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Comparing Risk Preference Elicitation Approaches in Field Experiments[1]

By

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Abstract

This paper studies the risk preferences of poor rural households in Malawi and compares the Holt and Laury (2002) (HL) multiple price list approach with hypothetical real-world framing and monetary incentive-compatible framing with the Tanaka, Camerer and Nguyen (2010) (TCN) monetary framing approach to elicit prospect theory parameters. The consistency of the results, the role of and potential bias attributable to measurement error, and correlations with socioeconomic characteristics are assessed. The study shows that measurement error can lead to upward bias in risk aversion estimates and over-weighting of low probabilities. The hypothetical real–world HL framing experiments are associated with higher sensitivity to background variation such as exposure to a recent drought shock and distance to markets/poor market access.

Key words: expected utility theory, prospect theory, risk preferences, loss aversion, probability weighting, field experiment, multiple price lists, measurement error, Malawi.

JEL codes: C93, D03, O12.

1 Introduction

Poverty and vulnerability are closely related. Poor and vulnerable people in developing countries live in risky environments and are only partly integrated into the market economy owing to high transaction costs and imperfect information, such that stochastic and covariate shocks contribute

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to pervasive failures in inter-temporal markets (Binswanger and Rosenzweig 1986; Fafchamps 2004). Climate change may impose higher future risks and more severe climatic shocks. Poor people are bound to be more exposed to these and will have to adapt to them to survive.

Although our understanding of poor people's responses to risk and shocks has improved over time, there are still fundamental gaps in our knowledge, and the internal and external validity of existing findings is still uncertain. For example, how important is prospect theory (PT) for explaining poor people's behavior? Does PT predict poor people's behavior better than expected utility theory (EUT)? Moreover, how suitable are experimental lab approaches for eliciting the risk preferences of poor people with limited education through the use of field experiments? A variety of approaches have been developed and tested in different environments (Binswanger 1980; 1981; Wik et al. 2004; Humphrey and Verschoor 2004a; 2004b; Harrison et al. 2009; Tanaka et al. 2010; Tanaka and Munro 2013), but very few careful comparisons of the consistency and reliability of alternative approaches in the field have been published. An exception is Jacobson and Petrie (2009), who assess the extent of inconsistent choices in risk preference experiments among adults in Rwanda. They found that more than half of their sample committed mistakes in a sequence of choice experiments. Risk aversion alone did not explain financial decisions, but inconsistent responses interacted with risk aversion such that they jointly explained behavior in a sensible way. Risk aversion was correlated with a higher probability of being in a savings group and reduced the likelihood of taking out informal loans. Those who committed mistakes in the experiments also made more mistakes in real-life choices.

It is clear that there are a number of additional challenges in eliciting preference parameters from poor people with limited education and numeracy skills. These respondents are typically computer illiterate and require much more elaborate explanations than do the typical students who are used in lab experiments in developed countries.

This paper makes three novel contributions to the literature on risk preferences and their measurement among poor people. First, it combines the Holt and Laury (2002) (HL) approach that rests on expected utility theory (EUT) with the Tanaka, Camerer and Nguyen (2010) (TCN) approach that is used to elicit prospect theory (PT) parameters on the same sample of households. We test the degree of consistency and correlation between the estimates with the two approaches applied to poor people with limited education in field experiments in rural villages in six districts in Malawi. Second, it uses a sequence of first hypothetical and then monetary HL choice series to assess the extent of within-subject inconsistency and learning that may reduce inconsistency; whether inconsistent responses bias risk aversion estimates; and whether this problem carries through to the TCN choice series that are introduced after the two types of HL series. Third, the effect of subjective probability weighting (elicited with the TCN series) is assessed separately in the hypothetical and monetary HL series by comparing the effect with the standard EUT approach and observing how this affects the parameter estimates for a vector of experimental and socioeconomic characteristics. Structural models using an expo-power (EP) utility function with stochastic (Luce) errors are used for this.

The results show that the hypothetical average HL risk aversion rank measures correlate less with the TCN–PT parameters than the average risk aversion ranks from the monetary HL series. The proxy variables for the measurement error of the HL risk aversion rank measures appear to bias the risk aversion measures upward. The monetary HL risk aversion measure and the TCN curvature measure of risk aversion (TCN sigma) are significantly correlated with loss aversion. More loss averse persons appear also to be more risk averse. Male respondents are significantly more loss averse than are women. Respondents with a greater tendency to over-weight low probabilities (lower TCN alpha parameters) also have more concave utility functions and PT value functions. The EP structural models for the hypothetical HL series without and with subjective probability weights from the TCN series give a significant gender difference in risk aversion, with males being less risk averse than females, similar to what has been found in other studies but surprising considering that men in our study are found to be more loss averse than women. Exposure to a recent drought shock and longer distance to markets (poorer market access) are associated with higher risk aversion in the hypothetical HL series models but are not significantly correlated with risk aversion in the monetary HL series models or the TCN monetary choice series models. Hypothetical real-world framing versus monetary framing in the HL series creates larger differences in the estimated results than running these models without and with subjective probability weights. The findings give reason to question whether monetary field experiments represent a silver bullet that is always better at eliciting preference parameters than hypothetical real-world framing can be in settings in which people are only partly integrated into markets. Hypothetical experiments have the advantage that they can include higher stakes, especially if losses are involved. More work is needed to test alternative methods to assess the robustness of the results involving poor people with limited numeracy skills who live in risky environments with highly imperfect markets.

2 Risk preferences of poor people – a literature review

Hans Binswanger (1980, 1981) is the first to study the risk preferences of poor people with an incentive-compatible experimental design. His seminal work in India is followed up by studies in other countries (El Salvador, Ethiopia, the Philippines, Thailand and Zambia) (Binswanger and Sillers 1983; Wik et al. 2004; Yesuf and Bluffstone 2009). These studies use an experimental approach with similar designs to that first used by Binswanger, with choices between two and two prospects, with trade-off between expected return and risk, and where good and bad outcomes have an equal probability of occurring. Measures of risk aversion are elicited based on expected utility theory with a constant partial risk aversion utility function. Binswanger and Sillers (1983) conclude based on early studies in India, The Philippines, Thailand and El Salvador that farmers in developing countries are nearly universally risk averse and that risk aversion may not vary greatly between different cultural or agro-climatic conditions; it also appears not to vary with wealth to any great extent. In contrast, using the same type of incentivized experimental design, Wik et al. (2004) (Zambia) and Yesuf and Bluffstone (2009) (Ethiopia) find that risk aversion declines with wealth. Binswanger (1980), Wik et al. (2004), and Yesuf and Bluffstone (2009) find that respondents are much more risk averse in games with gains and losses than in games with gains only. Risk aversion also increases substantially with the expected value of the game. Binswanger (1980) and Wik et al.(2004) find that luck in earlier game rounds makes respondents willing to take more risk (become less risk averse) in later games. This could also be because their subjective probabilities (relating to tossing a coin) could deviate from the objective probabilities.

Humphrey and Verschoor (2004a,b) introduce incentivized experiments in Uganda, Ethiopia and India in which the probabilities vary more (0, 0.25, 0.5, 0.75, and 1). Harrison, Humphrey and Verschoor (2009) further assess the same data and conclude that it may be misguided to search for one correct theoretical model because of heterogeneous behavior. Roughly half of the sample behaves according to EUT and the other half more according to PT. They find evidence of an S-shaped probability weighting function. Respondents classified as behaving more like EUT and PT also had different levels of risk aversion, with the PT respondents on average being classified as slightly risk loving. They find that respondent's age is highly significant in the PT sample, such that young respondents are risk averse and older respondents are risk loving. The authors do not assess whether differences in background risk could explain this variation in behavior, and experiments with losses are not included.

Tanaka, Camerer and Nguyen (2010) (TCN) use field experiments in Vietnam to elicit risk preferences, including loss aversion and subjective probability weighting based on PT. Three choice series are used: the first two are used to elicit the curvature of the utility function and the degree of subjective probability weighting. The third series includes losses and can, jointly with the elicited curvature of the utility function, be used to obtain a measure of loss aversion. They find that few of the choices are consistent with EUT. The parameters for the curvature of the value function are estimated at 0.59 and 0.63 in the north and south samples. They find that subjective probability weighting follows an inverted S-shape with an average α=0.74, where α=1 implies neutral probability weighting in a Prelec-type single-parameter probability weighting function. They refer to a study in China by Liu (2008), who uses a similar approach and finds $(\sigma,\alpha)=(0.48, 0.69)$. The average loss aversion (λ) is found to be 2.63, but Liu (2008) estimates it at 3.47 in the study in China. They also find that older and more educated respondents are more risk averse and that respondents who live in wealthier villages are less loss averse and also less risk averse. They do not find gender to be significant.

Tanaka and Munro (2013) report results from a large-sample field experiment in Uganda. They use four choice series, three that include gains only and a fourth that includes loss alternatives. The three series with gains only include a safe option and a risky option, and the probabilities vary from 0, 0.25, 0.5, 0.75, to 1. The large geographical coverage in the country allows for testing the importance of agro-climatic variation, which is an important source of risk for the responding households. They find significant differences in risk aversion and loss aversion across agro-ecological zones. The levels of risk aversion and loss aversion are highest in the areas with unimodal rainfall. They also assess the presence of subjective probability weighting and find evidence of this across the different agro-ecological zones. Most zones have an inverted

S-shaped probability function except for the unimodal rainfall zone, where probability weighting is S-shaped. Their study locations do not overlap with those of Humphrey and Verschoor (2004a, b), but this zonal variation may explain the variation in the findings in earlier studies. This indicates that context matters and gives reasons to be critical of the extent of external validity of the experimental results on risk preferences.

Jacobson and Petrie (2009) use experiments among adults in Rwanda in which part of the sample makes a sequence of decisions for which inconsistency in responses is recorded. They have some experiments with gains only, some with gains and losses, and some with high stakes, all with 50-50 probability of good and bad outcomes such that subjective probability weighting is not considered. Approximately 55% of the sample made at least one inconsistent choice. Risk aversion alone is found to explain very little of financial decisions; however, when risk aversion is interacted with the degree of inconsistent decisions, risk aversion, the degree of inconsistency, and their interaction all become significant. Risk aversion is positively related to being a member of a savings group and negatively related to taking out informal loans, and the degree of inconsistency in choices is related to making less optimal financial choices.

To summarize, the studies we reviewed that have elicited the risk preferences of poor people in developing countries through field experiments have used either a) the Binswanger approach, with no variation in probabilities; b) the Humphrey and Verschoor approach, with gains only series and with variation in probabilities between prospects; c) the TCN-PT approach, which uses three choice series to elicit three PT parameters; or d) variants of these with a safe option and a risky option. None of these studies has applied the Holt and Laury (2002) MPL approach whereby respondents always choose between two risky prospects and with multiple price lists, which allows for consistency checks and within-subject stochastic error. None of the earlier studies have compared the alternative approaches systematically. It is therefore an open question how sensitive the results from these experiments are to framing effects or to the specific approach chosen. This paper thus contributes by comparing the most commonly used approach in developed country settings, the Holt and Laury (2002) approach (with a high-stakes hypothetical version and a lower-stakes monetary version) with the TCN–PT approach, which has recently gained popularity in developing countries.

3 Sampling design and field experiment procedures

The experiments were implemented in Malawi, a country that in 2012 was ranked number 171 out of 187 countries on the Human Development Index for 2012 and where 74% of the population has an income below $1.25 (OECD, UNDP, UNECA and AFDB 2012).

3.1 Sampling

The social experiments that were used in this paper were implemented among a sample of rural households located in six districts in the central and southern regions of Malawi. The same households were surveyed four times in the period 2006 to 2012 using a standard household-farm plot questionnaire, and the last survey was just one week before the social experiments were introduced in 2012. A number of villages were sampled within each district, and a random sample of 450 households was used in the 2006 survey. In the 2012 social experiments, 349 of these households were present and included in the 2012 survey and experiments.

3.2 Training the experimental enumerators

Four bright young Malawian MSc degree holders (three female and one male) in agricultural economics were identified and trained for one week to run the social experiments. One of these had later to be replaced by another with a similar background. After having been introduced to the experimental designs (see the Appendix for the risk preference part that is used here), they applied the designs to each other, with emphasis on standardizing how to conduct the interviews given the respondents' limited education and numeracy. Next, they began the training with an out-of-sample village and households. This was combined with testing and refining the prototype designs of the experiments. Visual aids such as fingers, real money and a set of 10 playing cards were used to introduce concepts such as probabilities.

3.3 Field design

A one-day-per-village approach and organizing the respondents were used to prevent communication between those who had played the games and those who were still waiting to play. In most cases, a classroom in a nearby school was used, and the respondents were located one in each corner, with their backs to each other and the experimental enumerator in front of them. Respondents who had not yet played were located in one place at a distance such that they could not see what was happening. Those who had played were asked to leave and were not allowed to meet those who were still waiting to play.

3.4 Experimental design and implementation

The experimental protocol for the risk experiments is attached in Appendix 1. The risk preference experiments were introduced together with time preference experiments and input demand experiments. The ordering of these experiments was randomized to test whether the order mattered for the outcomes. The risk preference experimental payouts could have had more influence on the other experiments than the other way around if risk preferences are more stable than time preferences (something our design allowed us to test). Furthermore, there was only a 10% probability of payout in the time preference experiments, whereas everyone received a payout in the risk preference and input demand experiments.

The risk preference experiments were implemented in a specific order. The limited literacy and numeracy levels of the respondents made it necessary to introduce the experiments in a very careful way. The risk preference experiments were more difficult for the respondents to understand than the simpler time preference and input demand experiments. Concepts such as probabilities and expected outcomes were not familiar to the respondents, who were typical rural household heads with limited education. The instructions emphasized explaining probabilities in a real-world setting in the form of the probability of drought, using fingers and playing cards. Maize is the staple food crop, and households are typically food insecure owing to unreliable weather (droughts). Hypothetical maize varieties with different (reasonable) yields in good and bad years were used in the first four series to help the respondents understand the logic of the experiments (hypothetical HL series 1–4). In the choice series, the less risky maize variety had a bad year outcome of 1000 kg/ha and a good year outcome of 2000 kg/ha, and the more risky variety had a bad year outcome of 100 kg/ha and a good year outcome of 4000 kg/ha. In the second choice series, the good year outcome for the less risky maize variety was reduced to 1500 kg/ha, but otherwise there were no changes. In the third series, the bad year outcome for the risky maize variety was raised from 100 kg/ha to 500 kg/ha and the less risky maize variety was the same as in series two. In the fourth series, the bad year outcome for the risky variety was further raised to 800 kg/ha. Because the average farm size is roughly one ha and these maize yields cover the usual maize yield range in the study area, these quantities were close to realistic production levels and variations in the participants' main food crop. We hoped that this realistic framing would give them a better basis to understand the choice series and the probability concept and also help them to make decisions in games that resembled their real-life decisions. The probability of a drought year was varied within each series. A randomly identified starting point was chosen in each series by drawing a card from 10 cards that the experimental enumerators used to demonstrate probabilities and identify starting points and winning series in the experiments. Coin tosses were used to identify final outcomes in the form of the winning prospect for payout (or payback in loss aversion series).

Experiments with money and with the same structure of probabilities and outcomes (in Malawi Kwacha[2] (MK) instead of kg maize) were then introduced (real HL series 5–8), followed by two prospect theory (PT) series (TCN series 9–10) in which the good outcome in one of the prospects through the series varied but the probabilities were constant in each series but varied across series. The minimum daily wage rate (DWR) in Malawi was increased from 178 MK to 317 MK on July 1st, 2012, and it was then illegal to hire anyone at a lower rate. This new minimum wage was slightly above 1$/day in August 2012 when we began the experiments. This implies that the potential payout rates in the monetary HL series varied from 3.2 to 6.3 DWR for the less risky option versus 0.3 to 12.6 DWR for the riskier option. The potential payout rates varied from 3.2 to 12.6 DWR for the less risky option and from 0.8 to 157.7 DWR in the riskier option in the PT series with gains only. In the loss aversion series, the less risky option had payout/payback levels ranging from -1.3 to 3.9 DWR and the more risky option had DWR from -3.2 to 4.7. In the hypothetical HL series, the less risky option had outcomes in the range of 183.0–365.9 DWR, and the more risky option had outcomes in the range of 18.3–731.9 DWR, based on an average maize price of 58 MK/kg (Table A2.1 in Appendix 2).

A real payout was chosen for one randomly identified series (from series 5–10) and a randomly chosen task within this series. Finally, a loss aversion (LA) series, allowing for gains and losses,

[2] In August 2012, the exchange rate was 300 Malawi Kwacha (MK)/US$. The maize price was 64 MK/kg in southern Malawi and 52 MK/kg in central Malawi (FewsNet 2012).

was played after the respondents had first been allocated MK 1000 that they had to be prepared to lose in the game. This series had seven tasks, and one of the tasks was randomly chosen for real payout/payback. The PT and LA series were similar to those used by Tanaka, Camerer and Nguyen (2010). We call them the TCN or TCN-PT series.

4 Theoretical models and risk preference measures

For the HL series a combination of two approaches was used, building on rank-dependent utility models and EUT: a) simple average rank distance from the risk-neutral choice as a measure of risk aversion, combined with the standard deviation for these ranks, as a measure of consistency or accuracy/measurement error for each of the hypothetical and real HL series and b) estimation of a structural model with an expo-power utility function as in Holt and Laury (2002). These approaches were combined and compared with the TCN approach, which builds on PT (Tanaka et al. 2010). The details of each approach are explained below.

4.1 Simple rank measures of risk aversion

Here, we introduce a simple rank measure for risk aversion that imposes minimal assumptions about utility functions such as the rank-dependent utility function (Quiggin 1991). This approach builds on EUT, separation of probabilities and outcomes, and comonotonous utility functions for outcomes (Diecidue and Wakker 2001). It is applied to the Holt and Laury (2002) multiple price list (MPL) responses. In each row of the MPL, the respondent evaluates two risky prospects, A^s and A^r, where the first is less risky than the second and each has two states of nature, bad and good. Additionally, there is a common probability of bad (p_b^k) and good (1- p_b^k) outcomes, where k represents the step-wise increasing rank of the probability in a choice series. In each series, the outcomes are kept constant while the probabilities of bad outcome change step-wise in 10% intervals from 10% to 90%. The expected return on the less risky prospect is $E\left(a^s\right)=p_b^k A_b^s+\left(1-p_b^k\right)A_g^s$, and for the riskier prospect, it is $E\left(a^r\right)=p_b^k A_b^r+\left(1-p_b^k\right)A_g^r$. An individual with a specific utility function will evaluate the prospects as follows according to expected utility theory:

1) $EU_i\left(a^s\right)=p_b^k u_i\left(A_b^s\right)+\left(1-p_b^k\right)u_i\left(A_g^s\right)$ vs. $EU_i\left(a^r\right)=p_b^k u_i\left(A_b^r\right)+\left(1-p_b^k\right)u_i\left(A_g^r\right)$

For small p_b^k, $E\left(a^r\right)>E\left(a^s\right)$, but when p_b^k increases step-wise, a point is reached at which the relative sizes of the expected returns switch and are equal at some point between these: $E\left(a^r\right)=E\left(a^s\right)$. Let us set $p_b^k=p_b^K$ at this switch point. A risk-neutral person is indifferent between the two prospects at this probability level, whereas a risk averse person will prefer the less risky prospect. In a choice series in which only p_b^k increases, the expected returns from both the less and more risky prospects decline, but the decline is more rapid for the more risky prospect. In the opposite direction from the point at which $p_b^k=p_b^K$, even risk averse individuals may reach a point where $EU\left(a^r\left(p_b^{k<K}\right)\right) \approx EU\left(a^s\left(p_b^{k<K}\right)\right)$. With the experimental choice series increasing by 10% intervals in p_b^k, the exact indifference points are not likely to be identified, but a switch point can be identified such that;

$EU\left(a^r\left(p_b^k\right)\right) < EU\left(a^s\left(p_b^k\right)\right)$ while $EU\left(a^r\left(p_b^{k-1}\right)\right) > EU\left(a^s\left(p_b^{k-1}\right)\right)$. A simple rank measure of the degree of risk aversion is derived from the switch point and the probability level where expected returns are close to equal. If we denote the rank level *R* where a respondent switches from the safer to the more risky prospect as p_b^k is reduced, the rank *R* is defined as $p_b^{K-R} = p_b^K - 0.1R$. It is easy to see that a higher rank (*R*) implies a higher level of risk aversion.

With imprecise identification of the switch point, the identified rank $R \lesseqgtr R^*$ where R^* is the true rank. Using four choice series with hypothetical real-world framed paired prospects and four choice series with real money paired prospects, we can assess the degree of consistency and accuracy of the rank measures derived from these for each respondent. We derive the mean and the standard deviation of these ranks from the hypothetical and monetary prospects: $\overline{R}^H, \overline{R}^M, stdR^H$, and $stdR^M$. With measurement error, the mean rank from the four series should be a better proxy of the true rank than a single rank measure from one of the choice series, and the standard deviation of the risk aversion rank should be a proxy of the degree of measurement error or inconsistency of responses for each respondent. These measures are used in combination with the elicited TCN parameters to assess their correlation, reliability and consistency.

4.2 Structural model with expo-power utility function (Holt and Laury approach)

An alternative utility function is the expo-power (EP) utility function (Saha 1993), and it is used by Holt and Laury (2002) in their assessment of risk preferences using MPL:

2) $$U(x) = \frac{\left(1-\exp\left(-\alpha x^{1-r}\right)\right)}{\alpha}$$

This function allows relative risk aversion to vary with income as long as $\alpha \neq 0$, r = CRRA if $\alpha = 0$, and α = CARA if $r = 0$. This functional form is preferable to a simpler CRRA function if $\alpha \neq 0$.

In the estimation, we allow for stochastic error absorbed by a noise parameter, μ, with the Luce specification:

3) $$\nabla EU = EU_A^{1/\mu} / \left(EU_A^{1/\mu} + EU_B^{1/\mu}\right)$$

With the prospects and the utility function specified, it is possible to construct a log-likelihood function that is used for the maximum likelihood estimation of relevant parameters such as *r*, prospect characteristics (Z_j) and respondent/household/farm characteristics (X_i):

4) $\ln L\left(r; y, Z_j, X_i\right) = \sum_j ((\ln \Phi(\nabla EU) \mid y_i = 1) + (\ln \Phi(1 - \nabla EU) \mid y_i = 0))$

An advantage of this approach compared with using a CRRA utility function is that the utility function is more flexible. We also tested CRRA utility functions in the structural models, but the EP function was preferable in our case.

4.3 The Tanaka-Camerer-Nguyen (TCN) prospect theory (PT) approach

This approach is based on cumulative prospect theory, in which the value function is separated for gains and losses (convex for losses and concave for gains) and allowing for nonlinear probability weighting. Gains and losses are represented by a piecewise power function:

5) $v(x) = x^{\sigma}$ for gains and $v(x) = -\lambda(-x)^{\sigma}$ for losses

and the one-parameter probability weighting function (Prelec 1998):

6) $\pi(p) = 1/\exp\left[\ln(1/p)\right]^{\alpha}$

where *v*(.) is the value function, *x* is the outcome, σ (TCN sigma) represents the concavity of the value function, λ (TCN lambda) is the loss aversion parameter, *p* is the probability, and α (TCN alpha) represents the degree of nonlinearity in the probability weighting. With $\alpha<1$, low probabilities are over-weighted and large probabilities are under-weighted; with $\alpha=1$, equal weights are given to all probabilities; and with $\alpha>1$, low probabilities are under-weighted and high probabilities over-weighted. With EUT), $\alpha=1$ and $\lambda=1$. The λ loss aversion parameter captures the kink in the value function at the status quo level.

The TCN approach (Tanaka et al. 2010) is used to elicit the three PT parameters based on three choice series. The first two are used to elicit the α and σ parameter intervals, and the last choice series elicits the λ parameter interval; the arithmetic means of the upper and lower bounds for these are then used.

The systematic order of the choice series, with four hypothetical HL series followed by four real money HL series, and the three TCN series, including the loss aversion series as the last, was chosen to improve understanding and enhance the quality of the responses in the real money series. The HL series also facilitated assessing the stability of parameters/stochastic errors through the repetition of similar choice series. This approach does not give a clean test for the effect of hypothetical versus real experiments (hypothetical bias). Nevertheless, analysis of the hypothetical series can still give additional insights that are explored while keeping in mind that potential hypothetical bias is confounded with learning, and real-world framing with higher stakes, in the hypothetical series.

4.4 Estimation strategy

To test the consistency of the hypothetical and monetary HL series with the TCN series and the potential measurement bias, we regress the HL risk aversion rank measures on the TCN-PT elicited parameters and the standard deviations of the HL rank measures, separately for the hypothetical and real money HL choice series (eqn. 7):

$$7)\quad \begin{aligned} \overline{R}_i^H &= a_0 + a_1\sigma_i^T + a_2\alpha_i^T + a_3\lambda_i^T + a_4 stdR_i^H + e_i^H \\ \overline{R}_i^M &= b_0 + b_1\sigma_i^T + b_2\alpha_i^T + b_3\lambda_i^T + b_4 stdR_i^M + e_i^M \end{aligned}$$

It is expected that the rank measures will be negatively correlated with the TCN sigma parameter if both are reliable measures of individual risk aversion. A strong negative correlation would indicate the high accuracy of both measures. It is less clear how and whether the TCN alpha and TCN loss aversion parameters correlate with the HL risk aversion rank measures. It is possible that higher loss aversion is positively correlated with higher risk aversion; Tanaka et al. (2010) found such a correlation in their study in Vietnam. The standard deviation of the risk aversion rank measure is included to assess whether measurement error can lead to bias in the risk aversion rank measure and is used as a test as well as a correction for the bias. The RHS variables are included in a step-wise fashion to assess the parameters' robustness.

Next, the TCN sigma variable is used as the dependent variable and regressed on the other two TCN parameters as well as the HL risk aversion rank and variability measures to determine their degree of correlation with both the hypothetical and the real money HL series measures. This also allows us to assess whether the sigma parameter is biased because of individual stochastic error that the risk aversion rank variability measures are proxies for. Here also, the RHS variables are introduced step by step, and finally an assessment is made of the effect of removing outlier observations with very high risk aversion rank variability, an indication of poor understanding of the choice experiments, as robustness and reliability checks.

We perform a less rigorous assessment of how the TCN alpha and TCN lambda parameters correlate with the HL hypothetical and monetary average and variability measures before we assess how all three TCN parameters correlate with a vector of socioeconomic characteristics; see eqn. 8):

$$8)\quad \begin{aligned} \sigma_i^T &= c_{\sigma 0} + c_{\sigma 1}\alpha_i^T + c_{\sigma 2}\lambda_i^T + c_{\sigma 3}\overline{R}_i^H + c_{\sigma 4}\overline{R}_i^M + c_{\sigma 5} stdR_i^H + c_{\sigma 6} stdR_i^M + c_{\sigma 7} X_i + e_{\sigma i}^H \\ \lambda_i^T &= c_{\lambda 0} + c_{\lambda 1}\alpha_i^T + c_{\lambda 2}\sigma_i^T + c_{\lambda 3}\overline{R}_i^H + c_{\lambda 4}\overline{R}_i^M + c_{\lambda 5} stdR_i^H + c_{\lambda 6} stdR_i^M + c_{\lambda 7} X_i + e_{\lambda i}^H \\ \alpha_i^T &= c_{\alpha 0} + c_{\alpha 1}\sigma_i^T + c_{\alpha 2}\lambda_i^T + c_{\alpha 3}\overline{R}_i^H + c_{\alpha 4}\overline{R}_i^M + c_{\alpha 5} stdR_i^H + c_{\alpha 6} stdR_i^M + c_{\alpha 7} X_i + e_{\alpha i}^H \end{aligned}$$

We hypothesize that there is a learning effect that leads to more accurate responses in later series, such as in the real money series compared with the hypothetical series. This will also be reflected in stronger correlations between the TCN-PT parameters in the real money HL series than in the hypothetical HL series. The risk aversion rank variability proxy variables are included to assess whether stochastic error can also bias these TCN-PT parameter estimates. Finally, a vector of socioeconomic characteristics (X_i) is included.

Next, the flexible functional form (EP utility function) structural model with Luce stochastic errors is used to compare the EUT with objective probabilities with the PT formulation with subjective probability weights from the TCN series in the hypothetical and monetary HL series (see eqn. 2–4). This tests the sensitivity of relying on EUT rather than on PT in measuring risk aversion and allows us to assess how the choice between the two theories affects the correlation between the expo-power *r* parameter of risk aversion and a set of included RHS variables. These RHS variables include control variables (represented by vector F_j in eqn. 9), such as choice series and experimental enumerator dummy variables, as a test for starting point bias in each choice series (the starting point was randomized). Furthermore, socioeconomic variables (represented by X_{ij} in eqn. 9) are introduced in two steps, with only three variables in the first step, i.e., sex of respondent (male=1, female=0), land endowment (farm size in ha), and a dummy variable for exposure to recent drought shock (Table 9). In the second step, an extended number of socioeconomic variables such as family composition, endowments, labor market access, business activity, and market distance as well as district fixed effects are included (see eqn. 9) and Table 10). Superscript *H* represents a hypothetical choice series, superscript *M* represents a monetary choice series, superscript *E* represents models without subjective probability weighting (EUT), and superscript *P* represents models with subjective probability weighting (PT).

9)
$$\begin{aligned}
r^{HE} &= \eta_0^{HE} + \eta_1^{HE} F_j^{H} + \eta_2^{HE} X_{ij} + \upsilon_{ij}^{HE} \\
r^{ME} &= \eta_0^{ME} + \eta_1^{ME} F_j^{M} + \eta_2^{ME} X_{ij} + \upsilon_{ij}^{ME} \\
r^{HP} &= \eta_0^{HP} + \eta_1^{HP} F_j^{H} + \eta_2^{HP} X_{ij} + \upsilon_{ij}^{HP} \\
r^{HP} &= \eta_0^{MP} + \eta_1^{MP} F_j^{M} + \eta_2^{MP} X_{ij} + \upsilon_{ij}^{MP}
\end{aligned}$$

We hypothesize that including subjective probabilities for respondents leads to models with stronger predictive power and a closer correspondence between risk aversion and household characteristics. Regarding the socioeconomic variables, we hypothesize that risk aversion as captured by the *r* variable in the EP utility function is negatively related to sex of respondent (males are less risk averse) and to wealth (poor people are more risk averse) and that recent exposure to shocks makes poor people less risk averse if the value function is convex for those who have recently experienced a shock, as proposed by PT. A study in Australia (Page et al. 2014) found that respondents who had recently been badly affected by a flood in Brisbane became more willing to take a risky gamble than were respondents who had not been exposed to such a shock.

These models are estimated with Stata 13, using maximum likelihood and clustering standard errors at the respondent level. Robustness checks for clustering alternatively at the district, chiefdom (traditional authority), village and respondent levels revealed that standard errors were similar when clustering at the individual and village levels and lower when clustering at higher levels because of the small numbers of clusters (Cameron and Miller 2013).

5 Descriptive statistics

The means, medians and standard errors of the average risk aversion ranks from the hypothetical and real money HL choice series, the standard deviations of the same risk aversion ranks and the TCN sigma, alpha, and lambda are presented in Table 1.

Table 1. Descriptive statistics for HL and TCN variables

Stats	HL Hypothetical Risk Aversion Rank	HL Monetary Risk Aversion Rank	St.dev. Hypothetical Risk Aversion Rank	St.dev. Monetary Risk Aversion Rank	TCN sigma m	TCN alpha m	TCN lambda m
Mean	2.61	1.73	1.28	1.16	0.62	0.88	4.79
Median	2.25	1.50	1.15	0.96	0.60	0.80	4.23
Standard error	0.10	0.10	0.04	0.04	0.02	0.01	0.16

Source: Own experimental data

Table 1 shows that the hypothetical HL choice series gave average and median risk aversion responses that were higher than those for the HL real money choice series. As explained earlier, these variables capture the average rank distance from the risk neutral choice in these choice series and are proxy measures of risk aversion that do not depend on any particular functional form for the utility function (see Appendix 1 for the exact specification of the choice series) in which the hypothetical choice series are measured in kg of grain (maize), whereas the real money experiments are measured in the local currency (MK). The standard deviation variables for the hypothetical and real money HL choice series are derived from four series for each and are used as proxy variables for the extent of consistency (low standard deviation should indicate a higher level of consistency and fewer measurement errors) across choice series. The average TCN sigma is close to the median sigma (0.60 vs. 0.62), whereas the TCN mean alpha is 0.88 and the median is 0.80 with a standard error of 0.01, showing a clear tendency among the majority of the sample to over-weight low probabilities. The average TCN loss aversion parameter is 4.79 against the median of 4.23, and these values are substantially higher than the 2.63 found by Tanaka et al. (2010) in Vietnam and the 2.25 found by Tversky and Kahneman (1992); they are even higher than the estimate of 3.47 found by Liu (2008) for cotton farmers in China.

Table 2 provides the distribution of responses in TCN–PT series 9 and 10 that are used to derive the σ and α parameters. The bold (red) cells show the choices that are according to EUT, that is where α=1. The derived k-density parameter distributions of σ, α and λ from the TCN choice series are presented in Figures 1, 2 and 3 using the arithmetic mean of the lower and upper bounds identified from the switch points in the choice series. We can see that the distributions are skewed, with two peaks for the loss aversion parameter. There are also respondents with sigma and alpha values larger than one.

Table 2. The distribution of choices in the TCN – PT choice series 9 and 10 for identification of the alpha and sigma parameters

Choice series 10	Choice series 9 = PT series 1											
PT series 2	0	1	2	3	4	5	6	7	8	9	10	Total
0	7	0	**1**	1	7	1	1	5	5	0	5	33
1	0	1	**3**	**4**	**35**	**3**	2	4	0	4	10	66
2	1	0	0	5	9	7	**8**	**3**	**4**	4	4	45
3	1	1	2	2	7	3	3	2	1	**3**	**5**	30
4	0	0	2	1	1	2	0	3	3	3	**2**	17
5	0	0	2	0	0	2	5	3	3	3	**2**	20
6	0	1	0	0	2	5	5	5	3	2	**1**	24
7	1	0	0	0	0	3	8	2	3	1	**3**	21
8	0	0	1	1	0	3	1	4	4	5	4	23
9	1	0	0	0	0	0	0	1	2	5	2	11
10	3	2	2	0	2	0	5	3	3	5	35	60
Total	14	5	13	14	63	29	38	35	31	35	73	350

Note: The numbers in the cells show the number of responses with this combination of responses. The cells with bold red numbers are cells that represent behavior according to EUT (subjective probability weights =1)

Table 3 gives descriptive statistics of the socioeconomic conditions of the respondents and their households. Although mostly household heads were the game participants, a substantial share of the sample households were represented by another household member because the head was not available that day. We therefore included sex of respondent as well as sex of household head variables. Some of the study areas (mostly in the southern region, but partly in the central region as well) have matrilineal inheritance and matrilocal marriage/residence systems, whereas patrilineal inheritance and patrilocal marriage/residence systems are more common in the central region. Some may also have married and settled in a neutral village. We included two dummy variables to distinguish these cultural differences and locations of residences. Women have stronger positions in the matrilineal and matrilocal households.

Table 3. Respondent and household-farm characteristics

Variable	Obs	Mean	Std. Dev.	Min	Max
Sex of respondent, male=1	344	0.590	0.493	0	1
Sex of household head, 1=male	344	0.756	0.430	0	1
Residence, 1= Wife's village (base)	338	0.533			
2= Husband's village	338	0.414			
3= Neutral village	338	0.053			
Distance to market, km	339	20.628	10.939	.5	30
Age of head of household	343	46.880	16.072	1	85
Highest class attended in school	343	4.362	3.549	0	13
Male labor endowment	344	1.673	0.995	0	5.5
Female labor endowment	344	1.432	0.739	0	4.2
Consumer-worker ratio	343	1.284	0.235	1	2.75
Farm size in ha, gps-measured	334	1.234	1.443	.057	19.177
Drought shock 2012, dummy	350	0.686	0.465	0	1
Household formal employment, dummy	345	0.151	0.358	0	1
Non-agricultural business activity, dummy	344	0.451	0.498	0	1
Value of assets, '000 MK	342	4.759	15.005	0	182.6
Livestock endowment, TLU	350	0.636	2.114	0	30.92

Source: Own survey data.

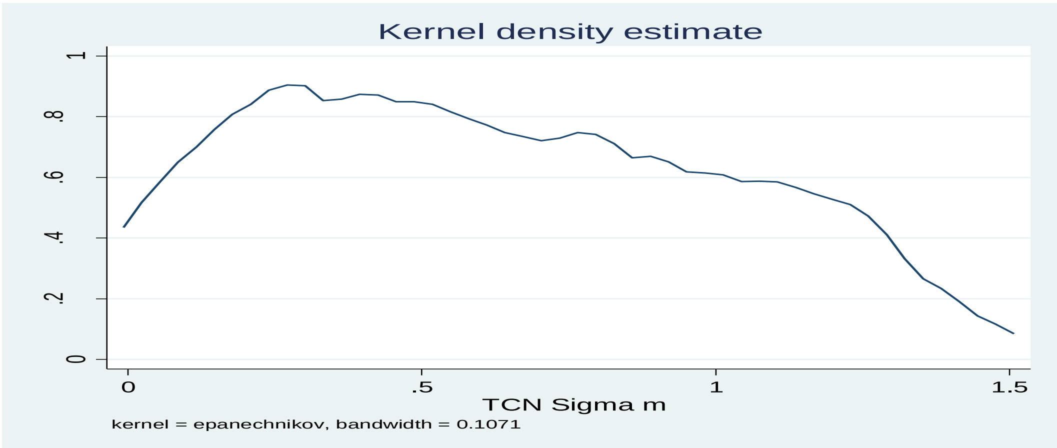

Figure 1. The distribution of the TCN sigma m parameter

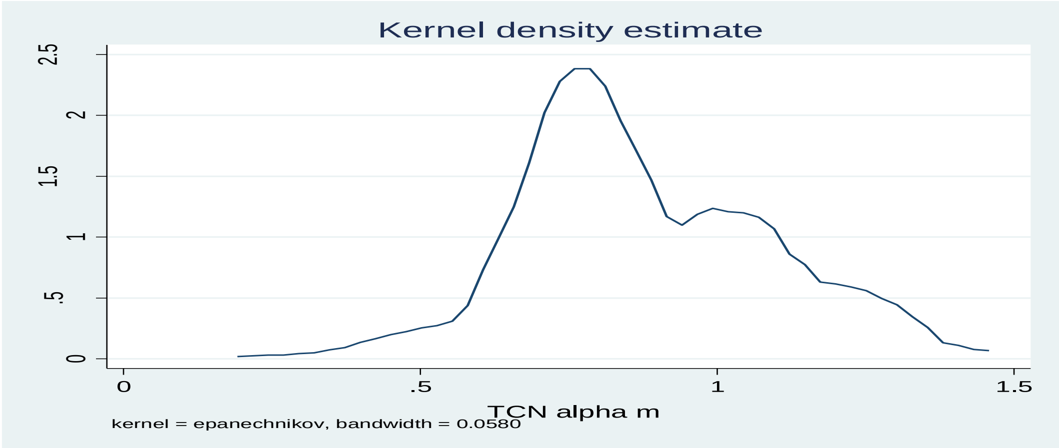

Figure 2. The distribution of the TCN alpha m parameter

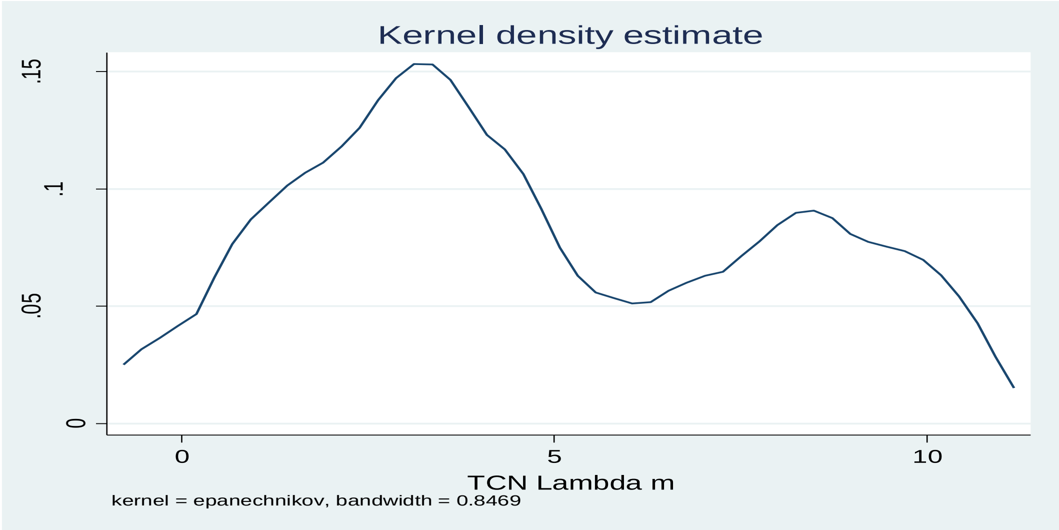

Figure 3. The distribution of the TCN lambda m parameter

6 Results

The results for the HL risk aversion rank models are presented first, including their correlations with the TCN-PT parameters. Second, the TCN sigma parameter is used as a basis for correlation analysis with other TCN–PT parameters and the HL risk aversion rank and variability estimates. Last, the structural EP utility function models of risk aversion with Luce stochastic error are presented, comparing the HL-EUT hypothetical and monetary series results with the HL-PT versions with subjective probability weighting.

6.1 HL risk aversion rank models

First, we assess the correlations and consistency of the risk aversion ranks from the hypothetical and monetary HL series with the parameters calibrated from the TCN series by regressing the first on the latter. Table 4 gives the results of these initial regressions.

Table 4. Deviation from risk-neutral choice in HL series vs TCN parameters from TCN series

	Hypothetical HL 1			Monetary HL 1		
	b		se	b		se
TCN sigma m	-1.469	****	0.321	-1.683	****	0.301
TCN alpha m	0.557		0.537	-0.782		0.486
TCN lambda m	0.025		0.035	0.087	***	0.032
Constant	2.923	****	0.436	3.069	****	0.401
Prob > F	0.000			0.000		
R-squared	0.084			0.202		
Number of observations	350			350		

Note: The dependent variable is the average deviation from the risk-neutral choice in four series, either hypothetical series or real money series. A larger positive value for the dependent variable indicates a more risk averse choice and is a step function in each choice series. OLS models with robust standard errors. Significance levels: *: 10%, **: 5%, ***: 1%, ****: 0.01%.

From Table 4, we can see good correspondence between the average deviation in the HL series and the average sigma parameter (significant at the 0.1% level) with the expected negative sign, implying that a larger average rank deviation in the HL series is associated with a lower sigma value (more curved value function). Although the alpha (probability weighting) and the lambda (loss aversion) parameters are not significantly correlated with the hypothetical HL risk aversion rank variable, the lambda parameter is positively correlated and significant at the 1% level in the monetary HL model. This may indicate that higher loss aversion is associated with more risk averse decisions in the monetary HL series after correcting for the curvature of the value function.

To further assess the reliability of the HL estimates, we included the standard deviation of the risk aversion rank variables in each of the hypothetical and real money series. A larger standard deviation may indicate that each series is a poorer approximation of the real underlying parameter. A large standard deviation may also indicate poor understanding of the questions, and that may have caused more random answers. If that is the case, we should worry whether such random answering may bias our results. We test this by assessing whether the standard deviation is correlated with the average risk aversion rank and by re-estimating the model after removing some of the observations with standard deviations higher than two (rank levels), based on a visual inspection of the standard deviation variable distribution. We used the same approach for the hypothetical and the real money models. As an additional test of the consistency between the hypothetical and real money series, we include the average rank score from the hypothetical series in the monetary series. The hypothetical and monetary average rank scores should be strongly positively correlated if they are reliable. The results of these models are presented in Table 5. The first two models are for the hypothetical HL games, with the first model including the standard deviations of the risk aversion rank score in the four hypothetical games and the second also removing the observations with risk aversion rank score standard deviations higher than two. The last three models are for the monetary HL series; the average risk aversion rank score for the hypothetical HL series is included as the RHS variable in all models, and the standard deviation of the risk aversion rank score in the monetary series is included in the last two models. Those observations with standard deviations above two in the monetary series are removed in the last model.

Table 5. Robustness checks of HL risk aversion ranks versus TCN parameters

	Hypothetical HL 2	Hypothetical HL 3	Monetary HL 2	Monetary HL 3	Monetary HL 4
TCN sigma m	-1.302****	-1.466****	-0.989****	-0.844****	-0.892****
TCN alpha m	0.663	0.821	-1.045***	-0.552	-0.316
TCN lambda m	0.024	0.019	0.075***	0.079***	0.086***
St.dev. Hyp. HL	0.617****	1.199****			
Hyp. HL average			0.473****	0.430****	0.458****
St.dev. Monetary HL				0.535****	1.065****
Constant	1.944****	1.394***	1.687****	0.635	-0.083
Prob > F	0.000	0.000	0.000	0.000	0.000
R-squared	0.142	0.156	0.415	0.464	0.495
Number of obs.	350	297	350	350	305

Note: The dependent variable is the average deviation from the risk-neutral choice in four series, either hypothetical series or real money series. A larger positive value for the dependent variable indicates a more risk averse choice and is a step function in each choice series. Significance levels: *: 10%, **: 5%, ***: 1%, ****: 0.01%.

Table 5 shows that the risk aversion rank variable standard deviations are highly significant and positive when they are included in both the hypothetical and real money models. This may imply that respondents who were less able to give good and consistent answers in these experiments caused an upward bias in the risk aversion estimates. Inclusion of the standard deviation variables substantially reduced the constant terms in the models. The significance of the coefficient on the TCN alpha parameter is also affected, and removing the less reliable respondents may lead to less correlation between over-weighting the low probabilities and the monetary HL risk aversion measure. Loss aversion remains strongly positively related to the monetary HL risk aversion rank measure in all models and appears therefore to be a robust result that is not “created” by measurement error.

The hypothetical HL average risk aversion rank variable is highly significant (0.1% level) in all models in which it is included and has a positive parameter value, showing a high level of consistency between the real money and hypothetical average risk aversion rank variables as measures of risk aversion. The same can be said for the TCN sigma measure of the curvature of the value function relative to the risk aversion ranks in the hypothetical and real money HL experiments. The parameter is always highly significant (0.1% level) with a negative parameter value, as expected by theory. This may indicate that all three of these estimates of risk aversion levels can be reasonably good approximations in a statistical sense. However, when we look at the R-square values in the regressions in Table 4, the TCN sigma parameter explains only approximately 8% of the variation in the average HL risk aversion measure in the hypothetical experiments and approximately 20% in the monetary HL risk aversion rank measure. It is therefore likely that these three measures are all approximated with substantial error. This is confirmed with the inclusion of the standard deviations from the HL series, whereas the TCN approach does not leave room for such a measure of potential measurement error. However, the field implementation revealed that the respondents had greater difficulties comprehending and responding to the first two TCN choice series that were used to derive the sigma and alpha parameters. This is also the reason for introducing these choice series to the respondents after the HL series, and this may have helped their understanding and reduced the potential measurement error problem in the TCN series.

To further assess the measurement error problem, the standard deviation measures for the hypothetical and monetary HL series are regressed on a set of household characteristic variables. The results are presented in Appendix 2, Table A2. These results reveal that the two measures of measurement error are closely positively correlated. However, their correlations with the socioeconomic variables are different (see the Appendix).

6.2 TCN parameter correlations

We will now assess how the TCN sigma parameter correlates with the HL average risk aversion rank and the risk aversion rank variable standard deviations. This should give additional insight into the sensitivity of the TCN parameters to possible measurement errors in the HL choice series. First, the HL variables are added in a step-wise fashion to assess changes in the parameters, without including the TCN alpha and lambda parameters that were jointly determined for each respondent (see Table 6). Second, we add these parameters as well to see how this affects the correlations between the TCN sigma parameter and the HL series variables (see Table 7).

Table 6 shows that the HL average hypothetical risk aversion rank variable is highly significantly and negatively related with the TCN sigma when it is included as the only RHS regressor. However, when the monetary HL risk aversion rank variable is also included, this new variable becomes highly significant with a negative sign, and the HL hypothetical risk rank variable becomes insignificant. This shows that there is a closer correspondence between the TCN sigma estimate and the monetary HL risk aversion rank measure than there is with the hypothetical HL risk aversion rank measure. When the standard deviation of the hypothetical and monetary HL risk aversion rank measures are also added (as proxies for measurement error or inconsistent HL estimates in models m3 and m5 in Table 6), these variables become significant with negative parameters. This could imply that the TCN sigma parameter is negatively biased owing to poor understanding among some respondents. After the respondents with particularly high standard deviations for the HL risk aversion rank variables (see models m4 and m6) are dropped, it appears that the downward bias in the TCN sigma estimates is reduced, as seen by the change in the constant term.

Table 6. Correlations between TCN sigma m estimates and HL risk aversion rank variables

	TCN sigma m1	TCN sigma m2	TCN sigma m3	TCN sigma m4	TCN sigma m5	TCN sigma m6
HL Hyp. Risk av. rank	-0.058****	-0.014	-0.008	-0.002	-0.013	-0.017
HL Monetary risk av. rank		-0.080****	-0.080****	-0.092****	-0.069****	-0.071****
St.dev. Hyp. Risk av. rank			-0.047*	-0.029		
St.dev. Monetary risk av. rank					-0.061**	-0.065
Constant	0.775****	0.800****	0.846****	0.832****	0.851****	0.868****
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.079	0.179	0.186	0.204	0.192	0.194
Number of obs.	350	350	350	297	350	305

Note: The dependent variable is TCN sigma m in all models. “HL Hyp. risk aversion rank” is the average rank deviation from risk neutral choice in the hypothetical risk choice series 1-4 while the “HL Monetary risk aversion rank” is the average rank deviation from the risk neutral choice in the real money risk choice series 5-8. Model m4 has dropped observations with Standard deviation of Hyp. risk aversion rank being two or larger and model m6 has dropped observations with Standard deviations of the monetary risk aversion rank being larger than two. Significance levels: *: 10%, **: 5%, ***: 1%, ****: 0.01%.

Do we obtain the same pattern if we include the TCN alpha and lambda parameter variables as additional controls? The results are shown in Table 7 and show that the HL risk aversion rank variables are negative and significant and that the risk aversion rank variable from the hypothetical HL series is significant in more of the models when the monetary HL risk aversion rank variable is included, compared with Table 6. In contrast, the standard deviations of the HL risk aversion rank variables are no longer significant.

We may draw other interesting lessons from Table 7. The TCN alpha parameter is highly significant and positively correlated with the TCN sigma dependent variable. This may indicate that respondents with higher alpha values are less risk averse and that respondents who tend to over-weight small probabilities are more risk averse; see Figure 2 for a depiction of the tendency toward TCN alpha<1. This result is more significant in Table 7 than in Tables 4 and 5, which show the same tendency. The TCN lambda variable is also significant with a negative sign in all model specifications, although the significance level is lower than that for the TCN alpha parameter. This may indicate that more loss averse respondents have more concave value functions.

Table 7. TCN sigma sensitivity to HL risk aversion rank and HL rank variability with additional TCN - PT parameters

	TCN sigma m11	TCN sigma m12	TCN sigma m13	TCN sigma m14	TCN sigma m15	TCN sigma m16
TCN alpha m	0.781****	0.689****	0.680****	0.669****	0.670****	0.673****
TCN lambda m	-0.016**	-0.012*	-0.011*	-0.016**	-0.012*	-0.014**
HL Hyp. risk av. rank	-0.049****	-0.022*	-0.019	-0.014	-0.022*	-0.025**
HL Real risk av. rank		-0.051****	-0.051****	-0.060****	-0.047****	-0.050****
St.dev. HL Hyp. risk av. rank			-0.027	-0.016		
St.dev. HL Real risk av. rank					-0.023	-0.018
Constant	0.143	0.221**	0.256**	0.274**	0.260**	0.273**
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.281	0.317	0.320	0.353	0.319	0.329
Number of obs.	350	350	350	297	350	305

Note: The same dependent variable as in Table 3 and same sequence of models except addition of the TCN alpha and TCN lambda parameter variables from TCN choice series. *Significance levels: *: 10%, **: 5%, ***: 1%, ****: 0.01%.*

Overall, we appear to find a tendency of a correlation between inaccurate HL risk aversion estimates, degree of risk aversion and a higher degree of over-weighting low probabilities, whereas risk aversion and loss aversion are positively correlated. Deviations from EU theory may therefore partly be attributable to the respondents' limited numeracy and limited comprehension of the experiments. These are novel contributions to the literature that we have been able to deduce by combining the two approaches.

In Table 8, the means of the TCN sigma, lambda and alpha parameter estimates are regressed on each other, on the HL risk aversion rank and standard deviations, and on the sex, farm size and shock exposure variables as well as an extended number of socioeconomic variables. We also include order of experiment and experimental enumerator dummy variables as additional controls. There is a loss of approximately 10% of the observations when we add all the socioeconomic variables.

Table 8. TCN parameters and correlations with HL parameters and socio-economic variables

	TCN sigma m	TCN sigma m	TCN lambda m	TCN lambda m	TCN alpha m	TCN alpha m
TCN alpha m	0.668****	0.619****	-0.025	0.292		
TCN lambda m	-0.008	-0.007			-0.000	0.001
TCN sigma m			-0.695	-0.550	0.221****	0.222****
HL Hypothetical risk aversion rank	-0.019	-0.009	-0.123	-0.076	0.016**	0.017**
HL Monetary risk aversion rank	-0.051****	-0.054****	0.399***	0.279**	-0.011	-0.007
St.dev. HL Hypothetical risk av. rank	-0.031	-0.042	0.127	-0.097	-0.000	0.006
St.dev. HL Monetary risk av. rank	-0.014	-0.011	-0.340	-0.574*	-0.044***	-0.043***
Sex respondent, 1=male	-0.005	0.024	0.709**	1.169***	-0.007	-0.023
Drought shock 2012	0.042	0.050	-0.596*	-0.316	-0.036*	-0.026
Farm size in ha	-0.028*	-0.031*	0.127	-0.094	0.011	0.007
Value of assets, '000 MK		0.002		-0.001		-0.000
Sex of household head, 1=male		0.034		0.245		-0.078**
Residence: 1= Wife’s village		Base		Base		Base
2= Husband’s village		0.047		0.050		0.028
3= Neutral village		-0.142*		0.389		0.070
Distance to market, km		0.003		0.037		-0.000
Age of household head		-0.001		0.005		-0.001
Highest class in school		-0.003		-0.019		0.002
Male labor endowment		0.034*		0.041		0.028**
Female labor endowment		0.036		-0.453*		0.002
Consumer-worker ratio		0.089		-0.651		-0.043
Formal employment, dummy		0.052		-1.120**		0.016
Non-agric. Business, dummy		0.011		-0.392		-0.001
Livestock endowment		-0.003		0.027		0.003
Order of experiment: Base=first						
Order of exp.: Second, after time pref. exp.		-0.030		-0.184		0.005
Order of exp.: Second, after input demand exp.		0.194***		-0.664		-0.029
Order of exp.: Last		-0.041		-0.143		0.012
District FE	No	Yes	No	Yes	No	Yes
Enumerator FE	No	Yes	No	Yes	No	Yes
Constant	0.288**	0.020	4.845****	4.827**	0.783****	0.844****
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
R-squared	0.335	0.428	0.081	0.233	0.260	0.321
Number of observations	331	301	331	301	331	301

Note: OLS models with robust standard errors, the table gives marginal effects. Significance levels: *: 10%, **: 5%, ***: 1%, ****: 0.01%.

Table 8 also reveals a close correspondence between the TCN sigma measure and the average HL monetary risk aversion rank measure, but TCN sigma appears not to be significantly biased by the variability in the HL risk aversion rank measures. Both models show a strong positive correlation between TCN sigma and TCN alpha, possibly indicating that more risk averse persons tend to over-weight small probabilities. TCN sigma is weakly negatively associated with the respondent wealth measure farm size, indicating that farm size is positively correlated with risk aversion. Few of the other socioeconomic variables are significantly correlated with TCN sigma.

TCN lambda (loss aversion) is significantly positively correlated with the HL monetary risk aversion rank and is significantly negatively related to the standard deviation of the HL monetary risk aversion rank measure in the second model with the extended set of socioeconomic variables. There is, therefore, no indication that measurement error or lack of comprehension can explain the high levels of loss aversion that are found. Male respondents appear to be significantly (at the 5% and 1% levels of significance) more loss averse than female respondents, and exposure to a recent drought is negatively associated with loss aversion; however, the latter result is only significant at the 10% level in one of the models. It is somewhat surprising that men are more loss averse than women. Female labor endowment is also negatively correlated with loss aversion (significant at the 10% level only). The matrilineal system that dominates in southern Malawi may give women greater security and possibly affect their loss aversion levels. Households with formal employment are significantly (at the 5% level) less loss averse.

The TCN alpha (subjective probability weighting) parameter is significantly (at the 5 % level in both models) positively correlated with the hypothetical HL risk aversion rank measure and significantly (at the 1 % level in both models) negatively associated with the standard deviation of the HL monetary risk aversion rank measure. The last result may indicate a problem with measurement error in the TCN alpha measure. Over-weighting of low probabilities may partly be attributable to comprehension problems and limited numeracy. Male household head is significantly (at the 5 % level) negatively related to TCN alpha, and male labor endowment is significantly (at the 5 % level) positively related to TCN alpha. TCN sigma is strongly positively correlated with TCN alpha, as was also found earlier.

6.3 Structural models based on the EP utility function with stochastic (Luce) errors

The structural models based on maximum likelihood estimation of the expo-power utility function with Luce error are presented below, first for the hypothetical HL choice series and then for the monetary HL choice series in Table 9. Each of these is run without and with the subjective probability weights elicited from the TCN-PT choice series. The models thus show the sensitivity of the HL EUT approach to the deviations in subjective probability weights. The models include dummies for choice series, controls for starting point bias and for effect of risk preference ordering, time preference and input demand experiments, and district and experimental enumerator dummies, in addition to sex of respondent, farm size and recent drought exposure shock as socioeconomic variables. We go on to include a number of additional socioeconomic variables in Table 10 to test their correlations with the EP *r* in the hypothetical and monetary HL choice series without and with subjective probability weighting.

Table 9 reflects significant changes in the gender and drought shock variables when subjective probability weights are included in the hypothetical HL series. Although the parameters of these variables do not change sign, they shift from being insignificant in the EUT-based models to becoming significant at the 1% and 5% levels, with females being significantly more risk averse than males under PT with subjective probability weights and exposure to a recent drought shock being significantly (at the 1% level) associated with more risk aversion. This is contrary to our hypothesis based on PT that respondents become less risk averse after a shock (Page et al. 2014).

One of the order of experiment dummy variables, for the risk experiment that was conducted last, is associated with significantly lower levels of risk aversion in both the EUT and PT specifications of the hypothetical HL series models. This could be attributable to the payout in the earlier experiment and to more familiarity with playing these types of games. The EP alpha parameter is also highly significant and negative in these hypothetical HL models, as is the EP Luce mu stochastic error parameter.

The models for the monetary HL choice series that test EUT with objective probabilities versus the TCN-PT subjective probability weights reveal no significant differences or correlations with the household characteristics variables. The parameter variability for the choice series dummy variables across the specifications shows the sensitivity of the maximum likelihood estimates to the objective versus subjective probability weighting. Unlike for the hypothetical HL series models, the EP alpha parameter is insignificant in the monetary HL models, whereas the EP Luce stochastic error parameter is significant with a positive sign, very different from the hypothetical HL series models.

In Table 10, a number of additional household characteristic variables are included to assess how they correlate with the EP *r* risk aversion measure in the hypothetical and monetary HL series without and with subjective probability weights.

Table 9. Structural models for hypothetical and monetary HL choice series with objective (EUT) versus subjective probability weighting (PT)

	Hypothetical HL EUT	Hypothetical HL with TCN-PT alpha	Monetary HL EUT	Monetary HL with TCN-PT alpha
Sex of respondent, male=1	-0.031	-0.042***	-0.011	0.013
Drought shock 2012, dummy	0.025	0.042**	-0.002	0.005
Farm size in ha, gps measured	0.003	0.003	-0.003	0.004
Choice series dummies: 1/5	Base=CS1	Base=CS1	Base=CS5	Base=CS5
CS no.2/6	-0.026	-0.013	0.029**	-0.046***
CS no.3/7	-0.019	-0.011	0.024*	-0.062****
CS no.4/8	-0.018	-0.008	0.008	-0.060***
Starting point bias test	0.007*	0.005	-0.001	-0.002
Order of experiment: Base=first				
Order of exp.: Second, after time pref. exp.	0.095	0.061	-0.040*	0.014
Order of exp.: Second, after input demand exp.	-0.024	-0.006	-0.012	0.387***
Order of exp.: Last	-0.067****	-0.100****	-0.023	0.003
Experimental enumerator FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Constant	1.264****	1.331****	0.841****	0.193
EP alpha parameter	-6.365****	-7.071****	-0.048	0.002
EP Luce mu parameter	-0.044****	-0.046****	0.027****	0.054****
Prob > chi2	0.000	0.000	0.021	0.000
Number of observations	10914	10914	11556	11556

Note: Models with expo-power utility function: factors correlated with the r parameter. Standard errors corrected for clustering at respondent level. Significance levels: *: 10%, **: 5%, ***: 1%, ****: 0.01%.

There is a striking difference in the results between the hypothetical HL series and the monetary HL series, whereas the difference between the objectively versus subjectively weighted probability specifications appears to be less significant. Different variables are significant in the monetary HL series models compared with the hypothetical HL series models, but the same variables are mostly significant with the same sign in the versions without and with subjective probability weighting for both the hypothetical and the monetary HL series.

Table 10. Structural models for hypothetical and monetary HL choice series with objective probabilities (EUT) versus subjective probability weighting (PT) with additional household characteristics

	Hypothetical HL EUT	Hypothetical HL with TCN-PT alpha	Monetary HL EUT	Monetary HL with TCN-PT alpha
Sex of respondent, male=1	-0.137****	-0.126****	0.011	0.013
Sex of household head, 1=male	0.049*	0.052*	0.017	0.008
Residence: 1= Wife's village				
2= Husband's village	0.051*	0.048****	-0.013	-0.010
3= Neutral village	-0.227****	-0.174****	-0.026	-0.025
Distance to market, km	0.012****	0.010****	0.000	0.000
Age of household head	0.001	0.001	-0.001	-0.001
Highest class in school	0.003	0.000	-0.006***	-0.005***
Male labor endowment	0.068****	0.069****	-0.029***	-0.021**
Female labor endowment	0.006	-0.009	-0.000	-0.002
Consumer-worker ratio	0.064***	0.035	-0.095**	-0.065*
Farm size in ha	0.022**	0.027**	0.001	0.002
Livestock endowment	-0.007	-0.013****	0.008****	0.006***
Value of assets, '000 MK	0.001*	0.001	-0.001	-0.000
Formal employment, dummy	0.016	-0.005	-0.026	-0.021
Non-agricultural business, dummy	-0.065****	-0.037*	-0.007	-0.005
Drought shock	0.063****	0.045****	-0.015	-0.012
Choice series dummies: 1/5	Base=CS1	Base=CS1	Base=CS5	Base=CS5
CS no.2/6	0.000	0.001	0.020**	0.023***
CS no.3/7	0.055****	0.049****	0.015	0.028***
CS no.4/8	0.064****	0.049****	-0.001	0.021*
Starting point bias test	-0.001	0.001	-0.002	-0.001
Order of experiment: Base=first				
Order of exp.: Second, after time pref. exp.	0.218****	0.133	-0.059***	-0.045**
Order of exp.: Second, after input demand exp.	0.025	0.077	-0.021	-0.015
Order of exp.: Last	0.024	0.028	-0.022	-0.014
Experimental enumerator FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Constant	1.032****	1.030****	1.065****	1.029****
EP alpha parameter	-11.058****	-9.537****	-0.068	-0.106
EP Luce mu parameter	-0.066****	-0.057****	0.029****	0.022****
Prob > chi2	0.000	0.000	0.000	0.001
Number of observations	10336	10336	10944	10944

Note: Models with expo-power utility function: factors correlated with the r parameter. Standard errors corrected for clustering at respondent level. Significance levels: *: 10%, **: 5%, ***: 1%, ****: 0.01%.

For the hypothetical HL series models, the sex of respondent variable is highly significant (at the 0.1% level of significance) with a negative sign in both models, and the drought shock exposure variable is significant at the 0.1% and 1% levels with a positive sign in both models. Male respondents therefore appear to be less risk averse, and drought shock appears to have made respondents more risk averse. The farm size variable is significant at the 5 % level in both models with a positive sign, consistent with what is found in Table 8 for TCN sigma: farm size is positively correlated with risk aversion. Male labor endowment is highly significant (at the 0.1 % level) with positive parameters, whereas livestock endowment and value of assets show less consistency in significance levels across the two models; their signs are, however, consistent. The nonagricultural business dummy variable is significantly (at the 0.1 and 10% levels) negatively correlated with risk aversion in the two models. It may not be surprising that households that are engaged in these types of businesses are less risk averse. The distance to market variable is highly significant (at the 0.1% level) with positive signs in both models, showing that households located farther away from markets are more risk averse. This may be because they face higher market access risk. This finding and the significance of the drought shock variable could indicate that risk aversion is sensitive to background risk perceptions, and the hypothetical real-world framing of these experiments revealed this.

In the monetary HL series models without and with subjective probability weighting in Table 10, we see that neither sex of respondent, farm size, nor drought shock are significant. In contrast, education (highest class in school attended) is significant at the 1% level in both models with a negative sign, indicating that more educated respondents are less risk averse in the monetary experiments. Male labor endowment is also significant (at the 1 and 5 % levels) with a negative sign, in striking contrast to the results in the hypothetical HL series models. Livestock endowment is highly significant (at the 0.1 and 1 % levels) with a positive sign. This variable also has signs opposite those found with the hypothetical HL series models. This result may indicate that more risk averse persons keep more livestock as a buffer. However, it is difficult to reconcile the stark differences between the hypothetical and monetary HL series models. The difference cannot be attributable to the sequencing (learning effect) of the experiments and hypothetical bias alone, both of which should give less reason to trust the hypothetical model findings. The high significance of a number of the socioeconomic variables shows that the real-world framing in these experiments triggered something that was not retained when we switched to the monetary experiments even though we may have benefited from improved comprehension by having run the hypothetical experiments first. The large differences in the EP alpha and EP Luce mu parameters in the hypothetical and monetary models may indicate that these models should not be pooled and run jointly. Attempts to do so also failed to find a solution.

These results may give a reason to question whether monetary (incentive-compatible) field experiments are necessarily silver bullets for eliciting poor people's risk preferences in developing countries, particularly if they live in economies with poorly functioning markets where commoditization is still at an early stage of development. An important reason for the large difference in results could also be that the stakes are much higher in the hypothetical series (57× given the average maize price at the time of the experiment). It is very costly to expose respondents to such large stake levels in field experiments and morally impossible to include games with losses at such levels. Our results indicate that realistic hypothetical real-world framing may be a useful complement to incentive-compatible monetary instruments. It may be useful to further explore and test hypothetical real-world framing versus monetary approaches in a variety of settings in which costs are otherwise prohibitively high and markets are imperfect. Similar to the study by Tanaka et al. (2010), this study was exploratory because we are still at an early stage of testing the suitability of different experimental approaches in the field in environments where respondents are poor and have limited education and markets are highly imperfect.

7 Conclusion

This paper used field experiments among poor rural respondents with limited education in Malawi to compare the Holt and Laury (2002) (HL) approach to estimating risk aversion based on EUT with the Tanaka et al. (2010) (TCN) approach to estimate three parameters, σ (curvature of value function), α (subjective probability weighting), and λ (loss aversion), based on PT. Hypothetical and monetary versions of the HL choice series were used sequentially before the TCN choice series to enhance the learning and understanding of the respondents, who had limited numeracy skills. The hypothetical HL series are framed in a real-world setting with dichotomous prospect choices of less and more risky maize varieties that gave different yields in good and bad (drought) years. Maize is the participants' main staple food crop and is susceptible to droughts that threaten their food security. Instead of imposing a specific utility function, less restrictive risk aversion rank measures consistent with rank-dependent utility are used, and their standard deviations are used as proxies for potential measurement error, derived from the HL series. Their correlations and consistency with the three elicited TCN parameters are assessed. Structural models with a flexible EP utility function with Luce error are estimated using maximum likelihood, comparing EUT-based specifications with objective probability with PT-based subjective probability weighting specifications for the hypothetical and monetary HL choice series.

The analysis reveals that the monetary HL risk aversion estimates correlate more closely with the TCN sigma risk aversion measure and that the average HL risk aversion measures may be upwardly biased because of measurement error related to inconsistent responses across the HL series. Including the standard deviation variables can help to test and control for such bias. The TCN probability weighting parameter is found to be negatively correlated with variability in the risk aversion rank measure in the monetary HL series. We therefore cannot rule out that the apparent over-weighting of small probabilities found in our study and others is partly a measurement error problem.

The theoretically more interesting findings are as follows: respondents who tend to over-weight small probabilities (have lower α parameters) are also more risk averse, and more risk averse individuals are also more loss averse. The structural EP utility function models with objective and subjective probability weights reveal that male respondents are less risk averse than female respondents in the hypothetical HL series and more loss averse in the TCN series. Recent exposure to a drought shock is associated with more risk aversion in the hypothetical HL series whether subjective probability weighting is included, whereas this exposure shows no significant correlation with risk aversion in the monetary HL and TCN data. Market distance is also highly significant and positively correlated with risk aversion in the hypothetical series but is insignificant in the monetary HL and TCN series. It appears, therefore, that the hypothetical real-world framing triggered sensitivity to background risk to a greater extent than did the monetary incentive-compatible series. Overall, the results indicate that our findings are sensitive to choice of risk elicitation method and framing, and this may be one reason for the diversity in the findings from earlier studies. More systematic comparison of methods is needed before we can have more confidence in the robustness of these results. This is an important area of future research to better understand and predict poor people's risk responses.

References

Binswanger, H. P. (1980). Attitudes toward risk: Experimental measurement in rural India. *American Journal of Agricultural Economics*, *62*(3): 395-407.

Binswanger, H. P. (1981). Attitudes toward risk: Theoretical implications of an experiment in rural India. *The Economic Journal*: 867-890.

Binswanger, H. P., and Sillers, D. A. (1983). Risk aversion and credit constraints in farmers' decision-making: A reinterpretation. *The Journal of Development Studies*, *20*(1): 5-21.

Binswanger, H. P. and Rosenzweig, M. R. (1986). Behavioural and material determinants of production relations in agriculture. *The Journal of Development Studies* 22(3): 503-539.

Cameron, A. C. and Miller, D. L. (2013). A Practitioner's Guide to Cluster-Robust Inference. Department of Economics, University of California – Davis, Davis. Version 15.October, 2013.

Diecidue, E., and Wakker, P. P. (2001). On the intuition of rank-dependent utility. *Journal of Risk and Uncertainty* 23(3): 281-298.

Fafchamps, M. (2004). *Rural Poverty, Risk and Development.* Northampton, MA: Edward Elgar.

FewsNet (2012). Malawi Food Security Outlook Update. September 2012. FewsNet, Lilongwe (www.fews.net/malawi).

Harrison, G. W. and Rutström, E. E. (2008). Risk Aversion in Experiments. *Research in Experimental Economics* 12: 41-196.

Harrison, G. W., Humphrey, S. J. and Verschoor, A. (2009). Choice under Uncertainty: Evidence from Ethiopia, India and Uganda. *The Economic Journal*, 120: 80-104.

Holt, C.A., and Laury, S.K. (2002). Risk Aversion and Incentive Effects. *American Economic Review* 92(5): 1644-1655.

Humphrey, S. J., and Verschoor, A. (2004a). Decision-making under risk among small farmers in East Uganda. *Journal of African Economies* 13(1): 44-101.

Humphrey, S. J., and Verschoor, A. (2004b). The Probability Weighting Function: Experimental Evidence from Uganda, India and Ethiopia. *Economic Letters* 84: 419-425.

Jacobson, S., and Petrie, R. (2009). Learning from mistakes: What do inconsistent choices over risk tell us? *Journal of Risk and Uncertainty* 38(2): 143-158.

Kahneman, D., and Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica* 47(2): 263-291.

OECD, UNDP, UNECA and AFDP (2012). The African Economic Outlook. Promoting Youth Employment – Malawi Country Note. OECD Development Centre, Issy les Moulineaux.

Page, L., Savage, D. A. and Torgler, B. (2014). Variation in risk seeking behavior following large losses: A natural experiment. *European Economic Review* 71: 121-131.

Prelec, D. 1998. The Probability Weighting Function. *Econometrica* 66(3): 497-527.

Quiggin, J. (1991). Comparative statics for rank-dependent expected utility theory. *Journal of Risk and Uncertainty* 4(4): 339-350.

Saha, A. (1993). Expo-Power Utility: A Flexible Form for Absolute and Relative Risk Aversion *American Journal of Agricultural Economics* 75(4): 905-913.

Tanaka, T., Camerer, C. F. and Nguyen, Q. (2010). Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review* 100(1): 557-571.

Tanaka, Y. and Munro, A. (2013). Regional Variation in Risk and Time Preferences: Evidence from a Large-scale Field Experiment in Rural Uganda. *Journal of African Economies* 23 (1): 15-87.

Tversky, A., and Kahneman, D. (1992). "Advances in Prospect Theory: Cumulative Representation of Uncertainty." *Journal of Risk and Uncertainty* 5: 297–323.

Wik, M., Aragie, T. K., Bergland, O. and Holden, S. T. (2004). On the Measurement of Risk Aversion from Experimental Data. *Applied Economics* 36: 2443-2451

Yesuf, M. and Bluffstone, R. A. (2009). Poverty, Risk Aversion, and Path Dependence in Low-income Countries: Experimental Evidence from Ethiopia. *American Journal of Agricultural Economics* 91(4): 1022-1037.

Appendix 1. Experimental protocol for risk preference experiments

Instructions to enumerators: Randomize the order of the risk preference, the time preference and the input demand experiments. All games should be played with the head of the household. Find a room in a school in the (neighborhood of the) village with tables and chairs where each of you can invite one player (household head) at the time to do the interview/experiments without disturbance. Give them an appointment.

They should get a participation amount (MK 1000) that they have to be prepared to lose (some of) in the experiments. There is a large number of tasks to be evaluated by each of the respondents. You have to take the time that is needed for them to think about each task such that they understand it and make proper selection based on their own preferences. Explain to them that a lottery will be used to identify which of the series of games that they will play that will be real and give them a real payout.

Risk preference experiments

First four series: Choice between alternative maize varieties. Two types of years: Bad years (drought) and good years (no drought). Varying probability of bad year (number of bad years out of 10) & varying yield outcome levels for varieties in good and bad years. When they choose the Variety they do not know what type of year they will get (good or bad), only the chance (in number of years out of ten) of a bad year. Based on this they should chose their preferred variety. Lotteries come in series, where your task is to identify the switch point in each series where typically only one variable (e.g. the probability of good or bad years) changes at the time. Rational behavior implies that there will be only one switch point in each of the series (or in some cases they will not switch at all). If they switch back and forth this is an indication that they have not understood the game or answer carelessly. Your task is to make sure that they understand and make careful (preferred choices). You therefore need to be patient, especially in the beginning to make them understand. Demonstrating the outcomes with money or other tools can be helpful. Such demonstration methods should be standardized in our initial testing of the survey instrument and framing methods. We use playing cards (cards 1-10) to illustrate probabilities and to randomly draw starting point values.

After careful completion of the whole interview and making of choices, there will be a random sampling of the series and game in the series that will give the actual payout. After this the household head will be given her/his reward based on the outcome of the sampling and actual choices made. After that they are asked to go home and should not talk to other households who have not yet been interviewed or played the game. It is important that they respect this.

Risk of starting point bias: Randomize the task you start with in each series (pull a card). Move towards the end point in the direction you expect a switch to check whether you get it. Narrow in on the switch point.

Instructions to players (household heads):
We have rewarded you with an initial payment of MK 1000 for coming to play the game. You are likely to win more but may also expect to lose some of the MK 1000 in the games to be played. Rewards depend on outcomes in lotteries and choices made by you during the game. If you make careful decisions you are more likely to get preferred rewards over less preferred rewards. The experiments include choices of maize varieties with different outcomes in drought years and years with good rainfall, alternative lotteries with money, lotteries with payments at different points in time, and lotteries with maize seeds (2 kg bags) and fertilizers (5 kg bags).
The rewards will vary in the different lotteries which come in series.
At the end a lottery will be used to identify which of the choice series will be for real payout. After they have received their reward(s) they should go home and not talk to anybody who has not yet played the game. That is very important.

Choice series 1 (Chose between Variety 1 and Variety 2 when probability of drought varies)

		Variety 1 (Lottery A)				**Variety 2 (Lottery B)**			
		Yields in kg/ha				**Yields in kg/ha**			
Task	Probability of bad year, %	Bad year	Good year	Expected yield	Choice	Bad year	Good year	Expected yield	Choice
11	10	1000	2000	1900		100	4000	3610	
12	20	1000	2000	1800		100	4000	3220	
13	30	1000	2000	1700		100	4000	2830	
14	40	1000	2000	1600		100	4000	2440	
15	50	1000	2000	1500		100	4000	2050	
16	60	1000	2000	1400		100	4000	1660	
17	70	1000	2000	1300		100	4000	1270	
18	80	1000	2000	1200		100	4000	880	

Choice series 2(Chose between Variety 3 and Variety 2 when probability of drought varies)

		Variety 3 (Lottery A)				**Variety 2 (Lottery B)**			
		Yields in kg/ha				**Yields in kg/ha**			
Task	Probability of bad year, %	Bad year	Good year	Expected yield	Choice	Bad year	Good year	Expected yield	Choice
21	10	1000	1500	1450		100	4000	3610	
22	20	1000	1500	1400		100	4000	3220	
23	30	1000	1500	1350		100	4000	2830	
24	40	1000	1500	1300		100	4000	2440	
25	50	1000	1500	1250		100	4000	2050	
26	60	1000	1500	1200		100	4000	1660	
27	70	1000	1500	1150		100	4000	1270	
28	80	1000	1500	1100		100	4000	880	

Choice series 3 (Chose between Variety 3 and Variety 4 when probability of drought varies)

		Variety 3 (Lottery A)				**Variety 4 (Lottery B)**			
		Yields in kg/ha				**Yields in kg/ha**			
Task	Probability of bad year, %	Bad year	Good year	Expected yield	Choice	Bad year	Good year	Expected yield	Choice
31	10	1000	1500	1450		500	4000	3650	
32	20	1000	1500	1400		500	4000	3300	
33	30	1000	1500	1350		500	4000	2950	
34	40	1000	1500	1300		500	4000	2600	
35	50	1000	1500	1250		500	4000	2250	
36	60	1000	1500	1200		500	4000	1900	
37	70	1000	1500	1150		500	4000	1550	
38	80	1000	1500	1100		500	4000	1200	
39	90	1000	1500	1050		500	4000	850	

Choice series 4(Chose between Variety 3 and Variety 5 when probability of drought varies)

		Variety 3 (Lottery A)				**Variety 5 (Lottery B)**			
		Yields in kg/ha				Yields in kg/ha			
Task	Probability of bad year, %	Bad year	Good year	Expected yield	Choice	Bad year	Good year	Expected yield	Choice
41	10	1000	1500	1450		800	4000	3680	
42	20	1000	1500	1400		800	4000	3360	
43	30	1000	1500	1350		800	4000	3040	
44	40	1000	1500	1300		800	4000	2720	
45	50	1000	1500	1250		800	4000	2400	
46	60	1000	1500	1200		800	4000	2080	
47	70	1000	1500	1150		800	4000	1760	
48	80	1000	1500	1100		800	4000	1440	
49	90	1000	1500	1050		800	4000	1120	

Instructions to players: The following experiments involve money (MK) rather than maize yields. Here is a chance of winning real money in these experiments. One of the experiments will be chosen for real payout. Your choices will affect a potential payout from the experiments. You should therefore make careful judgment and decisions. The game for payout will be sampled after you have responded to a series of lottery choices.

Choice series 5: Chose between Lottery A and Lottery B when probability of bad outcome varies

	Lottery A					Lottery B			
	Outcome in MK					Outcome in MK			
Task	Probabi-lity of bad outcome, %	Bad	Good	Expected	Choice	Bad	Good	Expected	Choice
51	10	1000	2000	1900		100	4000	3610	
52	20	1000	2000	1800		100	4000	3220	
53	30	1000	2000	1700		100	4000	2830	
54	40	1000	2000	1600		100	4000	2440	
55	50	1000	2000	1500		100	4000	2050	
56	60	1000	2000	1400		100	4000	1660	
57	70	1000	2000	1300		100	4000	1270	
58	80	1000	2000	1200		100	4000	880	
59	90	1000	2000	1100		100	4000	490	

Choice series 6: Chose between Lottery A and Lottery B when probability of bad outcome varies

	Lottery A					Lottery B			
	Outcome in MK					Outcome in MK			
Task	Probability of bad outcome, %	Bad	Good	Expected	Choice	Bad	Good	Expected	Choice
61	10	1000	1500	1450		100	4000	3610	
62	20	1000	1500	1400		100	4000	3220	
63	30	1000	1500	1350		100	4000	2830	
64	40	1000	1500	1300		100	4000	2440	
65	50	1000	1500	1250		100	4000	2050	
66	60	1000	1500	1200		100	4000	1660	
67	70	1000	1500	1150		100	4000	1270	
68	80	1000	1500	1100		100	4000	880	
69	90	1000	1500	1050		100	4000	490	

Choice series 7: Chose between Lottery A and Lottery B when probability of bad outcome varies

		Lottery A				**Lottery B**			
		Outcome in MK				**Outcome in MK**			
Task	Probability of bad, %	Bad	Good	Expected	Choice	Bad	Good	Expected	Choice
71	10	1000	1500	1450		500	4000	3650	
72	20	1000	1500	1400		500	4000	3300	
73	30	1000	1500	1350		500	4000	2950	
74	40	1000	1500	1300		500	4000	2600	
75	50	1000	1500	1250		500	4000	2250	
76	60	1000	1500	1200		500	4000	1900	
77	70	1000	1500	1150		500	4000	1550	
78	80	1000	1500	1100		500	4000	1200	
79	90	1000	1500	1050		500	4000	850	

Choice series 8: Chose between Lottery A and Lottery B when probability of bad outcome varies

		Lottery A				**Lottery B**			
		Outcome in MK				Outcome in MK			
Task	Probability of bad, %	Bad	Good	Expected	Choice	Bad	Good	Expected	Choice
81	10	1000	1500	1450		800	4000	3680	
82	20	1000	1500	1400		800	4000	3360	
83	30	1000	1500	1350		800	4000	3040	
84	40	1000	1500	1300		800	4000	2720	
85	50	1000	1500	1250		800	4000	2400	
86	60	1000	1500	1200		800	4000	2080	
87	70	1000	1500	1150		800	4000	1760	
88	80	1000	1500	1100		800	4000	1440	
89	90	1000	1500	1050		800	4000	1120	

Prospect theory series: In each of the following series probabilities stay constant across tasks but vary across prospects. Prospect A is kept constant within a series but good outcome is increasing with task number in Prospect B. Identify the switch point like in earlier series (expect switch from Prospect A to Prospect B at some point).

PT1		**Prospect A**								
Task	Probability of bad outcome, %	Bad	Good	Expected yield	Choice	Probability of bad outcome, %	Bad	Good	Expected yield	Choice
P1	60	1000	4000	2200		90	500	7000	1150	
P2	60	1000	4000	2200		90	500	10000	1450	
P3	60	1000	4000	2200		90	500	13000	1750	
P4	60	1000	4000	2200		90	500	16000	2050	
P5	60	1000	4000	2200		90	500	19000	2350	
P6	60	1000	4000	2200		90	500	22000	2650	
P7	60	1000	4000	2200		90	500	25000	2950	
P8	60	1000	4000	2200		90	500	28000	3250	
P9	60	1000	4000	2200		90	500	35000	3950	
P10	60	1000	4000	2200		90	500	50000	5450	

PT2		**Prospect A**				**Prospect B**				
Task	Probability of bad outcome, %	Bad	Good	Expected yield	Choice	Probability of bad outcome, %	Bad	Good	Expected yield	Choice
P11	10	1500	2000	1950		30	250	2500	1825	
P12	10	1500	2000	1950		30	250	2750	2000	
P13	10	1500	2000	1950		30	250	3000	2175	
P14	10	1500	2000	1950		30	250	3250	2350	
P15	10	1500	2000	1950		30	250	3500	2525	
P16	10	1500	2000	1950		30	250	3750	2700	
P17	10	1500	2000	1950		30	250	4000	2875	
P18	10	1500	2000	1950		30	250	4500	3225	
P19	10	1500	2000	1950		30	250	5000	3575	
P20	10	1500	2000	1950		30	250	6000	4275	

Payment for Risk preference games: Use 6 cards (1-6) to identify which of the 6 series with money above should be selected for payout. Then allow households to pick a card out of 10 to identify which of the tasks in the selected series will be used for payout. You use the Prospect they have chosen for that task, prospect A or B. For that chosen Prospect you identify the probability of Good and Bad outcomes and assign card numbers to each, e.g. 40% probability of Good outcome in PT1 game implies that you assign cards 1-4 to Good and cards 5-10 to Bad outcome. After that you shuffle the cards and ask the farmer to pull one card. If the card is 1-4 you pay them the Good outcome of MK 4000 for PT1 and you give them MK 1 000 if the card number they pick is above 4.

Payment in risk preference experiments:

Series chosen for payout (Respondent pulls 1 out of 6 cards):________________

Task chosen for payout (Respondent pulls 1 of 9 or 10 cards:________________

Identify whether the Respondent had chosen Prospect A or B for that Task: Prospect chosen:__________

Allocate cards according to probabilities in Task chosen, and ask respondent to pull a card to assess whether the number is associated to the Bad or Good Outcome.

Card pulled:_________

Card implies: 1=Win, 0=Loss

Amount won:__________

Signature for amount received:________________

Loss Aversion experiment (with money)

- The household head has been given 1000 MK that s/he will have to risk all or some of in the following game.
    - **Instructions to players**: You have a choice between participating in two lotteries. Each of them has a 50% chance of winning, and 50% chance of losing (by tossing a coin). First choice: "Lottery A will give you MK 1250 extra if the coin toss lands on Head, and you have to give back MK 200 if it lands on Tail. Lottery B will give you MK 1500 extra if coin lands on Head but you will lose all the MK 1000 if it lands on Tail. Do you choose Lottery A or Lottery B?
- **Instructions to instructors**: Introduce each of the seven lottery choices in a similar way as above to determine the switch point from Lottery A to Lottery B. Tick the preferred lottery (A or B) in each row. Only one of these seven games will be randomly sampled and played for real (by selecting one card out of seven numbered from 1 to 7. For the selected task you see whether they chose Prospect A or B. For the prospect they chose you toss the coin to identify whether they win or lose.
- There should typically be one switch point where they switch from Lottery A to Lottery B (consistent behavior) but always choosing one of the lotteries would also be consistent.

	Prospect A					**Prospect B**				
Task	Probability of bad outcome, %	Win	Loss	Expected yield	Choic e	Probability of bad outcome, %	Win	Loss	Expected yield	Choice
L1	50	1250	-200	525		50	1500	-1000	250	
L2	50	200	-200	0		50	1500	-1000	250	
L3	50	50	-200	-75		50	1500	-1000	250	
L4	50	50	-200	-75		50	1500	-800	350	
L5	50	50	-400	-175		50	1500	-800	350	
L6	50	50	-400	-175		50	1500	-700	400	
L7	50	50	-400	-175		50	1500	-550	475	

Mark the play that was sampled to be real: **Game no**:______

Outcome of the game: Amount lost:______________ Amount won:_________

Signature of player:__________________________

Appendix 2.

Table A2.1. Payment levels in experiments in daily wage rates (DWR)

	Less risky option		More risky option	
	Min	Max	Min	Max
HL series	3,2	6,3	0,3	12,6
HL hypothetical series[1]	183,0	365,9	18,3	731,9
TCN gain only series	3,2	12,6	0,8	157,7
TCN LA series	-1,3	3,9	-3,2	4,7

Note: [1] Assuming a maize price of 58MK/kg.

Table A2.2. Measurement error in HL series regressed on socio-economic variabes

	StdevHL Hyp.	StdevHL Monetary	StdevHL Hyp. with RHS: Stdev HL Monetary	StdevHL Monetary with RHS: StdevHL Hyp.
Sex of respondent, male=1	0.297***	0.094	0.276**	0.021
Sex of household head, 1=male	0.087	0.194	0.044	0.172
Residence: 1= Wife's village				
2= Husband's village	0.037	0.019	0.032	0.010
3= Neutral village	-0.291*	-0.282*	-0.229	-0.209
Distance to market, km	-0.001	-0.000	-0.001	0.000
Age of household head	0.009***	0.002	0.008***	-0.000
Highest class in school	-0.007	-0.012	-0.005	-0.010
Male labor endowment	0.013	-0.058	0.026	-0.061
Female labor endowment	-0.097	-0.038	-0.088	-0.014
Consumer-worker ratio	0.198	-0.174	0.236	-0.224
Drought shock	0.111	-0.070	0.126	-0.097
Farm size in ha	-0.061****	-0.030	-0.054***	-0.014
Formal employment, dummy	-0.032	-0.177	0.007	-0.168
Non-agricultural business, dummy	0.097	-0.050	0.108	-0.074
Tool index	-0.038	-0.034	-0.031	-0.024
Information index	0.104*	0.008	0.102*	-0.018
Sale revenue	0.000	-0.000	0.000	-0.000
Livestock endowment	-0.005	0.081**	-0.023	0.082***
Value of assets, '000 MK	0.002	0.001	0.002	0.001
District FE	Yes	Yes	Yes	Yes
Order of experiment, FE	Yes	Yes	Yes	Yes
Enumerator FE	Yes	Yes	Yes	Yes
Stdev HL Monetary			0.222****	
Stdev HL Hypothetical				0.249****
Constant	0.007	1.285**	-0.278	1.283**
Prob > F	0.015	0.004	0.000	0.000
R-squared	0.144	0.190	0.191	0.234
Number of obs.	300.000	300.000	300.000	300.000

Note: OLS models, the table gives marginal effects. Significance levels: *: 10%, **: 5%, ***: 1%, ****: 0.01%.

Table A2.3. Measurement error in HL series regressed on socio-economic variabes

	StdevHL Hyp.	StdevHL Monetary	StdevHL Hyp. with RHS: Stdev HL Monetary	StdevHL Monetary with RHS: StdevHL Hyp.
Sex of respondent, male=1	0.292***	0.113	0.268**	0.041
Sex of household head, 1=male	0.090	0.191	0.049	0.169
Residence: 1= Wife's village=base				
2= Husband's village	0.040	0.025	0.034	0.015
3= Neutral village	-0.297*	-0.283*	-0.235	-0.211
Distance to market, km	-0.000	0.001	-0.001	0.001
Age of household head	0.007**	0.001	0.007**	-0.001
Highest class in school	-0.004	-0.015	-0.001	-0.014
Male labor endowment	0.017	-0.069	0.032	-0.073
Female labor endowment	-0.101*	-0.053	-0.090	-0.028
Consumer-worker ratio	0.170	-0.240	0.222	-0.282
Drought shock	0.124	-0.073	0.140	-0.104
Farm size in ha	-0.053***	-0.034	-0.046**	-0.021
Formal employment, dummy	-0.037	-0.199	0.006	-0.190
Non-agricultural business, dummy	0.122	-0.055	0.134	-0.085
Value of assets, '000 MK	0.003	0.001	0.003	0.000
Livestock endowment, TLU	-0.005	0.078**	-0.022	0.079***
Stdev HL Monetary			0.218****	
Stdev HL Hypothetical				0.244***
District FE	Yes	Yes	Yes	Yes
Order of experiment, FE	Yes	Yes	Yes	Yes
Enumerator FE	Yes	Yes	Yes	Yes
Constant	0.082	1.348**	-0.212	1.328**
Prob > F	0.010	0.003	0.000	0.000
R-squared	0.135	0.186	0.181	0.230
Number of obs.	302	302	302	302

Note: OLS models, the table gives marginal effects. Significance levels: *: 10%, **: 5%, ***: 1%, ****: 0.01%.

Table A2.4. TCN parameter models with alternative extended set of socio-economic variables

	TCN sigma m	TCN sigma m	TCN lambda m	TCN lambda m	TCN alpha m	TCN alpha m
TCN alpham	0.651****	0.679****	0.195	-0.058		
TCN lambdam	-0.010	-0.007			0.001	-0.000
TCN sigmam			-0.832	-0.635	0.216****	0.229****
St.dev. HL Hyp.1_4	-0.030	-0.028	0.175	0.182	-0.003	0.000
St.dev.HL Mon.5_8	-0.014	-0.015	-0.357	-0.341	-0.045***	-0.042***
Av. HL risk av. Hyp.	-0.017	-0.018	-0.143	-0.098	0.015**	0.015**
Av. HL risk av. Mon.	-0.053****	-0.053****	0.413***	0.391***	-0.012	-0.010
Sex respondent	-0.023	-0.034	-0.277	-0.229	0.010	0.008
Drought shock 2012	0.046	0.034	-0.673*	-0.585	-0.042*	-0.038*
Farm size in ha	-0.026*	-0.028*	0.093	0.087	0.011	0.009
Hh. Formal employ		0.031		-0.746		0.004
Non-agric. business		-0.000		-0.421		0.002
Tool index		-0.007		0.042		0.008
Information index		0.033		0.081		-0.014
Sale revenue		0.000		0.000		0.000
Livestock endowm.		-0.004		-0.010		0.002
Constant	0.309**	0.274**	5.419****	5.390****	0.785****	0.755****
Prob > F	0.000	0.000	0.002	0.011	0.000	0.000
R-squared	0.330	0.352	0.073	0.079	0.256	0.267
Number of obs.	333	327	333	327	333	327

Note: OLS models, the table gives marginal effects. Significance levels: *: 10%, **: 5%, ***: 1%, ****: 0.01%.

Table A2.5. Structural models for hypothetical and monetary HL choice series with objective probabilities (EUT) versus subjective probability weighting (PT) with additional household characteristics

	Hypothetical HL EUT	Hypothetical HL with TCN-PT alpha	Monetary HL EUT	Monetary HL with TCN-PT alpha
Sex of respondent, male=1	-0.081****	-0.082****	-0.007	0.002
Drought shock 2012, dummy	0.081****	0.076***	0.010	-0.004
Farm size in ha, gps measured	0.023**	0.023	0.003	-0.000
Apply for loan in 2011/12 dummy	0.098***	0.097**	0.028	-0.023**
Household formal employment, dummy	-0.013	-0.015	0.019	-0.012
Non-agricultural business dummy	-0.038***	-0.039*	0.009	-0.002
Tool index	-0.014***	-0.014**	0.007	-0.003
Information access index	-0.019****	-0.020***	0.008	-0.003
Sale revenue in mMK	-0.057***	-0.048*	-0.003	-0.063
Livestock endowment (TLU)	-0.007****	-0.007****	-0.005	0.005**
Residence area: Husband's village	Base	Base	Base	Base
Wife's village	-0.037***	-0.032**	-0.020	0.018
Neutral village	-0.048****	-0.043****	-0.058	0.045**
Husband's and wife's village	0.087	0.105	-0.040	0.006
Choice series dummies: 1/5	Base=CS1	Base=CS1	Base=CS5	Base=CS5
CS no.2/6	-0.010**	-0.011	-0.044***	0.025***
CS no.3/7	-0.008	-0.010	-0.053**	0.030***
CS no.4/8	0.002	0.000	-0.043*	0.022**
Starting point bias test	-0.001	-0.002	-0.002	-0.000
Order of experiment: Base=first				
Order of exp.: Second, after time pref. exp.	0.136****	0.131***	0.022	-0.046**
Order of exp.: Second, after input demand exp.	0.066**	0.067*	0.115	-0.012
Order of exp.: Last	-0.073****	-0.072****	-0.030	-0.016
Experimental enumerator FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Constant	1.444****	1.438****	0.167	0.869****
EP alpha constant	-9.662****	-9.124****	0.001	-0.095
EP Luce mu constant	-0.058****	-0.054****	0.060****	0.022****
Prob > chi2	0.000	0.000	0.000	0.031
Number of observations	10642	10642	11268	11268

Note: Models with expo-power utility function: factors correlated with the r parameter. Standard errors corrected for clustering at respondent level. Significance levels: *: 10%, **: 5%, ***: 1%, ****: 0.01%.