WPS7137

Policy Research Working Paper 7137

Measuring Risk Preferences in Rural Ethiopia

Risk Tolerance and Exogenous Income Proxies

Ferdinand M. Vieider
Abebe Beyene
Randall Bluffstone
Sahan Dissanayake
Zenebe Gebreegziabher
Peter Martinsson
Alemu Mekonnen

WORLD BANK GROUP
Development Research Group
Environment and Energy Team
December 2014

Abstract

Risk-aversion has generally been found to decrease in income. This may lead one to expect that poor countries will be more risk-averse than rich countries. Recent comparative findings with students, however, suggest the opposite, giving rise to a risk-income paradox. This paper tests this paradox by measuring the risk preferences of more than 500 household heads spread over the highlands of Ethiopia and finds high degrees of risk tolerance. The paper also finds risk tolerance to increase in income proxies, thus completing the paradox. Using exogenous proxies, the paper concludes that part of the causality must run from income to risk tolerance. The findings suggest that risk preferences cannot be blamed for the failure to adopt new technologies. Alternative explanations are discussed.

This paper is a product of the Environment and Energy Team, Development Research Group. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://econ.worldbank.org. The authors may be contacted at fvieider@gmail.com.

Measuring risk preferences in rural Ethiopia: Risk tolerance and exogenous income proxies*

Ferdinand M. Vieider† Abebe Beyene‡ Randall Bluffstone§

Sahan Dissanayake¶ Zenebe Gebreegziabher‖ Peter Martinsson** Alemu Mekonnen††

Keywords: risk preferences; development; experimental methodology
JEL-classification: C93; D03; D80; O12

*This study was financed by the World Bank's Knowledge for Change Program and the Trust Fund for Environmentally and Socially Sustainable Development. The views expressed in the paper are the authors' alone and should not be attributed to the World Bank or its member countries. Tobias Schmidt and Roel van Veldhuizen provided helpful suggestions. All errors remain ours alone.

†Corresponding author: WZB Berlin Social Science Center, Risk & Development Unit, Reichpietschufer 50, 10785 Berlin, Germany. Email: ferdinand.vieider@wzb.eu; Tel: +49-30- 25491426

‡EfD Ethiopia
§Portland State University, USA
¶Colby College, USA
‖Mekelle University, Ethiopia
**University of Gothenburg, Sweden
††Addis Ababa University, Ethiopia

Measuring Risk Preferences in Rural Ethiopia: Risk Tolerance and Exogenous Income Proxies

1 Introduction

Uncertainty is a central fact in economic activity, and in human life in general. People in developing countries are especially exposed to the vagaries of fate, since their income strongly depends on highly variable weather patterns and formal insurance against catastrophic events rarely exists. Nevertheless, our understanding of risk preferences and the role they play in the lives of rural populations in developing countries is still quite limited.

Poor inhabitants of developing countries have long been considered to be quite risk averse (see Haushofer and Fehr, 2014, for a recent review). This conclusion is mostly based on the fundamental economic intuition that risk aversion should decline in wealth or income—an intuition that has indeed found considerable empirical support within various countries (Donkers, Melenberg and Van Soest, 2001; Dohmen, Falk, Huffman, Sunde, Schupp and Wagner, 2011; Hopland, Matsen and Strøm, 2013).[1] Recent cultural comparisons of risk preferences using student samples have, however, found risk aversion to be considerably *lower* in developing countries than in rich, developed countries (Rieger, Wang and Hens, 2014; Vieider, Lefebvre, Bouchouicha, Chmura, Hakimov, Krawczyk and Martinsson, 2014).[2] Taken together with the prevalent within-country result of risk

[1] Even though there is considerable support for this hypothesis, not all studies find evidence for the relationship. For instance, Tanaka, Camerer and Nguyen (2010) and von Gaudecker, van Soest and Wengström (2011) only found the correlation for gain-loss prospects, and not for pure gain prospects (see also Booij, Praag and Kuilen, 2010). Harrison, Lau and Rutström (2007) even found an effect to the contrary in the Danish population, while Noussair, Trautmann and van de Kuilen (2014) found a significant effect in a representative sample of the Dutch population only after controlling for household wealth.

[2] While there are other comparison studies, they have usually too few countries to allow for

aversion decreasing in income, the finding of risk aversion increasing in income per capita between countries yields a *risk-income paradox*.

In this paper, we test the generality of the paradox by measuring the risk preferences of a large sample of the Ethiopian rural population, covering regions of rural Ethiopia encompassing about 80% of the Ethiopian population and 70% of its landmass. Notwithstanding some growth over the last decade, Ethiopia remains one of the poorest countries in the world, with a GDP per capita of $1354 in 2013 using PPP. The paper makes three main contributions to the literature:

1. We expand the results from the country comparison using students reported by Vieider, Chmura and Martinsson (2012) and Vieider et al. (2014) to a large, rural population sample of one of the poorest countries in the world as measured by GDP per capita. Since we use the same type of experimental task, the results are comparable, which allows us to draw inferences on the similarity or difference of risk preferences.[3] Other than Vieider, Truong, Martinsson and Pham Khanh (2013), who use a geographically confined sample of Vietnamese farmers, we use a large sample of the rural population of the Ethiopian heartland.

2. We further test the risk-income paradox by examining the correlation of risk preferences with various proxies for income and wealth within our subject pool. Going beyond the correlational analysis in the previous literature, we obtain proxies that can plausibly be considered as exogenous to test for the direction of causality in the relationship between risk preferences and income. We also relate the risk preferences of our adult sample to their physical height and weight, which serve as a proxy for childhood socio-economic conditions (Peck and Lundberg, 1995). For Ethiopia in particular,

statistical between-country analysis. Liebenehm and Waibel (2014) recently compared African farmers to Asian rural subject pools. Weber and Hsee (1998) used a hypothetical lottery question to compare risk preferences in four countries.

[3]The large majority of previous investigations of risk preferences in developing countries use a task developed by Binswanger (1980). The latter is rather less well suited for comparisons, since it has rarely been used in the West—we will return to the implications of this in the discussion.

Dercon and Porter (2014) have shown that shocks in early childhood result in significantly lower physical stature in adulthood.

3. We show the power of certainty equivalents as a method to measure risk preferences in a development setting. While being a standard tool in decision theory (see e.g. Abdellaoui, Baillon, Placido and Wakker, 2011; Bruhin, Fehr-Duda and Epper, 2010, for recent applications), this technique has so far received little attention in development economics. Certainty equivalents have a number of virtues, and they are easy to explain and deploy. The possibility to represent choices physically through devices known to the subjects results in low inconsistency rates and rationality violations, even though 38% of our subjects are illiterate. We deploy a rich set of choices to be able to econometrically separate risk preferences from noise through an explicit stochastic model of the choice process. We further describe different modeling choices at some length, and discuss the importance of obtaining good data fit in order to have the most power in regression analysis and to avoid attenuation bias.

We find that the rural population of Ethiopia is highly risk tolerant, thus departing from traditional conclusions about developing country samples based on the use of measurement methods specific to developing countries (Haushofer and Fehr, 2014; Yesuf and Bluffstone, 2009). At the same time, we do find a strong correlation of risk tolerance with income proxies, indicating in agreement with the previous literature that more affluent households exhibit higher risk tolerance. By restricting our attention to exogenous income proxies, we then show that the causality runs from income to risk preferences. Finally, we discuss the implications of our findings in terms of the failure to adopt new technologies by poor households in developing countries, which has often been blamed on low risk tolerance.

This paper proceeds as follows. Section 2 describes the subject pool and provides details on the experimental tasks and procedures, as well as discussing data quality. Section 3 presents the results. We start out by presenting some

non-parametric data at the aggregate level, and then discuss the stochastic assumptions and econometric methods used to fit functional forms to the data. Then we look at correlations with socio-economic variables, in particular income proxies and indicators of socio-economic conditions in childhood. Finally section 5 discusses the results and concludes the paper.

2 Experimental setup

2.1 Subject pool characteristics

A total of 504 household heads were recruited in three regions in the Ethiopian highlands. The study was carried out in the context of an investigation of the effectiveness of improved cookstoves under the REDD+ program. This focus also determined the stratification technique used to select the sample. Subjects were selected from the three regions involved based on forest cover, with 20% of subjects from Amhara, 50% from Oromia, and 30% from the Southern Nations, Nationalities and Peoples Region (out of the total population of the three regions, Amhara has approximately 29%, Oromia 46%, and SNNP 15%). These regional states represent 80% of the population and over 70% of the land area of Ethiopia. Then, 36 sites were randomly picked from the three regions. Finally, 14 households were randomly picked from each site. The data were collected by a total of 25 fieldworkers (5 supervisors and 20 enumerators) who were trained on the experiments. The procedures were refined in a pilot before starting the actual experiment.

The average age of our subjects is 42.13 years (SD: 13.2), with a range between 20 and 90 years. Since the study was targeted at household heads, 89.9% of respondents are male. At 91% the overwhelming majority of our subjects work mainly in the agricultural sector, with the second largest group consisting of women doing house work (5%), and the third largest of people owning a business (2%). The median household has about 1.5 ha (about 3 acres) of land. About 38% of the respondents are illiterate, with the literate subjects having mostly only primary education (45% of the sample).

2.2 Experimental tasks and explanations

We measure risk preferences using certainty equivalents (*CEs*). CEs constitute a powerful tool to measure risk preferences. They are easy to construct and to deploy. Physical representations of the choice problems are straightforward. In contrast to tasks such as the one popularized by Holt and Laury (2002), which have been found to result in high rates of inconsistencies (Charness and Viceisza, 2012; Lönnqvist, Verkasalo, Walkowitz and Wichardt, 2011), only monetary amounts vary within a given choice list, while probabilities stay fixed. This makes it easy to lay out money on a table and represent probabilities physically, which is a great advantage given people's familiarity with money. CEs can also easily be used to estimate one's favorite decision model (although more CEs are typically required for more complex models). Finally, while they allow for structural model estimation, they are also straightforward to analyze non-parametrically.

In a typical task or *choice list*, a subject is offered repeated choices between a lottery or *prospect* and different sure amounts of money. The prospect offers a probability p of obtaining a prize, x, or else an outcome y with a complementary probability $1-p$. We will represent such a prospect as $(x, p; y)$. The sure amounts s_j are always included between the prize and the low outcomes of the prospect, i.e. $x \geq s_j \geq y$. The extreme outcome of the prospect, x and y, are explicitly included in the list of sure amounts to serve as a rationality check. As long as preferences are consistent, i.e. subjects switch only once (see below), the certainty equivalent can then be taken to be the mean between the first sure amount that is chosen over the prospect, and the last sure amount for which the prospect was preferred over the safe option.

In this experiment, we fix the prize of the prospect at 40 Birr and the lower outcome at 0 throughout. The prize of 40 Birr corresponds to about US \$6 in purchasing power parity (World Bank 2013), for an overall expected payoff from participating equal to \$3 PPP for a risk neutral participant. Considering that most of our subjects live on less than two Dollars a day, the money at stake was significant and well in line with stakes in similar experiments (Attanasio,

Barr, Cardenas, Genicot and Meghir, 2012; Yesuf and Bluffstone, 2009). We used a total of 7 choice lists, which offered a prize of 40 Birr with probabilities of $p = \{0.05, 0.10, 0.30, 0.50, 0.70, 0.90, 0.95\}$, and which were administered in random order. The sure amounts increased from 0 to 40 Birr (included) in steps of 1 Birr. Probabilities were implemented using 20 ping-pong balls, with winning balls of different colors. We chose to keep outcomes fixed across choice lists while changing probabilities, as we believe that for typical experimental stakes most of the interesting patterns emerge along the probability dimension (see also Fehr-Duda and Epper, 2012, on this point). This will restrict our model to one subjective dimension, so that more complex models which allow for two subjective dimensions, such as prospect theory, cannot be estimated based on our data. This methodology can, however, easily be expanded to the latter.[4]

Before beginning the actual experiment, subjects were carefully explained the process. All explanations and subsequent elicitations took place in individual interviews. Subjects were shown how the urn was composed. They were then shown the prospect, which was explained by laying out banknotes next to the associated colored ping-pong balls used as chance device. Subjects were asked to choose between this prospect and the sure amount, also physically laid out next to the prospect. The enumerator introduced the example by showing the participant the entire choice list. Subjects were then asked for their choice between the prospect and 0 Birr for sure; and then for their choice between the prospect and 40 Birr for sure. Given that for the first everybody ought to prefer the prospect and for the second everybody should prefer the sure amount, this quite naturally conveys the idea that subjects should only switch once (which was not enforced in case subjects still wanted to switch to and fro). Once a subject had understood this process, the enumerator began eliciting the preferences for different probability levels in random order. The total experiment including the explanations took about 30-40 minutes.

[4]In particular, some choice tasks varying outcomes at a given probability are needed to separate utility curvature from probability transformation in the econometric analysis. To obtain good power for the observations, prospects with a non-zero lower outcome are necessary in addition to varying upper outcomes.

At the end of the risk experiment, one of the choice lists was randomly selected for real play—the standard procedure in this kind of experiment (Baltussen, Post, van den Assem and Wakker, 2012; Cubitt, Starmer and Sugden, 1998). In that choice list, one choice between a given sure amount and the prospect was then extracted for play, so that overall each decision had the same probability of being played for real. This procedure had been thoroughly explained to subjects while presenting the example at the beginning of the experiment. Subjects were explicitly asked to repeat the randomization procedure to the enumerator before starting with the actual experiment. Subjects were also told explicitly that, given this procedure, it was in their best interest to treat every single decision as if it were the one that would be played for real money at the end.

2.3 Data quality

Overall data quality is good, reflecting the careful explanations of the experimental procedures. Only 3 out of 504 subjects, or 0.6% of our sample, switched multiple times from the prospect to the sure amount and back in the choice lists. We will exclude these subjects from the analysis, leaving us with 501 subjects. A further test of rationality are what we call strong violations of first order stochastic dominance, consisting in a preference for 0 Birr for sure over playing the prospect, or of playing the prospect over 40 Birr for sure. No subject preferred the sure 0 Birr to the prospect. On the other hand, 4 subjects, or 0.8% of the sample, indicated a preference for the prospect over 40 Birr for sure in at least one of the choice lists. These subjects will also be excluded from the analysis. Finally, for one subject we do not have responses to the questionnaire, leaving us with a total of 496 subjects.

We next look at (ordinary) violations of stochastic dominance. Such a violation occurs whenever a subjects indicates a certainty equivalent for a given prospect that is lower than the certainty equivalent indicated for another prospect offering a lower probability of obtaining the same prize, $CE(p_j) < CE(p_i)$, $p_j > p_i$. About 38% of our subjects violate stochastic dominance at least once. Seen that most violations are relatively small in terms of amounts, this appears

to lie within acceptable bounds, considering also the random ordering of the tasks. Vieider et al. (2013) found that about 25% of Vietnamese farmers violated stochastic dominance in a similar setting using a fixed ordering of tasks. Indeed, violation rates of about 20% are common in experiments in the West using individual or small group interviews with students (e.g., Abdellaoui, Bleichrodt, L'Haridon and Van Dolder, 2013). Violation rates in experimental sessions, where subjects are left to decide by themselves, are typically higher (L'Haridon, Martinsson and Vieider, 2013). Looking at total choices, our subjects violate first order stochastic dominance only in 5.4% of choices overall. Subjects who violated stochastic dominance are included in the analysis below. Excluding them from the analysis does not significantly affect our conclusions.

3 Aggregate data and modeling approach

3.1 Non-parametric representation of aggregate data

We start by conveying a feel for the data through non-parametric summary statistics for the different prospects, shown in table 1. Taking the mean CE over all the prospects (shown in the last row of the table), we find that subjects are on average significantly risk *seeking*. Looking at individual prospects, we see that subjects are risk seeking for small probabilities and risk averse for large ones, as has typically been found in the literature. However, the risk seeking behavior prevails up to and including a probability of $p = 0.5$, which is much higher than has been found in the West.

The findings are, on the other hand, consistent with recent findings across 30 countries with students using the same type of tasks reported by Vieider et al. (2012), confirming that subjects in poor countries tend to be considerably more risk tolerant than subjects in industrialized countries. For instance, converting the outcomes to PPP Euros, we observe an average risk premium, defined as $EV - CE$, of -0.452 ($se = 0.055$). This compares to a risk premium of 0.873 ($se = 0.178$) for American students. The subjects are also more risk seeking than the sample of farmers in Vietnam reported by Vieider et al. (2013), which

are approximately risk neutral (0.022, $se = 0.303$). This is consistent with the strong positive correlation of risk tolerance with per capita GDP, since Ethiopia is significantly poorer than Vietnam. The findings are also consistent with data obtained with Ethiopian farmers by Doerr, Toman and Schmidt (2011) using a different elicitation method.[5]

Table 1: Summary measures of aggregate risk preferences by prospect

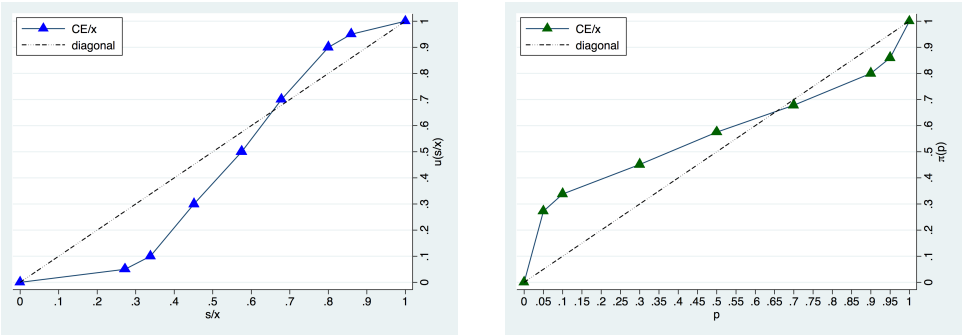
prob.	median CE	mean CE	SD	test =EV
0.05	7.5	10.88	10.37	$z = 18.21, p < 0.001$
0.10	9.5	13.53	10.19	$z = 17.84, p < 0.001$
0.30	15.5	18.05	10.05	$z = 11.51, p < 0.001$
0.50	22.5	23.01	9.12	$z = 6.26, p < 0.001$
0.70	29.5	27.13	8.58	$z = -1.49, p = 0.136$
0.90	34.5	32.01	8.51	$z = -7.33, p < 0.001$
0.95	37.5	34.38	8.17	$z = -6.54, p < 0.001$
mean	22.07	22.71	7.30	$z = 8.19, p < 0.001$

We can now show how our data fit into different models in a purely non-parametric way. Finding a good model to fit the data is important inasmuch this will improve our econometric analysis of the determinants of preferences, reducing potential attenuation bias. We start with an expected utility (EU) model. Since utility functions are unique only up to an affine transformation, we can arbitrarily fix the endpoints at $u(y) \equiv 0$ and $u(x) \equiv 1$. Plugging this into the general equivalence $u(CE_i) = p_i u(x) + (1 - p_i)u(y)$, we now simply obtain that $u(CE_i) = p_i$. The non-parametric mean utility function thus obtained is plotted in figure 1(a). This utility function resembles the one proposed by Markowitz (1952). Markowitz recognized that people may be risk seeking for some prospects while being risk averse for others, so that the utility function would have convex as well as concave sections. To accommodate this finding, he proposed to abandon initial wealth integration and to measure utility relative to a reference point given by current wealth.[6] This type of reference-dependence

[5]Similar results are also reported by Henrich and McElreath (2002), who found significant risk seeking in certainty equivalents over 50-50 prospects elicited from a Tanzanian tribe. They do, however, attribute this finding to the specific characteristics of the tribe. In contrast, Akay, Martinsson, Medhin and Trautmann (2012) found high levels of risk aversion eliciting CEs with poor farmers in Ethiopia. The latter finding, however, is driven mostly by subjects who consistently chose the sure amount for all choices.

[6]With initial wealth integration, convex and concave sections of the utility function might

has by now been widely integrated into EU models (Diecidue and van de Ven, 2008; Kőszegi and Rabin, 2007; Sugden, 2003; von Gaudecker et al., 2011), so that we will adopt it throughout whenever we speak of expected utility theory.



(a) Nonparametric EU function

(b) Nonparametric Dual function

Figure 1: Non-parametric functions

Markowitz based the derivation of this type of utility function on a simple thought experiment. In this experiment, he asked readers about their choices between a prospect offering a prize x with probability $p = 0.1$ or else nothing and the expected value of the prospect. For small x, most people would likely choose the prospect (e.g., most people would prefer a prospect offering a one in ten chance of \$10 over \$1 for sure). As x got larger, however, people would gradually switch to preferring the sure amount (e.g., most people would prefer a sure \$1,000,000 over a prospect offering a one in ten chance at \$10,000,000).

In our case, however, we kept the amounts fixed, and let probabilities vary instead, i.e. we elicited $CE_i \sim (\bar{x}, p_i; \bar{y})$, where the bar indicates that values are unchanging across choice lists and $\sim$ indicates indifference. Obviously, one could still perceive such behavior as being driven by the value of the prospect, since the expected value of the prospect increases with the probability of winning the prize. However, in a seminal paper Preston and Baratta (1948) let both outcomes and probabilities vary systematically across choices. What they observed was that outcome variation had a negligible effect on the data (although the outcomes did obviously not range up to the amounts indicated in Markowitz's thought exper-

co-exist at the same point, since the same pattern has been found for all kinds of wealth levels, thus giving rise to inconsistencies.

iment). Even more importantly, the pattern across different probability levels remained constant, no matter what the outcome level. This pattern gave rise to much experimentation by psychologists in subsequent years (see Edwards, 1954, for an early review), and hit the economic discipline when probability weighting was incorporated into prospect theory jointly with utility transformations and published in Econometrica by Kahneman and Tversky (1979).

This consistent pattern across probabilities, which we also find in our data, suggests a different approach to modeling the choices we observe. One could model risk preferences through a subjective transformation of probabilities into decision weights, rather than a subjective transformation of outcomes into utilities. In other words, we can represent a choice as being linear in outcomes and non-linear in probabilities, such that $CE = \pi(p)x + [1 - \pi(p)]y$, where we will impose that $\pi(0) \equiv 0$ and $\pi(1) \equiv 1$. In our case, we can again simply solve this, noting that in our setting $\pi(p_i) = \frac{CE_i}{x}$. This non-parametric *Dual* function is depicted in figure 1(b), and can be seen to exactly mirror the utility function to its left (see Yaari, 1987, for an axiomatization of the Dual function for rank-dependent utility).

If one were to put the utility transformation and the probability transformation together, one would obtain prospect theory (Tversky and Kahneman, 1992). However, our stimuli were not designed to elicit prospect theory. Indeed, prospect theory is most useful in situations where outcomes are either non-monetary (such that they cannot be entered linearly since there is no objective scale on which outcomes can be measured, e.g. for decisions involving health states), or in situations were monetary outcomes are large (making it plausible that the marginal utility of money starts declining).[7] We thus refrained from eliciting utility and probability weighting separately on purpose, given that prospect theory is somewhat cumbersome for regression analysis because of the collinearity in some of its parameters (Zeisberger, Vrecko and Langer, 2012). One can also make a normative argument under prospect theory that utility *should* be linear for moderate

[7]See Schoemaker, 1982, for an intriguing discussion of the different underlying concepts of utility; see Barseghyan, Molinari, O'Donoghue and Teitelbaum, 2013 for an empirical investigation of large-stake decisions where both utility and probability distortions matter.

stakes (Wakker, 2010).

Being the dual of each other, the two functions presented above are prima facie perfectly equivalent. Nonetheless, we have a strong preference for the dual function, for several reasons. As we will further discuss below, the coexistence of risk seeking and risk aversion requires two-parameter functions to fit the data. Such functions are much more common, and the parameters have a much clearer interpretation, under the dual theory than under EU. Furthermore, the same type of pattern—combining risk seeking for low and risk aversion for high probabilities—has been found for different outcome levels, which contradicts EU with a Markowitz-type utility function. Indeed, if the utility of money alone were at stake, the convex segments of the utility function would need to be confined to a certain range of monetary outcomes. An analysis using a one-parameter utility function is nonetheless reported in the stability analysis at the end of this paper.

3.2 Stochastic modeling

We have so far only derived non-parametric functions from the data. While this involves the least tampering with the data, such an approach completely neglects one of the strengths provided by a multiplicity of observations—the possibility to separate noise from genuine preferences. This will lead to attenuation bias in regression analysis, since the noise in the measurements will affect the correlations with our socio-economic variables. In this section, we will thus try to both reduce the number of parameters needed to describe the data (relative to the seven non-parametric data points), and to develop an explicit stochastic structure that allows us to filter out noise from the observations. Alas, this does not come for free. We will need to add some more assumptions, as well as some complexity to the data estimation. Annotated Stata programs for all estimations in the paper are available for download at www.ferdinandvieider.com/programs.html.

Following Bruhin, Fehr-Duda and Epper (2010), we econometrically represent decisions directly using the switching points from the prospect to the sure amount. This takes into account the structure of the experimental setup, in which we elicit certainty equivalents for prospects, $ce_i \sim \xi_i$, where the subscript i indicates

the particular prospect at hand, such that $\xi_i = (x, p_i; y)$. This approach takes into account that choices within a given choice list are not independent. It also provides a better fit to our data than an approach that uses binary choices between each single sure amount in a list and the prospect. All the results remain stable if a discrete choice approach is used instead.[8]

We start from the observation that at the switching point the utility of the certainty equivalent is by definition equal to the utility of the prospect. Since outcomes enter the equation linearly, we can simply write:

$$\hat{ce}_i = \pi(p_i)x + [1 - \pi(p_i)]\, y \tag{1}$$

where $\hat{ce}_i$ is the certainty equivalent predicted by our model. For several reasons, this predicted certainty equivalent will not necessarily be equal to the one observed in the actual data. For instance, decision makers may make mistakes when calculating the utility of a prospect, or our model may be mis-specified relative to the true underlying decision process. We can thus represent the relation between the predicted and observed certainty equivalent as follows:

$$ce_i = \hat{ce}_i + \epsilon_i \tag{2}$$

where $\epsilon_i \sim N(0, \sigma^2)$ is an error term which captures the deviations mentioned above. We can now express the probability density function $\psi(.)$ for a given prospect i as follows

$$\psi(\theta, \sigma_i, \xi_i) = \frac{1}{\sigma_i}\, \phi\left(\frac{\hat{ce}_{\theta i} - ce_i}{\sigma_i}\right) \tag{3}$$

where ϕ is the standard normal density function, and θ indicates the vector of parameters to be estimated. Finally, σ indicates a so-called Fechner error

[8]The switching point is encoded as the average between the first sure amount chosen and the last sure amount for which the prospect was chosen. Yet another alternative econometric approach would thus be to let the switching point fall somewhere between those two amounts, without specifying where exactly. Using such an alternative approach does not change our results.

(Hey and Orme, 1994). The subscript i to the error term σ serves to remind us that we allow noise in principle to depend on the characteristics of the single prospect. Since our prospects are, however, invariant except for the probability of winning the prize, this error term simply takes the form $\sigma_i = \sigma x$, which serves to standardize the error term of the model.[9]

The parameters of the model can be estimated by maximum likelihood procedures (see Myung, 2003, for an short and intuitive introduction to the concept of maximum likelihood). To obtain the overall likelihood function, we now need to take the product of the density functions above across prospects and decision makers:

$$L(\theta) = \prod_{n=1}^{N} \prod_{i} \psi(\theta_n, \sigma_{ni}, \xi_i) \tag{4}$$

where θ is the vector of parameters to be estimated such as to maximize the likelihood function. The subscript n to θ indicates that we will allow the estimated parameters to be linear functions of observable characteristics of decision makers in the regression analysis, such that $\hat{\theta} = \hat{\theta}_k + \beta X$, where $\hat{\theta}_k$ is a vector of constants and X represents a matrix of observable characteristics of the decision maker. The subscript n to the noise term σ indicates that the error is also made to depend on the observable characteristics of the decision maker. This addresses the issue raised by Andersson, Tyran, Wengström and Holm (2013), according to which spurious correlations may result if noise is not allowed to vary with observable subject characteristics.

Taking logs, we obtain the following log-likelihood function:

$$LL(\theta) = \sum_{n=1}^{N} \sum_{i} \ln \left[\psi(\theta_n, \sigma_{ni}, \xi_i)\right] \tag{5}$$

[9]Many other specifications are conceivable in principle, but a thorough investigation is beyond the scope of this paper. Wilcox (2011) proposed a contextual utility specification,whereby the error term is made to depend on the difference in utility between the highest and lowest outcome in the prospect. Notice that we are fulfilling this criterion, since in our setup either utility is linear or the utility endpoints are normalized to 0 and 1, and such endpoints are invariant across choice lists.

We estimate this function in Stata using the Broyden-Fletcher-Goldfarb-Shanno optimization algorithm. Errors are always clustered at the subject level.

We are now finally ready to fit functional forms to our preference data. In figure 2 we fit a 2-parameter function developed by Prelec (1998) to the data, which takes the form $\pi(p) = e^{-\beta(-ln(p))^{\alpha}}$. The result is vastly superior to to the fit of Prelec's 1-parameter function characterized by $\beta \equiv 1$, thus making the additional parameter worthwhile ($\chi^2(1) = 646.95, p < 0.001$, likelihood ratio test). An analysis in terms of a 1-parameter expected utility function will be provided in the stability analysis at the end of the paper.

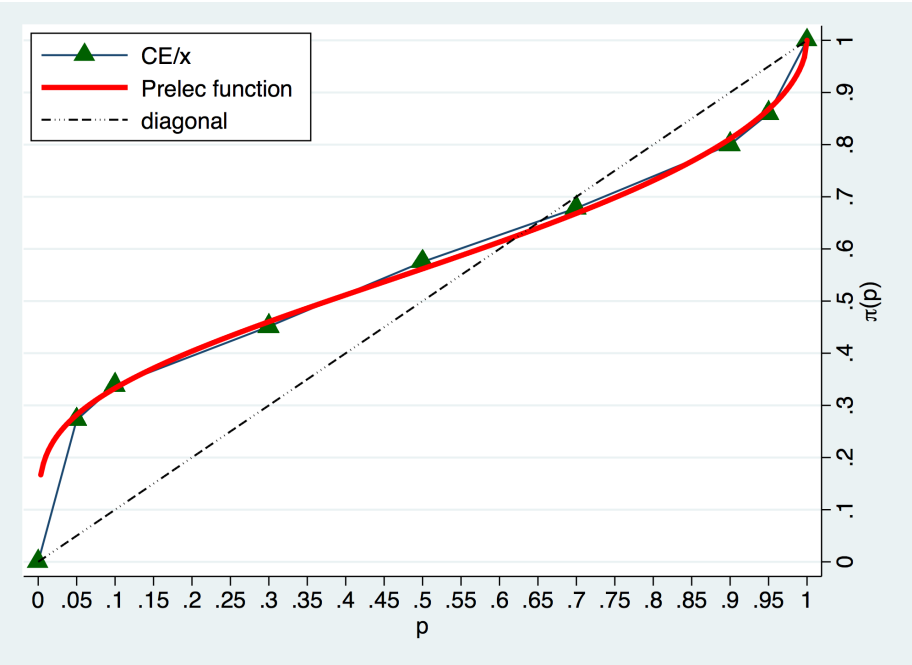


Figure 2: Fitting 2-parameter functions to the data

The parameters of the Prelec function have a precise behavioral interpretation. A parameter combination of $\alpha = 1$ and $\beta = 1$ in combination with linear utility indicates expected value maximization. The parameter β mostly governs the elevation of the function, with values >1 indicating a more depressed function and thus risk aversion under linear utility, and values <1 indicating a more elevated function, and hence risk seeking. The parameter α governs mostly the slope of the curve, with values <1 indicating *probabilistic insensitivity*, i.e. CEs that change less than proportionately with probabilities. This is a phenomenon

whereby people attribute greater weight to a given change in probability if it happens towards the endpoints of the scale close to $p = 0$ or $p = 1$ than if the same probability change occurs in an intermediate region. It is one of the most established findings in the prospect theory literature (Abdellaoui, 2000; Bleichrodt and Pinto, 2000; Wu and Gonzalez, 1996), and has been used to explain common violations of EU such as the common ratio and the common consequence effects (Allais, 1953). Since linear probability weighting is considered to be normative, probabilistic insensitivity is often perceived as a rationality failure (Tversky and Wakker, 1995). We will thus refer to the two parameters as the risk preference and the sensitivity parameter respectively.

4 Risk preferences and socio-economic conditions

4.1 Parametric analysis

We are now ready to examine the correlation of our measures with several characteristics of interest using our structural model (a non-parametric stability analysis is provided in the next section). We start by looking at indicators of wealth and income. While economists generally assume that more affluent people will be more risk tolerant, the evidence for this is not as clear as one might expect (see e.g. Hopland et al., 2013, for a discussion of the literature). Especially in developing countries there is a dearth of evidence on the effect of income, often because good income measures are difficult to come by amongst the poor inhabitants of the rural regions of developing countries, who more often than not are subsistence farmers. Vieider et al. (2013) recently presented evidence from Vietnam showing that farmers with higher income are more risk tolerant. The Vietnamese farmers of that study, however, were somewhat more affluent than our subjects in the present study, and produced mainly for the market, which made it easier to obtain good income measures.

Here we follow a different strategy. Rather than trying to obtain income measures, we look at some variables likely to be closely associated with income. Table 2 shows our regression results. Regression I looks at proxies for income.

The latter are a) land size, which for a farming population is likely to correlate strongly with income; b) distance to the nearest road, which may be taken as an indicator of the wealth or income of a village as a whole; and c) altitude, which in Ethiopia correlates strongly with the productivity of land, as well as the value of forest growing in the surrounding areas (the three measures are uncorrelated).[10]

Table 2: Income and wealth

	I			II		
	α	β	σ	α	β	σ
land size	-0.015	-0.060***	0.004	-0.069**	-0.067***	0.016
	(0.018)	(0.019)	(0.008)	(0.030)	(0.024)	(0.016)
distance to road	0.006	-0.021	0.007	0.009	-0.027	0.008
	(0.018)	(0.023)	(0.008)	(0.023)	(0.029)	(0.011)
altitude	0.052***	0.080***	-0.037***	0.062**	0.021	-0.018
	(0.016)	(0.024)	(0.006)	(0.029)	(0.027)	(0.015)
literate	0.013	0.066	0.004	0.001	0.105*	0.025
	(0.034)	(0.045)	(0.013)	(0.051)	(0.055)	(0.017)
middle school	0.052	0.115*	-0.002	0.102	0.154*	-0.011
	(0.053)	(0.070)	(0.019)	(0.079)	(0.080)	(0.020)
own business	-0.044	0.073	-0.032	-0.145	0.159	-0.002
	(0.097)	(0.147)	(0.054)	(0.097)	(0.175)	(0.066)
female	-0.105	0.215**	0.026	-0.074	0.180**	-0.037
	(0.066)	(0.089)	(0.028)	(0.070)	(0.083)	(0.024)
age	-0.007	0.052***	-0.014***	-0.008	0.105***	-0.015
	(0.018)	(0.020)	(0.005)	(0.032)	(0.035)	(0.010)
unmarried	0.025	-0.196**	-0.009	0.030	-0.307***	0.066
	(0.075)	(0.084)	(0.021)	(0.130)	(0.097)	(0.042)
Region fixed effects	✓	✓	✓	✓	✓	✓
constant	0.674***	0.631***	0.184***	0.678***	0.634***	0.124***
	(0.041)	(0.040)	(0.014)	(0.072)	(0.074)	(0.017)
Subjects	493	493	493	254	254	254
LL	$-12,338.49$	$-12,338.49$	$-12,338.49$	$-6,430.57$	$-6,430.57$	$-6,430.57$

Standard errors in parentheses; *p<0.1, **p<0.05, ***p<0.01
Continuous independent variables are entered as z-scores

In regression I we look at the three main income proxies, while controlling for basic demographics such as education, sex, age, and marital status. We find land size to be highly correlated with risk preferences, with larger land ownership being associated with higher risk tolerance[11] as indicated by a smaller β parameter, as we hypothesized. We also find higher altitudes to be related to

[10]The productivity of land decreases with altitude for several reasons. Rainfall is generally scarcer at high altitudes. This effect that is confounded by stronger winds, which tend to dry out the top soil. Furthermore, land at high altitude is often inclined, which means that water drains quickly and soil is easily eroded, leading to worse soil quality and hence lower agricultural productivity. And finally, the lower temperatures lead to slower growth of crops.

[11]Risk tolerance is defined in behavioral terms (Wakker, 2010); i.e. Peter is (strictly) more risk tolerant than Randy iff Peter's certainty equivalent for a given prospect is (strictly) larger than Randy's.

reduced risk tolerance, again as hypothesized. Higher altitudes are also associated with increased probabilistic sensitivity. Adding an interaction term between land size and altitude and the first two principal components of wealth calculated from a number of different indicators (Filmer and Pritchett, 2001), such as number of houses owned, number of rooms, whether the house has a water closet, materials of roof and wall, and whether the household has a private telephone, does not yield additional insights, and we do thus not report the regression. We also find some effect for the demographic controls. Most notably, we find unmarried subjects to be less risk averse, and older and female subjects to be more risk averse. These effects correspond to the majority of results in the literature, although not all of them are uncontroversial. For instance, while gender effects have often been found (Croson and Gneezy, 2009), they may be sensitive to elicitation tasks and decision context (Borghans, Heckman, Golsteyn and Meijers, 2009; Filippin and Crosetto, 2014). Notice, however, that females in our sample are usually female household heads. Female-headed households are also likely to be poorer than male-headed households on average, which may partially explain the strength of the gender effect.

There is little evidence to date on the direction of causality in the correlation between risk aversion and income or wealth. For instance, Gloede, Menkhoff and Waibel (2013) showed that risk preferences in Thailand and Vietnam are influenced by several types of shocks using experimentally validated survey questions (Hardeweg, Menkhoff and Waibel, 2013), but it is unclear whether the effect of these shocks passes purely through income or whether they have a direct, possibly psychological, effect on risk preferences. Given that there is little migration in Ethiopia (Di Falco and Bulte, 2013), the altitude at which a family lives can be taken as exogenous, so that it allows for causality to be detected. This in turn means that the effect of altitude shown in regression I can be taken as an indication that at least part of the causality must run from income to risk preferences. To expand on this issue, Regression II contains the same variables as regression I, but restricts the sample to the roughly 52% of subjects who declare to have inherited their land from their parents (as opposed to having acquired it them-

selves, 3%, or having obtained it through land redistribution, 44%). Restricting the sample in this way serves again to establish exogeneity of the variable, since the size of the land owned in this case has not been influenced by the household head.[12] If anything, the correlation between land size and risk tolerance is stronger in this sub-sample, suggesting indeed a causal relation running from income to risk tolerance.

The next step will be to explore correlations between risk tolerance and socio-economic conditions in childhood. We use physical stature as a proxy for such socio-economic conditions. Stature is well known to be an indicator of childhood socio-economic conditions in the epidemiological literature. For instance, Peck and Lundberg (1995) showed that hardship during childhood and larger families are both correlated with shorter stature in Swedish data, alongside with some more psychological factors induced by disunited families. In the specific case of Ethiopia, Dercon and Porter (2014) have recently shown that being exposed to a major famine in early childhood can lead to physical height in adulthood to be reduced by 5cm or more. We would thus expect physical height to result in higher risk tolerance (Dohmen et al., 2011), and possibly higher probabilistic sensitivity in adulthood (L'Haridon et al., 2013).

Table 3 shows two regression on physical characteristics. Regression I regresses the structural model on physical stature or *height*, including the usual controls. As predicted, we find a strong effect on risk tolerance, with taller people being on average more risk tolerant (see also Dohmen et al., 2011, for similar results in Germany). In addition, taller people are more probabilistically sensitive (marginally significant), and have lower levels of noise. Regression II adds the body mass index (BMI; defined as weight in kilograms divided by height in meters squared) as an additional measure of economic wellbeing. The effect of height is reinforced by this addition, with all three coefficients increasing and

[12] We have to caution that this variable is still only *plausibly* exogenous. Indeed, one may consider a story whereby parents have acquired the land, and have also passed on their risk preferences to their children. Such an account, however, appears much less plausible, mostly because the most likely mechanisms by which parents have acquired the land is redistribution rather than acquisition, and also because the levels of correlation around 0.2 typically found between risk preferences of parents and children (Dohmen, Falk, Huffman and Sunde, 2012) are probably too low to allow for this alternate account to be plausible.

Table 3: Physical stature and body mass

	I			II		
	α	β	σ	α	β	σ
height	0.044*	-0.060***	-0.030***	0.071***	-0.068***	-0.032***
	(0.025)	(0.012)	(0.004)	(0.025)	(0.015)	(0.006)
BMI				0.023***	-0.007	-0.002
				(0.007)	(0.009)	(0.003)
literate	0.028	0.057	-0.010	0.024	0.061	-0.009
	(0.035)	(0.044)	(0.014)	(0.035)	(0.044)	(0.014)
middle school	0.038	0.132*	-0.007	0.032	0.139*	-0.005
	(0.062)	(0.071)	(0.020)	(0.062)	(0.071)	(0.020)
business	0.025	0.071	-0.061	0.024	0.053	-0.060
	(0.095)	(0.168)	(0.053)	(0.094)	(0.183)	(0.057)
female	-0.057	0.193	-0.023	-0.021	0.174	-0.024
	(0.076)	(0.118)	(0.030)	(0.075)	(0.121)	(0.030)
age	-0.012	0.042*	-0.005	-0.012	0.043*	-0.006
	(0.016)	(0.023)	(0.006)	(0.016)	(0.023)	(0.006)
unmarried	0.010	-0.199*	0.020	0.021	-0.192*	0.024
	(0.083)	(0.111)	(0.028)	(0.083)	(0.111)	(0.030)
Region fixed effects	✓	✓	✓	✓	✓	✓
constant	0.702***	0.716***	0.170***	0.254*	0.860***	0.202***
	(0.038)	(0.037)	(0.015)	(0.148)	(0.181)	(0.069)
Subjects	496	496	496	496	496	496
LL	$-12,516.99$	$-12,516.99$	$-12,516.99$	$-12,507.92$	$-12,507.92$	$-12,507.92$

Standard errors in parentheses; *p<0.1, **p<0.05, ***p<0.01
Continuous independent variables are entered as z-scores

the sensitivity parameter now being highly significant. A higher BMI is further associated with more probabilistic sensitivity, although it has no significant effect on average risk tolerance. One interpretation of the latter is that it may be connected to the family's wealth and ability to cushion shocks, which in Ethiopia may easily lead to starvation. Indeed, about 12% of our sample exhibits a BMI smaller than 18.5, which is considered a cutoff for being underweight (World Health Organization).

4.2 Stability analysis

In this section, we replicate the main findings from above using non-parametric data and a one-parameter utility function. While non-parametric analysis will likely result in attenuation bias due to the noise incorporated in the measures, this is nevertheless useful in order to establish the stability of our main findings. Table 4 shows the four regressions from the two tables in the previous section, using OLS with robust standard errors. The dependent variable is now simply

constructed as the average certainty equivalent per person. Regression I shows that land size still shows the expected effect, with larger land holdings being correlated with larger certainty equivalents on average, and thus increased risk tolerance. Altitude shows the opposite effect, again as seen previously. With the reduced sample in regression II, the effect of land size remains intact, although the increased standard errors make it come out only marginally significant. The effect of altitude loses its significance, but this is of little concern, as regression II was inserted specifically for the land size effect. Regressions III and IV show that we no longer find a significant effect of height, while the BMI now shows a marginally significant on risk tolerance. While we can still establish the correlation with our most important income proxies, the effect most notably of height appears weakened.

Table 4: Nonparametric stability analysis

	I	II	III	IV
land size	0.969***	0.911*		
	(0.343)	(0.490)		
distance road	0.507	0.485		
	(0.376)	(0.496)		
altitude	-0.913***	-0.201		
	(0.345)	(0.428)		
height			-0.258	0.063
			(0.392)	(0.395)
BMI				0.249*
				(0.144)
literate	-1.249*	-1.722	-0.996	-1.050
	(0.756)	(1.107)	(0.773)	(0.772)
middle school	-1.961*	-2.107	-1.774	-1.902*
	(1.152)	(1.425)	(1.140)	(1.147)
business	-0.864	-1.928	-1.164	-1.115
	(2.175)	(3.135)	(2.114)	(1.981)
female	-3.619**	-3.383*	-4.112***	-3.683**
	(1.471)	(1.746)	(1.528)	(1.540)
age	-0.911**	-1.895***	-0.674*	-0.695**
	(0.361)	(0.594)	(0.345)	(0.347)
unmarried	2.825*	5.731***	2.441	2.463
	(1.492)	(1.963)	(1.527)	(1.527)
Region fixed effects	✓	✓	✓	✓
constant	24.457***	23.921***	23.280***	18.302***
	(0.737)	(1.431)	(0.641)	(2.931)
Subjects	493	254	496	496
R^2	0.06	0.08	0.03	0.03

Standard errors in parentheses; *p<0.1, **p<0.05, ***p<0.01
Continuous independent variables are entered as z-scores

It is at this point not clear whether the effects that are no longer significant disappeared due to the attenuation bias deriving from the noise in the data,

which is no longer filtered out by an explicit error structure, or rather because of passing from a 2-parameter model to a single parameter model. To determine this, we can estimate the same regressions using an expected utility franework with a power utility formulation. This will leave our econometric apparatus above intact, except that our predicted certainty equivalent now takes the following form:

$$\hat{ce}_i = u^{-1}\left[p_i u(x) + (1 - p_i)u(y)\right] \tag{6}$$

where utility takes the form $u(x) = x^{\rho}$. The fit of the resulting function to the nonparametric data is shown in figure 3. As already discussed above, this one-parameter function does not provide a good fit on average, as it cannot account for both risk seeking and risk aversion. Rather, it reflects the average pattern of risk seeking, resulting in a parameter estimate of $\rho = 1.634$ ($se = 0.065$), and thus a globally convex utility function.

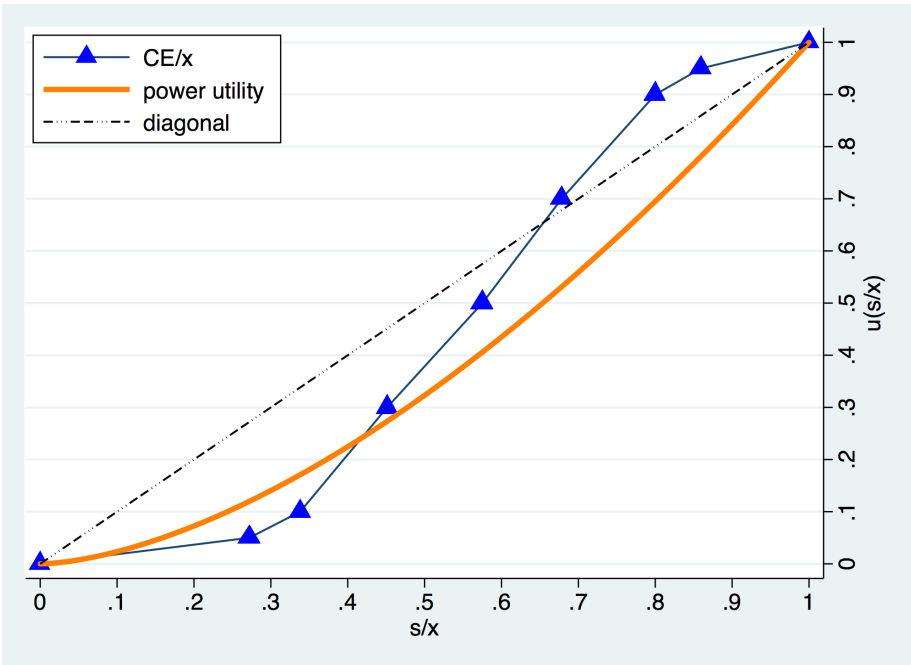


Figure 3: Fitting 2-parameter functions to the data

Table 5 shows the same four regressions as above using the expected utility formulation. Both land size and altitude have the expected significant effects

in regression I. In regression II, land size has an even higher coefficient and is marginally significant. Height, on the other hand, has significant effects in regressions III and IV only on the error term, with taller people having a lower error propensity, but not on utility curvature. BMI has no effect. The verdict is thus mixed. While the structural modeling improves our correlations somewhat relative to the non-parametric measures, several effects that were significant with the 2-parameter model are not picked up. This is likely due to the bad fit of the 1-parameter model. Indeed, the complex patterns of risk seeking combined with risk aversion visible from the nonparametric data points cannot be accommodated by such a function. This, in turn, means that error rates will be larger. And indeed we can see that the standard errors in the expected utility model are considerably larger than the ones seen in the dual model presented above.

Table 5: Stability analysis EU

	I		II		III		IV	
	ρ	σ	ρ	σ	ρ	σ	ρ	σ
land size	0.186***	0.007	0.293*	0.032*				
	(0.066)	(0.009)	(0.156)	(0.019)				
distance road	0.054	0.003	0.119	0.004				
	(0.081)	(0.009)	(0.132)	(0.014)				
altitude	-0.280***	-0.036***	-0.134	-0.019				
	(0.076)	(0.007)	(0.137)	(0.018)				
height					0.042	-0.023***	0.045	-0.030***
					(0.066)	(0.004)	(0.070)	(0.005)
BMI							0.005	-0.005
							(0.025)	(0.003)
literate	-0.159	0.002	-0.216	0.025	-0.187	-0.008	-0.203	-0.007
	(0.104)	(0.015)	(0.150)	(0.020)	(0.127)	(0.015)	(0.127)	(0.016)
middle school	-0.250	-0.005	-0.389	-0.029	-0.386	-0.010	-0.417*	-0.008
	(0.222)	(0.020)	(0.244)	(0.026)	(0.238)	(0.021)	(0.237)	(0.021)
business	-0.366	-0.030	-0.429	0.021	-0.430	-0.058	-0.363	-0.049
	(0.309)	(0.054)	(0.446)	(0.063)	(0.359)	(0.057)	(0.424)	(0.064)
female	-0.329*	0.040	-0.293	0.001	-0.500*	0.002	-0.479*	-0.003
	(0.188)	(0.029)	(0.254)	(0.029)	(0.262)	(0.032)	(0.277)	(0.033)
age	-0.179***	-0.012*	-0.290***	-0.017	-0.134**	-0.005	-0.135**	-0.006
	(0.048)	(0.007)	(0.074)	(0.012)	(0.060)	(0.007)	(0.059)	(0.007)
unmarried	0.446**	-0.003	1.027**	0.043	0.606**	0.025	0.613**	0.030
	(0.185)	(0.024)	(0.450)	(0.045)	(0.290)	(0.030)	(0.306)	(0.031)
region fixed effects	✓	✓	✓	✓	✓	✓	✓	✓
constant	1.830***	0.193***	1.915***	0.143***	1.578***	0.177***	1.482***	0.279***
	(0.117)	(0.015)	(0.252)	(0.022)	(0.118)	(0.017)	(0.506)	(0.070)
N_clust	493		254		496		496	
chi2	45.85		49.57		16.40		16.40	

Standard errors in parentheses; *p<0.1, **p<0.05, ***p<0.01
Continuous independent variables are entered as z-scores

5 Discussion and conclusion

We have examined the risk preferences of rural Ethiopian households using certainty equivalents. The results confirm recent findings according to which people in poor countries are on average more risk tolerant than people in rich, industrialized, countries. The positive correlation of income proxies with risk tolerance we find is in agreement with a large (if not always consistent) body of evidence from industrialized countries (Dohmen et al., 2011; Donkers et al., 2001; Hopland et al., 2013). Taken together with the high levels of risk aversion typically found in Western, industrialized countries, this gives rise to a risk-income paradox (Vieider et al., 2013).[13]

Most evidence on risk preferences in developing countries stems from studies using a single choice list (Binswanger, 1980; Giné, Townsend and Vickery, 2008; Yesuf and Bluffstone, 2009). Responses to such a list may, however, be contaminated by noise. One of the presumed virtues of the Binswanger list is that it does not allow for *any* noise to register in the response, given that subjects are asked to pick their favorite amongst a list of lotteries. This, however, makes it impossible to tease apart econometrically how much noise played into the response, and in general preference data and noise can thus not be separately identified. Andersson et al. (2013) showed how noise may systematically be counted towards risk aversion in some choice list designs, thus resulting in spurious correlations. This criticism particularly applies to the Binswanger design—given that the choice list is capped at risk neutrality, random choices will be systematically counted towards risk aversion. The advantage of our design is that it is easy to deploy and to explain, and that it can pick up a whole spectrum of risk preferences.

The findings of considerable risk tolerance by our subject raises the question

[13] Vieider et al. (2012) explain this paradox recurring to unified growth theory, and in particular the hypothesis developed by Galor and Michalopoulos (2012). In poor societies that find themselves in a Malthusian equilibrium, relatively affluent, risk tolerant people have the largest number of children. Since risk preferences are transmitted within the family, risk tolerance becomes prevalent. As societies grow richer, however, the affluent are the first to substitute quality for quantity of children (Becker, Murphy and Tamura, 1990). As more affluent families decrease the number of children, poorer families at first increase them, since the income constraint is no longer binding. This in turn leads to an inversion of the equilibrium and the spread of risk aversion.

what may be driving the reluctance to adopt new technologies that has often been observed in developing countries, and which has frequently been attributed to risk aversion. In the face of this evidence, such a conclusion does not appear to be tenable—at least not in any simple sense. One possible alternative explanation is that reluctance to switch to new technologies may be driven by downward risk exposure—the extent to which basic consumption needed for survival would suffer in the case of an adverse shock (Dercon and Christiaensen, 2011). Other explanations obviously exist as well, including low trust in the information provided by outsiders, slow information diffusion through social networks, etc. This is an important question raised by our data, the investigation of which will hopefully shed some fresh light on what induces people to take risks in real life decisions beyond their pure risk preferences as measured in economic experiments.

Risk preferences have often been shown to correlate with income (Dohmen et al., 2011; Hopland et al., 2013; Vieider et al., 2013). At the same time, parts of the literature have examined the correlation of risk preferences with behavior (Liu, 2012; 2013). An element that most of these studies have in common is that the direction of causality was either assumed away completely, or that only correlation results were presented. This approach may in part derive from the idea engrained in classical economics that preferences are exogenously given and invariant to experiences. In the present study, we took a first step in the direction of formally addressing causality by using exogenous proxies for income (see also Guiso and Paiella, 2008). While this showed that some of the causality seems to run from income to risk tolerance (see also Vieider et al., 2012, for similar conclusions on the macroeconomic level about aggregate risk preferences per country, using an instrumental variables approach), this does not exclude the opposite direction of causality. However, repeated observations in a panel structure with a rich set of variables on both income and behavior will be needed to fully disentangle this relationship.

Although not being the main point of our analysis, our results have shown that both allowing for a stochastic structure and choosing a flexible enough model to fit the data well may be important for correlation analysis. Clearly, our pre-

liminary insights into this issue are not conclusive, and more research is needed to determine the generality of this finding. An additional methodological point is that certainty equivalents, so far rarely used in development economics but a standard tool in decision theory, hold great promise for the application with poor and often illiterate subjects. Comparing different sure amounts of money to a prospect with a constant probability is easy to explain and represent physically, and appears to produce good results. In this paper, we have concentrated on eliciting such certainty equivalents for pure gain prospects. Indeed, they provide the cleanest test for our hypotheses, as one need not worry about giving subjects endowments from which losses are deducted as in pure loss or mixed prospects, and about whether subjects integrate these endowments into their decisions or not. Nonetheless, the method is easily extendable to pure loss and mixed prospects if the research questions makes this desirable, as is the case if one wants to find correlations with many real world decisions.

References

Abdellaoui, Mohammed (2000) 'Parameter-free elicitation of utility and probability weighting functions.' *Management Science* 46(11), 1497–1512

Abdellaoui, Mohammed, Aurélien Baillon, Lætitia Placido, and Peter P. Wakker (2011) 'The rich domain of uncertainty : Source functions and their experimental implementation.' *American Economic Review* 101, 695–723

Abdellaoui, Mohammed, Han Bleichrodt, Olivier L'Haridon, and Dennie Van Dolder (2013) 'Source-dependence of utility and loss aversion: A critical test of ambiguity models.' *University of Rennes 1 working paper*

Akay, Alpaslan, Peter Martinsson, Haileselassie Medhin, and Stefan Trautmann (2012) 'Attitudes toward uncertainty among the poor: an experiment in rural ethiopia.' *Theory and Decision* 73(3), 453–464

Allais, Maurice (1953) 'Le comportement de l'homme rationnel devant le risque: critique des postulats et axiomes de l'école américaine.' *Econometrica* 21(4), 503–546

Andersson, Ola, Jean-Robert Tyran, Erik Wengström, and Håkan J. Holm (2013) 'Risk aversion relates to cognitive ability: Fact or fiction?' *IFN Working Paper No. 964*

Attanasio, Orazio, Abigail Barr, Juan Camilo Cardenas, Garance Genicot, and Costas Meghir (2012) 'Risk pooling , risk preferences , and social networ.' *American Economic Journal: Applied Economics* 4(2), 134–167

Baltussen, Guido, Thierry Post, Martijn J. van den Assem, and Peter P. Wakker (2012) 'Random incentive systems in a dynamic choice experiment.' *Experimental Economics* 15(3), 418–443

Barseghyan, Levon, Francesca Molinari, Ted O'Donoghue, and Joshua Teitelbaum (2013) 'The nature of risk preferences: Evidence from insurance choices.' *American Economic Review* 103(6), 2499–2529(31)

Becker, Gary S., Kevin M. Murphy, and Robert Tamura (1990) 'Human capital, fertility, and economic growth.' *Journal of Political Economy* 98(5), S12–S37

Binswanger, Hans P. (1980) 'Attitudes toward risk: Experimental measurement in rural india.' *American Journal of Agricultural Economics* 62(3), 395–407

Bleichrodt, Han, and Jose Luis Pinto (2000) 'A parameter-free elicitation of the probability weighting function in medical decision analysis.' *Management Science* 46(11), 1485–1496

Booij, Adam S., Bernard M. S. van Praag, and Gijs van de Kuilen (2010) 'A parametric analysis of prospect theory's functionals for the general population.' *Theory and Decision* 68(1-2), 115–148

Borghans, Lex, James J. Heckman, Bart H. H. Golsteyn, and Huub Meijers (2009) 'Gender differences in risk aversion and ambiguity aversion.' *Journal of the European Economic Association* 7(2-3), 649–658

Bruhin, Adrian, Helga Fehr-Duda, and Thomas Epper (2010) 'Risk and rationality: Uncovering heterogeneity in probability distortion.' *Econometrica* 78(4), 1375–1412

Charness, Gary, and Angelino Viceisza (2012) 'Comprehension and risk elicitation in the field: Evidence from rural senegal.' *working paper*

Croson, Rachel, and Uri Gneezy (2009) 'Gender differences in preferences.' *Journal of Economic Literature* 47(2), 1–27

Cubitt, Robin P., Chris Starmer, and Robert Sugden (1998) 'On the validity of random lottery incentive systems.' *Experimental Economics* 1, 115–131

Dercon, Stefan, and Catherine Porter (2014) 'Live aid revisited: Long-term impacts of the 1984 ethiopian famine on children.' *Journal of the European Economic Association* 12(4), 927–948

Dercon, Stefan, and Luc Christiaensen (2011) 'Consumption risk, technology

adoption and poverty traps: Evidence from ethiopia.' *Journal of Development Economics* 96(2), 159–173

Di Falco, Salvatore, and Erwin Bulte (2013) 'The impact of kinship networks on the adoption of risk-mitigating strategies in ethiopia.' *World Development* 43, 100–110

Diecidue, Enrico, and Jeroen van de Ven (2008) 'Aspiration level, probability of success and failure, and expected utility.' *International Economic Review* 49(2), 683–700

Doerr, Ulrike, Omar Mahmud Toman, and Ulrich Schmidt (2011) 'Overconfidence and risk management of ethiopian farmers.' *Working paper, University of Kiel*

Dohmen, Thomas, Armin Falk, David Huffman, and Uwe Sunde (2012) 'The intergenerational transmission of risk and trust attitudes.' *Review of Economic Studies* 70(2), 645–677

Dohmen, Thomas, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G. Wagner (2011) 'Individual risk attitudes: Measurement, determinants, and behavioral consequences.' *Journal of the European Economic Association* 9(3), 522–550

Donkers, Bas, Bertrand Melenberg, and Arthur Van Soest (2001) 'Estimating risk attitudes using lotteries: A large sample approach.' *Journal of Risk and Uncertainty* 22(2), 165 – 95

Edwards, Ward (1954) 'The theory of decision making.' *Psychological Bulletin* 51(4), 380–417

Fehr-Duda, Helga, and Thomas Epper (2012) 'Probability and risk: Foundations and economic implications of probability-dependent risk preferences.' *Annual Review of Economics* 4(1), 567–593

Filippin, Antonio, and Paolo Crosetto (2014) 'A reconsideration of gender differences in risk attitudes.' SSRN Scholarly Paper ID 2441480, Social Science Research Network, Rochester, NY, May

Filmer, Deon, and Lant H. Pritchett (2001) 'Estimating wealth effects without expenditure data—or tears: An application to educational enrollments in states of india*.' *Demography* 38(1), 115–132

Galor, Oded, and Stelios Michalopoulos (2012) 'Evolution and the growth process: Natural selection of entrepreneurial traits.' *Journal of Economic Theory* 147(2), 759–780

Giné, Xavier, Robert Townsend, and James Vickery (2008) 'Patterns of rainfall insurance participation in rural india.' *World Bank Economic Review* 22, 539–566

Gloede, Oliver, Lukas Menkhoff, and Hermann Waibel (2013) 'Shocks, individual risk attitude, and vulnerability to poverty among rural households in thailand and vietnam.' *World Development*

Guiso, Luigi, and Monica Paiella (2008) 'Risk aversion, wealth, and background risk.' *Journal of the European Economic Association* 6(6), 1109–1150

Hardeweg, Bernd, Lukas Menkhoff, and Hermann Waibel (2013) 'Experimentally validated survey evidence on individual risk attitudes in rural thailand.' *Economic Development and Cultural Change* 61(4), 859–888

Harrison, Glenn W., Morten I. Lau, and Elizabeth E. Rutström (2007) 'Estimating risk attitudes in denmark: A field experiment.' *Scandinavian Journal of Economics* 109, 341–368

Haushofer, Johannes, and Ernst Fehr (2014) 'On the psychology of poverty.' *Science* 344(6186), 862–867

Henrich, Joseph, and Richard McElreath (2002) 'Are peasants risk averse decision makers?' *Current Anthropology* 43(1), 172–181

Hey, John D., and Chris Orme (1994) 'Investigating generalizations of expected utility theory using experimental data.' *Econometrica* 62(6), 1291–1326

Holt, Charles A., and Susan K. Laury (2002) 'Risk aversion and incentive effects.' *American Economic Review* pp. 1644–1655

Hopland, Arnt O., Egil Matsen, and Bjarne Strøm (2013) 'Income and choice under risk.' Working Paper Series 14313, Department of Economics, Norwegian University of Science and Technology

Kahneman, Daniel, and Amos Tversky (1979) 'Prospect theory: An analysis of decision under risk.' *Econometrica* 47(2), 263 – 91

Kőszegi, Botond, and Matthew Rabin (2007) 'Reference-dependent risk attitudes.' *The American Economic Review* 97(4), 1047–1073

L'Haridon, Olivier, Peter Martinsson, and Ferdinand M. Vieider (2013) 'All over the map: Heterogeneity of risk preferences across individuals, contexts, and countries.' *working paper*

Liebenehm, Sabine, and Hermann Waibel (2014) 'Simultaneous estimation of risk and time preferences among small-scale farmers in west africa.' *American Journal of Agricultural Economics, forthcoming*

Liu, Elaine M. (2012) 'Time to change what to sow: Risk preferences and technology adoption decisions of cotton farmers in china.' *Review of Economics and Statistics* 95(4), 1386–1403

_ (2013) 'Risk preferences and technology adoption decisions of cotton farmers in china.' *working paper*

Lönnqvist, Jan-Erik, Marrku Verkasalo, Gari Walkowitz, and Philipp C. Wichardt (2011) 'Measuring individual risk attitudes in the lab: Task or ask? an empirical comparison.' *Working Paper*

Markowitz, Harry (1952) 'The utility of wealth.' *Journal of Political Economy* 60(2), 151–158

Myung, In Jae (2003) 'Tutorial on maximum likelihood estimation.' *Journal of Mathematical Psychology* 47(1), 90–100

Noussair, Charles N., Stefan Trautmann, and Gijs van de Kuilen (2014) 'Higher order risk attitudes, demographics, and financial decisions.' *Review of Economic Studies* 21(1), 325–355

Peck, Maria Nyström, and Olle Lundberg (1995) 'Short stature as an effect of economic and social conditions in childhood.' *Social Science & Medicine* 41(5), 733–738

Prelec, Drazen (1998) 'The probability weighting function.' *Econometrica* 66, 497–527

Preston, Malcolm G., and Philip Baratta (1948) 'An experimental study of the auction-value of an uncertain outcome.' *The American Journal of Psychology* 61, 183–193

Rieger, Marc Oliver, Mei Wang, and Thorsten Hens (2014) 'Risk preferences around the world.' *Management Science*

Schoemaker, Paul J. H. (1982) 'The expected utility model: Its variants, purposes, evidence and limitations.' *Journal of Economic Literature* 20(2), 529–563. ArticleType: research-article / Full publication date: Jun., 1982 / Copyright © 1982 American Economic Association

Sugden, Robert (2003) 'Reference-dependent subjective expected utility.' *Journal of Economic Theory* 111(2), 172–191

Tanaka, Tomomi, Colin F. Camerer, and Quang Nguyen (2010) 'Risk and time preferences: Linking experimental and household survey data from vietnam.' *American Economic Review* 100(1), 557–571

Tversky, Amos, and Daniel Kahneman (1992) 'Advances in prospect theory: Cumulative representation of uncertainty.' *Journal of Risk and Uncertainty* 5, 297–323

Tversky, Amos, and Peter P. Wakker (1995) 'Risk attitudes and decision weights.' *Econometrica* 63(6), 1255–1280

Vieider, Ferdinand M., Mathieu Lefebvre, Ranoua Bouchouicha, Thorsten Chmura, Rustamdjan Hakimov, Michal Krawczyk, and Peter Martinsson (2014) 'Common components of risk and uncertainty attitudes across contexts and domains: Evidence from 30 countries.' *Journal of the European Economic Association, forthcoming*

Vieider, Ferdinand M., Nghi Truong, Peter Martinsson, and Nam Pham Khanh (2013) 'Risk preferences and development revisited: A risk-income paradox.' *WZB Discussion Paper SP II 2013–403*

Vieider, Ferdinand M., Thorsten Chmura, and Peter Martinsson (2012) 'Risk attitudes, development, and growth. macroeconomic evidence from experiments in 30 countries.' *WZB Working paper*

von Gaudecker, Hans-Martin, Arthur van Soest, and Erik Wengström (2011) 'Heterogeneity in risky choice behaviour in a broad population.' *American Economic Review* 101(2), 664–694

Wakker, Peter P. (2010) *Prospect Theory for Risk and Ambiguity* (Cambridge: Cambridge University Press)

Weber, Elke U., and Christopher Hsee (1998) 'Cross-cultural differences in risk perception, but cross-cultural similarities in attitudes towards perceived risk.' *Management Science* 44(9), 1205–1217

Wilcox, Nathaniel T. (2011) ''stochastically more risk averse:' a contextual theory of stochastic discrete choice under risk.' *Journal of Econometrics* 162(1), 89–104

Wu, George, and Richard Gonzalez (1996) 'Curvature of the probability weighting function.' *Management Science* 42(12), 1676–1690

Yaari, Menahem E. (1987) 'The dual theory of choice under risk.' *Econometrica* 55(1), 95–115

Yesuf, Mahmud, and Randall A. Bluffstone (2009) 'Poverty, risk aversion, and path dependence in low-income countries: Experimental evidence from ethiopia.' *American Journal of Agricultural Economics* 91(4), 1022–1037

Zeisberger, Stefan, Dennis Vrecko, and Thomas Langer (2012) 'Measuring the time stability of prospect theory preferences.' *Theory and Decision* 72(3), 359–386