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Risk preferences under heterogeneous environmental risk

Abstract

We elicit risk preferences and their determinants through a survey and field experiments for cattle farmers in Namibia who are subject to heterogeneous environmental risk. Survey data is complemented with precipitation data simulated by a climate model to analyze the relationship between risk preferences and individual precipitation risk. We find that risk aversion is inversely related to precipitation risk. When considering individual opportunity sets we find that background risk is not heterogeneous and that liquidity constraints do not influence risk aversion. The observed pattern in behavior towards risk and the interaction with environmental risk can thus be attributed to preferences.

JEL-Classification: D81, Q12, Q57

Keywords: risk preferences, environmental risk, experimental elicitation

I. Introduction

Behavior towards risk plays an important role in the management of coupled ecological-economic systems. In such systems, ecosystem users depend upon the specific spatio-temporal provision of ecosystem services, many of which are influenced by risks acting on various space scales. The manner in which users manage these risks depends on their risk behavior and may crucially affect the sustainability of the system (Quaas et al. 2007). It is thus important to understand what drives this behavior, and a rich literature exists that examines the effect of various socio-demographic determinants (e.g. Harrison et al. 2007, Guiso & Paiella 2008). The interaction between risk preferences and risk conditions, however, has received scant attention with the exception of studies that indirectly infer risk preferences from production and portfolio data (e.g. Rosenzweig & Binswanger 1993). In this paper, we approach the subject from a new angle by directly measuring risk preferences and relating these to the individual environmental risk faced by ecosystem users. Furthermore, by controlling for differences in opportunity sets we are able attribute differences in behavior towards risk to differences in risk preferences.

To accurately identify the underlying mechanism that explains risk behavior one has to identify the means through which risk behavior is influenced. One way is through risk preferences. People may self-select themselves into risky situations such as investments, occupations or locations according to their risk preferences. For example, less risk averse individuals choose to hold portfolios with higher shares of risky assets such as stocks and bonds (Guiso & Paiella 2005), choose riskier occupations such as self-employment (Guiso & Paiella 2005) and are more likely to migrate to locations with higher income risk (Heitmueller 2005) or imperfect information on income and leisure opportunities (Jaeger et al. 2007). Risk preferences may also be endogenous with respect to risk conditions. They may respond to past macroeconomic conditions, such as average stock market returns and average inflation that individuals experienced during their life (Malmendier & Nagel 2007) or to availability of market insurance (Palacios-Huerta & Santos 2004).

A second way to influence risk behavior is through the opportunity set available to the individual. Behavior towards one risk may depend on the presence of other, uninsurable background risks (e.g. Kimball 1993, Eeckhoudt et al. 1996). Guiso & Paiella (2008) found that risk averse behavior in Italian households is increasing in the variance of regional per-capita GDP, an uninsurable risk. More risk averse behavior may also be the consequence of

(future) liquidity constraints (Gollier 2000), as demonstrated by Guiso & Paiella (2008) for Italian household that had limited access to credit, low liquid assets or high debts.

We experimentally elicit risk preferences both in questionnaire experiments with hypothetical payouts and in in-field experiments with real payouts for commercial cattle farmers in Namibia in August 2008. This tightly coupled ecological-economic system is of high economic importance, contributing one-third of the agricultural output in Namibia (Directorate of Planning 2005), is subject to a variety of environmental, economic, political and social risks (Olbrich et al., in prep.) and is therefore a prime object of study for ecological economics (e.g. Quaas et al. 2007, Baumgärtner and Quaas 2009). Approximately 2,500 commercial farmers conduct cattle farming. Predominant among the risks farmers face is stochastic precipitation and the resulting stochastic production of forage. Namibia has a mean annual rainfall of approximately 270 mm, and precipitation is highly variable across the country with the coefficient of variation (CV) of annual precipitation ranging from below 30% to over 100% (Sweet 1998). We complement our survey data with simulated precipitation data from the REMO (REgional MOdel) climate model, developed by the Max-Planck-Institute for Meteorology, Hamburg (Jacob 2001)¹. With this model we are able to simulate precipitation at individual farms for the period 1978–2008 and calculate the interseasonal CV and mean of total rainy season precipitation as a measure of risk.

We find that risk aversion differs systematically with precipitation risk: ecosystem users are less risk averse under riskier precipitation conditions. An uninsurable background risk in the form of cattle price risk is present but identical for all farmers and thus cannot account for differences in risk behavior. Heterogeneity in liquidity constraints across farmers exists but does not influence risk aversion. We are thus able to attribute the observed pattern in behavior towards risk and the relation to precipitation risk to risk preferences². Whether precipitation risk is linked to preferences through self-selection or endogeneity of preferences remains an open question as we cannot disentangle both possible causes. Nonetheless, to our knowledge this is the first study which demonstrates a relationship between directly measured risk preferences and environmental risk.

¹ As detailed in Section II.2, actual precipitation data was available from the Namibian Meteorological Service, but coarse spatial resolution and numerous gaps in the time series precluded the use of this data in our analysis. However, we validated REMO data with what actual data was available and found both to be highly correlated.

² A third way, apart from risk preferences and opportunity sets, to explain behaviour towards risk focuses on the role of subjective beliefs about risky outcomes. We assume that subjects in our study can assess environmental conditions realistically which transforms into subjective probabilities assigned to outcomes that closely approach objective probabilities. We are mindful of this caveat and will consider it in subsequent analyses.

The paper is organized as follows. Section II reviews and comments on previous findings for risk preferences in semi-arid regions, and on the methods used to collect and analyze our data. Results are presented in Section III. Finally, Section IV concludes.

II. Literature, data collection and statistical specification

II.1 Previous findings concerning risk preferences in semi-arid regions

Risk preferences have been extensively studied in arid and semi-arid regions using the expected utility framework. One approach is the econometric estimation of preferences from production data. This approach has for example been applied in studies on farming in India (Antle 1987, Rosenzweig & Binswanger 1993), Israel (Bar-Shira et al. 1997) or Cyprus (Groom et al. 2008). A different approach is the one we take in this paper, i.e. the direct elicitation of risk preference through experiments involving real or hypothetical payouts. This approach was performed in studies on farming in India (Binswanger 1980), Madagascar (Nielsen 2001), Zambia (Wik et al. 2004), Ethiopia, Uganda and India (Harrison et al. 2009) and Ethiopia (Benzabih 2009, Yesuf & Bluffstone 2009).

These studies found that farmers are on average risk-averse. Furthermore, risk preferences vary systematically with socio-demographic determinants. However, comparing the results on the effect of determinants between studies leads to often ambiguous conclusions. Less educated farmers are more risk averse (Binswanger 1980). Risk aversion has been found to be higher for females (Wik et al. 2004) or lower (Harrison et al. 2009). Age has a positive (Yesuf & Bluffstone 2009) or negative (Harrison et al. 2009) effect on risk aversion, and risk aversion increases (Yesuf & Bluffstone 2009) or decreases with household size (Wik et al. 2004). Farm business characteristics such as area of land or number of livestock are negatively related to risk aversion (Yesuf & Bluffstone 2009), and investment into risk management strategies is either related (Bezabih 2009) or unrelated (Wik et al. 2004). Thus, the effect of socio-demographic determinants is highly specific to the individual case study and no clear picture evolves on the sign of many determinants. Furthermore, none of these study that directly measure risk preferences analyzed the relation of risk preferences with individual risk conditions. Thus, our paper fills an important gap in the literature.

II.2 Data sources

Description of the survey

In August 2008, we elicited risk preferences, personal, farm business and environmental characteristics of commercial cattle farmers in Namibia in a survey, consisting of a mail-in questionnaire and in-field experiments. A detailed description of the survey and its conduction can be found in Olbrich et al. (2009).

Prior to the design of the survey we undertook two research journeys to Namibia in March and October 2007 to acquire a sound understanding of system dynamics, decision making and management strategies in commercial cattle farming. During these journeys we conducted a series of qualitative interviews with farmers, experts and decision makers of the agricultural, political and financial sector. Based on the information gained therein we designed the questionnaire and revised it with feedback gained in two pre-testing rounds in October 2007 and June 2008.

We sent out questionnaires to all cattle farming members of the Namibia Agricultural Union (NAU), the main interest group of commercial farmers, and to all farmers that deliver cattle to MeatCo, Namibia's largest slaughterhouse. We mailed out a first batch of questionnaires in the period 19th – 21st of August 2008, and a second batch as a follow up on the 15th of September 2008.

Additionally, we randomly selected 39 NAU members for participation in in-field risk experiments. We visited the majority of participants (79.4%) on their respective farms, and the remaining ones at public locations in major cities. With one exception,³ each session of experiments started with the participant filling in the questionnaire and was followed by the experiments. Duration of sessions varied between one and two-and-a-half hours.

Altogether, we reached 1,916 of the estimated 2,500 commercial cattle farmers (76.6%). 399 questionnaires were returned, equaling a return rate of 20.8%. In the returned questionnaires, response rate for non-sensitive questions exceeded 95% for most questions, and response rate was greater than 90% for the sensitive questions such as income. Of special note is that an optional question for identification of the farm was answered by 75.1% of survey participants.

³ Upon arrival at the meeting the farmer remarked that his time would not permit both filling-in of the questionnaire and conducting experiments. We thus chose to elicit only selected data in the questionnaire and directly proceeded to the experiments. After the experiments, we asked the farmer to mail or fax us a completed questionnaire, but unfortunately the farmer never sent a questionnaire.

This questions enables us to pinpoint the location of the farm and link the survey data to data from external sources such as precipitation data from the REMO climate model.

Elicitation of risk preferences

We elicited risk preferences in the sense of von-Neumann-Morgenstern expected utility theory (von Neumann & Morgenstern 1944) by an adapted multiple price list format, both through experiments with hypothetical payouts within the questionnaire (“questionnaire experiments”) and through in-field experiments (“field experiments”) with payouts of real money. The method was pioneered in the elicitation of risk preferences by Binswanger (1980) and has since been regularly employed (e.g. Holt & Laundry 2002, Andersen et al. 2008, Harrison et al. 2009). Subjects choose in a number of scenarios between participating in a lottery or receiving a certain payment instead. Scenarios differ in regard to the certain amount, which increases from the first to the last scenario. Subjects in these experiments typically prefer the lottery when the certain amount is low, and switch once the certain amount is deemed high enough.

We aimed at analyzing how different participants value the same lotteries, thus income from and probabilities of outcomes of each lottery were objectively defined and communicated to the participants. In the questionnaire experiments we presented farmers with six scenarios, where we framed the lottery in the context of selling cattle at an auction (Table 1a). The auction had two possible outcomes, N\$90,000⁴ and N\$130,000, each occurring with equal probability of 1/2. The expected value of the auction (N\$110,000) corresponds to about 1/3 of the annual net income of the average farmer. Instead of taking part in the uncertain auction, farmers could chose to sell to a trader for a certain amount which started at N\$100,000 in the first scenario and increased in steps of N\$2,500 to N\$112,500 in the sixth scenario.

In the field experiments the lottery was context-free with equally possible outcomes of N\$500 and N\$2,500. The expected value of N\$1,500 corresponded to the value of a calf (Table 1b). The certain amount started at N\$550 in the first scenario and increased to N\$1,900 in the last scenario. To achieve a higher resolution of risk aversion measures, 16 scenarios were presented. After the subject had made their choices for all scenarios one was chosen at random and played out, i.e. the subject either received the certain amount or the lottery in turn was played out. Due to monetary constraints we could pay only 10% of farmers which were randomly selected by letting farmers draw lots. Payments were made in cash instantly.

⁴ On the 1st of August 2008, N\$1,000 equalled €8.14 or US\$137.50.

Based on the choices observed in each scenario parameters of an expected utility function can be estimated. Expected utility functions that exhibit Constant Relative Risk Aversion (CRRA) are a parametric family of functions that is often used in empirical studies on risk preferences (e.g. Andersen et al. 2006, Harrison et al. 2009), and CRRA has been shown to adequately explain individuals' choices over local income domains (Holt & Laury 2002). We assumed in this paper that CRRA holds at least locally for our study population and used the specific function $U(y) = y^{(1-r)} / (1-r)$ where y was income and r the coefficient of Constant Relative Risk Aversion. Based on this function, indifference between the lotteries and the certain amount in the different scenarios corresponded to values of the CRRA coefficient in the range -1.40 and 6.32 for the questionnaire experiments, and -1.46 and 8.27 in the field experiments, respectively.

Precipitation data

Actual precipitation data from the Namibian Meteorological Service was available for the period 1913–2008. However, this data is collected at only few weather stations across Namibia and the time series has many gaps. Thus, we use simulated precipitation data for our analysis instead. This data was generated through the application of REMO (REgional MOdel) (Jacob & Podzun 1997, Jacob 2001), which is a numerical, three-dimensional, hydrostatic atmospheric circulation model. REMO was developed at the Max-Planck-Institute for Meteorology, Hamburg, on the basis of the *Europamodell*, the former weather prediction model used by the German Weather Service (Majewski 1992). In its original version, the physical parameterizations of REMO were based on those of the global climate model ECHAM4 (Roeckner et al. 1996). The model may continuously run for a period of decades while being forced at the lateral boundaries with historical climate data taken from analysis/reanalysis products as well as with output from global climate models every six hours. For the current study, output data of REMO is reported with a temporal resolution of six hours and a spatial resolution of 18km * 18km.

We used the model to generate data for the period 1978–2008 for those farm locations that farmers revealed through answering the optional farm identification question in the survey. As the model is not designed to predict every single weather event accurately in space and time and therefore cannot directly be used at the point scale, we calculated total precipitation per rainy season (November till April) as a weighted mean over nine adjacent model gridboxes.

We validated simulated data with what actual precipitation data was available from the Namibian Meteorological Service for the period 1978–2008. We matched REMO data for

farm locations with data for the nearest weather station of the Namibian Meteorological Service while requiring a maximal distance of 5km between farm location and weather station. We then calculated interseasonal mean and CV of total rainy season precipitation for both data sets separately and correlated the respective measures⁵. Measures were highly correlated between both data sets and significant at the 0.1%-level, with a Pearson correlation coefficient of 0.74 ($p < 0.001$, $n = 26$) and 0.76 ($p < 0.001$, $n = 26$) for mean and CV, respectively. We thus conclude that simulated data closely conform to actual precipitation data.

Cattle price data

Price data for cattle sales on auctions across Namibia were obtained from Agra Co-operative Ltd. (Agra) for the period 2000–2008. Agra is the largest retailer for farm equipment in Namibia and organizer of almost all cattle auctions. Cattle prices on auctions are primed by averaged national cattle prices published weekly by the MeatBoard of Namibia, and during our qualitative interviews Agra officials mentioned that cattle prices do not differ between auctions at different locations on a given date. Inspecting the price data confirmed that prices between locations are highly correlated: Pearson correlation coefficients were no smaller than 0.97 and significant at the 0.1%-level for correlation between any two locations. We thus considered background risk in the form of cattle price risk to be identical for all farmers and did not consider it in our further analyses.

II.3 Statistical specification

Socio-demographic determinants and risk measure

Based on the information gained from our qualitative interviews we selected those socio-demographic determinants that we deemed relevant for our analysis as well as a control variable for experimental type (questionnaire versus field experiments). Table 2 lists the respective variables, their sample mean and standard deviation.

For the risk measure we employed the inter-seasonal coefficient of variation (CV) of total rainy season precipitation while controlling for the inter-seasonal mean of total rainy season precipitation. If individuals are risk averse, a given distribution in precipitation is more risky in respect to another distribution if it is a mean preserving spread of the latter distribution

⁵ We choose these measures since they constitute our measure of risk, as detailed in Section II.3

(Rothschild & Stiglitz 1970). Furthermore, if distributions are log-normal – as is usually assumed for rainfall in semi-arid regions (Sandford 1982) and as was also the case in our study⁶ – then a mean preserving spread is equivalent to a higher CV for a given mean (Levy 2006). Thus, precipitation risk can be measured by the CV while controlling for the mean with a riskier distribution being characterized by a higher CV for a given mean. As mentioned above, this measure only applies to risk averse individuals. We thus excluded all individuals that were not risk averse.

We calculated inter-seasonal CV and mean of total rainy season precipitation for those farms that we knew the location of from our survey. Furthermore, as we are interested in the precipitation risk that individual farmers experienced we only used the precipitation data for the period that the farmer operated the farm. Since CV estimates fluctuate wildly if based on only few observations we additionally required a minimum operation period of 5 years. Thus, risk measures are available for all farmers that are risk-averse, indicated their farm location and operated for at least 5 years, and are calculated from precipitation data for a period of up to 30 years (the maximum period for which REMO precipitation data was available).

Maximum likelihood specification

We followed in our econometric specification of the expected utility function the approach which was applied in studies in semi-arid areas by Harrison et al. (2009) and which is detailed in Harrison (2008). The expected utility of the lottery, i.e. the auction in the questionnaire experiments and simply the lottery in the field experiments, is defined as

$$EU_i^L = p_1 U(y_1) + p_2 U(y_2)$$

with p_1 and y_1 being probability and income for outcome 1, p_2 and y_2 probability and income for outcome 2 and i an index for the scenario. Since probabilities and incomes were the same for all scenarios, it follows for the questionnaire experiments that

$$EU_i^L = 0.5 U(N\$90,000) + 0.5 U(N\$130,000)$$

and for the field experiments that

$$EU_i^L = 0.5 U(N\$500) + 0.5 U(N\$2,500)$$

⁶ We tested all distributions of total rainy season precipitation that were simulated by the REMO model for log-normality using the Shapiro-Wilk W test. The hypotheses of log-normality could not be rejected for any distribution at the 5%-level.

The expected utility for income from the certain amount is defined accordingly. Since this income was certain, the expected utility function reduces to $EU_i^C = U(y_{ci})$ where y_{ci} is the certain income from the trader in the questionnaire experiments and the certain payout in the field experiments for scenario i .

We estimated the coefficient r using choices for all scenarios with a maximum likelihood estimation. This estimation assumed a cumulative standard normal distribution defined over EU difference for the observed choices in each scenario, that is $\nabla EU = EU^L - EU^C$. Thus, the log-likelihood function, conditional on the expected utility model and our CRRA specification being true, is

$$\ln L^{EUT}(r; z, X) = \sum_i [\ln(\Phi(\nabla EU)) | z_i = 1) + (\ln(1 - \Phi(\nabla EU)) | z_i = 0)]$$

where $z_i = 1$ (0) denotes whether the subject chose the lottery (certain income) in scenario i and where X is a vector of determinants as described in the previous section.⁷ We assumed that the parameter r is a linear function of these determinants.

We further assumed that responses of a single farmer are correlated (i.e. that the choice in one scenario was not independent from the choices in the other scenarios). We thus corrected the standard errors by clustering all the responses for a single farmer. By doing so we effectively created a panel which is stratified by farmers.

When analyzing raw responses for the risk experiments it became apparent that 23.4% of farmers who mailed in questionnaires made choices in the questionnaire experiment that would have characterize them as extremely risk averse or extremely risk attracted. Such a pattern was not apparent for those 39 farmers that completed the questionnaire in the presence of a researcher (during our experimental sessions). A two sample Kolmogorov-Smirnov test for equality of distributions revealed significant differences between both groups ($p=0.032$). In the sessions where a researcher was present we observed that it frequently took farmers a long time to complete the hypothetical risk experiment in the questionnaire. Furthermore, after having filled in the questionnaire some of those farmers who were characterized as

⁷ As proposed in Harrison (2008), we included in our initial analyses error specifications for individual choices as discussed by Hey and Orme (1994), and originally stated by Fechner (1860). Under this specification, individual choice is described by $\nabla EU = EU^L - EU^C + \varepsilon$, with ε being a normal distributed error term with mean of 0 and standard deviation of σ . This specification can be interpreted as the individual having well-specified preferences as represented by the utility function, but making some sort of error regarding the processing of information when evaluating the alternatives (Loomes and Sugden, 1995). Our analyses, however, showed that this error term was not significant, and that its inclusion did not fundamentally change our results. Thus, we only report analyses performed without the error term.

extremely risk averse or extremely risk attracted remarked that they had a personal dislike for selling at auctions or to a trader, respectively.

Based on these observations, we considered the extreme responses of those farmers who mailed-in questionnaires likely to be experimental artifacts that do not reflect true risk preferences. As a robustness check we therefore excluded these farmers in our analyses. A subsequent two sample Kolmogorov-Smirnov test was no longer significant ($p=0.332$). The above described maximum likelihood-estimation is thus at the tails defined only over responses from the 39 experimental participants for which we were certain that they indicated true risk preferences. Figure 1 displays the ensuing histogram of CRRA coefficients as calculated from questionnaire experiments when only considering the information of at which scenario individuals switched from the lottery to the certain amount.⁸

III. Results

We now proceed in two steps: we will at first conduct an analysis of the relation of risk preferences with socio-demographic determinants and experimental type (questionnaire versus field experiments) but exclude the risk measure for comparison with those results found in the literature. To this end, we employ the complete survey population. In a second step we analyze the relationship between risk preferences and precipitation risk, thus we additionally include the risk measure, i.e. the interseasonal CV and mean of total rainy season precipitation. As detailed in Section II.3, in order to perform the latter analysis we include only those farmers who are risk averse, indicated their farm location and operated their farm for at least 5 years⁹.

Relation of risk preferences with socio-demographic determinants and experimental type

When conducting the analysis without any determinants, we found that farmers are on average risk averse with a CRRA-coefficient of 0.78 which is significant at the 0.1%- level (Table 3). This coefficient is higher than values reported from other field studies using the same functional specification, but not out of range of values that can be found in laboratory

⁸ Using only the information of at which point individuals switch from the lottery to the certain amount, interval measures of the CRRA coefficient can be inferred. For example, if individuals indicate preference for the lottery for scenarios 1 to 3 and for the certain amount for scenarios 4 to 6, they reveal a CRRA coefficient in the interval [1.4; 2.8].

⁹ As mentioned before, we imposed this minimum period of operation since calculation of CV leads to widely fluctuating values if based on only few observations. Our results are stable when we impose shorter or longer minimum periods. However, for the sake of being conservative we hold to the minimum period of 5 years.

experiments. For example, Harrison et al. (2009) found a CRRA-coefficient of 0.54 in a field study in India, Uganda and Ethiopia, and Harrison et al. (2007) a coefficient of 0.67 in a field study in Denmark, while Andersen et al. (2006) reported a value of 0.79 for laboratory experiments in Denmark.

Repeating the analysis with determinants results in a smaller base value of the CRRA-coefficient of 0.58, likewise significant at the 0.1%-level (Table 3). Of the included determinants by far the largest effect comes from participation in the field experiments that involved real payouts, resulting in an increase of risk aversion by 0.20 ($p < 0.001$). The effect is essentially the same when analyzing only those 39 farmers that participated in both questionnaire and field experiments (value: 0.15, $p < 0.001$)¹⁰. One possible explanation for this difference is payout level, which was almost 75 times higher in the questionnaire experiments. If this is indeed the case, then one would have to conclude globally Decreasing Relative Risk Aversion (DRRA) when one would instead expect globally Increasing Relative Risk Aversion (IRRA) (Holt & Laury 2002). However, the observed difference in risk aversion may also be due to i) payout structure, i.e. hypothetical payouts in questionnaire experiments and real payouts in field experiments, or ii) framing which encompasses the number of scenarios, elicitation in the presence of a researcher and the specific context in which the experiments were phrased. Holt & Laury (2002) reported that for a given payout level¹¹, half of their subjects behaved more risk averse when confronted with real payouts versus hypothetical payouts. In regards to the effect of framing, Harrison et al. (2007) found that different frames such as the order of scenarios may change the value of the CRRA coefficient by up to 0.30. Thus, an effect of experimental type on estimates of risk aversion is not surprising, but the precise reason remains elusive since our experiments were not designed to clarify this aspect. Given that the estimated base parameter of risk aversion in our model is highly significant, we assume that CRRA holds at least locally for a given income domain, a result which has been demonstrated in lab and field studies alike (Holt & Laury 2002, Harrison et al. 2007)¹². Furthermore, in the light of the aforementioned results from the

¹⁰ When we conduct the analysis with only those 39 farmers and employ as the only determinant a control variable for experimental type, we find the following estimates: constant = 0.73 ($p < 0.001$), control variable = 0.15 ($p < 0.001$).

¹¹ They reported this observation for their 20x treatment which involved lottery prices between \$2 and \$77.

¹² We also tested for the effect of payout level on Relative Risk Aversion using the power-expo function employed by Holt & Laury (2002) and included a dummy to account for differences in experimental type other than payout level. The power-expo function is defined as $U(y) = (1 - \exp(-a \cdot y^{1-r})) \cdot 1/a$. The parameters a and r impact on Relative Risk Aversion which for this function is $r + a \cdot (1-r) \cdot y^{(1-r)}$. The function exhibits IRRA if $a > 0$, DRRA if $a < 0$ and CRRA if a approaches 0. We find the following estimates: $r = 0.90$ ($p < 0.001$), control on r for experimental type = 0.10 ($p < 0.001$), $a = 1.83$ ($p = 0.097$), error term = $2.14 \cdot 10^{-8}$ ($p = 0.78$). Since a was not significant at the 5%-level, we cannot reject the hypothesis of global CRRA using this function.

literature for difference between experimental types, we conclude that our estimates of risk aversion from questionnaire experiments are reasonably close to those from field experiments.

Only two other determinants have a significant influence on risk aversion. Male farmers are mildly more risk averse than female farmers with an increase in risk aversion of 0.08 ($p < 0.001$). This result echoes what Harrison et al. (2009) found in their study of India, Uganda and Ethiopia, but is at odds with other results from semi-arid regions (e.g. Wik et al. 2004). Residence on the farm, our proxy for full-time farming, is likewise significant ($p=0.005$) with full-time farmer being 0.04 more risk averse than part-time farmers. The latter group of farmers usually derives their primary income from non-farming sources and often considers farming as a secondary income source or hobby. Thus, these results suggest that farmers who are fully dependent on income from farming are more risk averse in the light of wrong farm management decisions having a more detrimental impact.

We find no effect of ethnicity, education, age, household size or area of rangeland (a proxy for wealth). Of interest is that the liquidity constraint does not impact on risk aversion. This indicates that the observed behavioral pattern is indeed due to differences in preferences and not due to differences in the constraint. Altogether, our study detects surprisingly few significant determinants, but this not uncommon in other studies (e.g. Tanaka et al. 2007).

Relation of risk preferences with precipitation risk

When testing for the impact of precipitation risk, we find a significant relationship ($p=0.031$) between the interseasonal CV of total rainy season precipitation and risk aversion while controlling for the interseasonal mean of total rainy season precipitation (Table 4). Farmers under more risky precipitation conditions are less averse to risk than those under more stable conditions. The effect seems exceedingly large with a change in risk aversion by -0.53 per unit CV. However, the CV of precipitation for those farmers included in this analysis ranged only from 0.22 to 0.47. Thus, even when comparing farmers at the extremes the difference in risk aversion would only have been $\frac{1}{4}$ of the estimated value, or 0.133.

Again, the liquidity constraint has no effect on risk aversion. Furthermore, as we discussed earlier, cattle prices, the main background risk, is not heterogeneous across farmers. Thus we have strong indication that the opportunity set is not responsible for the observed pattern of behavior towards risk, unlike demonstrated by Guiso & Paiella (2008) for Italian households. At least for cattle farmers in Namibia, the observed pattern in behavior towards risk and the interaction with risk conditions can thus be attributed to preferences.

Precipitation risk is thought to influence farmers through its effect on pasture condition and thus ultimately on income. For log-normal rainfall, this effect was shown by Quaas et al. (2007) for grazing in semi-arid regions in Namibia. We thus assume this effect is also responsible in our study. However, the causal mechanism in the relation between risk preferences and risk conditions remains elusive. The observed pattern may be the results of farmers selectively purchasing and migrating to farms at least partly in accordance with their risk preferences. Thus, less risk averse farmers would self-select themselves under more risky precipitation conditions. Such a sorting or self-selection mechanism has been observed in other contexts, for example in job migration: less risk averse individuals are more likely to migrate between labor markets in Germany (Jaeger et al. 2007), and an inverse relationship between risk aversion and income variability has been found for migration with the European Union (Heitmueller 2005).

Another explanation for the causal mechanism may be endogenous preferences, i.e. the formation of preferences in response to individual precipitation risk. Malmendier & Nagel (2007) showed that risk preferences may be formed by average stock market returns and average inflation that individuals experience during their life¹³. Palacios-Huerta & Santos (2004) demonstrated that risk aversion may decrease with reduced availability of market insurance and hypothesized one possible explanation to be the formation of less risk averse preferences as a form of self-insurance. Ultimately, our survey was not designed to explore these causal mechanisms, and we thus cannot provide any conclusive explanation.

Results for other determinants are not overly different from the previous analysis with the whole survey population. The significant determinants that we already identified are likewise significant and retain the same sign but differ slightly in magnitude. One additional determinant, education, is significantly negative related to risk aversion (value: -0.64, $p=0.04$). These findings are in accordance with those of other studies (e.g. Binswanger 1980, Shaw 1996). Education constitutes an investment into human capital whose returns are risky due to uncertainty in the precise nature of skills to be acquired and in the future payoff of these skills. The same reasoning may apply to farmers in our study. They frequently grow up on farms and thus already acquire essential skills which enables them to lead a farm business. Pursue of higher education may be viewed as risky as farmers may be uncertain if and to what extent the farm business might benefit from the acquisition of additional skills.

¹³ Malmendier & Nagel (2007) could not disentangle whether heterogeneity of behavior towards risk was mediated through differences in risk beliefs or risk preferences. Their alternative explanation is thus that macroeconomic experiences impacted not on preferences but beliefs.

IV. Conclusion

Our analysis shows the importance of not only considering socio-demographic determinants but also the risk conditions that individuals face when explaining behavior towards risk. Our results indicate that individuals living under heterogeneous environmental risk conditions can differ substantially in their risk preferences, with lower risk aversion found in those confronted with higher environmental risk. Furthermore, we are able to separate preferences and constraints as possible means for influencing risk behavior. Background risk is not relevant in our study since cattle price risk, the main uninsurable background risk, was identical for all farmers. We find heterogeneity in the liquidity constraint but it clearly does not impact on risk aversion. We thus can attribute the observed heterogeneity in risk behavior and with it the relation to environmental risk to risk preferences.

The underlying mechanism for the causal relationship between risk preferences and environmental risk remains elusive. The observed pattern may be the result of self-selection where less risk-averse farmers systematically choose to farm under more risky environmental conditions. Such an explanation assumes the existence of a perfect market for farm sales and purchases. Alternatively, risk preferences may be endogenous. In this case, less risk-averse preferences may have been formed in response to more risky environmental conditions.

Due to confidentiality issues we could not elicit in our survey the information necessary to clarify this point. However, from qualitative interviews that we conducted with farmers and decision makers we infer that i) farmers often inherit farms from their parents or acquire farms in the vicinity to where they grew up, and ii) farm sales are restricted. We thus strongly lean towards the hypothesis that preference formation is the cause for the relation of risk preferences and environmental risk. We plan to return to Namibia for further data collection in March 2010. Given the high participation in this survey we feel confident that we can now elicit the life-history information necessary to approach this question of causality.

Our results have implications for the design of institutional frameworks that provide risk management to ecosystem users. Selection into insurance products may not only be the result of personal characteristics but may also depend on risk conditions, thus entail advantageous selection where individuals under less risky conditions preferentially purchase insurance. Results become also relevant when considering which actions lead to a sustainable use of ecosystem services under uncertainty since ex-ante concepts of sustainability under uncertainty like viability (Baumgärtner & Quaas 2009) require knowledge of risk preferences for the design of adequate actions. The design of such actions may have to be highly

individual and not only be tailored to specific population segments but also to the individual risk conditions.

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Table 1: Experimental design for risk preference elicitation. a) Questionnaire experiments. b) Field experiments.

a) Questionnaire experiments

Context provided in the questionnaire:

“In the following question, we would like you to respond to a hypothetical situation.

Let’s assume you are forced to sell fifty weaners (due to financial or grazing reasons) and can do so at auction. However, you are uncertain about the amount of money they will fetch. You have a 50% chance that the fifty weaners combined will fetch N\$ 90 000 and a 50% chance that they will fetch N\$ 130 000.

Instead of selling at auction, you can sell the weaners to a reputable trader for a fixed amount of money. The trade procedures (i.e. driving to the venue, paperwork, etc.) are similar regardless of whether you sell at auction or to the trader.

For each of the following six scenarios, please choose whether you prefer to take part in the auction having a 50% chance of fetching either N\$ 90 000 or N\$ 130 000, or prefer to sell to the trader offering you increasing higher amounts of money.

→ Please check only one box for each of the six scenarios.”

Scenario	Lottery		Certain amount
	Outcome 1	Outcome 2	
1	N\$ 90,000; ½	N\$ 130,000; ½	N\$ 100,000
2	N\$ 90,000; ½	N\$ 130,000; ½	N\$ 102,500
3	N\$ 90,000; ½	N\$ 130,000; ½	N\$ 105,000
4	N\$ 90,000; ½	N\$ 130,000; ½	N\$ 107,500
5	N\$ 90,000; ½	N\$ 130,000; ½	N\$ 110,000
6	N\$ 90,000; ½	N\$ 130,000; ½	N\$ 112,500

a) Field experiments

No specific context provided.

Scenario	Lottery		Certain amount
	Outcome 1	Outcome 2	
1	N\$ 500; ½	N\$ 2,500; ½	N\$ 550
2	N\$ 500; ½	N\$ 2,500; ½	N\$ 600
3	N\$ 500; ½	N\$ 2,500; ½	N\$ 650
4	N\$ 500; ½	N\$ 2,500; ½	N\$ 700
5	N\$ 500; ½	N\$ 2,500; ½	N\$ 800
6	N\$ 500; ½	N\$ 2,500; ½	N\$ 900
7	N\$ 500; ½	N\$ 2,500; ½	N\$ 1,000
8	N\$ 500; ½	N\$ 2,500; ½	N\$ 1,100
9	N\$ 500; ½	N\$ 2,500; ½	N\$ 1,200
10	N\$ 500; ½	N\$ 2,500; ½	N\$ 1,300
11	N\$ 500; ½	N\$ 2,500; ½	N\$ 1,400
12	N\$ 500; ½	N\$ 2,500; ½	N\$ 1,500
13	N\$ 500; ½	N\$ 2,500; ½	N\$ 1,600
14	N\$ 500; ½	N\$ 2,500; ½	N\$ 1,700
15	N\$ 500; ½	N\$ 2,500; ½	N\$ 1,800
16	N\$ 500; ½	N\$ 2,500; ½	N\$ 1,900

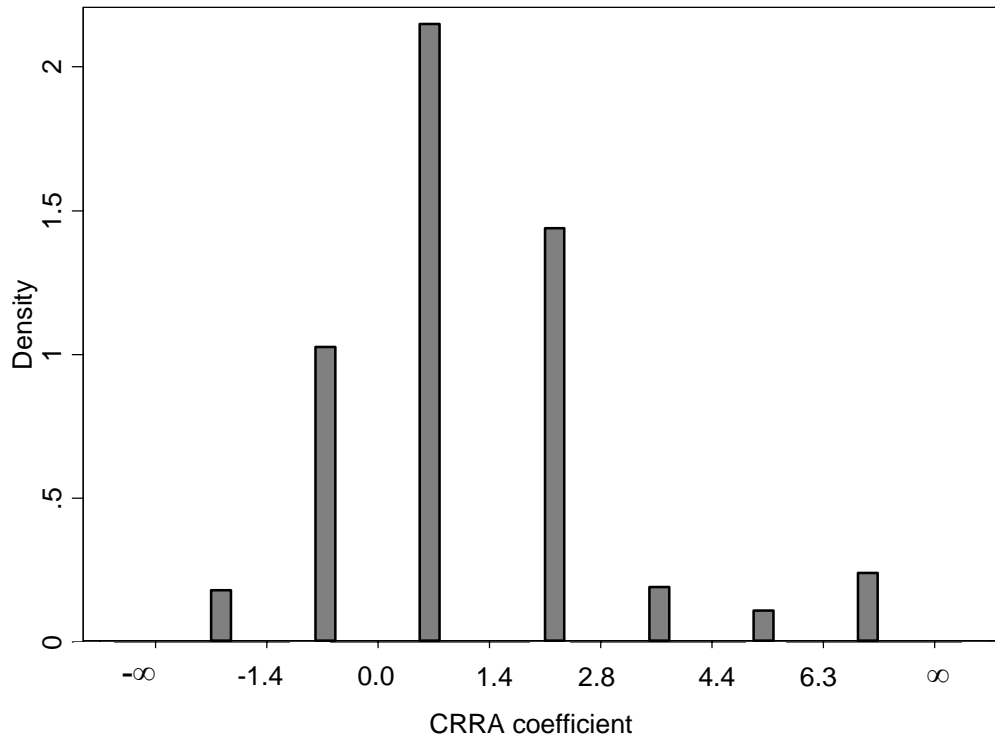


Figure 1: Histogram of CRRA coefficients as calculated from questionnaire experiments using only the information of at which scenario individuals switched from the lottery to the certain amount. Values are displayed at the midpoint of CRRA coefficient-intervals corresponding to the respective scenarios.

Table 2: Variable list and descriptive statistics.

Variable	Definition	Sample Mean (Stand. Deviation)
Field experiment	Participation in field experiment with real payout	9.77%
Male	Male	94.76%
Afrikaans	Of Afrikaans decent	43.98%
Other ethnicity	Of German, English or indigenous decent	56.02%
No higher education	No post-secondary education	24.39%
Higher education	Post-secondary education	75.61%
Age in years	Age in years	54.89 (12.06)
Persons in household	Number of persons in household	3.31 (1.71)
Living on farm	Living on farm during the week, proxy for full-time farming	79.76%
Area of rangeland	Are of rangeland in hectares	7802.93 (4899.14)
Liquidity constraint	Liquidity constraint, importance of which is measured on a six-item Likert scale	3.00 (1.63)
Mean of precipitation	Interseasonal mean of total rainy season precipitation in mm	284.48 (86.56)
CV of precipitation	Interseasonal coefficient of variation (CV) of total rainy season precipitation	0.29 (0.06)

Table 3: Maximum likelihood estimation of expected utility model of choice with socio-demographic determinants and control variable for experimental type only. a) Estimation without determinants and control variable. b) Estimation with determinants and control variable.

Variable	Estimate	Standard Error	p-Value	95% Confidence Interval	
a) Without determinants and control variable					
Constant	0.779***	0.023	0.00	0.733	0.824
Observations	1956				
Clusters by individual	222				
b) With determinants and control variable					
Constant	0.579***	0.051	0.00	0.479	0.679
Field experiment	0.203***	0.024	0.00	0.157	0.250
Male	0.076***	0.023	0.00	0.031	0.121
Non-Afrikaans	-0.001	0.018	0.97	-0.036	0.034
Higher education	-0.031	0.020	0.12	-0.070	0.008
Age in years	0.000	0.001	0.51	-0.001	0.002
Persons in household	0.005	0.005	0.35	-0.005	0.014
Living on farm	0.040**	0.016	0.01	0.010	0.071
Area of rangeland	-0.000	0.000	0.20	-0.000	0.000
Liquidity constraint	-0.000	0.005	0.97	-0.010	0.009
Observations	1850				
Clusters by individual	207				
Wald Chi-square	95.96				
p-value	0.0000				

*** p<0.001, ** p<0.01, * p<0.05

Table 4: Maximum likelihood estimation of expected utility model of choice with socio-demographic determinants, control variable for experimental type and risk measure.

Variable	Estimate	Standard Error	p-Value	95% Confidence Interval	
Constant	0.661***	0.131	0.00	0.405	0.917
Field experiment	0.198***	0.033	0.00	0.132	0.263
Male	0.117***	0.031	0.00	0.056	0.178
Afrikaans	0.002	0.025	0.93	-0.046	0.050
Higher education	-0.064*	0.031	0.04	-0.124	-0.004
Age in years	0.000	0.001	0.84	-0.002	0.002
Persons in household	0.008	0.008	0.30	-0.007	0.023
Living on farm	0.082**	0.026	0.00	0.032	0.133
Area of rangeland	-0.000	0.000	0.85	-0.000	0.000
Liquidity constraint	-0.000	0.006	0.98	-0.013	0.012
Mean of precipitation	0.000	0.000	0.60	-0.000	0.000
CV of precipitation	-0.534*	0.248	0.03	-1.020	-0.048
Observations	1036				
Clusters by individual	106				
Wald Chi-square	64.54				
p-value	0.0000				

*** p<0.001, ** p<0.01, * p<0.05