Risk aversion in agricultural water management investments in Northern Ghana: Experimental evidence

1. Introduction

Farming is risky. Farmers live with risk and make decisions every day that affect their farming operations. Many of the factors that affect the decisions that farmers make cannot be predicted with 100 percent accuracy: weather conditions change; prices at the time of harvest could drop; hired labour may not be available at peak times; machinery and equipment could break down when most needed; draught animals might die; and government policy can change overnight. Sub-Saharan Africa (SSA) is one of the regions in the world most affected by food price volatility and production variability. The continent's recurrent and long history of rainfall fluctuations of varying lengths and intensities along with inadequate infrastructure, limited storage facilities and market imperfections are among the major causes for food price and supply variability (WB/OECD, 2015).

While all farmers face agricultural risks, poor small-scale farmers in SSA who are less able to access resources often exhibit risk averse behaviour. On the one hand, risk-averse farmers might consider adopting a water-efficient irrigation technology in order to reduce the production risk they face during periods of water shortage (Koundouri et al., 2006). On the other hand, risk-averse farmers may be less willing to undertake investments in land and water management technologies that have higher expected outcomes, but carry with them risks of failure. For example, it has been found that farm households use less fertilizer and are more reluctant to adopt irrigation technologies than they would have used had they simply maximized expected profits (Yesuff and Bluffstone, 2007; Muzari et al., 2012; Hill et al. 2013).

Given risk's potentially central role in farm investment decisions in SSA, better understanding of risk behaviour is essential for identifying appropriate farm-level strategies for adaptation to food price volatility and production variability by low-income farmers. However, there have been few attempts in the empirical literature to measure the degree of risk aversion of farm households in SSA. Most of these have applied experimental approaches to derive farm household risk aversion estimates (Bruntup, 2000; Brauw and Eozenou, 2011). To the best of our knowledge, no study has investigated risk aversion attitudes of farmers in relation to agricultural water management (AWM) investments in SSA.

The actual and potential positive and significant impacts of investments on AWM technologies on output supply and net returns of small-scale farmers in Northern Ghana have been widely recognized (Faltermeier and Abdulai, 2009; deGraft-Johnson et al., 2014). Despite evidence from previous studies on the effect of risk aversion on farm investment in Ghana (Ayamga et al., 2006; Bendig et al., 2009; Karlan et al., 2014), the magnitude and nature of risk aversion of farm households in relation to AWM investments remains largely unexplored. To partially close this gap, this paper uses an experimental approach applied to 137 households in two communities in Northern Ghana.

This paper's contribution to the empirical literature on the nature and level of behavioural responses to risks in rural areas of Northern Ghana is three-fold. First, we provide evidence on the perceived level of risk of land and water management investments from a participatory ranking exercise. Second, using an experimental approach with hypothetical payoffs, we estimate risk aversion attitudes of North Ghanaian households in relation to investment in land and water management interventions. By incorporating both small and large stakes and gains and losses into the experiment, we test for the presence of low stake risk aversion and loss aversion. Third, these experimental results are used as data in an econometric model to explain those behavioural choices in terms of household, game structure, and site-specific characteristics.

The rest of the paper is organized as follows. The next section describes the study setting in Northern Ghana and presents key descriptive statistics. Section 3 presents the methodology used for the experimental design and the empirical model. Sections 4 and 5 present and discuss results respectively, while section 6 concludes the paper.

2. Description of the Study Site and Household Descriptive Statistics

Primary data collection was conducted in November 2014 in two communities in Northern Ghana, Duko and Nyangua, which are part of the intervention sites selected by the Africa Research in Sustainable Intensification for the Next Generation (Africa RISING) program. Africa RISING selected 52 communities to guarantee an adequate coverage of the spectrum of biophysical and socio-economic conditions prevailing in the targeted districts, allowing for a broad assessment of the interventions in areas with different agricultural potential (Guo et al., 2013). The location of these communities is depicted in Figure 1.

[Insert Figure 1 near here]

A random sample of 137 farm households was chosen to participate in the experiment. We considered 137 households to be representative of the population in the villages while remaining within the financial constraints of the project. The populations of Nyangua and Duko are 2,520 and 1,200 respectively (Ghana Statistical Service 2014a, 2014b).

The villages studied are very typical of Northern Ghana and representative of the area as a whole. Both communities, as most in this area, are severely affected by drought, low fertility levels of soils and insufficient fertilizers, lack of improved varieties and seeds, low prices of produce in the markets, and other problems. The whole north of the country (comprised by the Northern, Upper West and Upper East

Regions) is characterized by small land holdings of low input– output farming systems with low yields and household food and nutritional insecurity. Improved land and water management practices have the potential to enhance farmers' livelihoods in the region. However, farmers have to decide which package of options would work best for them and adopt those.

In terms of their representativeness within their districts, Table 1 outlines a number of relevant community-level variables (distance to weekly market, population, cultivable land and exposure to different type of shocks) and show how Duko and Nyangua compare to the average values at the district level (Savelugu-Nanton and Kassena-Nankana East) and to other villages in these districts also selected by Africa RISING. As depicted in Table 1, Nyangua and Duko are not systematically different from an average village in their districts and do not represent outliers.

[Insert Table 1 near here]

Duko is located in the Savelugu Nanton District, along the Tamale – Bolgatanga Road. The main ethnic group of the community is the Dagomba and the main language is the Dagbani. The patrilineal system of inheritance is practiced, with land being distributed and sold by the Chief. The community is located in a generally flat area with gentle undulating low relief and is drained by the White Volta and its tributary. The area receives erratic rainfall at the beginning of the season and experiences an annual rainfall of 600mm to 1000mm as the season advances, considered enough for a single farming season. The vegetation sustains the cultivation of rice, groundnut, yams, cassava, maize, cowpea etc. There are dispersed trees of Shea and Dawadawa. Only traditional rainy season farming is practiced in the community, with farmers using holing and cutlasses to plough and prepare their land.

Nyangua in the Kassena Nankana East District lies within the Guinea Savannah Woodlands. The main ethnic group of the community is the Kassena, but there are also Nankan and Bulis settlers and they co-exist peacefully. The main language of the community is the Kassen. The patrilineal system of inheritance is practiced, with land being distributed and sold by the Chief. The community's climate is characterized by the dry and wet seasons which is primarily influenced by North-East Trade Winds (Harmattan air mass) and the South-Westerlies (tropical Maritime). During the dry season, rainfall is virtually absent due to the low relative humidity, which rarely exceeds 20%, and low vapour pressure of less than 10mb. The community is mainly covered by groundwater laterite and interspersed with Savannah Ochrosols. It lies on a low lying area and falls within the Tono Dam catchment. Many farmers have dug wells in their farms for dry season gardening and there are few dug out areas which are also used for farming and livestock watering. The main occupation of the local economy is farming, and the main crops grown include maize, rice, millet, groundnut, tomato, onion and pepper. The use of cutlasses and hoes are predominant in their farming activities, with few people using animals and tractors to prepare land in their farms.

2.1. Descriptive household statistics

Table 2 presents descriptive statistics for the sample households. Almost half of the farmers interviewed were female. Most respondents are illiterate and the average number of dependents is about 3.7. Farms tend to be small, with a mean of 1.63 hectares and a maximum of almost 11 hectares spread over an average of 3.42 plots. Farm plots in these villages tend to be small. In Northern Ghana, land is owned by Chiefs and farm households are granted user rights. As a result, there is no land market. This makes land a very constrained resource and key to various farming decisions.

[Insert Table 2 near here]

A t-test of difference in means indicates that the villages are significantly different in all descriptive variables, except for demographic characteristics such as gender, age and number of dependents. Almost a quarter of the farmers interviewed in Nyangua were literate, as opposed to less than 5% in Duko. Farmers in Nyangua work on more plots of smaller size than those in Duko, probably suggesting a higher level of agricultural diversification. Livestock rearing is a key livelihood activity in Nyangua (almost every farmer owns one bullock at least), but it seems to hold little importance in Duko.

3. Methodology

3.1. Theoretical framework

There exist two common features to most characterizations of risk. The first is the notion that multiple outcomes are possible. In this study, this is given by the amount of rainfall received during the cropping season. The second is the notion that the eventual outcome is a matter of chance. For example, before making important production decisions, like which land and water management options to invest in, farmers do not know how much rain will fall during the cropping season.

Our theoretical framework is founded on the predominant theory in economics for explaining risky decisions, which is based on the expected utility hypothesis, first posited by Daniel Bernoulli in 1738 and later refined and reintroduced by von Neumann and Morgenstern (1944). The expected utility hypothesis asserts that a farmer makes choices to maximize expected utility. There are three components to expected utility: the possible outcomes, the likelihood of possible outcomes, and the utility of possible outcomes. The likelihood of outcomes is characterized in terms of a probability distribution that is often conditioned on a farmer's choices. Bringing these three components together, in a discrete model, expected utility can be defined as $EU(x) = \sum_{k=1}^{K} p_k(x)U(c_k)$ where x reflects a farmer's choice over alternative activities that affect the distribution of outcomes (like the investment on a certain land and water management option), K is the number of discrete income levels, c_k is the k^{th} level of income, $U(c_k)$ is the utility of outcome c_k and $p_k(x)$ is the probability of the k^{th} level of income given choice x. The utility derived from a particular outcome serves as a device for capturing farmers' attitudes toward risk.

A farmer's risk attitudes can be characterized by the risk premium, which is the difference in the expected outcome and the certainty equivalent outcome, $RP(x) = Ec(x) - CE(x)$ where $Ec(x)$ is the expected outcome and $CE(x) = U^{-1}(EU(x))$ is the certainty equivalent given the inverse utility function U^{-1}. The risk premium measures how much a farmer is willing to give up in order to receive the average outcome for certain. Farmers with a positive risk premium are called risk averse. Farmers with no risk premium are called risk neutral. Farmers with a negative risk premium are called risk loving or preferring.

Whether a farmer is risk averse, neutral or preferring depends on the shape of their utility function U(c). Invariably, c is defined such that the utility function is strictly increasing (the first derivative of the utility function is positive: U'(c) > 0), which implies farmers always prefer more to less and a positive marginal utility. A farmer is risk averse if the utility function is increasing at a decreasing rate implying the utility function is strictly concave and a decreasing marginal utility (the second derivative of the utility function is negative: U''(c) < 0). A farmer is risk neutral if the utility function is increasing at a constant rate implying it is linear and a constant marginal utility (U''(c) = 0). A farmer is risk preferring if the utility function is increasing at an increasing rate implying the utility function is convex and an increasing marginal utility (U''(c) > 0).

The three most commonly used measures for characterizing risk attitudes are absolute risk aversion ($A(c) = -\frac{U''(c)}{U'(c)}$), relative risk aversion ($R(c) = -c\frac{U''(c)}{U'(c)}$) and partial risk aversion ($P(c_0, m) = -m\frac{U''(c_0+m)}{U'(c_0+m)}$), where m is a monetary gain or loss, c_0 is initial income and c (=c_0+m) is the final income level (Pratt, 1964; Menezes and Hanson, 1970; Zeckhauser and Keeler, 1970; Arrow, 1971). Absolute risk aversion traces the behaviour of a farmer toward risk when his/her income rises and the prospect remains the same. Decreasing Absolute Risk Aversion (DARA) implies that a farmer will be more willing to accept a risky prospect as income increases. Partial risk aversion examines behaviour when the prospect changes, but income remains the same. Increasing Partial Risk Aversion (IPRA) implies a decrease in the willingness to take a gamble as the scale of the prospect increases. Relative risk aversion looks at behaviour when both the initial income and the level of the prospect rise proportionally. Increasing Relative Risk Aversion (IRRA) indicates that a farmer's willingness to accept a risky prospect declines when both the outcome and income increase proportionally. In our study, we explicitly test for IPRA-type behaviour but we cannot calculate relative risk aversion nor test for IRRA or DARA, as we do not have a good measure on wealth or income.

3.2. Description of the experiment

Farmers were asked to rank the following six land and water management investment options according to their perceived level of risk: (i) Hand-dug well and bucket; (ii) Lined well and bucket; (iii) No investment at all; (iv) Runoff collection in a pit; (v) Improved fertilizer application; and (vi) Lined well and motorized pump. They were told to assume there is a 50 percent probability (same chances) that the following year will be a good or bad rainfall year. Then, they were asked to rank the options from 1 to 6, with 1 being the less risky or the safest option (they get the same profits regardless of whether it is a good or a bad rainfall year) and 6 being the riskiest option (they get very high profits if it is a good rainfall year but very low if it is a bad rainfall year because the investment cost is high). In the next step, these rankings were used to derive the profits of each option in a good or a bad year individually for each farmer, according to their perception of risk of each alternative.

The Appendix presents the payoffs for the three choice sets offered to respondents. Though the amounts may seem low, it must be recalled that incomes in the study area are very low[1], so the amounts listed indeed provide significant incentive for respondents to carefully consider the options and reveal their true preferences. Alternative choices to invest in land and water management options reveal farmers' risk preferences for both small and large stake outcomes and gains and losses. To examine the nature of partial risk aversion for each farm household, we increase the outcome of the first choice set by factors of 10 and 20. These are represented as Sets 2 and 3 in the Appendix. To test for significant differences in behaviour when faced with the possibility of losses as opposed to gains-only, choice sets involving losses to farm households were incorporated into the experiment. This tells us something about whether farm households are more responsive to the possibility of agricultural losses than gains.

We follow the experimental design developed by Binswanger (1980) to reveal risk preferences and frame the choices to reflect real life farming decisions. Although the Holt and Laury (2002) approach is the most

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[1] The concentration of poor persons is mainly observed in the northern than the southern districts of Ghana. Considering a poverty line of GHC 1,314 per year, the poverty head count (% of people below the poverty line) in Savelugu-Nanton is 32.3 and in Kassena-Nankana East is 24.2. These figures are significantly higher to regional averages in the south of Ghana (6.6 in Accra Region, 13.6 in Ashanti Region, 19.2 in Western Region, 19.6 in Central Region and 22 in Eastern Region), but they are lower than regional averages in the North of Ghana (44.2 in Northern Region, 45.9 in Upper East Region and 69.4 in Upper West Region), due to the prevalence of pockets of deep poverty in these regions (Ghana Statistical Service 2015).

commonly used approach to elicit risk preferences through field experiments (in developed country settings) since it allows for consistency checks and within-subject stochastic error, we decided the best option for the characteristics of our choice set was the Binswanger (1980) approach. Holt and Laury (2002) elicit decisions between only two options and vary the probability of the high and low payoffs through 10 hypothetical scenarios. However, in our study farmers are allowed to choose among six land and water management options, not two. Thus, instead of estimating the risk aversion class by the cross over point from a less risky to a more risky lottery, we estimated it based on a one-time choice among six lotteries and one probability function.

The basic structure of the experiment using Set 1 as an example is given in Table 3. After individually ranking the dry season land and water management options from least to riskiest, the farmers were shown the good and the bad outcomes of each of the six different options depending on a 50 percent probability of a good or bad rainfall year. For each alternative, the expected gain and spread increased. Respondents were asked to choose one of the options. It is typically useful to compute a risk aversion coefficient that can serve as a measure of household level of risk aversion. For this purpose we employ a Constant Partial Risk Aversion (CPRA) utility function of the form $U = (1-\gamma)CE^{(1-\gamma)}$, where γ is the coefficient of risk aversion, and CE is the certainty equivalent of a prospect. The upper and lower limits of the CPRA coefficients for each prospect of our experiment are given in Table 3.

[Insert Table 3 near here]

3.3. Empirical model

The experimental results were used as data in an econometric model to examine the determinants of risk. Our experimental data has the feature that it is ordinal in nature, ranging from 1 (extreme risk aversion) to 6 (risk loving behaviour). With such ordinal data, an ordered probit model is most appropriate. This approach has the advantage that we need not assume a particular form of the utility function and instead use the underlying latent variable to model the risk averting behaviour of farm households. The ordered probit model impose what is called the proportional odds assumption on the data, also known as the parallel lines or parallel regressions assumption. We tested the validity of this assumption, using the gologit2 command in STATA, and found that all variables, except for farm size and the village dummy, violate the parallel lines assumption. While the generalized ordered logit model provides an alternative model in which some variables are constrained to meet the parallel lines assumption while others are not (making it more parsimonious and interpretable than non-ordinal methods, such as multinomial logistic regression), it is very sensitive to low frequency counts (e.g., small cell sizes). Thus, it is often necessary to combine the dependent variable categories that have low frequencies with adjacent categories in order for the estimation procedure to work. However, combining categories may also lead to a loss in information, especially if the underlying latent variable is multi-levelled or continuous. As a result, we have chosen to present the results from the ordered probit model. A larger sample size and fewer explanatory variables would have made the use of generalized models more feasible.

Assume there is a latent variable ${y_i}^*$ measuring the degree of risk aversion of the i^{th} decision maker as described in equation (1).

$$ {y_i}^* = x_i\beta + u_i \tag{1} $$

for a kx1 parameter vector β, stochastic disturbance term u_i, and a vector of regressors x. We assume the disturbance term has a standard normal distribution yielding the ordered probit model. The six outcomes for the observed variable y_i are assumed to be related to the latent variable through the observability criterion in equation (2), for a set of threshold parameters α_0 to α_6, where $\alpha_0 < \alpha_1 < \alpha_2 < \alpha_3 < \alpha_4 < \alpha_5 < \alpha_6$, $\alpha_0 = -\infty$ and $\alpha_6 = \infty$.

$$y_i = m \quad if \quad \alpha_{m-1} \leq y_i^* \leq \alpha_m \quad for \quad m = 1, \ldots, 6 \tag{2}$$

Several characteristics of the game are included as regressors. First, to formally test the IPRA hypothesis we include the expected value of each game level as a scale variable. Second, in order to test differences in behaviour between gains-only games and games involving losses, we include dummy variables for games involving real losses. As discussed earlier, this is one way of formally testing for loss aversion. If we find this coefficient to be statistically significant, then we can conclude that decision makers treat opportunity losses differently from real losses.

We include several characteristics of the respondent, including age, gender, and literacy, without any *a priori* expectations of the signs. As part of household characteristics, we also include number of dependents in our model and expect a positive relationship with risk aversion. Farm size and number of plots are included to capture wealth. Although the literature on technology adoption suggests that wealthier households can better insulate themselves from shocks and will thus be less risk averse, for a farmer who lives near the poverty threshold, the lower his wealth is, the less risk averse he becomes as well. Thus, we do not have any a priori expectation on the sign of this coefficient. Finally, we include a site dummy in the model for all sites.

4. Results

4.1. Perceived risk of water management options

We start our analysis by exploring the responses of participants to rank the relative riskiness of the six land and water management investment options. Table 4 presents the distribution of farmers' perceptions for the least and most risky investment options.

[Insert Table 4 near here]

Improved fertilizer is perceived as the least risky option, particularly in Duko (Northern Region) where most farmers do not have any experience on dry season irrigation. In most cases, no investment in any land or water management option was considered as the riskiest option, which indicates that the majority of farmers understand the effect of rainfall variability on their profits and are willing to invest on their farms to buffer this risk. The most cited reasons for their rankings were as follows (in no particular order):

1. Capital: availability of financial resources to invest.
2. Size of farm: farmers with larger farms tend to choose lined well and pump as a safer option.
3. Labour: availability of on-farm labour for the most demanding investment options.
4. Age: older farmers tend to choose less labour-demanding options.
5. Location: farms far from water sources tend to choose improved fertilizer as least risky.

6. Nature of land: farmers who own flat lands tend to choose fertilizer as least risky because it does not wash off easily when it rains, while farmers on sloppy areas tend to choose investing in pumps to reduce their movements.
7. Previous knowledge on farming: more experienced farmers tend to choose fertilizer as the least risky option because they have witnessed the significant loss of nutrients in their lands over the years.

4.2. Risk aversion attitudes

We start our analysis of risk aversion attitudes by exploring the responses of participants to each set of the experiment. Table 5 presents the distribution of risk averting behaviour for each level of the experiment. In gains-only games, a majority of the farm households exhibit extreme risk aversion.

[Insert Table 5 near here]

Our results on the distribution of risk averting behaviour for each level of the experiment are inconclusive with regards to whether farmers become more or less risk averse as the size of the stakes increases. Two findings would indicate that farmers become less risk averse: (i) the proportion of households that chose the alternative representing extreme risk aversion decreases as stakes increase, and (ii) the proportion of households that chose the alternatives representing neutral or risk loving increases as stakes increase. However, as the proportion of households that chose the alternatives representing the rest of the risk categories does not follow a clear trend when stakes are increased, we do not have sufficient evidence yet to claim whether farmers become more or less risk averse with the size of the stakes.

A comparison of choices between games involving only gains and gains and losses shows a surprising inclination of farm households to be less risk averse when there are losses. The results of the gamma and taub tests are summarized in Table 6. The null hypothesis that the subjects' risk preferences are equivalent in both kinds of games is rejected for each portion of the experiment.

[Insert Table 6 near here]

Table 7 presents median levels of risk aversion for each level of the game along with the CPRA coefficients corresponding to each risk category. Farmers in Duko seem to be slightly less risk averse than their counterparts in Nyangua. We see that farmers in the whole sample are more risk averse (intermediate median risk aversion) at the lowest level of the game than at the highest level (moderate median risk aversion) in the gains-only games. The trend in the gains-and-losses game is fairly constant at moderate risk aversion for all stakes. These findings suggest that even when both gains and losses are possible and the probability of each outcome is the same, increasing the stakes does not cause households to become more risk averse. Variance reduction may not be the most important outcome for low income farmers who live near the poverty threshold, and thus place little value on reducing risk by itself. This result indicates that optimal risk behaviour in the face of income thresholds may not be adequately captured by a mean-variance utility maximization framework, and a poverty trap avoidance utility function may be more appropriate (Osgood and Shirley, 2010).

[Insert Table 7 near here]

Given the current situation in Northern Ghana, we argue that one reason farmers do not always seek to minimize variance is that they may be very near a poverty trap threshold, and are therefore less willing to give up additional expected income in exchange for decreased income variance. The implication for insurance programs is that it may be best for implementers to utilize insurance to unlock increases in productivity as opposed to variance reduction per se. As productivity increases depend on crop specific gaps, these programs can also maximize their impact on poverty reduction by other measures, such as promoting crop diversification and investments in equipment to farm during the dry season and to reduce post-harvest losses.

4.3. Econometric Analysis of Risk Averting Behaviour

The results of the ordered probit model are given in Table 8, where the dependent variable is the respondent's risk aversion category (1 to 6) for each game played. The sample size is therefore greater than 137, because all respondents played more than one game.

[Insert Table 8 near here]

Because extreme risk aversion takes the value one and risk-loving is indicated by a value of six, a positive coefficient sign indicates a negative relationship with risk aversion. Of all the wealth indicators only the number of plots in Duko is significant but negative at the 10 percent level, indicating that more wealth is not correlated with a lower or higher degree of risk aversion. Particularly if a farmer owns plots far away from each other, the investment on dry season irrigation may be much higher than if the whole farm area is in the same plot (for example if he/she is investing in lined wells, he/she will have to dig and line more than one well and transport the pump from one plot to another or use several pumps).

All parameter estimates for the variables indicating the game characteristics are significant and formally confirm the basic results presented in Tables 5 and 7. First, as indicated by a statistically significant loss-game dummy variable, people are less risk averse in games involving losses than in gains-only games. Second, there is a negative relationship between the expected payoff variable and the degree of risk aversion, implying that people are likely to take more risk when high gains are at stake. This result rejects the IPRA hypothesis and suggests that under the current circumstances in Northern Ghana most farmers' current wealth put them at risk of falling into a poverty trap so that they are not variance minimizers, but rather are looking for a way to maximize productivity in a way that does not require them to sacrifice a lot of their expected income.

A number of respondent characteristics are also significantly related to risk aversion. Age is negatively correlated with the degree of risk aversion, indicating that people become less risk averse as they age. This is probably because they have more assets or a wider social network to fall back on if they do not recover their investment due to a bad rainfall year. Although males are the major decision makers in most households in Ghana, in our model, male respondents are not found to be less risk averse than females. Literacy is negatively correlated with risk aversion only in Duko, literate farmers may be more productive or have other sources of income not captured in the model, which makes them less risk averse.

Significant site dummies indicate systematic, but unobservable differences in risk aversion across study sites besides their dry season irrigation practices. Duko farmers are less risk averse than those at Nyangua and one reason for this difference may be because they are poorer. In this case, the goal of most farmers is to avoid falling into a poverty trap, so then the lower their income is, the less risk averse they becomes in the mean-variance utility maximization framework. While farmers in both communities are less risk averse in games involving losses than in gains-only games, in Nyangua the difference in risk attitudes between both types of games is larger. An increase in stakes reduces risk aversion equally in Nyangua and Duko (farmers become less risk averse).

5. Discussion

This section situates the key findings of this study within the wider literature of experimental elicitation of risk aversion in SSA and suggests opportunities for future improvements. Risk aversion attitudes in our sample are somehow in contrast with those found by other studies in SSA, as implied by the risk aversion distributions corresponding to different game levels. Around 60% of farmers were risk-averse in the gains-only games, compared to 79 to 98% found by Yesuff and Bluffstone (2007) in Ethiopia. In addition, as the game level rose, the distribution shifted to the right, i.e., farmers became less risk averse, contrary to results of studies in Zambia (Wik et al. 2004) and Ethiopia (Yesuff and Bluffstone, 2007). Selected results of the regression analysis relating risk aversion to demographic and socioeconomic factors mirror those of previous studies in SSA, such as higher literacy leading to less risk averse farmers (Wik et al., 2004; Liebenehm and Waibel, 2012). However, while the number of bullocks has been found to lead to less risk averse farmers in Ethiopia, Mali and Burkina Faso (Yesuff and Bluffstone, 2007; Liebenehm and Waibel, 2012), we found no significant effect of this variable, just as gender and the number of dependents, on which previous literature is inconclusive.

Risk attitudes and discount rates are not merely a reflection of personal preferences but represent economic and other conditions of the individuals and households. Despite the potentially important insight to be gained from analysing the regional variation in risk and time preferences, most experimental studies have lacked such analyses due to limited sample sizes and geographical variation. In our study, we compared two communities in different regions of the North of Ghana and discovered systematic differences in risk aversion across them. A number of reasons, based on the results of a few studies in SSA, may explain this difference:

- Hysteresis (path dependence) in risk preference formation. Households in Nyangua may have experienced more shocks than those in Duko, being the area drier and more vulnerable to drought. This past failure may make them less likely to choose more risky propositions. Similarly to findings in Ethiopia by Yesuff and Bluffstone (2007), even in very poor regions success can build on success, with people being more willing to accept risk if the past has gone well.
- Distance to nearest local market. Lower levels of risk aversion in Duko may be partly explained by a shorter distance to the local market and to the major urban centre of Tamale, capital of the Northern Region. This is intuitive in the sense that we would expect people in villages that are closer to local markets to have more access to information, resulting in more risk-neutral preferences.
- Local environment. Risk preferences may differ significantly across agricultural climatic zones, proving that participants in the experiment were affected by regional factors and background risks posed by the local environment, as found by Tanaka and Munro (2014) in Uganda. Farmers in the agro-climatically least favourable zone that receives less rainfall on average and is more prone to drought (Nyangua) are the most risk averse.
- Cultural factors. In a similar study in Tanzania, Henrich and McElreath (2002) found that culture was the only factor that was consistently related to the observed variation in risk aversion. Cultural heuristics may be an important driver of risk attitudes in our sample as the farmers in Duko and Nyangua belong to different ethnic groups.

The present study could be improved by exploring the sensitivity of the results to the choice of the Binswanger (1980) over the Holt and Laury (2002) approach. However, this test would entail increasing the number of choice series each participant would have to face, as he or she would now have to compare five pairs separately (choose between management option 1 and option 2, option 2 and 3, etc.), instead of all six options at once. An additional refinement of the present study would be test the relevance of Prospective Theory (PT) versus EUT to predict poor farmers' behaviour. The Tanaka et al. (2010) approach, which has recently gained popularity in developing countries, uses three choice sets between pairs to elicit three PT parameters. This approach would allow us to consider both subjective probability weighting and loss aversion in addition to the curvature of the utility function, thus differentiating among different sources of risk aversion (Holden and Quiggin, 2016).

Finally, the results of the present study could also be enhanced by a comparison of risk aversion attitudes at the individual vs. household level. Experimental elicitation techniques are based on individual answers to hypothetical questions regarding risk alternatives or risky games. Studies in developing country settings that have computed risk aversion at the household level, selected households and later used the responses of one person in the household (usually household heads). The individual responses of this participant are then presented as household level risk aversion, but they are actually the results of one individual's attitudes. In our study, we selected one individual of each household but preferred to present the results as individual risk aversion attitudes as investments on water and land management are usually done at the individual level. This also allowed us to explore the effect of individual factors (such as gender or age) on risk aversion. Future studies are needed to develop approaches to assess household level risk aversion, as this analysis may yield very relevant results in terms of intra-household heterogeneity in risk aversion attitudes and its implications on income distribution, empowerment and livelihoods by gender and age.

6. Conclusions

Despite risk's potentially central role in farm investment decisions, there have been few attempts to estimate the magnitude and nature of risk aversion of farm households in Sub-Saharan Africa. This study is one attempt to reveal farmers' risk preferences in relation to agricultural water management investments. Using household data from Northern Ghana we find that the use of improved fertilizer is usually perceived as the least risky option, especially in areas where most farmers have little or no experience on dry season irrigation. The option of not investing in any land or water management option was considered as the riskiest option by the majority of farmers, indicating an understanding of the effect of rainfall variability on farm profits.

Contrary to what is usually perceived, only 30 percent of the households fell into the severe to extreme risk aversion categories. This contrasts with other studies in SSA, where most household decision-makers exhibit severe to extreme risk aversion. In regards to the determinants of risk averting behaviour, we find that age and literacy have a statistically and statistically significant effect in decreasing risk aversion. We also find that households that stand to lose as well as gain something from participation in games are statistically significantly less risk averse than households playing gains-only games. This result suggests that, under the current circumstances in Northern Ghana, most farmers' current wealth put them at risk of falling into a poverty trap. Thus, farmers in the area are not variance minimizers, but rather looking for a way to maximize productivity in a way that does not require them to sacrifice a lot of their expected income.

The finding that even with the possibility of losses households are less risk averse when stakes are higher, suggests again that farmers close to poverty traps are willing to take on larger gambles. The immediate welfare implications of these findings are obvious: in a region characterized by poverty trap dynamics, poor farmers are more likely to take seemingly excessive risks and fall into a poverty trap. From a policy perspective, evidence that the losses from the riskiest investments on AWM technologies may fall more heavily on the poor suggests that additional efforts be given to the creation of viable insurance mechanisms. While there are a few pilot projects attempting to implement these ideas, it remains to be seen if insurance mechanisms coupled with loans for AWM investments can be successfully employed to diminish the forces that contribute to the intergenerational transmission of poverty.

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Appendix: Risk Games Used in the Experiment

Set 1: Low range of payoffs

Gains-only game

Investment option	Profits (GHC)		Risk aversion class
	Bad rainfall	Good rainfall	
1	5	5	Extreme
2	4.5	9	Severe
3	4	12	Intermediate
4	3	15	Moderate
5	1	19	Slight to neutral
6	0	20	Neutral to preferring

Notes: 1USD=3.2GHC

Gains and losses game

Investment option	Profits (GHC)		Risk aversion class
	Bad rainfall	Good rainfall	
1	0	0	Extreme
2	-0.5	4	Severe
3	-1	7	Intermediate
4	-2	10	Moderate
5	-4	14	Slight to neutral
6	-5	15	Neutral to preferring

Notes: 1USD=3.2GHC

Set 2: Medium range of payoffs

Gains-only game

Investment option	Profits (GHC)		Risk aversion class
	Bad rainfall	Good rainfall	
1	50	50	Extreme
2	45	90	Severe
3	40	120	Intermediate
4	30	150	Moderate
5	10	190	Slight to neutral
6	0	200	Neutral to preferring

Notes: 1USD=3.2GHC

Gains and losses game

Investment option	Profits (GHC)		Risk aversion class
	Bad rainfall	Good rainfall	
1	0	0	Extreme
2	-5	40	Severe
3	-10	70	Intermediate
4	-20	100	Moderate
5	-40	140	Slight to neutral
6	-50	150	Neutral to preferring

Notes: 1USD=3.2GHC

Set 3: Large range of payoffs

Gains-only game

Investment option	Profits (GHC)		Risk aversion class
	Bad rainfall	Good rainfall	
1	100	100	Extreme
2	90	180	Severe
3	80	240	Intermediate
4	60	300	Moderate
5	20	380	Slight to neutral
6	0	400	Neutral to preferring

Notes: 1USD=3.2GHC

Gains and losses game

Investment option	Profits (GHC)		Risk aversion class
	Bad rainfall	Good rainfall	
1	0	0	Extreme
2	-10	80	Severe
3	-20	140	Intermediate
4	-40	200	Moderate
5	-80	280	Slight to neutral
6	-100	300	Neutral to preferring

Notes: 1USD=3.2GHC

Figure 1: Map of the two communities surveyed in Northern Ghana

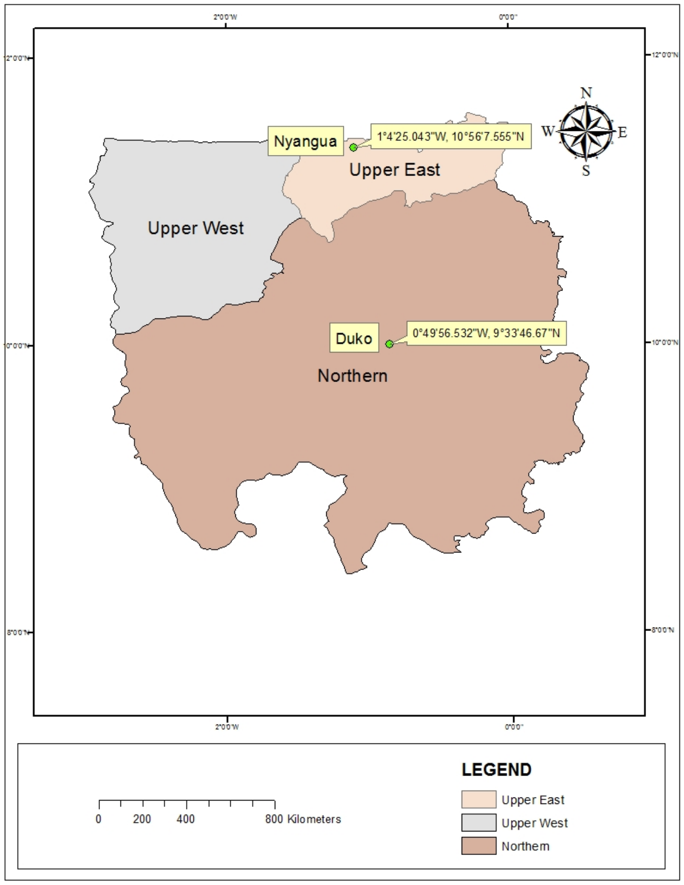

Table 1. Biophysical and socioeconomic characteristics of Nyangua and Duko with respect to other villages in the same district and district averages.

Africa Rising communities	Distance to weekly market (min)	Cultivable land: % of total land	Population total	% households affected by shocks				
				Drought	Crop disease /pest	Livestock disease	Large rise in input prices	Large fall in crop sale prices
Savelugu-Nanton District								
Botingli	35	80	1600	100	100	0	0	0
Disiga	30	60	1500	100	100	100	100	0
Duko	**15**	**46**	**1300**	**100**	**100**	**100**	**100**	**0**
Gushie	30	95	1135	0	100	75	0	100
Jana	30	0	2000	100	100	100	100	0
Kadia	45	60	No inf.	100	100	100	100	100
Kpallung	105	50	1800	100	100	100	100	100
Kpelung	60	70	700	100	100	100	0	25
Kukobila	40	34	1016	100	100	100	100	100
Nabogu	15	70	3450	100	100	100	100	100
Pigu	120	60	3200	100	100	100	100	100
Tibali	20	50	2400	100	100	100	100	0
Tindan	45	70	1235	100	100	100	100	0
Average	**45**	**57**	**1778**	**92**	**100**	**90**	**77**	**48**
Kassena Nankana East District								
Bonia	30	80	6000	100	30	50	80	80
Gia	60	80	600	100	20	40	0	40
Nyangua	**60**	**60**	**2520**	**70**	**40**	**20**	**0**	**0**
Tekuru	90	80	2500	70	20	60	80	0
Average	**60**	**75**	**2905**	**85**	**27**	**42**	**40**	**30**

Source: International Food Policy Research Institute (IFPRI), 2015. "Ghana Africa Research in Sustainable Intensification for the Next Generation (Africa RISING) Baseline Evaluation Survey", doi:10.7910/DVN/QUB9UT.

Table 2. Descriptive statistics (n=137)

Variable	Mean (Standard deviation)		Difference in means (Standard error)
	Nyangua	Duko	
Gender (1=female)	0.49	0.43	**0.06* (0.09)**
Age	36.41	40.10	**-3.69* (1.96)**
Literacy (1=if yes)	0.24	0.04	0.20 (0.06)
Number of dependents	3.71	3.70	**0.01* (0.33)**
Number of plots	4.64	2.61	1.63 (0.35)
Farm size (hectares)	1.06	2.19	-1.13 (0.23)
Number of bullocks	0.82	0	0.82 (0.14)

Notes: * denotes a difference in means that is NOT significant with 95% confidence.

Table 3. The basic structure of the experiment

Investment options	Bad rainfall profits	Good rainfall profits	Expected gain	Standard deviation	CPRA Coefficient	Risk classification
1	5	5	5	0	∞ to 7.47	Extreme
2	4.5	9	6.75	3.18	7.47 to 2.00	Severe
3	4	12	8	5.65	2.00 to 0.85	Intermediate
4	3	15	9	8.49	0.85 to 0.32	Moderate
5	1	19	10	12.73	0.32 to 0	Slight to neutral
6	0	20	10	14.14	0 to -∞	Neutral to preferring

Table 4. Distribution of perceptions on riskiness of land and water management investments (%)

Investment options	Perceived as least risky	Perceived as riskiest
Hand dug well + bucket	19.71	4.38
Lined well + bucket	12.41	0
No investment at all	8.03	91.24
Runoff collection pit	8.03	0
Improved fertilizer	34.31	0

Lined well + pump	25.55	0

Table 5. Distribution of risk averting behavior by set (%)

Risk category	Gains-only games			Gains-and-loses games		
	1	2	3	4	5	6
Extreme	28.47	27.01	21.90	10.95	8.76	9.49
Severe	10.22	10.22	10.95	18.25	10.95	14.60
Intermediate	11.68	17.52	12.41	19.71	19.71	21.17
Moderate	10.22	8.76	18.98	19.71	27.01	17.52
Slight to neutral	13.87	14.60	15.33	10.22	16.06	17.52
Neutral to preferring	25.55	21.90	20.44	21.17	17.52	19.71

Table 6. Gamma and taub tests for equivalence of risk preferences for gains-only and gains-and-loss games.

Hypothesis	Statistics (p-values)	
	Gamma	Taub
Gain-only game in experiment 1 is equivalent to loss game in experiment 1	0.2054 (0.09)	0.1693 (0.075)
Gain-only game in experiment 2 is equivalent to loss game in experiment 2	0.1941 (0.093)	0.1596 (0.077)
Gain-only game in experiment 3 is equivalent to loss game in experiment 3	0.1837 (0.092)	0.1530 (0.077)

Notes: Gamma and taub are measures of association between two ordinal variables (both have to be in the same direction, i.e. negative to positive, low to high). Both go from -1 to 1. Negative shows inverse relationship, closer to 1 a strong relationship. Gamma is recommended when there are lots of ties in the data. Taub is recommended for square tables.

Table 7. Median levels of risk aversion.

Experiment sets	Gains-only games			Gains-and-losses games		
	Duko	Nyangua	All	Duko	Nyangua	All
1	4	3	3	4	3.5	4
2	3	3	3	4	4	4
3	4	3	4	4	4	4

1=Extreme ($\gamma=\infty$ to 7.47), 2= Severe ($\gamma=2.00$ to 7.47), 3=intermediate ($\gamma=0.85$ to 2.00), 4=moderate ($\gamma=0.32$ to 0.85), 5=slight to neutral ($\gamma=0$ to0.32), 6=neutral to loving(0 to - ∞)

Table 8. Ordered probit models of risk aversion

Variable	Parameter estimates		
	Duko	Nyangua	All sites
Gender	0.175 (0.140)	0.030 (0.109)	0.0854 (0.0826)
Age	0.008* (0.004)	0.017*** (0.006)	0.011*** (0.003)
Literacy	0.755*** (0.276)	-0.110 (0.129)	0.001 (0.111)
Number of dependents	0.043 (0.033)	-0.048 (0.031)	0.015 (0.021)
Number of plots	-0.093* (0.049)	0.005 (0.026)	-0.028 (0.020)
Farm size	-0.009 (0.015)	0.073 (0.046)	-0.017 (0.013)
Number of bullocks	Omitted because of collinearity	0.015 (0.046)	0.021 (0.045)
Site dummy (=1 for Duko)			0.193* (0.099)
Dummy for loss games (=1 for a loss game)	0.494*** (0.117)	0.566*** (0.116)	0.526*** (0.082)
Expected payoff	0.007*** (0.001)	0.007 ***(0.001)	0.007*** (0.001)
Cut 1	-0.053 (0.295)	0.299 (0.276)	0.122 (0.188)
Cut 2	0.350 (0.298)	0.828 (0.279)	0.581 (0.190)
Cut 3	0.807 (0.299)	1.383 (0.281)	1.079 (0.192)
Cut 4	1.211 (0.300)	1.947 (0.285)	1.549 (0.194)
Cut 5	1.597 (0.301)	2.545 (0.290)	2.013 (0.196)
Log likelihood function	-681.434	-692.274	-1398.150
Wald Chi-squared	76.93	69.91	128.48
Pseudo R2	0.053	0.048	0.043
Number of observations	414	408	822

Dependent variable: degrees of risk aversion (1=extreme…….6=neutral to risk loving)
Figures in parenthesis are standard errors.
***, **, * indicate significance levels at the 1%, 5% and 10% levels respectively.