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A Field Experiment in Vietnam

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Risk Preferences and Development Revisited
A Field Experiment in Vietnam*

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Abstract

We obtain rich measures of risk preferences of poor farmers in Vietnam, and estimate structural models that capture risk preferences over different probability levels and across different domains (gains and losses). The results break radically with the previous literature on risk preferences, in developed and developing countries alike. Far from being particularly risk averse, our Vietnamese farmers are on average risk neutral. At the same time, we find our preference measures to perform well at predicting behavior, from the purchase of lottery tickets to risk management on the farm. We also find strong direct evidence of a risk-income paradox. While risk aversion is strongly decreasing in income within our farmer subject population, our Vietnamese farmers are significantly less risk averse than subjects in Western countries according to measurements obtained using the same decision tasks and procedures.

Keywords: risk preferences; development; external validity;

JEL-classification: C93; D03; D80; O12

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1 Introduction

Poor people in developing countries have generally been assumed to be very risk averse, with such risk aversion resulting in sub-optimal behavior. We experimentally measure the risk preferences of poor Vietnamese farmers. The richness of the data collected is unprecedented in a development context, and allows us to revisit the issue through the estimation of structural models, backed up by nonparametric data. We show that—far from conforming to the stereotype of extreme risk aversion—Vietnamese farmers are on average quite risk tolerant. Comparing their risk preferences to those of American students obtained with the same experimental procedures, we conclude that Vietnamese farmers are significantly *less* risk averse than American students (or for that matter, general Western population samples). At the same time, our measures are validated by their good performance at predicting real world behavior, from the purchase of lottery tickets to risk-coping strategies on the farm. While aggregate behavior does not conform to the risk aversion stereotype, relative poverty within our farmer sample shows significant effects on preferences. We do indeed find a strong positive relation between risk tolerance and income amongst farmers. Together with the comparison to typical data from the West, this indicates a risk-income *paradox*, whereby risk tolerance increases with income within countries, but decreases with national income between countries.

Given the high levels of risk tolerance we find, we need to ask ourselves why such risk tolerance has not been detected before. Most of the development economics papers measuring risk preferences conclude that poor farmers in developing countries are very risk averse (Akay, Martinsson, Medhin, and Trautmann, 2011; Binswanger, 1980; Yesuf and Bluffstone, 2009). This seems to derive in large part from the use of a task introduced by Binswanger (1980), which has proved extremely popular in development economics due to its ease of administration (for some recent applications, see Bauer, Chytilová, and Morduch, 2012; Cole, Giné, and Tobacman, 2012; Giné, Menand, Townsend, and Vickery, 2010; Yesuf and Bluffstone, 2009; Attanasio, Barr, Cardenas, Genicot, and Meghir, 2012). While being excellent for measuring relative risk *aversion*, the Binswanger task has, however, the distinctive feature of capping risk preferences at risk neutrality, so that it cannot detect risk seeking behavior.[1] A slight modification of that task, developed by Eckel and Grossman (2008), has indeed been shown empirically to overestimate risk aversion relative to other tasks (Reynaud and Couture, 2012).

[1]The nature of the task is also likely to create reference point effects, which will further exacerbate risk aversion. See appendix A for a description of the task and a short model formalizing such effects.

Yet another reason for the high levels of risk aversion found may ba that most studies have picked the poorest of the poor as their subject pool. To the extent that risk tolerance depends on income—and our results strongly suggest that it does—this will further increase the tendency to find risk aversion (e.g., Akay et al., 2011 may be an example of this). We are aware of only two studies that depart from the conclusion of high risk aversion. Henrich and McElreath (2002) found risk seeking in experimental measures obtained with the Sangu tribe in Tanzania and the Mapuche tribe in Chile. They did, however, attribute these finding to special traits of the specific tribes, lacking a general population comparison group in Tanzania and finding risk aversion in a second tribe in Chile (the Huincas). Doerr, Toman, and Schmidt (2011) found high levels of risk taking by Ethiopian farmers, but do not discuss this finding further.

Given the high levels of risk tolerance we find, aggregate risk preferences *per se* cannot plausibly explain reluctance to adopt new technologies or suboptimal risk management strategies, as has been hypothesized in some of the development economics literature (Tanaka, Camerer, and Nguyen, 2010; Yesuf and Bluffstone, 2009). There is, however, little doubt that poor farmers do adopt risk averse coping strategies. Rosenzweig and Binswanger (1993) famously showed that farmers in India cope with rainfall risk by planting crop varieties that reduce their exposure to this risk, but that also yield a lower payoff on average. Jayachandran (2006) showed that poor farmers often sell their labor at low rates instead of more profitably attending to their own farms.

Risk averse strategies on the farm can, however, be reconciled with relatively high overall risk tolerance by the observation that risk averse coping behavior may to a large extent be driven by external constraints, rather than or in addition to individual preferences (Feder, Just, and Zilberman, 1985). Dercon and Christiaensen (2011) relate the willingness to take risks in production to the severity of the welfare consequences resulting from adverse shocks. Maccini and Yang (2009) showed that rainfall during the first year after birth significantly affects the lifetime outcomes of girls, with bad rainfall during that year resulting in smaller body size, less education, and reduced lifetime income. Risk aversion may indeed be the optimal action in the face of such extreme exposure (notice also the stark contrast with the tendency of over-insuring even modest risk in Western countries—see Sydnor, 2010).[2] The absence of borrowing and credit facilities furthermore makes it nigh-impossible to smooth income or consumption without recurring to risk averse strategies (Morduch, 1994; 1995). While some informal risk sharing mechanisms may exist, the latter are usually imperfect. There

[2]This is also consistent with theories that model the poor to be risk averse until a subsistance income is achieved, and much more risk tolerant thereafter—see e.g. Moscardi and Janvry (1977); Lopes and Oden (1999); Young (1979)

is increasing evidence that farmers switch to higher-payoff crops if they can cover themselves at least partially against their high levels of risk exposure (Cole, Giné, and Vickery, 2013; Karlan, Osei, Osei-Akoto, and Udry, 2012; Kurosaki and Fafchamps, 2002; Mobarak and Rosenzweig, 2012).

Nevertheless, we also find evidence that individual preferences *do* play a role in production decisions. This contributes to the debate on the extent to which measurements of preferences can be used to predict real world behavior (Samuelson, 2005). The external validity of risk preference measures is controversial. Investigating how risk and time preferences relate to real world behavior of a large sample of adolescents, Sutter, Kocher, Glätzle-Rützler, and Trautmann (2013) recently concluded that experimentally measured risk preferences had almost no predictive value for real world behavior (although time preference measures performed better). Dimmock, Kouwenberg, and Wakker (2012) found only weak predictive power of experimentally measured ambiguity preferences on stock market participation. Giné, Townsend, and Vickery (2008) and Cole, Giné, and Tobacman (2012) even found risk aversion to bear a *negative* relation to insurance purchase decisions. Contrary to the findings in these papers, our measures of risk preferences perform rather well at predicting behavior. Our risk preference measures significantly correlate with lottery buying behavior and precautionary saving. They also correlate significantly with risk coping behavior on the farm, from renting out one's land instead of farming it oneself, to migration behavior.

We attribute this increased external validity of our measures mostly to the richness of our measures, which can capture within-subject variability in preferences across different probability levels and domains (gains versus losses). Such elements have proved helpful in explaining many different types of real world behavior (see Barberis, 2013, for an extensive review). Most recently, Barseghyan, Molinari, O'Donoghue, and Teitelbaum (2012) showed that allowing for non-linear transformations of probabilities adds significant explanatory power in the modeling of insurance deductible choices. The overwhelming majority of preference studies in development obtain only one single estimate per subject. This may have further limited the predictive power of such measures, since typical measurement over 50-50 gains are likely to provide a poor approximation for behavior involving, e.g., small probability losses, such as insurance decisions. They also do not allow for the estimation of stochastic models of choice, and may thus be contaminated by noise.

We are only aware of two studies obtaining somewhat more detailed measurements of risk preferences in developing countries, both with poor farmers in Vietnam. Tanaka, Camerer, and Nguyen (2010) measured risk preferences using three choice lists, and solved a parallel equation system to estimate the parameters of a prospect theory model (PT ; Kahneman and Tversky, 1979). Nguyen, Villeval, and Xu (2012) estimated PT functionals using the same design with the same type of subject population, and related them to trust attitudes. Both these studies estimate multi-parameter models which have been shown to be descriptively superior to more basic models (Camerer, 1989; Loomes, Moffatt, and Sugden, 2002; Starmer, 2000; Wakker, 2010). The authors do, however, make simplifying assumptions which we deem—and show to be—quite restrictive. In particular, their functional assumptions limit the extent to which a probability weighting function—and hence risk preferences more in general—can differ from the typical aggregate functions found in the West. We show that, if we use the same functional forms on our own data, we obtain results that are virtually identical to theirs. If, on the other hand, we use a more flexible functional form, the pattern of probability weighting we detect is very different indeed, indicating considerable risk tolerance. The latter finding is confirmed by our non-parametric data, so that it cannot be dismissed as an artifact of the model we estimate. Finally, having many more observations, we can explicitly model a stochastic error structure, thus separating noise from actual preferences.

Our data also shed new light on the relationship between income and risk preferences. While risk aversion is generally thought to decrease in income, the empirical evidence is less strong than one might think. Barsky, Kimball, Juster, and Shapiro (1997), Donkers, Melenberg, and Van Soest (2001), and Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011b) all report evidence from survey questions that points in the direction of a negative association between risk aversion and income. Harrison, Lau, and Rutström (2007) report evidence going in the same direction coming from incentivized measures with a Danish general population sample. However, von Gaudecker, van Soest, and Wengström (2011) find evidence of this relationship only for gain-loss prospects in a representative Dutch sample, while Noussair, Trautmann, and van de Kuilen (2013) find no significant evidence of the relationship. Gächter, Johnson, and Herrmann (2010) even found evidence going in the opposite direction for gain-loss prospects. Most recently, Hopland, Matsen, and Strøm (2013) found evidence of the relation in a game show with very high stakes.

The evidence from the developing world is even less conclusive. Tanaka et al. (2010) showed subjects from richer villages in Vietnam to be more risk tolerant over gain-loss prospects than subjects from poorer villages, and Yesuf and Bluffstone (2009) found risk tolerance to increase in cash liquidity in Ethiopia, which is likely to correlate with income. There are, however, several studies that find no effect of income on risk preferences (Cameron and Shah, 2012). Our data contain strong evidence that risk aversion is decreasing in income. Farmers with higher income are found to be more risk tolerant—an effect that is highly significant and economically important.

In addition to a strong effect of relative income within our farmer subject pool, we find our farmers in the aggregate to be much more risk tolerant than student or general subject populations in the West. Taken together, these two sets of results provide direct evidence for a risk-income *paradox*, as initially discussed by Vieider, Chmura, and Martinsson (2012) using data collected with students in 30 different countries. Indeed, between countries there are clear indications that subjects from poorer countries are more risk tolerant (see also Bruhin, Fehr-Duda, and Epper, 2010; Rieger, Wang, and Hens, 2011; Weber and Hsee, 1998, for additional evidence).

Beyond the effect of income on risk aversion, we find indicators of rationality, such as departure from linear probability weighting (Tversky and Wakker, 1995), to vary with population characteristics in interesting ways. In particular, we find the degree of deviation from linear probability weighting (and thus from expected utility maximization, generally taken to be the normative model of decision making under risk; Schoemaker, 1982) to increase with age, but to decrease in education. This corresponds closely to recent results on violations of rationality principles obtained by Choi, Kariv, Müller, and Silverman (2013) in a general sample of the Dutch population.

Our data also hold an interest outside of the development context. There has recently been an increased move towards the collection of data with non-student population samples. Donkers et al. (2001) analyzed risk attitudes of a representative sample of the Dutch population with a hypothetical lottery question. Dohmen et al. (2011b) and Dohmen, Falk, Huffman, and Sunde (2011a) analyzed risk attitudes of German general population samples, also through survey questions. Harrison et al. (2007) estimated attitudes in a Danish sample through an incentivized measure. All of these measurements have in common that they are relatively simple, and do not allow for the estimation of structural decision-making models. Booij, Praag, and Kuilen (2010) obtained hypothetical measurements allowing for the estimation of structural models, and von Gaudecker, van Soest, and Wengström (2011) used several incentivized measures with a representative sample of the Dutch population. Most recently, Barseghyan et al. (2012) estimated a model of risk taking based on choices of deductible plans in home and auto insurance. Choi, Kariv, Müller, and Silverman (2013) studied budget allocations of a Dutch general population sample and investigated their conformity to basic rationality principles.

We add to these studies in several ways. For one, we obtain measurements that are fully incentivized conducting a controlled experiment. Our data are, furthermore, very rich, allowing for the estimation of structural models of decision-making that have been shown to be descriptively more accurate. For instance, von Gaudecker et al. (2011) estimate a model of reference-dependent expected utility, but are forced by their data to assume that the utility function is the same for gains and losses and are unable to test for the presence of non-linear probability weights. Barseghyan et al. (2012) estimate non-parametric models that in addition to utility transformations find significant explanatory power of probability transformation. Since they work with insurance data, however, their insights are confined to small probability losses. We can estimate models that allow for reference dependence, utility curvature, and nonlinear probability transformations. We can furthermore allow all of these transformations to differ between gains and losses relative to the reference point. We do, however, have a subject pool that is representative only of the local village population, and not of the country at large.

This paper proceeds as follows. Section 2 introduces the theoretical setup and discusses the econometric specifications used. Section 3 describes our subject pool, the measurement tasks, and the general setup of the experiment. Section 4 presents the aggregate results and puts them into perspective by comparing them to the risk attitudes of Vietnamese students, as well as to those of American students and typical findings from the West. Section 5 presents results on the determination of risk preferences and their predictive power, with sub-section 5.1 introducing an empirically tractable method; 5.2 looking into general population characteristics; and 5.3 examining the predictive power of our risk preference measures. Section 6 discusses the results and concludes the paper.

2 Theoretical and econometric model

We adopt prospect theory (PT) as our main model of choice (Kahneman and Tversky, 1979). PT has generally been found to be descriptively superior to expected utility theory (Barberis, 2013; Barseghyan et al., 2012; Starmer, 2000). Using a likelihood ratio test to compare the PT specification to a nested reference-dependent EUT specification (Kőszegi and Rabin, 2007; Sugden, 2003; von Gaudecker et al., 2011), we find the former to have vastly superior descriptive power ($\chi^2(4) = 1403.24, p < 0.001$).

Under PT, utility is generated over changes in wealth rather than over total wealth as under original EUT. This reference-dependence implies that outcomes are evaluated relative to a reference point, usually taken to be 0—a standard convention that we will adopt throughout. This is indeed plausible in our data set, as it is the highest possible amount that can be obtained with certainty (by the same reasoning, in the Binswanger task the reference point is likely to coincide with the safe outcome offered in the first prospect; see appendix A for a model of reference-dependence in the Binswanger task). Preferences are furthermore rank-dependent (Quiggin, 1982), so that decision weights are assigned to outcomes starting from the highest to the lowest (and vice versa for losses).

We describe decisions for binary prospects. For outcomes that fall purely into one domain, i.e. $x > y \geq 0$ or $0 \geq y > x$, we can represent the utility of a prospect ξ, $U(\xi)$, as follows:

$$U(\xi) = w^j(p)v(x) + (1 - w^j(p))v(y) \tag{1}$$

whereby the probability weighting function $w(p)$ is a strictly increasing function that maps probabilities into decision weights, and which satisfies $w(0) = 0$ and $w(1) = 1$; the superscript j indicates the decision domain and can take the values $+$ for gains and $-$ for losses; and $v(.)$ represents a utility or value function which indicates preferences over outcomes, with a fixed point such that $v(0) = 0$, and $v(x) = -v(-x)$ if $x < 0$. Contrary to EUT, utility curvature cannot be automatically equated with risk preferences, since the latter are determined jointly by the utility and the weighting function (Schmidt and Zank, 2008). For mixed prospects, where $x > 0 > y$, the utility of the prospect can be represented as:

$$U(\xi) = w^+(p)v(x) + w^-(1 - p)v(y) \tag{2}$$

In order to specify the model set out above, we now need to determine the functional forms to be used. For the utility function, we use a power function. This is the most popular function in the empirical literature and it has some desirable theoretical qualities (Wakker, 2008); it also fits our data better than alternative functional forms. Our conclusions do not change qualitatively if we were to use an exponential value function instead (see supplementary materials). We thus adopt the following functional form:

$$v(x) = \begin{cases} \frac{x^{1-\mu}}{1-\mu} & \text{if } x > 0 \\ -\lambda\frac{-x^{1-\nu}}{1-\nu} & \text{if } x \leq 0 \end{cases} \tag{3}$$

where λ indicates the loss aversion parameter, generally represented as a kink in the utility function at the origin (Abdellaoui, Bleichrodt, and Paraschiv, 2007; Köbberling and Wakker, 2005). This functional form provides a better fit than a simpler formulation of the power function, and has recently been used e.g. by Choi, Fisman, Gale, and Kariv (2007).[3] For weighting, we adopt the 2-parameter weighting function proposed by Prelec (1998):

$$w(p) = exp(-\beta^j(-ln(p))^{\alpha^j}) \tag{4}$$

[3]This functional form is commonly know as the constant relative risk aversion (CRRA) formulation, whereby μ is the Pratt-Arrow coefficent of relative risk aversion. Notice, however, that the coefficient cannot be interpreted in this way in our model, in which risk preferences will depend on probability weights as well as utility curvature.

For $\beta = 1$, this function conveniently simplifies to the 1-parameter function proposed by Prelec, which has a fixed point at $1/e \simeq 0.368$, a property which will turn out to be convenient below. In its complete specification, β is a parameter that governs mostly the elevation of the weighting function, with higher values indicating a lower function. Since this indicates the weight assigned to the best outcome for gains, and the weight assigned to the worst outcome for losses, a higher value of β indicates increased probabilistic pessimism for gains, and increased probabilistic optimism for losses. The parameter α governs the slope of the probability weighting function, with $\alpha = 1$ indicating linearity of the weighting function (the EUT case), and $\alpha < 1$ representing the typical case of *probabilistic insentivity*.

The latter is best characterized in terms of upper or lower subadditivity (Tversky and Wakker, 1995), whereby the same difference in terms of probabilities results in a smaller difference in probability weights away from the endpoints of $p = 0$ and $p = 1$ than close to them. This results in the characteristic inverse S-shaped weighting function (Abdellaoui, 2000; Bleichrodt and Pinto, 2000; Kilka and Weber, 2001; Wu and Gonzalez, 1996). Lower subadditivity is often referred to as the *possibility effect* and can be formalized for a constant $\epsilon \geq 0$ as $w(q) - w(0) \geq w(q+p) - w(p)$ whenever $q + p \leq 1 - \epsilon$. Upper subadditivity is commonly known as the *certainty effect*, and can be formalized for a constant $\epsilon' \geq 0$ as $w(1) - w(1-q) \geq w(p+q) - w(p)$ whenever $p \geq \epsilon'$. Other functional forms from the two-parameter family deliver similar results. One-parameter forms are, on the other hand, not well suited to describe our data, for reasons that will become apparent below.

The model considered so far is fully deterministic, assuming that subjects know their preferences perfectly well and execute them without making mistakes. This is clearly not realistic, and a stochastic structure is increasingly recognized to be necessary for the estimation of structural models (Hey, 1995; Loomes et al., 2002). We start by assuming that the utility of a prospect ξ is given by its representation in (1), plus an error term ϵ. The prospect ξ will now be chosen over an alternative prospect ζ whenever $U(\xi) + \epsilon_1 > U(\zeta) + \epsilon_2$, so that the probability Π of ξ being chosen over ζ can be represented as

$$\Pi(\xi|\mu, \nu, \lambda, \alpha^+, \beta^+, \alpha^-, \beta^-, \theta) = \Phi\left(\frac{U(\xi) - U(\zeta)}{\theta}\right) \tag{5}$$

where $\Phi(.)$ is the standard normal cumulative distribution function and $(\epsilon_2 - \epsilon_1) \equiv \theta \sim N(0, \sigma^2)$. This error is assumed to occur in the calculation phase, whereby given one's utility of a prospect, errors in calculation or implementation of these utilities may lead to deviations from the choices suggested by the deterministic model. We follow Hey and Orme (1994) and Bruhin et al. (2010) in implementing this Fechner-type error term into the maximum likelihood estimations of our structural model laid out above. Errors are clustered at the subject level, and the Broyden-Fletcher-Goldfarb-Shanno optimization algorhythm is used throughout.

3 Experimental setup

We recruited 207 farmers in the Vietnamese villages of Vĩnh Xuong and Vĩnh Hùa, An Giang province, close to the border with Cambodia alongside the Tien river (one of the two major arms into which the Mekong breaks up as it crosses into Vietnam). The households were randomly chosen from a complete population list of the two villages. The experiment had the official backing of the local communist party authorities, which meant that there was a 100% participation rate of our target population.[4] This means that our sample is representative of the local village reality, although we cannot claim representativeness outside of this specific subject pool.

The median household in our sample has an income of 9.9m Dong per capita per year. This corresponds to \$1.32 per capita per day for the median households in current exchange rates at the time of the experiment, and to \$2.89 in purchasing power parity (*PPP*; calculated using World Bank data for 2011). The corresponding means are \$2.26 (sd: 3.38) and \$4.95 (sd: 7.39) respectively. Our subjects are thus decidedly poor, with about 18% of them falling below the official \$1.25 poverty line in PPP terms. We also have significant variation in terms of age with a mean of 49.9 years and a standard deviation of 13.5 (range: 23-87), and education, recorded in 9 categories, with a mean of 2.2 and a standard deviation of 0.92. All subjects were literate. All but 1 household head were male.

Table 1: decision tasks, amounts in 1000s of Dong

gains	losses	mixed
(1/2: 40; 0)	(1/2: -40; 0)	0∼(1/2: 160; z*)
(1/2: 80; 0)	(1/2: -80; 0)	
(1/2: 160; 0)	(1/2: -160; 0)	
(1/2: 240; 0)	(1/2: -160; -40)	
(1/2: 240; 80)	(1/2: -160; -80)	
(1/2: 240; 160)		
(1/8: 160; 0)	(1/8: -160; 0)	
(1/8: 160; 40)	1/8: -160; -40)	
(2/8: 160; 0)	(2/8: 160; 0	
(3/8: 160; 0)	(3/8: -160; 0)	
(5/8: 160; 0)	(5/8: -160; 0)	
(6/8: 160; 0)	(6/8: -160; 0)	
(7/8: 160; 0)	(7/8: -160; 0)	
(7/8: 160; 40)	(7/8: -160; -40)	

We elicit certainty equivalents (*CEs*) to measure risk preferences. CEs

[4]No party official was present during any of the experiments or questionnaire tasks.

provide a rich amount of information, are easy to explain to subjects, and the sure amounts of money to be used in the elicitation are naturally limited between the lower and upper amount of the prospect. They are also flexible enough to allow for the detection of risk-seeking as well as risk neutral and risk averse behavior. This makes them a formidable tool if one wants to estimate structural models (Abdellaoui, Baillon, Placido, and Wakker, 2011; Bruhin et al., 2010). By varying the outcomes and the probabilities involved, it is easy to create the type of orthogonality needed to separate attitudes towards outcomes from attitudes towards probabilities, reflected in the utility function and the probability weighting function respectively.

Overall, we elicited 44 CEs per subject. The tasks used for the elicitation procedure where chosen so as to be orthogonal along the relevant dimensions, and were tested in extensive pilots with students before being deployed in the field. Table 1 provides an overview of the decision tasks, and figure 1 shows an example of a choice list. Prospects are described in the format $(p : x; y)$, where p is the probability of obtaining x, and y obtains with a complementary probability $1 - p$, $|x| > |y|$. Outcomes are shown in thousands of Dongs. The highest loss is smaller than the largest gain. This was necessary to limit financial exposure, since all subjects who were randomly selected to play the loss part would be given an endowment equal to the highest loss possible. In addition to the prospects over gains and losses, we used one mixed prospect, which is necessary to obtain a measure of loss aversion. In this case, we obtained the value z* which satisfies the indifference $0 \sim (1/2 : 160; -z)$, where z varied in a choice list from 160 to 16.[5]

Gains were administered before losses, which took part from an endowment (see Etchart-Vincent and L'Haridon, 2011, for evidence that it does not matter whether losses take place from an endowment or are real). We also had ambiguous prospects that will not be analyzed here, and which were always presented in block after the risky prospects. The prospects were presented to subjects in a fixed order, whereby first 50-50 prospects were presented in order of ascending expected value, and then the remaining prospects were presented in order of increasing probability. The fixed order was kept so as to make the task less cognitively demanding for subjects, since in the fixed ordering only one element would change from one decision task to the next, which could be easily pointed out by the enumerator. To test whether such a fixed ordering of tasks might influence decisions, we ran a large-scale pilot at Ho-Chi-Minh-City University involving 330 sub-

[5]The choice tasks (though not the instructions, this experiment being run in individual interviews) and payoffs were the same as the ones used by L'Haridon, Martinsson, and Vieider, 2013 in experiments with students across 30 countries. For an overview of the tasks, see the instructions available for download at www.ferdinandvieider.com/instructions.html.

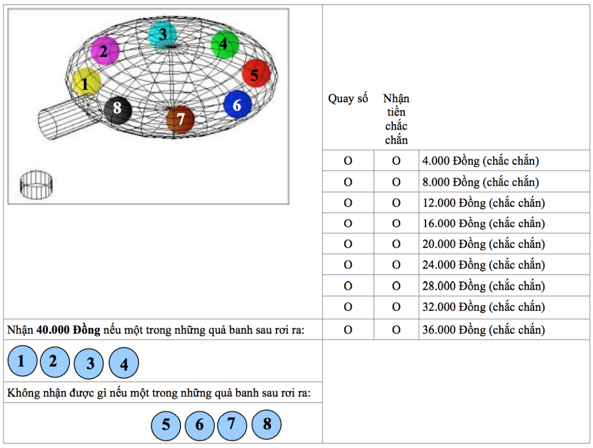

Figure 1: Example of choice list to elicit a CE

jects. The pilot compared the fixed ordering used here to five other orders: 1) probabilities increasing from the lowest to the highest; 2) probabilities decreasing from the highest to the lowest; 3) an order in which ambiguity came before risk; 4) an order in which losses came before gains; and 5) a condition in which decision tasks were randomized within each block (gain, loss, risk, and ambiguity). The only significant difference we found was one of decreased probabilistic sensitivity relative to the order used in this paper when the tasks were presented in order of decreasing probability (results available upon request).

CEs were elicited in individual interviews by a team of 18 enumerators. The enumerators were extensively trained before going to the field, and had acquired experience by running the same experiment with students. They were furthermore supervised in the field by one of the authors. We did not find any systematic enumerator fixed effects. The actual experiment was preceded by a careful explanation of the decision tasks involved. The subjects were told that they would face choices between amounts of money that could be obtained for sure and risky allocations, in which different amounts would obtain with some probabilities indicated next to them. They then learned that the interview would consist in a number of such tasks that would differ in the amounts they offered as well as the likelihood with which these amounts obtained. At the end, one of the tasks would be extracted at random, and one of the lines in which they had indicated a choice between a sure amount and the prospect would be played for real money (the standard procedure in this sort of task: Abdellaoui et al., 2011; Baltussen, Post, van den Assem, and Wakker, 2010; Bruhin et al., 2010; Choi et al., 2007). Losses were only introduced once all the gain prospects had been played. Small breaks were taken between the different parts of the elicitation procedure.

Once a subject had understood the general structure, he was presented an example of a decision making task for risky gains. The enumerator then explained why for a safe amount equal to the lower amount in the prospect, he would likely prefer to take the prospect. Equivalently, once the sure amount reached the highest amount to be won in the prospect, the subject would be explained that he would most likely prefer the sure amount. This would lead naturally to a point at which a subject should switch from the prospect to the sure amount. At which amount this would happen would be purely up to the farmer's preference. Most farmers understood this very quickly. If farmers wanted to switch multiple times in the example, they were explained once why this may not be desirable. If they still wanted to switch multiple times thereafter, enumerators were instructed to record such choices without further ado. This, however, never happened.

Since all farmers were literate, they were shown the lottery depiction and the amounts involved on the interview sheet. Every time a major change occurred in the decision tasks (e.g. from risk to ambiguity or from gains to losses), the enumerator pointed out the change and gave additional explanations of what this would involve. In the course of the explanation, farmers were also shown bags containing numbered ping pong balls that would be used for the random extraction, and were encouraged to examine their contents. This served to make the decision problems more tangible and concrete.

The prospects concerned payoffs between 0 and 320,000 Dong, which were added to a fixed participation payment of 8,000 Dong. These are substantial sums, with the expected payoff from participation corresponding to about 6 days' per capita income of the median household, and the highest prize to over 10 days. This indicates a general tendency by which PPP conversions used for developing countries underestimate the amounts used if one were to employ income instead of prices as a gauge. Notice how, given the well-established finding of risk aversion increasing in stakes (Binswanger, 1980; Fehr-Duda, Bruhin, Epper, and Schubert, 2010; Holt and Laury, 2002; Kachelmeier and Shehata, 1992; Santos-Pinto, Astebro, and Mata, 2009), this tends to bias our findings *against* risk tolerance. Notice also that the payoffs we offer are at least as high as most of the payoffs offered in similar studies in developing countries (for instance, Attanasio et al., 2012, have average payoffs of about \$2, corresponding to about 1 day's pay; Yesuf and Bluffstone, 2009 have an average payoff of about 3 days of pay).

The overall quality of our data is good, which likely reflects the careful procedures followed in explaining the tasks. About 25% of our subjects violated first order stochastic dominance at least once for gains, and about 31% for losses. This is in line with violations obtained with student samples from the West. Abdellaoui, Bleichrodt, L'Haridon, and Van Dolder (2013) found about 20% of subjects to violate stochastic dominance in a laboratory experiment with students. L'Haridon et al. (2013) observe violation rates between 17% and 37% with Western student subjects. Birnbaum (1999) reports violation rates around 50% in experiments run over the internet with general population samples. Overall violations relative to total number of CEs in our farmer data amount to only about 3.0% for gains, and to 4.3% for losses. These figures are slightly lower than the ones observed for Vietnamese students, for whom violations amounted to 3.4% and 10.5% for gains and losses respectively.

We also obtained detailed data on household characteristics, income, and some farming activities. The variables relevant for this study will be introduced and described as the need arises. Interviews to obtain such data were conducted on a different day, in order not to tire our subjects too much.

4 Aggregate risk preferences in perspective

We start by describing risk preferences in the aggregate. To put the findings into perspective, we show the estimates obtained for farmers together with estimates for students in Vietnam and in the USA. The data for the Vietnamese students were obtained by the same enumerators, using the same procedures as for farmers. The comparison data in the USA are taken from L'Haridon et al. (2013), and represent the typical pattern found in Western countries. They were obtained using the exact same experimental tasks and payoffs obtained by careful PPP conversion. The US data were, however, collected in an experimental session instead of individual interviews. The latter are meant only as a general point of comparison to typical data from the West. Comparing our data to the ones obtained using the same functional form for the weighting function summarized by Booij et al. (2010), our parameters for American students are at the lower end of the spectrum in terms of probabilistic pessimism for gains and risk aversion typically found in the West (some of which were collected in individual interviews), thus constituting a very conservative benchmark.

Table 2 shows the point estimates of the different parameters for all three subject populations.[6] The curvature of the value function does not significantly differ between the different population groups for gains. It is concave for gains for all three groups, while the predominant pattern for losses is convexity—although we cannot statistically exclude linearity for

[6]One may also worry that simple demographic differences between our samples may bias the comparison. A regression controlling for demographics shows that the comparison results between farmers and students are unaffected by this issue. We will return to the point of individual chacteristics below.

any but the US subject population. Loss aversion is highest for farmers, lower for Vietnamese students, and lowest for US students.

Table 2: point estimates of model parameters with 95% confidence intervals

	farmers Vietnam	students Vietnam	students USA
μ (value function gains)	0.090	0.154	0.137
95% CI	[0.038 , 0.142]	[0.056 , 0.252]	[0.054 , 0.220]
ν (value function losses)	0.035	0.132	0.090
95% CI	[-0.021, 0.091]	[-0.004 , 0.268]	[0.006 , 0.174]
λ (loss aversion)	1.926	1.595	1.362
95% CI	[1.649 , 2.202]	[1.329 , 1.862]	[1.139 , 1.585]
α^+ (sensitivity gains)	0.702	0.870	0.736
95% CI	[0.603 , 0.801]	[0.760 , 0.979]	[0.664 , 0.808]
β^+ (pessimism gains)	0.861	0.692	1.052
95% CI	[0.739 , 0.983]	[0.556 , 0.827]	[0.939 , 1.165]
α^- (sensitivity losses)	0.722	0.758	0.851
95% CI	[0.625 , 0.820]	[0.598 , 0.918]	[0.760 , 0.942]
β^- (optimism losses)	1.226	0.957	0.860
95% CI	[1.069 , 1.383]	[0.746 , 1.169]	[0.767 , 0.954]
Number of subjects:	207	52	75

The equality in the curvature of the utility function for gains is convenient inasmuch as we can now discuss differences in probability weighting functions directly in terms of risk preferences. Figure 2 shows the probability weighting functions for gains for the three subject populations. Compared to Vietnamese students, our farmers are less sensitive to changes in probability. If we take probabilistic sensitivity as a rationality indicator (Tversky and Wakker, 1995), then we would expect exactly this to happen based on the difference in education. Indeed, the finding is consistent with the one in L'Haridon et al. (2013), who found sensitivity to increase in grade point average; and with the results reported by Choi et al. (2013), who found violations of the generalized axiom of revealed preferences to decrease in education.[7] Farmers are also significantly more pessimistic than Vietnamese students. This finding is in general agreement with an account of risk tolerance increasing in income, a point to which we will return below.

We next compare our farmers to American students. While American students tend to be more sensitive to probabilistic change than Vietnamese farmers, the difference fails to reach significance. This would appear to exclude explanations of our data based on error or cognitive ability—a point to which we will return in the discussion. The most surprising result, however, obtains in terms of pessimism: Vietnamese farmers are significantly

[7]We also find significantly higher levels of noise for farmers than for students. This is quite usual when comparing students to general subject populations, see e.g. Huck and Müller (2012)

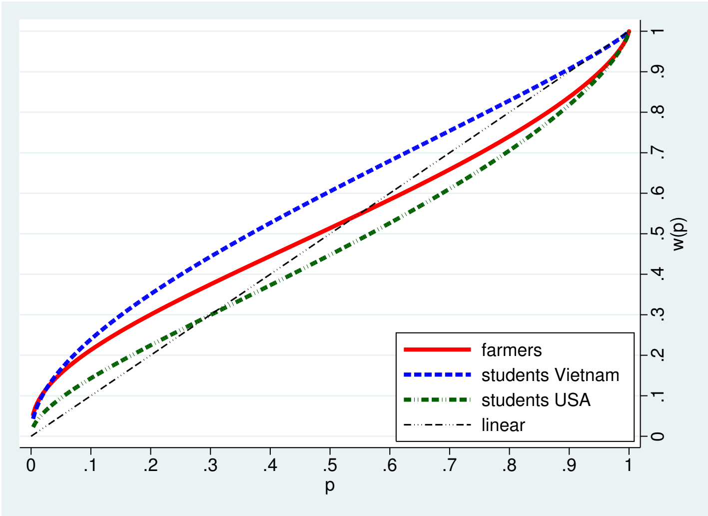

Figure 2: Weighting functions for gains, farmeres versus students

less pessimistic than American students. American students exhibit the typical probability weighting function found with Western subjects, characterized by an inverse S-shape and a crossing point of the diagonal close to 0.3, with a value of β not significantly different from 1. Vietnamese farmers also exhibit probabilistic insensitivity, but the function crosses the diagonal far to the right close to 0.6. Indeed, the value of β estimated for Vietnamese farmers is significantly smaller than 1, making them probabilistically *optimistic* on average over the probability space, and thus also more risk tolerant (an direct analysis in terms of risk preferences can be found in the supplementary materials).

This finding differs strikingly from previous results obtained in Vietnam by Tanaka et al. (2010) (henceforth: TCN) and Nguyen et al. (2012) (henceforth: NVX), who find much less optimism. Indeed, TCN conclude that their "values are similar to the corresponding means [...] in Wu and Gonzalez (1996) laboratory experiments with Western students". This is not surprising. The 1-parameter version of the Prelec probability weighting function they use puts $\beta = 1$ by definition, so that it cannot pick up higher probabilistic optimism. Estimating a 1-parameter weighting function such as theirs using our own data, we obtain results that are virtually identical to theirs. What is more, the high risk tolerance we observe is also not reflected in utility, which remains unaffected by the change in weighting functions. Using their functional assumptions, thus, we would have reached the exact same conclusions. Appendix B shows our estimations using their functional forms, and compares the resulting parameters to the ones obtained by TCN and NVX in detail.

A different question is whether the differences we find are economically significant. To answer this question, we can take a look at risk premia. For our farmers, the median non-parametric risk premium for a 50-50 prospect over 160k Dong or nothing is 2.5% (the mean is -2.3%; see appendix C for a complete list of risk premia and certainty equivalents). This compares to a risk premium of 18.9% for American students. Vietnamese students, on the other hand, are risk seeking for typical 50-50 prospects, with a risk premium of -11.5% (see supplementary materials for nonparametric data for students). This pattern is indeed quite typical for students in very poor developing countries (L'Haridon et al., 2013).

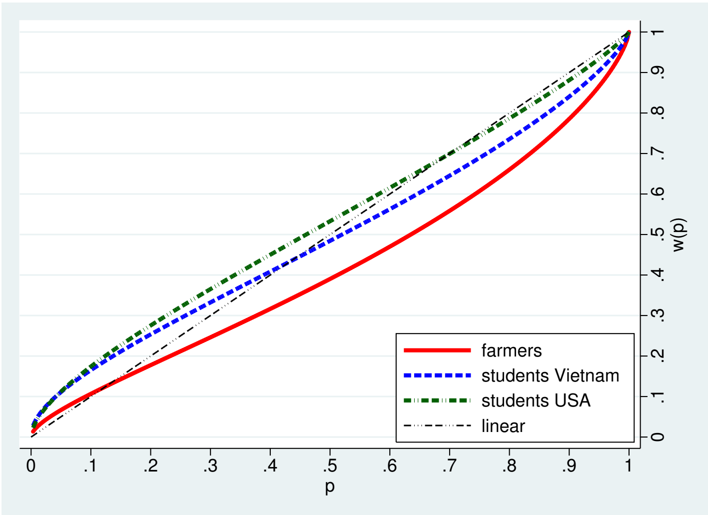

Figure 3: Weighting functions for losses, farmers versus students

For losses we again find increased optimism in Vietnam relative to the US.[8] This time, however, students are less optimistic than farmers. This tendency is, however, in part counteracted by a more concave value function for losses for farmers. Indeed, an analysis in terms of risk preferences (see supplementary materials) indicates that Vietnamese farmers and students are not statistically different with regards to their propensity to accept risk for losses.

[8]Our losses were implemented from an endowment. While being the only ethically admissible option other than hypothetical choices, this creates the issue of what proportion of subjects integrate the endowment with their choices, thus finding themselves effectively in a gain frame, and what proportion do not. Our comparison between groups thus needs to be taken with a grain of salt, since differences may reflect in part differences in the degree of integration.

5 Preferences, demographics, and behavior

5.1 Developing an empirically tractable method

We have presented our aggregate results using the full theoretical apparatus of prospect theory. While being a powerful setup for the description of real world decisions, this theoretical framework has the disadvantage of not being very practical for regression analysis, at least if what we are interested in are overall risk preferences. The multiplicity of parameters may create issues of multicollinearity, whereby some effects that would be significant in terms of risk preferences disappear, since they are split between different parameters (which would be *jointly* significant), while in other cases perfect null results in terms of risk preferences may appear as significant results in both utility curvature and probability weighting, with both canceling each other out in terms of risk preferences. This section is dedicated to developing a methodology that is empirically more tractable, while preserving the main advantages of PT in the description of experimental data.

Several recent models and empirical estimations have adopted some elements of prospect theory, while rejecting others. This has greatly increased the descriptive power of the models, while keeping the theories tractable. Indeed, having a multiplicity of parameters is taxing from a modeling perspective, as well as putting high demands on the data in econometric estimations. The main approach has been to adopt reference-dependence, while maintaining linearity in probabilities, resulting in a reference-dependent version of EUT (Diecidue and van de Ven, 2008; Kőszegi and Rabin, 2006; Sugden, 2003; von Gaudecker et al., 2011; henceforth *RDEU*). This allows for loss aversion, and different utility curvature for gains and losses relative to a reference point (however defined).

In our view, however, probability weighting is one of the strongest parts of PT, given how it can explain the contemporary uptake of insurance and lottery play. We thus consider abandoning utility curvature the least costly strategy in the description of our experimental data. We propose to use a dual version of RDEU, whereby probabilities are transformed non-linearly, while utilities enter the equation in a linear fashion (Yaari, 1987). Other than in the original formulation, we still define our model over gains or losses relative to a reference point. Notice how this obtains directly from the theoretical apparatus presented above, by setting $v(x) = x$. We can then still estimate the same functional forms for probability weighting. Since these do now indicate risk preferences directly instead of a probability weighting function, we will call them *risk-preference* functions.

To be clear, we do not claim universal applicability for this model, or that it is as descriptively valid as the full theory above. For instance, it is unsuitable for non-monetary outcomes, and will become less accurate as outcomes grow larger. Be that as it may, the goal of introducing this model is not to increase the descriptive validity in general, but rather to obtain a more tractable method to analyze risk preferences in our experimental data. Adopting this model has indeed several advantages. For one, we can keep using the 2-parameter weighting function, and can now directly interpret it in terms of risk preferences. This also makes it easy to discuss effects of independent variables in the regression, since risk preferences are now entirely represented in the risk-preference function. We will thus henceforth use this model as our main tool of analysis. All results reported below are stable to using the full PT specification, which are reported in the supplementary materials.

5.2 Risk preferences and income

Above we have speculated that the difference in risk tolerance between students and farmers is likely due to income differences. The median monthly income per capita of farmers is 825,000 Dong, while students' families have a monthly income per capita of 1,800,000 Dong.[9] Nevertheless, there are several possible confounds. In particular, students are younger on average, and obviously also more highly educated. To disentangle these effects, we will now control for differences in age, education and income within the farmer sample. Table 3 shows the results of the regressions. Our subject pool is reduced to 197 subject, since for the remaining subjects one of the three observable characteristics is not reported. Including those subjects by attributing to them the mean values does not change our main results.

Table 3: Effects of income, education, and age on risk preferences

N=197	λ	α^+	β^+	α^-	β^-
income	-0.099*	0.008	-0.108***	0.015	0.187**
	(0.055)	(0.076)	(0.041)	(0.061)	(0.091)
education	0.209**	0.095*	0.023	0.114*	0.203*
	(0.089)	(0.056)	(0.063)	(0.060)	(0.120)
age	0.071	-0.116**	-0.009	-0.122**	-0.073
	(0.080)	(0.052)	(0.074)	(0.057)	(0.094)
constant	1.646***	0.668***	0.922***	0.761***	1.357***
	(0.075)	(0.050)	(0.061)	(0.052)	(0.096)

Standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01

Looking at loss aversion, we find two main effects. On the one hand, loss aversion increases in education. On the other, loss aversion is found to decrease with income. Both effects are contrary to the findings of Gächter

[9]The figure on students' household income is taken from a different experiment with students randomly drawn from the same sample.

et al. (2010). They are, on the other hand, in agreement with the findings by TCN and von Gaudecker et al. (2011). We next turn to the risk-preference function for gains. Probabilistic sensitivity is found to increase with education and to decrease with age for both gains and losses. Given how sensitivity is taken to be an indicator of rationality, this corresponds well to what we would expect. Also, the result corresponds closely to the results of L'Haridon et al. (2013), who find sensitivity to decrease in age and increase in grade point average. It is also in general agreement with findings by Choi et al. (2013), who found violations of rationality principles to increase with age and decrease with education and income (the latter effect is not significant in our data).

We next look at the elevation of the risk preference function, and thus risk aversion. For both gains and losses, we find risk aversion to strongly decrease in income. What is more, it is also economically significant. While a farmer with the mean income will be approximately risk neutral for a 50-50 prospect, a farmer with an income that lies 1 standard deviation above the mean is risk seeking. For losses, the effects are similarly strong. Together with the comparison to data obtained in the West discussed above, this constitutes strong indication of a risk-income paradox, whereby risk tolerance increase in income within countries, but decreases in income per capita between countries. We will return to this paradox in the discussion.

An important issue is whether our findings are indeed driven by income, and not by wealth. Wealth has sometimes been used as a proxy for risk preferences in the development economics literature, with larger farmers assumed to be less risk averse (Feder et al., 1985). To capture wealth levels we use the first two components from a principal component analysis in which all variables capturing wealth in our data set are entered (Filmer and Pritchett, 2001). Table 4 reproduces the results from table 3 controlling for these wealth indicators.[10] The wealth controls do not show any significant effects. This goes against the traditional assumption of risk tolerance increasing in wealth, a point to which we will return in the discussion.

More importantly for the purpose of this section, the effect of income only results reinforced from the introduction of wealth controls. Increased income results in reduced loss aversion, strongly decreased risk aversion for gains, and strongly increased risk seeking for losses. Given the large effect of income and the absence of wealth effects on risk preferences, this raises the question of the origin of the relationship between the two. We cannot directly address issues of causality in our data set. Nevertheless the strong relation between risk preferences and income, taken together with the detachment of risk preferences from wealth levels, makes it plausible

[10] Wealth is positively correlated with income, as one might expect. However, the correlations of our income measure with the first principal component is relatively modest at r=0.377.

Table 4: Income regression with wealth controls

N=185	λ	α^+	β^+	α^-	β^-
income	-0.108*	0.018	-0.118***	0.025	0.236**
	(0.059)	(0.095)	(0.043)	(0.079)	(0.113)
education	0.187**	0.117*	0.024	0.154**	0.230
	(0.093)	(0.063)	(0.065)	(0.067)	(0.156)
age	0.040	-0.106*	-0.000	-0.128*	-0.069
	(0.084)	(0.059)	(0.080)	(0.074)	(0.129)
wealth pc 1	0.035	0.002	0.032	0.008	-0.068
	(0.054)	(0.046)	(0.057)	(0.055)	(0.108)
wealth pc 2	0.110	0.047	0.050	0.085	-0.102
	(0.083)	(0.065)	(0.069)	(0.082)	(0.109)
constant	1.662***	0.673***	0.921***	0.781***	1.390***
	(0.079)	(0.054)	(0.064)	(0.061)	(0.115)

Standard errors in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.01$;

that risk preferences have an effect on income generating activities. The next section thus looks at correlations of risk preferences with behavior. We will return to the issue of causality in the discussion.

5.3 Predicting behavior

In this section, we address the question whether risk preferences as we measured them can 'predict' real world behavior, i.e. whether they correlate with activities we would expect them to correlate with. Previous evidence is mixed on this point, but predominantly concludes that this kind of preference measurements performs badly at predicting real world behavior (see Liu, 2012, and Liu and Huang, 2013, for recent exceptions). For instance, Sutter et al. (2013) recently found in a large-scale study that risk preferences had almost no predictive value for adolescents' behavior. Giné et al. (2008) and Cole, Giné, and Tobacman (2012) measured risk preferences in randomized controlled trials to study the uptake of rainfall insurance in India, and even found risk aversion to be *negatively* correlated with insurance purchase decisions. We hypothesize that part of this low predictive power of experimentally measured risk preferences may be due to the restrictiveness of the measures obtained. For instance, all three studies mentioned obtained measures for 50-50 prospects over gains.[11] The risks involved in

[11]Several other explanations for a negative relation between risk aversion and insurance purchase are possible. Clarke (2011) derives a EUT-based model in which insurance purchase is hump-shaped in risk aversion in the presence of basis risk. Liquidity constraints of the poorest farmers, who are also likely to be the most risk averse, is another potential explanation. And moving beyond EUT, to the extent that the Binswanger task used in these studies measures mainly loss aversion, even in the absence of basis risk such loss aversion may play against purchasing insurance if monetary outlays are modeled as losses (see Bateman, Kahneman, Munro, Starmer, and Sugden, 2005, for a discussion).

decisions such as smoking or insurance purchase, however, may be better characterized as low probability losses.

To explore whether our data perform better at predicting behavior, we start by correlating our structural estimates with a number of general types of behavior that one may expect to be influenced by risk preferences, such as saving, buying lottery tickets, and smoking. We also control for the same population characteristics as above. There is one more methodological caveat to be mentioned. In order to be able to estimate a structural model with several parameters, we maintain the econometric structure set forth above. Conceptually, however, it must be clear that the behavioral variables in the regression ought now to be seen as *dependent* variables, with the risk preferences taking the place of the explanatory variables. The alternative would be to estimate the parameters at the individual level and to then enter them into a regression as independent variables. This has, however, the disadvantage that only point estimates of the parameters are used, and that they are all treated as independent entries. This is avoided in a structural estimation, which we thus consider to be methodologically sounder.

The regression is reported in table 5. We start by looking at lottery buying behavior, encoded as a dummy variable indicating whether farmers buy (1) or do not buy (0) lottery tickets. This is often indicated as a classical case where objectively given probabilities describe the outcome generating process well (especially the type of lottery tickets typically bought by farmers have a given probability of winning, unlike state lotteries where the prize will in part depend on the number of tickets with the winning combination of numbers). We find two significant effects: the likelihood of buying lottery tickets decreases in loss aversion, and it increases in risk seeking for gains. Given that buying a lottery means incurring a certain loss to obtain a risky gain, this exactly fits a model of lottery buying behavior.[12]

We also find some interesting effects for saving behavior, entered as total liquid savings (1000s of Dong). Arguably, saving may be determined by many factors, amongst which time preferences, on which we have no data. Nevertheless, risk aversion may play a role in determining so-called precautionary saving.[13] We find savings to increase in risk seeking for gains and in risk aversion for losses. Risk aversion for losses resulting in larger amounts of saving exactly indicates a pattern of precautionary saving as hypothesized above. The pattern for gains is harder to interpret. The most likely explanation is that farmers with higher income save more, as well as

[12]This conclusion assumes that monetary outlays to obtain a good are perceived as losses. This is not uncontroversial. For a summary of the dispute, and an adversarial collaboration finding that oulays are indeed perceived as losses, see Bateman et al. (2005)

[13]Savings amounts are quite small, so that this variable cannot be though of as capturing wealth, which we have seen above to only have very weak effects at best.

Table 5: predicting risk behavior

N=197	λ	α^+	β^+	α^-	β^-
lottery	-0.442***	0.052	-0.293**	-0.040	0.132
	(0.167)	(0.096)	(0.140)	(0.110)	(0.196)
savings	-0.040	0.009	-0.119*	-0.051	-0.212**
	(0.115)	(0.101)	(0.061)	(0.088)	(0.103)
smoking	0.253*	0.130	0.026	0.097	-0.195
	(0.138)	(0.113)	(0.097)	(0.117)	(0.185)
education	0.207**	0.081	0.041	0.123*	0.248*
	(0.088)	(0.060)	(0.068)	(0.072)	(0.145)
age	0.031	-0.127**	-0.029	-0.134**	-0.071
	(0.079)	(0.054)	(0.074)	(0.062)	(0.099)
income	-0.056	0.007	-0.069	0.039	0.222**
	(0.057)	(0.100)	(0.042)	(0.076)	(0.103)
constant	1.771***	0.547***	1.117***	0.736***	1.461***
	(0.159)	(0.103)	(0.125)	(0.114)	(0.228)

Standard errors in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.01$

being more risk tolerant. This explanation is made plausible by the fact that savings are significantly correlated with income (r=0.41, $p<0.001$), and that the effect of income disappears in the regression once we insert savings. Notice, however, how this cannot explain the findings for losses. Indeed, income remains a strong predictor of risk preferences for losses even when savings are inserted into the regression, and it is actually the more risk *averse* farmers who save more. We do not find significant predictive power of our preference measures for smoking behavior (except that more loss averse subjects are marginally significantly more likely to smoke, an effect that is somewhat puzzling). This may be due to the low awareness of the health dangers implied by smoking in Vietnam.

We next look at some types of behavior that relate more closely to risk management practices on the farm. These are, in particular, whether a farmer rents out his land to cope with the risk of flooding (the largest environmental risk to our farmers living alongside the Mekong), and whether he adapts by taking on non-farm labor locally, both of which are unequivocally risk averse strategies. We also include a dummy indicating whether the household head migrates to the city in order to work there for part of the year, and whether he has borrowed significant sums of money over the last five years, both of which may be seen as signs of risk tolerance.[14]

[14] A variable of much interest in the literature is technology adoption, often under the form of willingness to switch to new crops. We did capture such behavior in our data. It turns out, however, that the switching behavior is very much influenced by command and control policies of the party. From interviews we thus gathered that some farmers had switched to new rice varieties proposed by the government, while others had switched back after observing poor performace of the newly adopted varieties. In sum, it is unclear whether switching crop indicates a risk seeking or risk averse strategy

Table 6: predicting risk behavior on the farm

N=197	λ	α^+	β^+	α^-	β^-
rent out land	0.653	-0.316	1.299**	-0.646*	-1.150**
	(0.620)	(0.205)	(0.645)	(0.360)	(0.466)
migration	-0.517**	-0.160	-0.322*	-0.151	1.090**
	(0.263)	(0.229)	(0.170)	(0.219)	(0.431)
off-farm job	-0.014	0.011	0.146	0.248	-0.015
	(0.189)	(0.130)	(0.144)	(0.220)	(0.176)
borrowed money	0.104	-0.079	0.145	0.063	-0.073
	(0.162)	(0.135)	(0.122)	(0.126)	(0.247)
income	-0.084*	-0.002	-0.102***	0.031	0.229
	(0.051)	(0.104)	(0.034)	(0.079)	(0.171)
education	0.178**	0.100*	0.004	0.116*	0.256**
	(0.088)	(0.058)	(0.061)	(0.064)	(0.125)
age	0.044	-0.125**	-0.015	-0.151**	-0.056
	(0.081)	(0.054)	(0.068)	(0.064)	(0.107)
constant	1.602***	0.742***	0.821***	0.728***	1.411***
	(0.140)	(0.122)	(0.095)	(0.095)	(0.224)

Standard errors in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.01$; controls are z-scores

Table 6 shows the regression results. We start from the risk averse coping strategies. Leasing out one's land instead of cultivating it oneself is found to correlate with all parameters but sensitivity for gains and loss aversion: a farmer is more likely to lease out his land the more insensitive he is to probabilities of losses, and the more risk averse he is, with the latter of these effects holding for both gains and losses. Leasing out one's land is indeed a very risk averse strategy. From a few interviews conducted subsequently with farmers who leased out their land, it appears that the risk premium paid is around 50% on average, i.e. the rental fee obtained is 50% lower than the average income from cultivating the land (although this figure overestimates risk aversion as it does not include income from potential alternative occupations by farmers who rented out their land, such as fishing). We do not obtain any effects for finding local off-farm labor. In terms of risk tolerant strategies, we again find no effect for the indicator whether the household has borrowed money over the last five years. However, the likelihood of migration to work in the city is decreasing in loss aversion (suggesting a status quo effect, see Kahneman, Knetsch, and Thaler, 1991) and in risk aversion for gains, and is increasing in risk acceptance for losses. Taken together, this provides strong evidence of the predictive power of our experimental measures of risk preferences.

in our sample, or part of both, so that the variable is not well suited for this analysis.

6 Discussion

The results presented in this paper break radically with some assumptions on risk preferences of poor developing populations. Far from finding high levels of risk aversion amongst poor farmers, we find farmers in Vietnam to be quite risk tolerant in comparison to typical Western populations—although they are less risk tolerant than Vietnamese students. At the same time, our measures appear to be validated by their high predictive power. We have also shown a clear increase in risk tolerance with income, both using the comparison between farmers and students, and within the farmer population itself. This is the first paper to show such a clear relationship between risk tolerance and income in the developing world.

Given how strong the relationship with income is, it seems unlikely that other factors would constitute a better explanation for these aggregate risk preferences. In particular, we do not think that our data can be explained in any way by noise or systematic error. While answering randomly on our choice lists would produce risk neutrality on average, the choice patterns we find are clearly not random. Indeed, the number of violations of first order stochastic dominance of our farmers are comparable to violation rates observed in the West with students. In terms of our own data, overall violation rates are indeed slightly *lower* for farmers than for Vietnamese students. The violations are also considerably lower than for American students, which is probably explained by the fact that data for American students were collected in sessions rather than in individual interviews.

Another indication comes from the slope of the probability weighting function. In the presence of high levels of noise, we would expect the slope parameter to move towards zero. This follows directly from the construction of the choice lists. For low probabilities, there is much more space to switch above the expected value of the prospect than below it. Subjects who have a high likelihood of responding at random could thus be expected to appear as more risk seeking for small probabilities. By the same reasoning, the opposite should occur for large probabilities, thus resulting in very low probabilistic sensitivity.[15] This is indeed what shows up in the effect of education, with more highly educated subjects in our sample being somewhat more sensitive towards changes in probabilities. Overall, however, our farmers are undistinguishable in terms of probabilistic sensitivity from our American students, thus excluding an explanation in terms of noise. The latter is further made unlikely by the high risk tolerance found with

[15] Andersson, Tyran, Wengström, and Holm (2013) make a similar argument in terms of choices between non-degenerate lotteries. They also provide an critical review of the literature on the connection between cognitive ability and risk aversion, concluding that the latter seems largely spurious and due to the connection between cognitive ability and noise.

Vietnamese students.

For the development literature, this poses the issue of what may hold back technology adoption on the farm. To the extent that preferences cannot be blamed for this, we may look at other factors that hinder adoption. Indeed, Feder (1980) remarks how "risk and risk-aversion have been used to explain differences in input use and the relative rate of adoption of modern technologies by farmers of different sizes. But different patterns of behavior are observed in different regions, and thus the impact of risk and risk-aversion needs to be examined in relation to other factors and constraints [...]" (p. 263). Several indications in this direction are also provided in the recent literature. Karlan et al. (2012) present results suggesting that it is the sheer amount of risk exposure that makes investments unprofitable in some cases. Mobarak and Rosenzweig (2012) present evidence that risk taking in production goes up once farmers are sheltered from the worst risks through insurance.

While we can thus not confirm the relevance of *average* risk preferences—under the form of high risk aversion causing reluctance to innovate—we still find risk preferences to be important at the individual level. Indeed, our data perform well in terms of external validity, predicting behavior from the purchase of lottery tickets and precautionary saving, to renting out one's land as a risk-averse farming strategy and migrating to far-away cities as a risk-seeking strategy to obtain higher income. Far from concluding that risk preferences are not relevant, thus, we conclude that they seem to play a major role in determining people's behavior. They are, however, not sufficient to explain general aversion to innovation or technology adoption. The latter seems to stem rather from extremely high risk *exposure*, which can only be covered very imperfectly.

In relation to this issue, it is interesting to return to the strong correlation between risk preferences and income, and the absence of correlations with wealth levels. While we cannot solve the issue of causality here, it is likely that risk averse behavior results in lower levels of income, in addition to any influence income may have on risk preferences. In some of the development literature, however, wealth rather than income has been taken as a proxy for risk preferences, with wealthier individuals supposed to be more risk tolerant (Binswanger, 1981). This derives from the observation that the adoption of new technologies has often been observed to correlate with wealth (Feder et al., 1985). Our results, then, suggest a different account of this phenomenon. Indeed, wealth may limit risk *exposure*, since assets can be sold to smooth income after a shock. In this sense, risk management may be determined by risk preferences and by wealth levels jointly. Unfortunately, our data do not allow us to address this issue, and panel data are needed to properly disentangle the causality relationship, so that the investigation of this relationship must be left for future research.[16]

Beyond the immediate development context, the relation we find between risk and income suggests a paradox. Within countries, more affluent people have been shown to be more risk tolerant. Between countries, countries with higher GDP per capita appear to be more risk averse. L'Haridon et al. (2013) show this effect in experiments with students across 30 different countries. They also show some evidence on the within-country variation, although their data are much weaker in this respect. In this paper, we have shown strong evidence on the within-country relation, together with evidence that our farmers are more risk tolerant than American students, or in general Western populations. Together this evidence clearly shows the paradox (see Vieider et al., 2012, for a potential explanation of the paradox). Indeed, the data here presented also constitute further evidence that the student comparison is not driven by selection into university based on income. Even relatively poor Vietnamese farmers are found to be more risk tolerant than typical students from the West.

[16]There is also a much simpler explanation of such findings. To the extent that wealth correlates with income, it may pick up the effect income has on risk preferences, especially in the absence of good income measures.

A Reference dependence in Binswanger

In this appendix we try and model reference point effects for CEs and in Binswanger, within the PT formulation laid out above. Since PT is silent about the determination of the reference point itself, we need to start from a plausible assumption on how the reference point is formed. As already discussed above, a natural choice of reference point seems to be the lowest outcome which can be obtained with certainty, i.e. independently of the vagaries of nature. In other words, this is the lowest amount that can be secured by one's own actions assuming an evil nature that will try to minimize one's outcome. Using this assumption, we will now proceed to derive reference-dependant models for the tasks used in this paper and for the task proposed by Binswanger (1980).

A.0.1 Reference points for CEs

A typical elicitation task will offer a choice between a prospect that offers an outcome $x > 0$ with probability p, and a lower outcome $y < x$ with a complementary probability $1 - p$, which we will represent as $(x, p; y)$. This prospect will then be compared to certain amounts increasing from x to y in some given step, and one of the choices will finally be extracted for real payout. The switching point then produces the certain value that is equally good as the prospect, $CE^* \sim (x, p; y)$, or CE of the prospect.

Following the discussion above, a natural choice of reference point in this task is the lowest outcome, y, which is generally (but not necessarily) set equal to 0. Indeed, this is the highest outcome that can be obtained with certainty independently of chance (i.e. by always choosing the safest option). We can thus represent the decision problem as follows:

$$v(CE) = w(p)v(x) + (1 - w(p))v(y) \tag{6}$$

The distinctive feature of this representation is that we remain entirely inside the gain domain. In other words, reference-dependence plays no role here.

A.0.2 Reference point effects in Binswanger (1980)

Table 7 shows the choice list proposed by Binswanger using the original monetary values (in pre-1980 Rupees), together with some parameters to which we will return below. This task offers subjects a choice between a number of different 50-50 prospects, $(x_i, 0.5; y_i)$, $i \in \{0, ..., n\}$, where $x_0 = y_0$, and $x_i > x_0 > y_i \; \forall \, i > 0$. The first thing to note is that the last prospect in the series (indicated as nr. 7 in the table) is also the one with the highest expected value. A risk neutral subject should thus always choose prospect 7.

However, the highest outcome that can now be obtained with certainty is x_0, which is generally larger than 0, and which thus constitutes a natural candidate for the reference point. This is indeed recognized by Binswanger himself, who remarks that "an individual who chose [prospect] 0 simply got Rs. 50; i.e., participation in the game resulted in an automatic and sure increase in wealth by Rs. 50. [...] By not choosing [prospect] 0 he stood to lose Rs. 20, but could gains Rs. 100." (p. 396). We will subscript outcomes with the number of the prospect indicated in the table, with $(x, y)_7 \equiv (x, y)_n$.

Table 7: Binswanger choice list

probability:	1/2	1/2	$\lambda \leq$(optimizer)	$\lambda \leq$(sequential)
0	50	50	n/a	n/a
1	45	95	≤ 9	≤ 9
2	40	120	≤ 7	≤ 5
3	35	125	≤ 5	≤ 1
4	30	150	≤ 5	≤ 5
5	20	160	≤ 3.66	≤ 1
6	10	190	≤ 3.5	≤ 3
7	0	200	≤ 3	≤ 1

We start by looking at a comparison between a generic prospect i and the reference prospect. This means that the reference point is state-dependent, i.e. it may differ for different states of the world (Sugden, 2003). Models incorporating state-dependent reference points have been successfully employed to describe preference reversals under both risk (Schmidt, Starmer, and Sugden, 2008) and ambiguity (Trautmann, Vieider, and Wakker, 2011). They are also the only way to incorporate reference-dependence into asset selling decisions, which makes them empirically important.

A given prospect ξ_i will be chosen over another prospect prospect ξ_r, which serves as a reference prospect, iff its value *relative to prospect* ξ_r is larger or equal than 0. Formally we have:

$$w^+(p)v(x_i|x_r) - \lambda w^-(p)v(y_i|y_r) \geq 0 \tag{7}$$

Solving this for the loss aversion parameter and resolving the conditionality as a difference relation, we obtain

$$\lambda \leq \frac{w^+(p)}{w^-(p)} \frac{v(x_i - x_r)}{v(y_i - y_r)} \tag{8}$$

In words: prospect ξ_i will be chosen over prospect ξ_r only if loss aversion is lower than the product between the ratios of the decision weights for gains and losses and the ratio of the utilities attributed to the distance to the reference point. Our conclusion will now partially depend on this difference. Relative to linearity in outcomes, we would expect the utility ratio to push the value to the right downward: This observation is based on two empirical observations: a) the difference is typically smaller for losses than it is for gains (assuming that there is indeed loss aversion), such that any decreasing sensitivity in the utility function will have a larger impact on the gain part; and b) utility curvature is generally more pronounced and stable for gains than for losses, i.e. while almost all studies find concave utility for gains, many studies find linear utility for losses, and some even concave utility. Weighting functions may either drop out if they are equal for gains and losses (which is often assumed, although the evidence points rather in the direction that this does not hold empirically, see e.g. Cohen, Jaffray, and Said, 1987; Schoemaker, 1990), may counteract the effect of utility of the function for losses is less elevated than for gains, or reinforce it if it is more elevated. The evidence here is rather mixed. Some studies in the West have found higher elevation for losses, while our own data rather indicate the opposite.

Given this controversy, we will assume linearity in utilities, which is a plausible assumption for small stakes. We will also assume the probability weights to drop out of the equation, assuming that differences between weighting for gains and losses are likely to be of second order. At this point, however, we face an additional problem. Indeed, the choice of reference point may depend on the sequence in which pairwise comparisons are carried out. This derives from the nature of the choice problem, whereby one prospect out of the eight available prospects needs to be picked. We consider two extreme choice behaviors, which we will describe in turn: 1) optimizing: a subject picks his or her optimal choice out of the 8 available choices, by considering all the parameters of the eight prospects before making a fully informed decision; 2) sequential choice: subjects start by evaluating ξ_1 relative to ξ_0; if they prefer ξ_1, this becomes the new reference point as they move on to ξ_2.

We start from the optimizing behavior. Let us first look at the comparison between the extreme prospects. Assuming linearity in outcomes and probabilities, it follows immediately that all subjects with $\lambda \leq 3$ will choose the highest-risk, highest payoff prospect. For prospect 6 the cutoff value is 3.5, and so on increasing until 9 for prospect 1. It is also easy to se that these comparisons between the extreme prospects constitute the decision set, i.e. a subject who prefers prospect 7 over 0 will also prefer 7 over 1, 2, 3 etc. We have thus fully described the choice problem.

Sequential behavior starts from the assumption that the certain prospect is compared to the subsequent prospect (more generally, one could compare any pair of prospects and then move on to another prospects; sequentiality, however, seems the most plausible order). If the next prospect is seen as preferable, this prospect becomes the new reference point and is compared to the subsequent one. This kind of behavior was also suggested in the continuation of the quote above by Binswanger, who then adds that "compared to B [prospect 2], which was more relevant, the potential losses and gains in going to C [prospect 3] were Rs. 10 and Rs. 30 respectively." This indeed seems to suggest sequential comparison.

Looking at the comparison between the first two prospects, the cutoff value of λ is obviously the same as before. This, however, changes for subsequent steps. The values are again reported in the table. One can see that indeed the cutoff point for the highest prospect is now $\lambda \leq 1$, so that we would expect very few subjects to choose the highest prospect. What is more, there are two other prospect with the same cutoff points much farther down. We would thus expect much more risk averse choices.

While being testable in principle, we cannot address here which reference-dependent model is the 'true' model. In all likelihood, there will be heterogeneity in the type of choice behavior, with some subjects optimizing and some choosing sequentially; we would also expect some to choose almost randomly. That said, our prediction would be that subjects are more likely to choose sequentially than to optimize. Indeed, sequential choice is less cognitively demanding, and given the obvious evolution of the series of outcomes, with x increasing and y decreasing as one moves down, this may be quite an obvious strategy to follow. What is more, the same will hold if the sure prospect is presented in a different position, e.g. as the last prospect in the series, since it is likely to stand out from the other prospects thanks to the perfect certainty it provides.

B Explaining differences with TCN and NVX

We have seen how the aggregate risk preferences of our sample of Vietnamese farmers differ significantly from what we would expect based on previous results from the West. Why are our results so different from those reported by TCN and NVX?

Table 8: Comparing our estimates to TCN and NVX

	P2*	P1*	TCN (south)	NVX (south)
μ (value function gains)	0.090	0.090	0.60	0.569
95% CI	[0.038 , 0.142]	[0.025, 0.156]	not reported	[0.509 ; 0.609]
ν (value function losses)	0.055	0.054	= gains	n/a
95% CI	[-0.021 , 0.091]	[-0.011 , 0.121]		
λ (loss aversion)	1.926	1.594	2.59	2.676
95% CI	[1.649 , 2.202]	[1.446 , 1.742]	not reported	[2.002 , 3.350]
α^+ (sensitivity gains)	0.702	0.800	0.72	0.645
95% CI	[0.603 , 0.801]	[0.656 , 0.944]	not reported	[0.592 ; 0.698]
β^+ (pessimism gains)	0.861	$\equiv 1$	$\equiv 1$	$\equiv 1$
95% CI	[0.739 , 0.983]			
α^- (sensitivity losses)	0.722	0.638	=gains	n/a
95% CI	[0.625 , 0.820]	[0.524 , 0.752]		
β^- (optimism losses)	1.226	$\equiv 1$	$\equiv 1$	n/a
95% CI	[1.069 , 1.383]			

*uses the CRRA formulation of the value function

Table 8 shows the parameter values estimated by TCN and by NVX using the same method. Since the parameters they estimate are virtually identical, we will concentrate on the values obtained by TCN in the discussion below. Next to them, we put our own estimates using their parametric specification, i.e. a Prelec (1998) 1-parameter function (henceforth *P1*), as well as showing the 2-parameter specification from above (henceforth: *P2*). While the model of TCN and NVX is fully deterministic, we keep our error structure, since the richness of our data can better be fit by a stochastic model, whereas TCN and NVX derive their estimates for the two parameters they use from the solution to two parallel equations (and loss aversion is obtained from a third).

Yet another difference is to be found in the utility function. TCN and NVX use a simpler formulation of the power function, whereby $v(x) = x^{\mu}$. This functional form provides a worse fit to our data, and we thus maintain our original formulation. This also serves to nicely highlight how the curvature of the value function estimated in conjunction with the P1 weighting function is identical to the curvature estimated using the P2 function.[17]

[17] If we estimate the P1 specification using the same power specification as TCN,

Any differences in the P1 weighting function from the P2 function estimated above can thus be directly interpreted in terms of risk preferences.

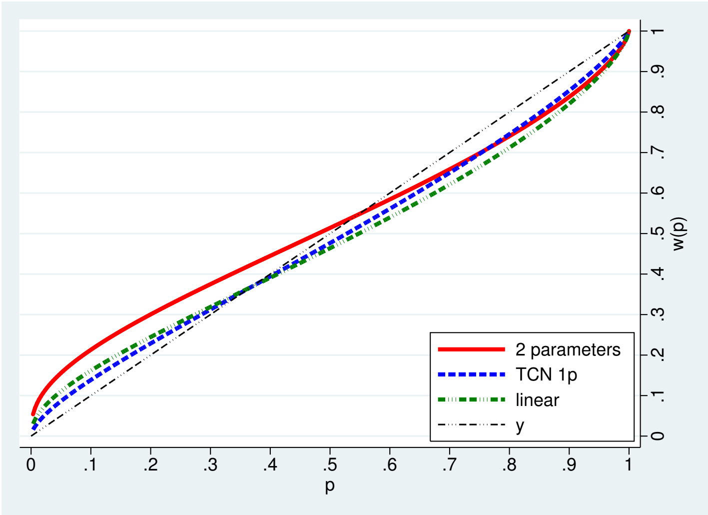

Figure 4: P2 versus P1 weighting functions for gains, farmers

We can now turn to the weighting function. The results show how our weighting parameter using the P1 specification does not significantly differ from the one estimated by TCN. This, however, seems to underestimate the risk tolerance found above. For the P1 function is simply derived from the P2 function by setting $\beta \equiv 1$. In the P2 specification we see, however, that β is significantly smaller than 1, indicating probabilistic optimism. That is, by simplifying the functional form we force our estimation results to coincide with the typical aggregate patterns observed in the West.

We also provide estimation results using P1 for losses. TCN do not have a question to estimate either weighting or utility for losses. They thus simply assume the function to be the same as for gains. Again, their estimate corresponds rather closely to our own estimates for losses. Nonetheless, it is far removed from the value we find if we use the more flexible form, for which β is significantly larger than 1, indicating probabilistic optimism. Figure 5 compares our P2 function to TCN's function, as well as our own 1-parameter function. While the two P1 functions are again virtually identical, the P2 function shows a quite different picture. Indeed, β

we obtain a curvature parameter $\mu = 0.91$ (full estimation shown in supplementary materials). This value is significantly higher than the one obtained by TCN, indicating reduced concavity and thus lower levels of risk aversion ceteris paribus. This may derive from the fact that they report *mean* values of the parameters instead of our medians. In any case, their value function being more concave than ours does only reinforce our general argument in terms of risk preferences. Also, the expected value from their gain choice lists overall is about 50,000 Dong—about 1/3 of the expected value in our tasks—which again goes to reinforce our results given typical findings on stake effects

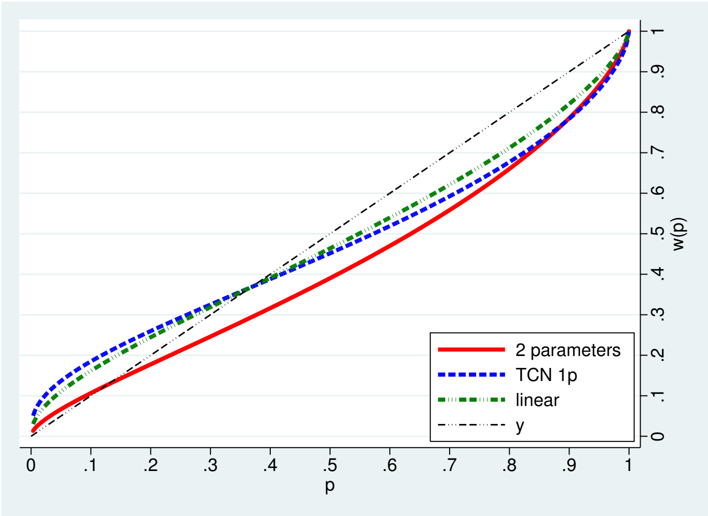

Figure 5: P2 versus P1 weighting functions for losses, farmers

is now significantly larger than the value of 1 assumed by the P1 functions. Functions from the one-parameter family seem thus generally inadequate to estimate preferences even at the aggregate level, especially when new population groups are investigated.[18]

This leaves the differences in loss aversion to be discussed. Not having a weighting or utility function for losses, TCN adopt a 'behavioral form' of loss aversion, simply given by the elicited indifference $0 \sim (x : p; y)$, $x > 0 > y$, which is solved for $\lambda = {}^{x}\!/_{-y}$. This is indeed a definition that is employed frequently in the literature (see, e.g., Gächter et al., 2010), and that may be preferable for empirical analysis, giving a purer measure of loss aversion that is unaffected by other parameters of the estimation. In our model, on the other hand, λ is estimated within the structural model, so that both utility curvature and probability weighting contribute to determining its value (see Schmidt and Zank, 2005, for a discussion). Adopting a behavioral definition ourselves, the mean value we find is 2.66 (median: 1.70) which is very close to (and not statistically distinguishable from) the value reported by TCN.

[18] We have only shown results for the Prelec 1 parameter function. The function developed by Tversky and Kahneman, which does not force the crossing point, performs somewhat better, but shows the same general pattern of underestimating risk tolerance.

C Nonparametric data points

Below we show the non-parametric mean and median data points for framers. Equivalent tables for the student subject populations can be found in the supplementary materials.

	Risk premium		Certainty equivalents			
Prospect	Mean	Median	Mean	SD	Median	IQR
(40,0.5;0)	-0.239	-0.300	24.78	15.44	26.00	20.00
(80,0.5;0)	-0.124	-0.050	44.96	25.04	42.00	44.00
(160,0.5;0)	-0.023	0.025	81.86	49.30	78.00	76.00
(240,0.5;0)	0.043	0.150	114.87	52.92	102.00	80.00
(240,0.5;80)	0.030	0.038	155.12	53.16	154.00	84.00
(240,0.5;160)	0.009	0.010	198.19	27.80	198.00	40.00
(160,0.125;0)	0.009	0.010	198.19	27.80	198.00	40.00
(160,0.125;40)	-0.451	-0.345	79.80	38.89	74.00	56.00
(160,0.25;0)	-0.386	-0.050	55.43	48.84	42.00	68.00
(160,0.375;0)	-0.080	0.033	64.78	48.21	58.00	64.00
(160,0.625;0)	0.091	0.020	90.85	49.17	98.00	80.00
(160,0.75;0)	0.146	0.083	102.48	48.17	110.00	76.00
(160,0.875;0)	0.186	0.071	113.94	48.57	130.00	68.00
(160,0.875;40)	0.133	0.048	125.69	38.05	138.00	56.00
(-40,0.5;0)	-0.009	0.100	-20.18	13.27	-18.00	24.00
(-80,0.5;0)	0.085	0.050	-36.61	24.02	-38.00	32.00
(-160,0.5;0)	0.200	0.225	-64.03	43.26	-62.00	48.00
(-160,0.5;-40)	0.134	0.180	-86.58	36.99	-82.00	44.00
(-160,0.5;-80)	0.099	0.150	-108.09	26.44	-102.00	36.00
(-160,0.125;0)	-0.514	0.100	-30.27	40.84	-18.00	40.00
(-160,0.125;-40)	-0.186	-0.055	-65.23	34.56	-58.00	36.00
(-160,0.25;0)	-0.054	0.050	-42.17	40.80	-38.00	56.00
(-160,0.375;0)	0.080	0.100	-55.20	42.70	-54.00	56.00
(-160,0.625;0)	0.167	0.180	-83.28	45.87	-82.00	52.00
(-160,0.75;0)	0.202	0.150	-95.80	45.91	-102.00	52.00
(-160,0.875;0)	0.218	0.129	-109.54	48.87	-122.00	64.00
(-160,0.875;-40)	0.180	0.103	-118.95	38.87	-130.00	56.00
(160,0.5;-y)			-95.70	56.01	-94.00	112.00

Amounts in 1000s of Dong. Risk premia are calculated as (EV-EC)/EV;
for losses, insurance premia are the risk premium

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SUPPLEMENTARY MATERIALS

D Nonparametric data for students

Table 9: Nonparametric data of US students

	Risk premium		Certainty equivalents			
Prospect	Mean	Median	Mean	SD	Median	IQR
(40,0.5;0)	-0.038	0.100	20.76	5.98	18.00	4.00
(80,0.5;0)	0.025	0.050	38.99	9.43	38.00	8.00
(160,0.5;0)	0.146	0.175	68.35	21.11	66.00	24.00
(240,0.5;0)	0.195	0.183	96.56	28.50	98.00	40.00
(240,0.5;80)	0.100	0.138	144.02	34.46	138.00	40.00
(240,0.5;160)	0.002	0.010	199.61	24.09	198.00	32.00
(160,0.125;0)	0.002	0.010	199.61	24.09	198.00	32.00
(160,0.125;40)	-0.125	-0.055	61.88	17.51	58.00	20.00
(160,0.25;0)	0.073	0.050	37.09	14.92	38.00	12.00
(160,0.375;0)	0.196	0.100	48.23	19.42	54.00	28.00
(160,0.625;0)	0.204	0.140	79.57	25.64	86.00	36.00
(160,0.75;0)	0.164	0.117	100.27	32.75	106.00	44.00
(160,0.875;0)	0.085	0.043	128.14	29.29	134.00	20.00
(160,0.875;40)	0.060	0.021	136.35	24.14	142.00	16.00
(-40,0.5;0)	-0.149	-0.100	-22.99	15.56	-22.00	4.00
(-80,0.5;0)	-0.096	-0.050	-43.86	16.67	-42.00	8.00
(-160,0.5;0)	-0.090	-0.025	-87.20	21.12	-82.00	24.00
(-160,0.5;-40)	0.028	0.020	-97.22	19.01	-98.00	12.00
(-160,0.5;-80)	0.009	0.017	-118.91	15.27	-118.00	8.00
(-160,0.125;0)	-0.496	-0.100	-29.92	29.13	-22.00	28.00
(-160,0.125;-40)	-0.163	-0.127	-63.98	20.85	-62.00	16.00
(-160,0.25;0)	-0.138	-0.050	-45.51	25.85	-42.00	20.00
(-160,0.375;0)	-0.049	-0.033	-62.95	24.80	-62.00	20.00
(-160,0.625;0)	-0.023	-0.020	-102.33	20.71	-102.00	16.00
(-160,0.75;0)	-0.001	-0.017	-120.14	19.24	-122.00	20.00
(-160,0.875;0)	0.032	0.014	-135.57	23.36	-138.00	16.00
(-160,0.875;-40)	0.087	0.048	-132.35	23.24	-138.00	24.00
(160,0.5;-y)			-88.60	41.24	-82.00	32.00

Amounts in 1000s of Dong. Risk premia are calculated as (EV-EC)/EV;
for losses, insurance premia are the risk premium
Conversion: 40,000 Dong=6 USD

Table 10: Nonparametric data of Vietnamese students

	Risk premium		Certainty equivalents			
Prospect	Mean	Median	Mean	SD	Median	IQR
(40,0.5;0)	-0.273	-0.100	25.46	9.03	22.00	10.00
(80,0.5;0)	-0.250	-0.250	50.00	18.46	50.00	22.00
(160,0.5;0)	-0.114	-0.025	89.15	32.54	82.00	32.00
(240,0.5;0)	-0.056	-0.017	126.69	41.46	122.00	58.00
(240,0.5;80)	-0.060	-0.062	169.62	44.93	170.00	62.00
(240,0.5;160)	-0.022	0.010	204.31	24.59	198.00	34.00
(160,0.125;0)	-0.022	0.010	204.31	24.59	198.00	34.00
(160,0.125;40)	-0.555	-0.418	85.54	31.37	78.00	46.00
(160,0.25;0)	-0.319	-0.300	52.77	33.80	52.00	48.00
(160,0.375;0)	-0.138	-0.067	68.31	36.81	64.00	56.00
(160,0.625;0)	-0.032	-0.020	103.15	34.91	102.00	46.00
(160,0.75;0)	-0.028	-0.117	123.31	33.69	134.00	32.00
(160,0.875;0)	0.001	-0.100	139.92	29.68	154.00	20.00
(160,0.875;40)	0.006	-0.090	144.08	24.31	158.00	16.00
(-40,0.5;0)	0.096	0.100	-18.08	8.40	-18.00	8.00
(-80,0.5;0)	0.100	0.100	-36.00	14.81	-36.00	20.00
(-160,0.5;0)	0.062	0.075	-75.08	32.23	-74.00	38.00
(-160,0.5;-40)	0.135	0.180	-86.46	28.05	-82.00	36.00
(-160,0.5;-80)	0.101	0.150	-107.92	18.75	-102.00	24.00
(-160,0.125;0)	-0.546	0.000	-30.92	39.05	-20.00	34.00
(-160,0.125;-40)	-0.236	-0.055	-68.00	32.21	-58.00	34.00
(-160,0.25;0)	0.004	0.150	-39.85	34.89	-34.00	32.00
(-160,0.375;0)	0.151	0.200	-50.92	32.81	-48.00	34.00
(-160,0.625;0)	0.073	0.060	-92.69	32.72	-94.00	22.00
(-160,0.75;0)	0.094	0.083	-108.77	31.64	-110.00	36.00
(-160,0.875;0)	0.129	0.029	-122.00	32.29	-136.00	36.00
(-160,0.875;-40)	0.130	0.048	-126.15	27.37	-138.00	48.00
(160,0.5;-y)			-114.77	36.16	-102.00	74.00

Amounts in 1000s of Dong. Risk premia are calculated as (EV-EC)/EV;
for losses, insurance premia are the risk premium

E Stability of farmer-student comparison

E.1 Exponential utility function

The paper uses a CRRA specification of the value function. In this section, we show that our results are stable to using a CARA (exponential) specification instead. We thus reproduce the table presented in the paper using the following specification of the value function:

$$v(x) = \begin{cases} \frac{e^{-\mu x}}{\mu} & \text{if } x > 0 \\ -\lambda \frac{e^{-\nu(-x)}}{\nu} & \text{if } x \leq 0 \end{cases} \tag{9}$$

Somewhat surprisingly, this function seems to perform slightly less well, resulting in lower values of the maximized log likelihood function.

Table 11 shows the point estimates of the model parameters for farmers, students in Vietnam, and students in the US using the exponential utility function. In general, value functions for losses now tend to be convex instead of linear as with the CRRA function. Loss aversion is generally lower. Also, farmers have now a more linear value function for gains, and more so than either student subject pool. This reduced concavity is reflected in a somewhat higher value of pessimism for gains. Nevertheless, the farmers are still more optimistic than American students (and less so than Vietnamese students). All the main comparison results for gains are thus confirmed with this alternative specification of the value function.

Table 11: point estimates of model parameters with 95% confidence intervals

	farmers Vietnam	students Vietnam	students USA
μ (value function gains)	0.008	0.023	0.022
95% CI	[0.001 , 0.016]	[0.009 , 0.037]	[0.012 , 0.033]
ν (value function losses)	0.031	0.028	0.028
95% CI	[0.021 , 0.041]	[0.008 , 0.048]	[0.014 , 0.042]
λ (loss aversion)	1.455	1.310	1.191
95% CI	[1.347 , 1.563]	[1.199 , 1.421]	[1.118 , 1.265]
α^+ (sensitivity gains)	0.716	0.932	0.786
95% CI	[0.612 , 0.820]	[0.821 , 1.043]	[0.716 , 0.856]
β^+ (pessimism gains)	0.884	0.672	1.025
95% CI	[0.760 , 1.008]	[0.553 , 0.790]	[0.924 , 1.127]
α^- (sensitivity losses)	0.742	0.856	0.916
95% CI	[0.641 , 0.844]	[0.701 , 1.011]	[0.829 , 1.003]
β^- (optimism losses)	1.064	0.976	0.815
95% CI	[0.940 , 1.187]	[0.812 , 1.139]	[0.747 , 0.884]
Number of subjects:	207	52	75

For losses, on the other hand, we do find some differences. Farmers are still significantly more optimistic than American students, and have the same utility curvature for losses. They are also more optimistic than Vietnamese students. Under an equal utility function, however, this effect is no longer significant. Using this specification of the utility function, we thus conclude that both Vietnamese and farmers and students are more risk seeking for losses than American students, but there is no difference between the two subject populations.

E.2 Yaari risk-preference functions

We here reproduce the findings from the paper using the Yaari-type functionals employed in subsequent sections of the text, i.e. assuming that utility over outcomes in linear. Table 12 shows the results.

Table 12: point estimates of model parameters, linear utility

	farmers Vietnam	students Vietnam	students USA
λ (loss aversion)	1.643	1.387	1.810
95% CI	[1.495 , 1.791]	[1.224 , 1.550]	[1.630 , 1.989]
α^+ (sensitivity gains)	.669	0.849	0.737
95% CI	[0.686 , 0.929]	[0.714 , 0.983]	[0.666 , 0.807]
β^+ (pessimism gains)	.920	0.797	1.182
95% CI	[0.799 , 1.040]	[0.671 , 0.923]	[1.104 , 1.260]
α^- (sensitivity losses)	0.768	0.773	0.864
95% CI	[0.578 , 0.740]	[0.594 , 0.952]	[0.758 , 0.969]
β^- (optimism losses)	1.307	1.088	0.936
95% CI	[1.059 , 1.348]	[0.913 , 1.264]	[0.852 , 1.020]
Number of subjects:	207	52	75

Farmers are again less probabilistically sensitive than students by and large, although this effect is not significant in all comparisons. We are here more interested in risk preferences, however. For gains, farmers are on average risk neutral, whereas Vietnamese students are risk seeking and American students are risk averse. Once again, the results confirm that our Vietnamese farmers are more risk averse than Vietnamese students, but less risk averse than American students. Figure 6 shows the risk-preference functions for the three subject groups.

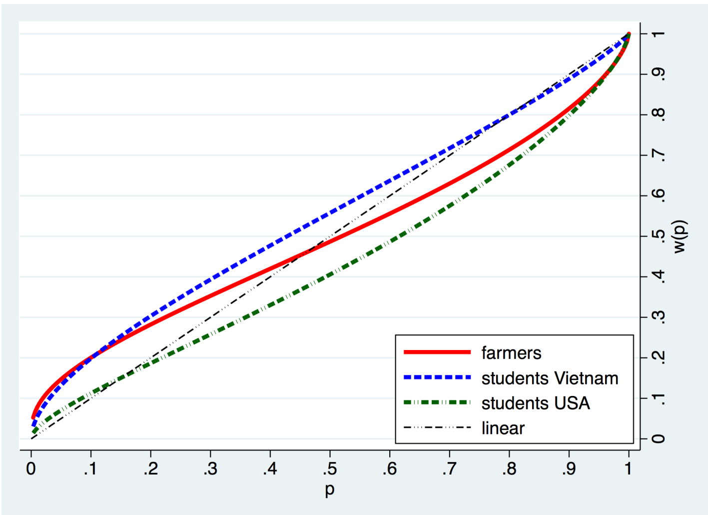

Figure 6: Farmer-student comparison for gains, linear utility

This leaves losses to be discussed. We find American students to display higher probabilistic sensitivity for losses than either Vietnamese group. In terms of risk seeking, we find American students and Vietnamese students to be risk neutral on average (although the latter tend towards risk seeking).

Our Vietnamese farmers, on the other hand, are clearly risk *seeking*. Figure 7 shows the risk-preferences functions for losses. This again confirms the main findings already discussed in the paper.

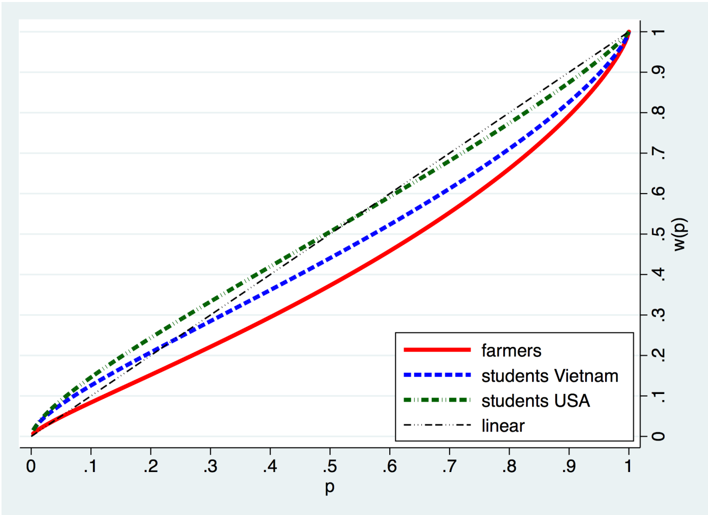

Figure 7: Farmer-student comparison for losses, linear utility

F Comparison with 1-parameter formulations

F.1 Prelec 1-parameter function with power utility

In the paper we have used the CRRA specification for the value function in conjunction with the Prelec 2-parameter function. This had the advantage of ensuring direct comparability with our 2-parameter function estimated earlier. The CRRA formulation was also found to converge more easily. Table 13 shows the regression for the Prelec 1-parameter and the Prelec 2-parameter specification in combination with a simple power formulation of the value function as used by TCN, $v(x) = x^{\mu}$.

Table 13: Weighting functions with power utility

N=207	Prelec P1	Prelec P2
μ (value function gains)	0.913	0.919
95% CI	[0.863,0.963]	[0.869,0.969]
ν (value function losses)	0.955	0.956
95% CI	[0.908,1.002]	[0.902,1.010]
λ (loss aversion)	1.602	1.890
95% CI	[1.471,1.733]	[1.619,2.161]
α^{+} (sensitivity gains)	0.810	0.702
95% CI	[0.649,0.971]	[0.603,0.800]
β^{+} (pessimism gains)	$\equiv 1$	0.867
95% CI		[0.747,0.988]
α^{-} (sensitivity losses)	0.625	0.722
95% CI	[0.513,0.738]	[0.625,0.819]
β^{-} (optimism losses)	$\equiv 1$	1.217
95% CI		[1.062,1.371]

Once again, we find the utility curvature parameter to be virtually identical between the two specifications for both gains and losses. Utility is concave for gains, and linear for losses (with a slight tendency towards convexity). Loss aversion is different, but as we have already discussed in the main text, this derives mostly from the different weighting functions estimated under the two specifications—our main interest here. In terms of the latter, we confirm the main results from the paper. While we obtain similar sensitivity parameters under the two functional specifications, the elevation parameter in the P2 function is significantly different from 1 for both gains and losses. The P1 formulation thus systematically overestimates pessimism for gains and underestimates optimism for losses. Given the equality in utility function, this means that the P1 formulation also systematically overestimates risk aversion for both gains and losses.

G The risk-income paradox

G.1 Stability analysis: full PT specification

The first task will be to show the stability of the results obtained with the reduced model in the paper. We start by looking at the foremost variable of interest—income. It is immediately apparent that the finding of risk tolerance increasing increasing in income holds for gains. Indeed, we observe significantly lower levels of pessimism as indicated by β^{+}, which is combined with a more linear utility function (though not significantly so). We have seen in the main paper that this effect is also economically significant. Figure **??** shows the risk-preference functions (thus assuming again linear utility) for the mean income level, as well as one standard deviation above and below. Subjects one standard deviation above the mean income can be seen to be clearly risk seeking for a typical 50-50 prospect. Subjects one standard deviation below, on the other hand, have a function that resembles somewhat the typical probability weighting function found in the West. This, however, does not account for the fact that 1) utility is linear here, so this is still higher risk taking than found in the West; and 2) given the skew in distribution, 1 standard deviation below the mean would indicate negative income levels.

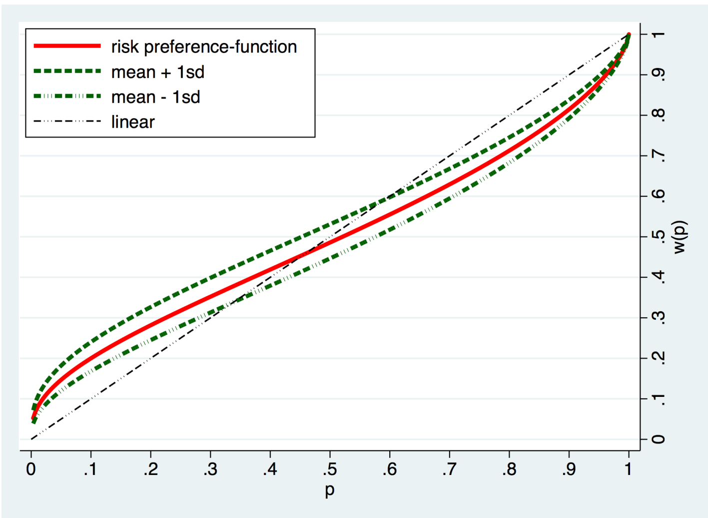

Figure 8: Risk preference for mean income, ± 1 sd

For losses the issue is now somewhat more tricky, since higher levels of probabilistic optimism are accompanied by a less convex utility function. To determine the direction of the difference, we can now look at insurance premia. For a typical 50-50 prospect, the insurance premium is -27.3% for a subject with the mean income level, indicating substantial risk seeking. For a subject with income 1 standard deviation above that, the insurance premium declines to -29.8%. It is thus clear that also for losses the effect of income goes in the direction of increased risk tolerance. Testing for the joint significance of the effects on utility curvature and elevation of the weighting function using a Wald test, we can also conclude that this increased risk seeking is indeed significant ($\chi^2(2) = 11.48, p = 0.003$). We thus confirm the most important results from the paper.

Table 14: Complete PT specification, income regression

N=197	μ	ν	λ	α^+	β^+	α^-	β^-
income	-0.027	-0.049***	-0.088*	-0.049	-0.085**	-0.035	0.154**
	(0.018)	(0.018)	(0.049)	(0.051)	(0.038)	(0.026)	(0.065)
education	-0.037*	-0.053**	0.189**	0.033	0.051	0.072*	0.151
	(0.021)	(0.022)	(0.080)	(0.059)	(0.060)	(0.043)	(0.123)
age	0.065**	0.078***	0.064	-0.054	-0.022	-0.037	-0.064
	(0.026)	(0.027)	(0.072)	(0.058)	(0.076)	(0.047)	(0.083)
constant	0.090***	0.019	1.619***	0.693***	0.871***	0.700***	1.259***
	(0.024)	(0.026)	(0.071)	(0.053)	(0.065)	(0.051)	(0.077)

Standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01; z-scores

We next look at the effects of age and education. Age results in more pronounced utility curvature for both gains and losses, with utility thus becoming more concave with age for gains and more convex for losses. There are now no significant effects on probabilistic sensitivity, although the tendency continues to be that the latter is reduced with age. For education the effects are more complex. For gains, we find unequivocally reduced risk aversion as education increases, indicated by a more linear utility function. For losses we see utility becoming more concave for higher levels of educations, while we also observe somewhat increased probabilistic sensitivity.

G.2 Graphical analysis of Yaari method

We start by analyzing graphically the appropriateness of the regression technology we use. We have seen in the text that our reference-dependent Yaari specification generally performs worse than the full PT specification. This issue is clearly visible from figure 9, which shows the risk preference-function estimated on our aggregate data and compares it to non-parametric data on median normalized certainty equivalents. Indeed, it is apparent that the data points constituting outliers relative to the risk-preference function concern the lower amounts obtaining with 50-50 probability. Indeed, for such amounts we observe a larger degree of risk seeking. The location of the CEs for the higher-outcome prospects indicates also that our assumption of linear utility is a good approximation for such prospects, while the deviations causing the concavity of the utility function indicate mostly risk seeking for smaller amounts.

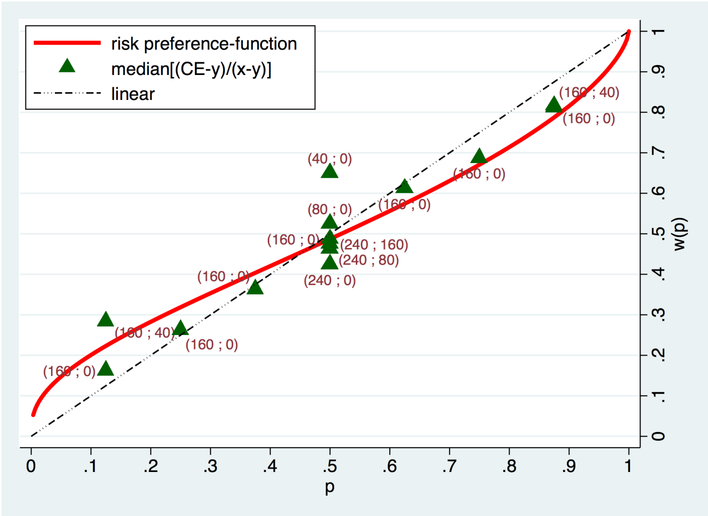

Figure 9: Risk preference function and normalized CEs for gains; label: (x ; y)

A very similar picture emerges concerning losses, depicted in figure 10. Once again, most of the deviations from the risk-preference function are observed for 50-50 prospects, and mostly prospects having either relatuvely large lower outcomes or relatively small higher outcomes. Once again, this is not surprising, as this dimension was introduced into the experimental elicitation with the explicit purpose of estimating utility curvature, and separating the latter from the elevation of the probability weighting function.

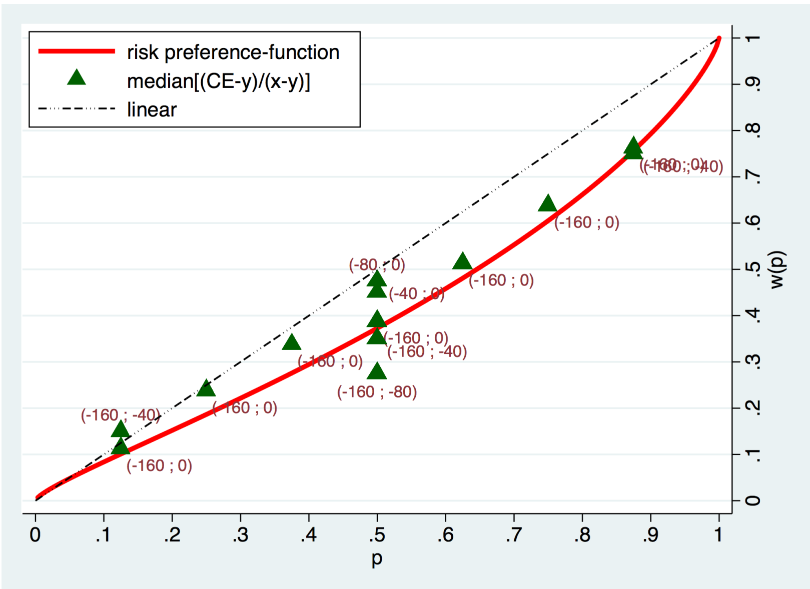

Figure 10: Risk preference function and normalized CEs for losses; label: (x ; y)

H Predicting behavior

H.1 Stability using full PT specifications

Table 15: Complete specification, predictions 1

	μ	ν	λ	α^+	β^+	α^-	β^-
lottery	-0.019	-0.008	-0.036	-0.020	-0.270**	-0.068	0.050
	(0.058)	(0.060)	(0.295)	(0.123)	(0.131)	(0.108)	(0.179)
savings	-0.088***	-0.152***	-0.272	-0.064	-0.065	-0.084*	-0.084
	(0.032)	(0.031)	(0.167)	(0.067)	(0.061)	(0.043)	(0.072)
smoking	-0.023	0.035	0.150	0.036	0.038	0.058	-0.160
	(0.066)	(0.062)	(0.200)	(0.166)	(0.112)	(0.119)	(0.131)
education	-0.029	-0.043**	0.343	0.042	0.063	0.089*	0.178
	(0.024)	(0.020)	(0.220)	(0.072)	(0.063)	(0.054)	(0.121)
age	0.056**	0.071**	0.064	-0.074	-0.042	-0.044	-0.056
	(0.027)	(0.029)	(0.165)	(0.068)	(0.067)	(0.056)	(0.084)
income	-0.009	-0.020	0.387*	-0.025	-0.064*	-0.015	0.194***
	(0.030)	(0.018)	(0.219)	(0.099)	(0.037)	(0.034)	(0.069)
constant	0.162**	0.057	1.903***	0.684***	1.011***	0.724***	1.328***
	(0.078)	(0.070)	(0.281)	(0.173)	(0.134)	(0.126)	(0.182)

Standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01; z-scores

In this section we look at the stability of the prediction exercises in the paper to using a full PT specification. Table 15 shows the predictions for lottery buying, precautionary saving, and smoking. As in the paper, we find the likelihood of buying lottery tickets to strongly decrease in risk aversion for gains, here captured by probabilistic pessimism. The effect of loss aversion is no longer significant. This is however mostly due to the different definition of loss aversion employed in this regression—see discussion in text. Total savings are still found to decrease in probabilistic optimism for gains, although this effect is only marginally significant. Most of the precautionary saving motive is now captured in the utility curvature for losses, with total saving declining in convexity. We also confirm the somewhat more puzzling effect for gains, which is not reflected in utility curvature. Once again, we find no effects for smoking, and also the marginally significant effect in terms of loss aversion is gone now (although this is likely again an issue of definition).

Table 16 looks at risk management on the farm, in the familiar categories of leasing out one's land, migrating to the city, looking for off-farm labor, and borrowing money. Leasing out one's land is again significantly related to a number of different variables. The effect is clearest for losses, where the likelihood of leasing out the land decreases as the weighting function becomes more linear and decreases in probabilistic optimism. This is thus exactly the effect we would expect. For gains, we again find the likelihood of leasing out one's land to decrease in the linearity of the weighting function.

The picture is somewhat more complicated in terms of risk preferences, since the likelihood of leasing out one's land increases in probabilistic pessimism, but also decreases in the concavity of the utility function. Overall, however, the effect of probabilistic pessimism is overwhelming, such that the result is in agreement with the one found in the text in terms of risk-preference functions.

In terms of migration, we again confirm the main results found in the paper. The likelihood of migrating to the city decreases in loss aversion. It also decreases in probabilistic pessimism for gains, and increases in probabilistic optimism for losses. In other words, farmers who are less risk averse either over gains, losses, and mixed prospects are more likely to migrate to the city to look for a job. Contrary to the results in the paper, we now find also an effect in terms of looking for off-farm jobs. The latter increases in the concavity of the utility function for losses—farmers who are more risk averse for losses are more likely to look for an off-farm job. This effect is further reinforced by the effect in terms of probability weighting, which is however not significant. We do find also an effect for gains that goes in the opposite direction, with the likelihood of looking for off-farm labor decreasing as the utility function becomes more concave. This effect is not as one might expect it to be. It is, however, counterbalanced by an opposite (though not significant) effect in terms of the probability weighting function, so that the net effect is close to zero.

Table 16: Complete specification, predictions 2 (farming)

N=197	μ	ν	λ	α^+	β^+	α^-	β^-
leasing land	-0.362***	-0.089	0.595	-0.546**	1.248***	-0.523***	-0.887**
	(0.125)	(0.107)	(0.567)	(0.213)	(0.392)	(0.171)	(0.417)
migration	0.160	0.040	-0.466**	0.077	-0.407*	-0.144	0.894**
	(0.113)	(0.109)	(0.235)	(0.449)	(0.211)	(0.130)	(0.363)
off-farm job	-0.117**	-0.134**	-0.013	-0.050	0.155	-0.035	-0.070
	(0.057)	(0.067)	(0.172)	(0.141)	(0.127)	(0.120)	(0.134)
borrow money	-0.044	-0.047	0.094	-0.189	0.199	0.022	-0.031
	(0.058)	(0.061)	(0.146)	(0.158)	(0.134)	(0.111)	(0.206)
education	-0.019	-0.032	0.162**	0.077	0.014	0.075	0.214*
	(0.024)	(0.022)	(0.080)	(0.084)	(0.064)	(0.048)	(0.112)
age	0.073***	0.074**	0.040	-0.052	-0.042	-0.052	-0.026
	(0.028)	(0.031)	(0.074)	(0.065)	(0.068)	(0.055)	(0.093)
income	-0.054**	-0.068***	-0.076*	-0.085**	-0.068**	-0.035	0.147**
	(0.021)	(0.019)	(0.046)	(0.039)	(0.028)	(0.023)	(0.074)
constant	0.123**	0.055	1.582***	0.857***	0.742***	0.723***	1.286***
	(0.049)	(0.050)	(0.129)	(0.154)	(0.105)	(0.084)	(0.176)

Standard errors in parentheses, * p<0.10, ** p<0.05, *** p<0.01; z-scores

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