0.72
Loss Aversion ( $\lambda$ )	3.93	1.88	5.34	3.83	6.98	3.39	2.72
Discount Rate (r)	47.5	27.4	50.6	47.3	66.7	55.2	38.5
No. of households	1040	115	232	369	112	97	115

**Table 5: Predictors of Risk Aversion (Interval Regression)**

	(A)	(B)	(C)
<u>Village Characteristics</u>			
Agro-climatic Zones <sup>1</sup>			
Bi – Low	0.516** <sup>2</sup> (2.45)	0.429* (1.70)	0.536** (1.91)
Bi – Medium	0.482** (2.30)	0.080 (0.34)	-0.017 (-0.07)
Bi – High	0.744*** (4.26)	0.611*** (3.24)	0.647*** (3.15)
Uni – Modal	1.423*** (5.30)	1.130*** (4.09)	1.140*** (3.95)
Eastern Highlands	0.906*** (3.93)	0.981*** (4.05)	0.986*** (3.80)
Distance to town		-0.008 (-1.25)	-0.010 (-1.37)
All Tarmac dummy		0.672*** (2.38)	0.592** (2.01)
Distance to town * All tarmac dummy		-0.035*** (-2.70)	-0.037*** (-2.71)
Population Density		-0.000 (-0.59)	-0.000 (-0.63)
Number of schools		0.032 (0.88)	0.04 (1.13)
Log of average asset value		-0.004 (-0.04)	-0.058 (-0.54)
Log of average land size		0.560*** (4.65)	0.529*** (3.99)
<u>Household Characteristics</u>			
Household Size			-0.007 (-0.30)
Dependency Ratio			0.063 (0.83)
Log of Land Size			0.096 (1.24)
Log of Asset Value			-0.021 (-0.31)
Expected Value			-0.002*** (-9.11)
<u>Individual Characteristics</u>			
Age			-0.007 (-1.56)
Female			0.296* (1.76)
Schooling			0.015 (0.85)
Head			0.071 (0.38)
Constant	0.660*** (4.55)	0.04 (0.03)	11.05*** (6.10)
Log Likelihood	-6249	-6214	-5747
Observations	3120	3120	2898

Note: 1. The base dummy for agro-climatic zones is the south-western highlands. 2. Robust z-statistics in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

**Table 6: Predictors of Loss Aversion (Interval Regression)**

	(A)	(B)	(C)
<u>Village Characteristics</u>			
Agro-climatic Zones <sup>1</sup>			
Bi – Low	-0.824*** <sup>2</sup> (-2.73)	0.051 (0.13)	-0.345 (-0.80)
Bi – Medium	2.000*** (5.22)	2.354*** (5.16)	2.034*** (4.17)
Bi – High	0.928*** (2.99)	0.879*** (2.52)	0.545 (1.45)
Uni – Modal	3.135*** (6.14)	3.317*** (6.09)	3.153*** (5.55)
Eastern Highlands	0.681* (1.64)	1.061*** (2.39)	0.735 (1.52)
Distance to town		0.012 (0.95)	0.019 (1.35)
All Tarmac dummy		-1.497*** (-3.24)	-1.089** (2.29)
Distance to town * All tarmac dummy		-0.003 (-0.18)	-0.016 (-0.78)
Population Density		0.001*** (4.07)	0.001*** (4.01)
Number of schools		0.212*** (2.36)	0.203** (2.03)
Log of average asset value		-0.292 (-1.60)	-0.153 (-0.77)
Log of average land size		-0.511** (-2.12)	-0.723*** (-2.82)
<u>Household Characteristics</u>			
Household Size			0.141*** (3.65)
Dependency Ratio			-0.207 (-1.61)
Log of Land Size			0.147 (1.04)
Log of Asset Value			-0.244** (-1.96)
<u>Individual Characteristics</u>			
Age			-0.019** (-2.07)
Female			-0.437 (-1.41)
Schooling			-0.099*** (-2.87)
Head			-0.073 (-0.21)
Constant	2.856*** (12.05)	6.778*** (2.84)	9.127*** (3.47)
Log Likelihood	-2619	-2588	-2369
Observations	1040	1040	966

Note: 1. The base dummy for agro-climatic zones is the south-western highlands. 2. Robust z-statistics in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

**Table 7: Predictors of Discount Rate (Interval Regression)**

	(A)	(B)	(C)	(D)
<u>Village Characteristics</u>				
Agro-climatic Zones <sup>1</sup>				
Bi – Low	-11.26*** <sup>2</sup> (-3.16)	-8.48** (-2.03)	-12.20*** (-2.64)	-12.65*** (-2.73)
Bi – Medium	11.54*** (2.76)	13.29*** (2.72)	12.01** (2.30)	8.056 (1.56)
Bi – High	8.02** (2.07)	7.174* (1.77)	5.616 (1.35)	3.477 (0.84)
Uni – Modal	26.66*** (4.69)	27.49*** (4.67)	27.75*** (4.57)	19.83*** (3.40)
Eastern Highlands	16.22*** (2.99)	16.49*** (3.18)	15.83*** (2.87)	12.36** (2.27)
Distance to town		-0.033 (-0.25)	-0.045 (-0.31)	-0.053 (-0.36)
All Tarmac dummy		-13.37*** (-2.49)	-10.85** (-1.93)	-11.26** (-1.98)
Distance to town * All tarmac dummy		0.466** (2.03)	0.445* (1.82)	0.640*** (2.51)
Population Density		0.006*** (2.59)	0.005** (2.25)	0.004* (1.79)
Number of schools		0.851 (1.33)	1.120* (1.71)	0.597 (0.87)
Log of average asset value		-5.197** (-2.48)	-3.992* (-1.79)	-3.506 (-1.56)
Log of average land size		-2.050 (-0.86)	-2.428 (-0.91)	-2.300 (-0.81)
<u>Household Characteristics</u>				
Household Size			0.402 (0.98)	0.165 (0.39)
Dependency Ratio			-0.862 (-0.56)	-0.784 (-0.51)
Log of Land Size			-0.773 (-0.50)	-1.459 (-0.97)
Log of Asset Value			-0.072 (-0.06)	0.566 (0.46)
Present Bias Dummy			12.36*** (9.83)	12.37*** (9.85)
Risk aversion parameter				3.051*** (4.38)
Loss aversion parameter				4.676*** (3.30)
<u>Individual Characteristics</u>				
Age			-0.045 (-0.39)	0.004 (0.04)
Female			-3.123 (-0.94)	-2.993 (-0.93)
Schooling			-1.095*** (-2.75)	-1.026*** (-2.65)
Head			7.412** (2.09)	7.112** (2.04)
Constant	38.97*** (12.77)	106.41*** (3.94)	89.84*** (3.01)	63.59** (2.10)
Log Likelihood	-11407	-11373	-10523	-10463
Observations	4160	4160	3864	3864

Note: 1. The base dummy for agro-climatic zones is the south-western highlands. 2. Robust z-statistics in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

**Appendix Table 1: Payoff Matrix for the Risk Preference Experiment**

Row	Column A				Column B				EV <sup>A</sup> - EV <sup>B</sup>	CRRA interval if switches to B under EUT		
	Pr (p)	Prize (M)	Pr (1-p)	Prize (M)	Pr (p)	Prize (M)	Pr (1-p)	Prize (M)				
1-1	1.0	4000			0.5	4000	0.5	2000	1000	n/a		
1-2	1.0	4000			0.5	5500	0.5	2000	250	$-\infty$	$<\sigma\leq$	-0.62
1-3	1.0	4000			0.5	6000	0.5	2000	0	-0.62	$<\sigma\leq$	0.00
1-4	1.0	4000			0.5	7000	0.5	2000	-500	0.00	$<\sigma\leq$	0.66
1-5	1.0	4000			0.5	8000	0.5	2000	-1000	0.66	$<\sigma\leq$	1.00
1-6	1.0	4000			0.5	8000	0.5	3000	-1500	1.00	$<\sigma\leq$	2.91
1-7	1.0	4000			0.5	8000	0.5	3500	-1750	2.91	$<\sigma\leq$	3.64
1-8	1.0	4000			0.5	8000	0.5	4000	-2000	3.64	$<\sigma\leq$	$\infty$
2-1	1.0	4000			0.75	4000	0.25	2000	500	n/a		
2-2	1.0	4000			0.75	4500	0.25	2000	125	$-\infty$	$<\sigma\leq$	-0.82
2-3	1.0	4000			0.75	5000	0.25	2000	-250	-0.82	$<\sigma\leq$	0.92
2-4	1.0	4000			0.75	5500	0.25	2000	-625	0.92	$<\sigma\leq$	1.62
2-5	1.0	4000			0.75	6000	0.25	2000	-1000	1.62	$<\sigma\leq$	2.00
2-6	1.0	4000			0.75	7000	0.25	2000	-1750	2.00	$<\sigma\leq$	2.39
2-7	1.0	4000			0.75	7000	0.25	3000	-2000	2.39	$<\sigma\leq$	3.79
2-8	1.0	4000			0.75	7000	0.25	4000	-2250	3.79	$<\sigma\leq$	$\infty$
3-1	1.0	4000			0.25	4000	0.75	2000	1500	n/a		
3-2	1.0	4000			0.25	7000	0.75	2000	750	$-\infty$	$<\sigma\leq$	-1.15
3-3	1.0	4000			0.25	10000	0.75	2000	0	-1.15	$<\sigma\leq$	0.00
3-4	1.0	4000			0.25	13000	0.75	2000	-750	0.00	$<\sigma\leq$	0.41
3-5	1.0	4000			0.25	16000	0.75	2000	-1500	0.41	$<\sigma\leq$	0.62
3-6	1.0	4000			0.25	16000	0.75	3000	-2250	0.62	$<\sigma\leq$	1.60
3-7	1.0	4000			0.25	16000	0.75	3500	-2625	1.60	$<\sigma\leq$	3.04
3-8	1.0	4000			0.25	16000	0.75	4000	-3000	3.04	$<\sigma\leq$	$\infty$
4-1	0.5	6000	0.5	-500	0.5	6000	0.5	-4000	1750			
4-2	0.5	4000	0.5	-500	0.5	6000	0.5	-4000	750			
4-3	0.5	1000	0.5	-500	0.5	6000	0.5	-4000	-750			
4-4	0.5	500	0.5	-500	0.5	6000	0.5	-4000	-1000			
4-5	0.5	500	0.5	-500	0.5	6000	0.5	-3000	-1500			
4-6	0.5	500	0.5	-1000	0.5	6000	0.5	-3000	-1750			
4-7	0.5	500	0.5	-1000	0.5	6000	0.5	-2000	-2250			
4-8	0.5	500	0.5	-1000	0.5	6000	0.5	-1000	-2750			

Note: the table shows all of the prizes/payoffs (M) and the attached probabilities (p,1-p) for choices A and B in the four risk games. “EV<sup>A</sup>-EV<sup>B</sup>” is the difference in the expected value between lottery A and lottery B. The range of sigma  $\sigma$  given in the last column is calculated by equating the expected utilities from lottery A and lottery B assuming CRRA utility function (see main text, Section 3.3.2, for the calculation method).

**Appendix Table 2: Payoff Matrix for the Time Preference Experiment**

Row	Column A		Column B		Front-end	Discount Rate interval if switches to B (A for game 6 & 8)		
	Month (t)	Prize (M)	Month (t)	Prize (M)	Delay			
5-1	0	10,000	2	12,000	no	0	$< r \leq$	9.54
5-2	0	10,000	2	14,000	no	9.54	$< r \leq$	18.32
5-3	0	10,000	2	16,000	no	18.32	$< r \leq$	26.49
5-4	0	10,000	2	18,000	no	26.49	$< r \leq$	34.16
5-5	0	8,000	2	18,000	no	34.16	$< r \leq$	50.00
5-6	0	6,000	2	18,000	no	50.00	$< r \leq$	73.21
5-7	0	4,000	2	18,000	no	73.21	$< r \leq$	112.13
5-8	0	2,000	2	18,000	no	112.13	$< r \leq$	200.00
6-1	6	12,000	4	10,000	yes	0	$< r \leq$	9.54
6-2	6	14,000	4	10,000	yes	9.54	$< r \leq$	18.32
6-3	6	16,000	4	10,000	yes	18.32	$< r \leq$	26.49
6-4	6	18,000	4	10,000	yes	26.49	$< r \leq$	34.16
6-5	6	18,000	4	8,000	yes	34.16	$< r \leq$	50.00
6-6	6	18,000	4	6,000	yes	50.00	$< r \leq$	73.21
6-7	6	18,000	4	4,000	yes	73.21	$< r \leq$	112.13
6-8	6	18,000	4	2,000	yes	112.13	$< r \leq$	200.00
7-1	0	10,000	1	11,000	no	0	$< r \leq$	10.00
7-2	0	10,000	1	12,000	no	10.00	$< r \leq$	20.00
7-3	0	10,000	1	13,000	no	20.00	$< r \leq$	30.00
7-4	0	10,000	1	14,000	no	30.00	$< r \leq$	40.00
7-5	0	9,000	1	14,000	no	40.00	$< r \leq$	55.56
7-6	0	8,000	1	14,000	no	55.56	$< r \leq$	75.00
7-7	0	7,000	1	14,000	no	75.00	$< r \leq$	100.00
7-8	0	5,000	1	14,000	no	100.00	$< r \leq$	180.00
8-1	6	11,000	5	10,000	yes	0	$< r \leq$	10.00
8-2	6	12,000	5	10,000	yes	10.00	$< r \leq$	20.00
8-3	6	13,000	5	10,000	yes	20.00	$< r \leq$	30.00
8-4	6	14,000	5	10,000	yes	30.00	$< r \leq$	40.00
8-5	6	14,000	5	9,000	yes	40.00	$< r \leq$	55.56
8-6	6	14,000	5	8,000	yes	55.56	$< r \leq$	75.00
8-7	6	14,000	5	7,000	yes	75.00	$< r \leq$	100.00
8-8	6	14,000	5	5,000	yes	100.00	$< r \leq$	180.00

Note: the table shows all of the prizes/payoffs (M) and the timing (t) of payment for choices A and B in the four time games. The range of discount rate  $r$  given in the last column is calculated by equating the discounted value from lottery A and lottery B (see main text, Section 3.3.3, for the calculation method).

**Appendix Table 3: Respondents with Rational and Irrational Answers**

	Rational	Irrational	Difference
	(a)	(b)	(a)-(b)
<u>Individual Characteristics</u>			
Gender (Female=1)	0.32 (0.47)	0.32 (0.47)	0.00
Age	44.0 (14.4)	47.9 (15.7)	-3.6***
Schooling	5.90 (3.68)	4.90 (3.40)	1.04***
Head	0.75 (0.43)	0.78 (0.42)	-0.03
<u>Household Characteristics</u>			
Household Size	7.65 (3.84)	7.23 (2.90)	0.41
Dependency Ratio	1.17 (0.92)	1.13 (0.93)	0.03
Value of Assets (US\$)	320.7 (1505.1)	243.4 (410.1)	77.3
Own Land Size (acre)	7.04 (21.2)	5.24 (8.2)	1.80
No. of Observations	1040	237	

Note: in parenthesis are standard deviations. \* indicates significance level at 10%, \*\* at 5%, \*\*\* at 1%.

**Appendix Table 4: Probability Weighting and Risk Aversion**

	Risk Aversion	Probability Weighting
	r	$\gamma$
<u>Agro-climatic Zone<sup>1</sup>:</u>		
Bi – Low	0.007 (0.93) <sup>2</sup>	-0.049** (-2.36)
Bi – Medium	0.030*** (4.81)	-0.030 (-1.44)
Bi - High	0.019*** (3.41)	-0.057*** (-3.28)
Uni – Modal	0.062*** (8.41)	0.244*** (8.80)
Eastern Highlands	0.013* (1.78)	-0.074*** (-3.67)
EVA	0.000*** (11.42)	-0.000 (-0.77)
Constant	0.391*** (10.72)	0.983*** (11.61)
Observations	24960	24960

Note: 1. The base dummy for agro-climatic zones is the south-western highlands.

2. Robust z-statistics in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

**Appendix Table 5: Robust Estimation with Controls for Ethnic Groups**

	Risk Aversion		Loss Aversion		Discount Rate	
	(A)	(B)	(C)	(D)	(E)	(F)
<b>Village Characteristics</b>						
<b>Agro-climatic Zones<sup>1</sup></b>						
Bi – Low	0.438 (1.59)	0.839*** (2.67)	-0.343 (-0.79)	-0.628 (-1.31)	-12.32*** (-2.65)	-15.27*** (-2.62)
Bi – Medium	0.029 (0.11)	0.408 (1.23)	1.929*** (3.80)	-0.464 (-0.87)	6.205 (1.18)	0.185 (0.03)
Bi – High	0.656*** <sup>2</sup> (3.21)	1.118*** (3.96)	0.441 (1.17)	-1.010** (-2.28)	2.254 (0.55)	-2.750 (-0.46)
Uni – Modal	1.392*** (4.58)	2.402*** (5.69)	2.958*** (5.08)	2.449*** (3.31)	17.89*** (3.03)	21.89*** (2.39)
Eastern Highlands	1.009*** (3.89)	2.301*** (5.21)	0.549 (1.09)	1.396* (1.81)	10.78** (1.98)	17.63* (1.72)
<b>Ethnic Groups<sup>3</sup></b>						
Bantu	0.585** (2.09)		0.035 (0.07)		-8.449 (-1.52)	
Luo	0.322 (0.70)		1.604* (1.79)		8.185 (0.70)	
Nilohamitic	0.370 (1.13)		0.883 (1.29)		-0.849 (-0.13)	
Ethnicity dummies included <sup>3</sup>	No	Yes	No	Yes	No	Yes
Village Characteristics included	Yes	Yes	Yes	Yes	Yes	Yes
Household Characteristics included	Yes	Yes	Yes	Yes	Yes	Yes
Individual Characteristics included	Yes	Yes	Yes	Yes	Yes	Yes
Constant	8.875*** (4.89)	8.434*** (4.45)	8.569*** (3.22)	6.050*** (2.36)	65.86** (2.16)	83.40*** (2.66)
Log Likelihood	-5737	-5708	-2365	-2245	-10452	-10430
Observations	2898	2898	966	966	3864	3864

Note: 1. The base dummy for agro-climatic zones is the south-western highlands. 2. Robust z-statistics in parentheses: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

The base dummy for the ethnic groups is 'Other'. 3. Ethnic group dummies included are: Acholi, Badama, Bafumbira, Baganda, Bagisu, Bakiga, Bakonjo, Banyankore, Banyole, Basoga, Batooro, Iteso, Samia, Baruli, Sebei.

**Figure 1: Selected Villages and Agro-Climatic Zones of Study Area in Uganda**

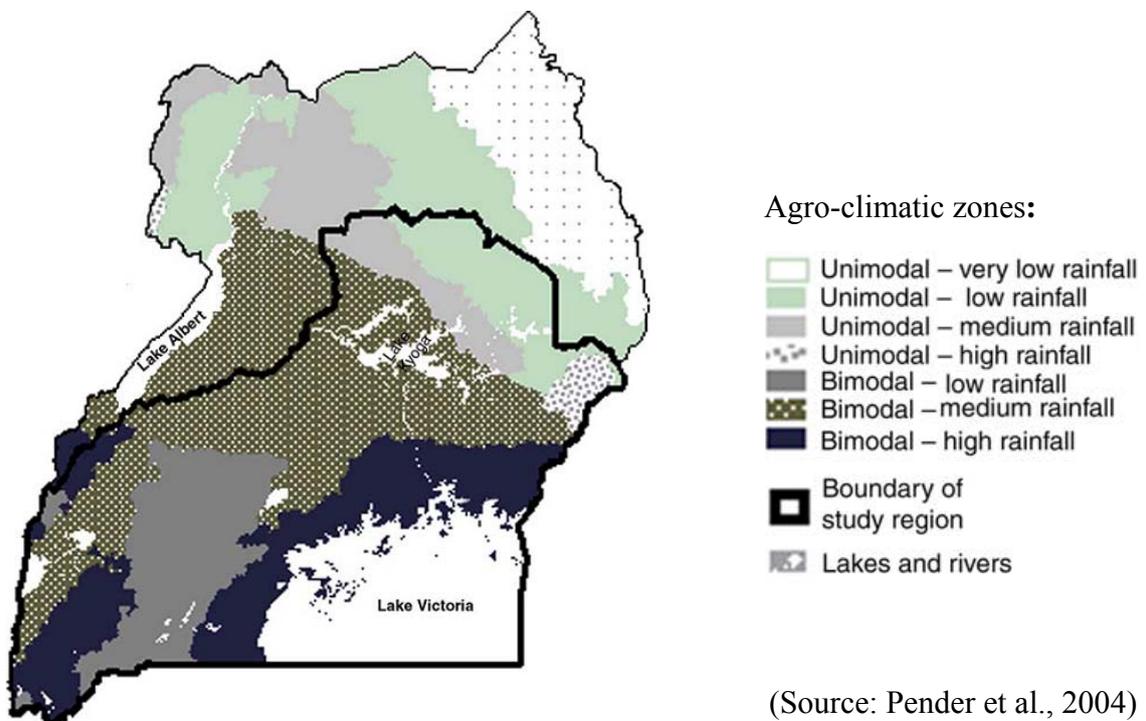
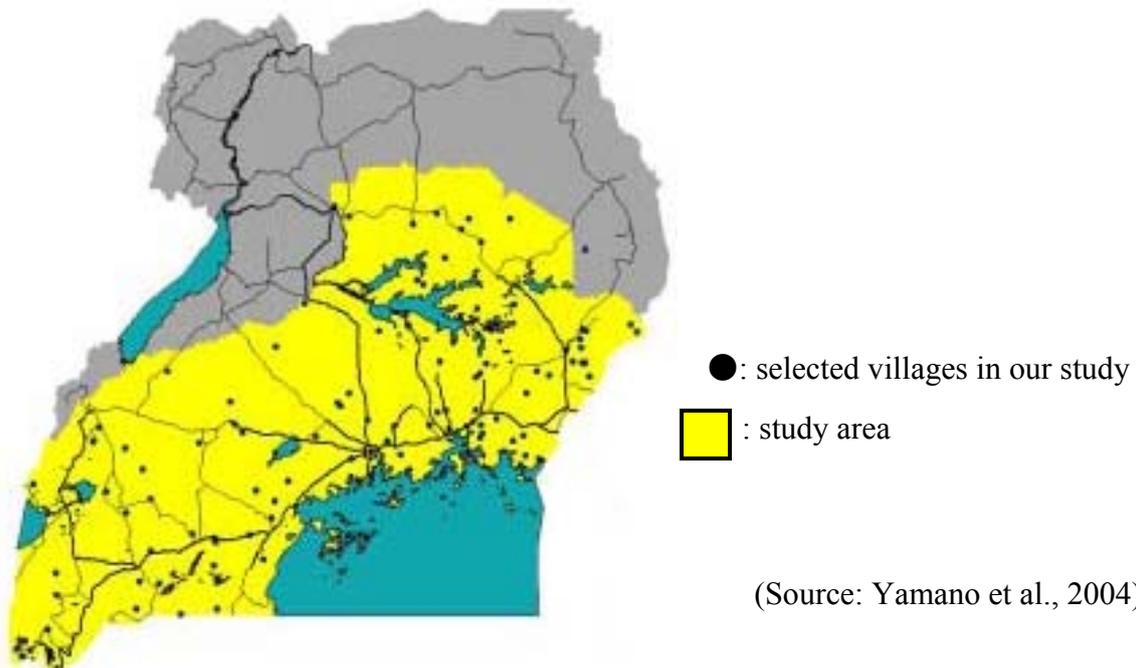
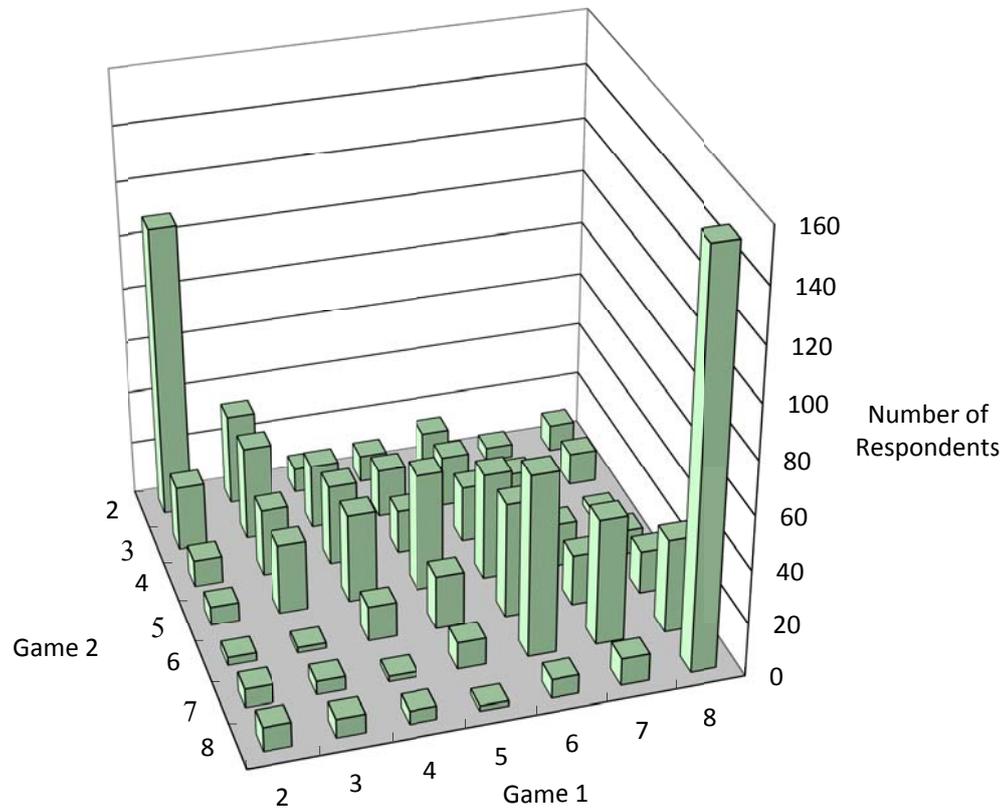


Figure 2: An Excerpt from the Answer Sheets for the Risk Experiment

	<b>A</b>	<b>B</b>	Do you prefer A or B?
	①②③④	①②③   ④	
2-1	4,000	4,000   2,000	
2-2	4,000	4,500   2,000	
2-3	4,000	5,000   2,000	
2-4	4,000	5,500   2,000	
2-5	4,000	6,000   2,000	
2-6	4,000	7,000   2,000	
2-7	4,000	7,000   3,000	
2-8	4,000	7,000   4,000	

**Figure 3: Responses from Game 1 and 2**

Note: the columns represent the number of respondents that chose the particular combination of rows in game 1 and 2.

**Figure 4: Ethnic Groups of Study Area in Uganda**



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