Measuring risk aversion among the urban poor in Kolkata, India

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Abstract

We examine risk preferences in an urban setting in a low-income developing country with non-student subjects by adapting the experimental approach of Holt and Laury (2002). We conducted 22 group experiments (n= 404) and used in-kind payoffs. The average midpoint of the CRRA intervals among participants was 0.53, or "risk-averse", roughly in line with most similar studies in poor countries. Like most studies, we find weak correlations between risk aversion most socioeconomic characteristics. Importantly, a sizeable minority had difficulty understanding the experiment, and participants were influenced by the context in which the experiments occurred. These problems are not unique to our study, however, and our paper adds to a growing literature that suggests that risk aversion elicitation approaches are sensitive to context and the abilities of participants. Many experimental risk studies, however, are designed to make it difficult or impossible to detect if participants are confused.

1. Introduction

An important question in development economics is how the poor make choices under uncertainty. The answer has significant implications for both predicting household responses to policy interventions and for normative evaluation of investment projects. Risk attitudes are especially important in agriculture and in public health, and experts in these two fields seem to have reached different conclusions about risk preferences of people in less developed countries. In the agricultural sector, many development economists have concluded that the poor are very risk averse and are difficult to persuade to make investments (in crop choice, seeds or farming techniques) that have very high expected returns but large variances. Public health professionals tell a different story. Many believe that the poor simply do not understand risks. In this view, the poor are fatalistic and have health behaviors which are inconsistent or irrational with respect to the risks of the adverse health outcomes. One step towards reconciling these views is to observe how the poor make risk decisions in controlled experiments.

A number of researchers have now used experimental approaches to measure empirically the risk preferences of the poor, as we discuss below. Because of the focus on agricultural decision-making, the vast majority of these have been in rural areas. We recruited 404 participants for our experiments from one representative neighborhood in Kolkata, India. Although our experiments in India are not the first attempt to measure risk preferences in an urban population of a developing country, we believe they are the first to use a non-elite (i.e. non-student) population. We use a novel adaptation of the experimental approach primarily used in industrialized countries, following Holt and Laury (2002, henceforth HL), and use real (though in-kind) payoffs. We find average risk preferences that are roughly in line with results from studies done in rural areas, though we find a somewhat larger fraction of risk-loving participants. Like most other studies, we find weak correlations between the experimental risk behavior and socioeconomic characteristics. We use the simplest analysis approach (OLS regressions of the number of "safe" choices) for clarity, but provide additional analysis approaches in an extensive supplementary appendix,[1] including a more recent maximum likelihood approach following Harrison *et al*. (2009).

One important result, however, is a negative one: nearly half of participants may not have understood the task, despite considerable work by the research team to adapt the game. They were, not surprisingly, more likely to be relatively poor and have lower levels of education. Our study adds to growing evidence that a non-trivial fraction of participants in low-education settings struggle with probabilities and risky choices. A majority of experimental risk preference studies in poor countries, however, are designed in a way that makes it difficult or even impossible to detect misunderstanding. This would suggest that we should interpret existing results somewhat cautiously and devote attention in future research to detecting confused participants and tailoring experimental designs for "non-elite" settings. We now turn to surveying this literature with an eye towards the ability of various designs to detect participant confusion.

[1] The supplementary appendix is available on the first author's faculty website: http://faculty.washington.edu/jhcook/research.html

2. Measuring risk preferences in poor countries

Binswanger (1980, 1981) conducted the first studies to measure risk preferences experimentally in a developing country. His participants were 240 poor rural farmers in India. Participants chose between eight different lotteries, each of which had a "good luck" and a "bad lack" payout determined by a coin toss. Payout varied and probabilities were held constant (i.e. 50-50) because he believed that the low education levels of the participants precluded choices with more complicated probabilities. To test the reliability of responses, however, two of the eight lotteries were "risk inefficient" choices. These provided the same expected value as one of the other six lotteries, but with higher variance. Participants made choices individually and were given the sheets describing the lotteries several days in advance. They were faced with 8 – 10 of these choice tasks over a period of two weeks. The tasks varied in the payoff scale (0.5, 5, 50 and 500 Indian rupees). Some tasks involved real cash payments while others used hypothetical payments. Binswanger found that three-quarters of his 240 rural participants showed "intermediate" or "moderate" risk-aversion ($0.32 < r < 1.7$),[2] with the level of risk aversion increasing with the scale of payoff (increasing partial relative risk aversion). Figure 1 plots Binswanger's observed distribution of risk preferences along with other studies of risk preferences in developing countries (described below).[3]

Several subsequent studies conducted in developing countries followed Binswanger's approach: Miyata (2003) in rural Indonesia, Barr (2003) in 23 rural villages in Zimbabwe,[4] and Wik *et al*. (2004) in

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[2] $U(x) = x^{1-r}$, where r is the coefficient of constant relative risk aversion and x is money. Where r=1 the natural logarithm is used, and when r > 1 the function is $U(x) = x^{1-r}/(1-r)$. With this form, r=0 implies risk-neutrality, r>0 implies risk aversion, and r<0 implies risk-seeking or risk-loving.

[3] The figure also demonstrates the difficulty in comparing results from these existing studies since the choice tasks (which define the implied intervals for r) differ across studies. This is an advantage of the maximum likelihood approach, where the average value of r can be directly estimated from all responses rather than grouping responses into intervals.

[4] Barr (2003) used a "which-hand-is-it-in" game common in Zimbabwe rather than a coin toss. Furthermore, the primary focus is on risk pooling behavior when commitment level and information symmetry varies. These experiments elicited subjects' risk preferences in two rounds. After the first round of experiments (exactly similar to Binswanger in format and payoff structure), Barr allowed subjects to form groups to pool risk in the second round. Experimental conditions varied in the second round. We report here only results from the first round of risk experiments, compiled from the cross-tabulations in Barr's Figure 5.

six rural villages in Northern Zambia. Yesuf and Bluffstone (2009) provided the Binswanger-type lotteries to participants in rural Ethiopia with the context of real farming decisions; participants chose among different farming systems with different output levels depending on the "good" or "bad" harvests (p=0.5). Yesuf and Bluffstone found very high levels of risk aversion which were lower in households with more wealth and assets and which increased with higher payoffs. Fletschner *et al.* (2010) used a variant of this approach where one outcome is certain and the other is a risky outcome dependent on a coin toss.[5] In a study of couples in rural Vietnam, they find women are more risk averse than men.

Several studies in industrialized countries varied the probabilities, rather than the payouts, to identify risk aversion (Holt and Laury 2002, Harrison *et al*. 2005, Eckel *et al*. 2002, Harbaugh *et al*. 2002). Using a "multiple price list" (MPL) approach, participants are shown ten lottery pairs at once (i.e. on a sheet or computer screen, similar to Table 1), and asked to mark their preference (lottery A or lottery B) in each row.

Although MPL experiments elicit the same type of information as the Binswanger coin-toss protocol, there are at least two important differences. First, MPL experiments rely on participants having a better grasp of probability than a simple coin toss. More importantly, MPL experiments provide more opportunities to observe whether participants understand the exercise in the way that the researcher assumes. In Binswanger's protocol, the only way to detect a lack of understanding is if a participant chooses one of the two "risk inefficient" lotteries among the eight lottery choices. Suppose a participant who was completely confused chose one of lotteries at random. There are only 2 chances in 8 that such behavior would be recognized as meaningless. Furthermore, three of the Binswanger replications above did not include an "inefficient" lottery choice (Wik *et al*. 2004, Yesuf and Bluffstone 2009, and Barr 2003), making it very difficult to detect problems of comprehension. By comparison, confused participants in MPL experiments may switch multiple times between lottery A and B or never switch at all. This behavior could be due to a lack of salience in the monetary incentive or indifference over the

[5] The gambles were for hypothetical winnings. This is similar to the structure of the risk questions in the U.S. Health and Retirement survey since 1992.

interval of choices in which the participant switches back and forth. Indeed, most MPL studies in industrialized countries find this behavior, though it is generally a low percentage (~10% or less) of participants. Dave *et al.* (2010) test the MPL and Binswanger approaches head-to-head in a sample of 881 Canadians. Among participants with low-math skills, 21% switched multiple times (compare to 6% in the remainder of the sample), and the Binswanger approach had less noise in the data. They also find that the two approaches produced surprisingly different estimates of risk aversion.

Recent studies have used a modified form of the MPL experiment in rural populations in Uganda (Humphrey and Verschoor 2004a), Rwanda (Jacobson and Petrie 2009), and Vietnam (Tanaka *et al*. 2010).[6] Harrison *et al*. (2010) and Humphrey and Verschoor (2004b) combine experimental data from the Uganda study with data from India and Ethiopia. We describe some of the main findings of these studies with respect to risk aversion and its correlation with socioeconomic characteristics when discussing our results below. These studies adapted the MPL approach in different ways. Because some of their results differed -- particularly with respect to participant understanding -- and because we also adapted the MPL in a unique way, it is important to understand in detail the different methods used.

We begin with the approach used in Humphrey and Verschoor (2004a, 2004b) and Harrison *et al*. (2010). Probabilities varied and were not limited to a coin toss, though they were limited to 25% to aid understanding. Lotteries were explained to participants as drawing colored marbles from a bag. Different colors corresponded to different real payoff levels (e.g. a blue marble = $2.50 prize, a red marble = $5.50 prize, a black marble = no prize). For example, for a lottery involving two outcomes (win $5.50 with p=0.5 or win nothing with p=0.5), the researcher would place two black balls and two red balls in the bag. A second lottery was constructed with a second bag, and participants were asked to choose which lottery

[6] We are also aware of several as-yet unpublished working papers in this area (Botelho et al. 2005, Galarza 2009, Liu 2008). We focus our discussion primarily on the published studies because the methods in these working papers followed other published work. In addition, three studies have examined risk preferences by eliciting certainty equivalents among Chinese university students (Kachelmeier and Shehata 1992), a random sample of 965 adults in Lima, Peru (Barr and Packard 2005), and a random sample of 230 adults in Santiago, Chile (Barr and Packard 2002). Certainty equivalents do not require assumptions about the specific form of the utility function and are thus somewhat difficult to compare with our results and the other studies described above.

or "bag" they would prefer. The binary lottery choices were presented sequentially, rather than simultaneously as in the MPL approach; the authors refer to this as a Random Lottery Pair (RLP) design. The lotteries were designed with the primary goal of distinguishing behavior consistent with expected utility theory (EUT) versus prospect theory (PT). It would appear that there is no way in their design to distinguish *individual* participants who did not understand the game, though it is certainly possible to examine whether the pattern of all responses is similar to a pattern of randomly-choosing participants.

Tanaka *et al*. (2010) described lotteries as drawing balls from a bingo cage. Participants completed three "series" of 15 binary choice tasks. Within one series of lottery choice tasks, the probabilities were fixed (10, 30, 50, 70 and 90%) but the payoffs changed. Unlike the sequential RLP approach just described, Tanaka *et al*. presented participants with a "record form" with all 15 binary choice tasks (i.e. a MPL design like HL). Unlike HL, however, participants were not asked to make 15 individual decisions for each choice task. Because the payoffs in the "risky" lottery changed monotonically compared to the "safe" lottery (as in our experiment), participants were simply asked to identify the choice task in which they would first choose the "risky" lottery (i.e. their switchpoint). Subjects were also allowed to indicate that they would choose the "safe" lottery in all rows or the "risky" lottery in all rows. Again, the series of experimental choices were designed primarily to test prospect theory and probability weighting; it is very difficult to detect if any individual participant misunderstood. Subjects who always chose the safe game might in fact be extremely risk-averse, but it may also indicate that they did not understand the task in the way the researchers intended. Although Tanaka *et al*. do not report the percentage who never switched, the large peaks in the corners of their Figure 1 would indicate that it was a significant fraction.

The approach most like the one described in this paper is that of Jacobson and Petrie (2009) in Rwanda. The researchers administered a Binswanger-style risk aversion treatment to 442 participants that did not include an "inefficient" choice and therefore could not detect mistakes, but also administered an HL-style binary choice treatment to 181 participants that allowed participants to switch multiple times. Like our study, the choices were presented sequentially rather than simultaneously on one sheet (like HL or Tanaka *et al*.). Unlike HL and our study, though, probabilities were fixed at 50/50 and payoffs changed. Despite the fact that the participants doing the sequential choice lottery were similar in nearly all observable characteristics to those doing the Binswanger treatment, Jacobson and Petrie found significantly higher risk aversion among the Binswanger participants than the sequential binary choice lottery participants. Among the latter, fully 55% made inconsistent choices by switching multiple times. Like HL, they find that the fraction of inconsistent choices was smaller in games with high stakes compared to low stakes, though no other demographic characteristics were statistically-significant predictors of mistakes, including years of education. Although a risk aversion measure alone did not explain financial decisions like joining a savings groups or taking out an informal loan, a joint model with both risk aversion and the probability of making a mistake in the experiment did. Subjects who made mistakes were more likely to take out a risky informal loan rather than joining a savings group as they became more risk averse.

Finally, Chakravarty and Roy (2009) administered a HL MPL experiment to 85 students in the Indian Institute of Management in Ahmedabad, the country's top business school.[7] Like HL, students were shown the list of binary choices, and circled a decision for each row. Although this design allowed for observing inconsistent choices, the authors report only one of the 85 students made such a choice. They note, though, that "these participants are amongst the brightest management students in India."

3. Experimental procedure and participants

3.1. Setting

Kolkata (formerly Calcutta) is the third largest city in India, with a population that is thought to be approximately 13 million. We conducted risk aversion experiments in the Beliaghata neighborhood of

[7] An as-yet unpublished manuscript (Chakravarty *et al.* 2010) uses the same experimental procedure among the same subject pool but interestingly examines risk preferences over other subjects' money. The paper does not report whether some subjects switched more than once.

the city. Beliaghata, a predominantly Hindu area, has a diverse set of living conditions and incomes and thus may be broadly representative of the city as a whole. It contains many middle-class families living in apartment buildings that are in relatively good condition, but also has several small slums (*bustees*) with very crowded living conditions and poor housing stock. According to India's 2001 Census,[8] the two wards that make up Beliaghata (Wards 33 and 34) had a combined population of 72,000 and a literacy rate slightly higher than the city as a whole (90% in Beliaghata vs. 81% city-wide). Beliaghata had a higher percentage of residents living in slums (49%) than the city as a whole (33%).

3.2. Recruitment

Participants were recruited from among participants in companion stated preference surveys of private demand for cholera and typhoid vaccines in the Beliaghata ward of Kolkata, India (Whittington *et al*. 2008). At the end of all stated preference interviews in Beliaghata, enumerators handed the participant an "entrance ticket" for the experiment. The ticket had a pre-stamped unique questionnaire identifier that enabled us to link the participants' behavior in the experimental session to other socioeconomic and attitudinal information elicited during the stated preference survey. The "ticket" said:

> "We would also like to invite you to participate in a game where you will win a prize. It will not cost you anything to play the game. We will be playing the game in the Bottala Balak Sangha Club at the dates and times listed below. You can come at any of these times. In addition to the prize, we will reimburse you Rs. 10 for transportation to the club. This form is your entrance ticket: to play the game, <u>you must bring this form. No one else can play the game except you</u>."

Enumerators read this passage to illiterate participants.

We conducted 22 experimental sessions on 14 evenings with a total of 404 participants. In each session, participants sat in one large room and were instructed as a group (more details below), though they answered the risk preference questions individually and privately. An average of 18 people participated in each session; the largest session had 33 participants. Each session lasted approximately one hour. In total, 42% of the stated preference participants who were invited to participate in the risk

[8] http://www.censusindia.net/results/2001census_data_index.html

aversion experiments did so. We report socioeconomic differences in the self-selected participants in Table 2.

3.3. Experimental procedure

We adapted the experimental risk elicitation for a setting where many participants have little or no education.[9] The moderator began each group session by welcoming participants and explaining the basic concept of chance with a coin toss. She then projected an image of a colored spinner that represented the chance of a coin landing heads or tails (Figure 2). After a considerable amount of discussion with local colleagues, we decided that colored spinners offered the clearest approach to communicating probabilities and lotteries to our participants. At the time, we were unaware of the studies using colored marbles in India, Ethiopia, and Uganda, nor the bingo-ball approach in Vietnam, as these studies had not yet appeared in the literature. Our use of a different probability tool adds a potentially important confound in comparing our results to those studies, though we see no reason to think that one approach is better than other without directly testing both in a specific population of interest.

The moderator then passed the corresponding physical spinner (see Figure 3) around the group, having each participant spin it once. The moderator recorded the outcomes of each spin and announced the outcomes (how many heads and tails in the group). This exercise served two purposes: it let participants practice with the spinners that would be used throughout the experiment, and it helped them understand the correspondence between the familiar coin toss and the unfamiliar spinner.

The moderator then introduced a sample choice task where the lottery winnings were bars of soap (Figure 4). She began by explaining only one of the lotteries in isolation ("Spinner B" on right in Figure 4). The moderator explained that the chance of winning 8 bars of soap was much smaller than the chance of winning 1 bar, and that if one spun the wheel 100 times, it would probably land on blue 10 times and on red 90 times. She projected the image of the spinner for this lottery on the wall and passed around the

[9] The full bilingual experimental protocol and the English and Bengali versions of the slides projected on the screen to the group are available at the first author's faculty website: http://faculty.washington.edu/jhcook/research.html

physical spinner. Each participant spun it once and the moderator announced the outcome to the group.

She then showed participants the other lottery in the sample binary choice task (“Spinner A” in Figure 4). She projected both lotteries (e.g. spinners) onto the wall and asked participants to think about which of the lotteries they would prefer (i.e. “which spinner they would want to spin”). They did not record their answers and were asked to keep their choice to themselves.

The moderator told participants that they would be asked to make ten more similar binary choices. Like the Random Lottery Pair (RLP) method, these choices were made sequentially not simultaneously. She told participants that after they had made their ten choices they would randomly choose one of the ten tasks by picking a number out of a jar that contained numbered, folded pieces of paper. The participant would spin whichever spinner she had chosen for that task to determine the number of prizes won. Each participant was given a pen and a blank answer form with spaces to mark their preferences for each of the ten tasks, and the moderator explained how to fill in the form. Other research staff were on hand to assist anyone who needed help filling out the form, though few did.

In each of the 22 experimental sessions, we asked for a volunteer from the group to do the remainder of the experimental procedure in front of the others. In seven very large groups we asked for two volunteers to play simultaneously. We projected the ten binary choice tasks (Table 1, described more below) sequentially onto the wall, each time pausing to allow the volunteer to make his or her choice and mark the answer form privately. The volunteer then randomly selected which task to play for real winnings, spun the spinner corresponding to the lottery that he had chosen for that task, collected his winnings, and left. This approach allowed the other participants time to think about their choices before they actually completed the experiment and gave them a chance to see the entire experimental procedure from beginning to end. We judged that this benefit outweighed the potential cost – that other participants could be influenced by the volunteer’s winnings. Although the other participants could not observe all ten of the volunteer’s choices (they could not see his or her form), they did observe the volunteer’s choice on the randomly-chosen task which was played for winnings. They also observed the volunteer’s actual winnings. One might expect that a volunteer who made a risky choice but still (by good luck) won the maximum number of prizes could induce similarly risky behavior in the remaining members of the group.

3.4. Payments

Because our local research partners would not allow us to pay participants in cash, we paid participants in kind. We worked hard, however, to make the in-kind winnings seem as much like cash as possible. In place of cash amounts, the lotteries referred to the number of "prizes" participants could earn. We told participants that each prize was worth about Rs. 10 (US$ 0.22)[10] and handed them a "one-prize note" for each prize they won in the experiment. This note was similar in shape to an actual Rs.10 banknote and had the words "one prize" written on it in Bengali. The prizes were redeemable in our "store", which was set up in one corner of the room at the beginning of the session. We stocked our store with six goods, each worth approximately Rs. 10. We chose these goods after consulting with local staff and pretest participants to identify goods that are commonly purchased by all types of households in Kolkata. The six goods were, in order of popularity among participants, rice, sugar, soap, razors, washing powder, and garam masala, a commonly-used spice. Rice is the most common staple in West Bengal, unlike other parts of India. Participants were allowed to mix and match the types of goods on which they spent their prize certificates. Average winnings were 4.6 "one prize certificates" worth approximately Rs. 46 (US$1.02), roughly equal to the average daily per capita household income observed in our full sample of Beliaghata households (Table 2).

3.5. Task order

We varied the order in which we presented the ten choice tasks to test for ordering effects ("forward" and "reverse" order in Table 1). After initial pretests with a convenience sample of 28 project staff at the Institute for Cholera and Enteric Diseases (NICED)[11] and several experimental sessions,

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[10] We use an exchange rate of 1US$ = 45 Rs throughout. This was the prevailing exchange rate in the summer of 2004.
[11] We do not use any of the data from this convenience sample in the results below.

however, it was clear that participants in sessions where the tasks were presented in “reverse” order were much more likely to understand the task than those in “forward” order sessions. We suspected this was because both of the lotteries in the first task in “reverse” order were certain (i.e Lottery A: win $1.11 with p=1.0; Lottery B: win $1.78 with p=1.0), while the lotteries in the first task in “forward” order involved non-zero probabilities. In the remaining sessions, we used a “revised forward” order where the first choice involved lotteries with certainty (Table 1). Of the 22 sessions, 11 were conducted in “reverse” order (186 participants), three in “forward” order (70 participants), and eight in “revised forward” order (148 participants).

4. Modeling approach

The most common modeling strategy is to assume an expected utility (EU) framework with a constant relative risk aversion (CRRA) utility function of the form $U(x) = x^{1-r}$, where x is lottery winnings. The participants’ choices allow us to create an interval on their implied values of r, which can be reported in raw form as the distribution of risk preferences in the sample. To explore the role of socioeconomic characteristics, one can either regress the number of “safe choices” using OLS model (Holt and Laury 2002), or use an interval regression model (Wik *et al*. 2004). To maintain easy comparability with these previous studies, we report our raw data in interval form and use the OLS model to explore socioeconomic determinants.

In a supplementary appendix, we also use a more recent modeling approach with flexible functional forms that are less dependent on *a priori* assumptions about the underlying decision-making process. Following Harrison *et al*. (2010), and Harrison (2008), we directly code maximum likelihood models for both an expected utility (EU) theoretical framework and a prospect theory (PT) framework with subjective probability weighting (Tversky and Kahneman 1992).

5. Results

5.1. Socioeconomic profile of participants

The typical participant in our experiment is a 35 year old woman with 6-9 years of formal education (fourth column of Table 2). Her household has five members and per capita monthly income is on the order of $20 (2004US$). Thirteen percent of participants said they are unable to read a newspaper. Compared to the full sample of stated preference participants, the people who decided to participate in the risk aversion experiments were more likely to be female, lower income, and less educated. They were also more likely to report their economic status relative to their neighbors as “below average” or “much worse than average” (Table 2). We do not attempt to correct for this selection effect in the model results below, in part because there is also a second complicating selection effect in that a nonrandom group of participants did not understand the task. We do, however, explore double-selection OLS models in the supplementary appendix.

5.2. Did participants understand the tasks?

All participants were presented with a “certainty” task where probabilities were 0 and 1; one lottery clearly dominated (first and last rows of Table 1). Seventy-seven participants (19%) answered these “certainty” tasks incorrectly. Four additional participants were unable to fill out the form correctly, even with help. These participants clearly did not understand the task in the way we intended, and are dropped from the analysis.

It is more difficult to judge whether participants who switched multiple times understood the task. Figure 5 plots the raw response intervals over which people switched in our sample. The figure is categorized into panels by the risk aversion category implied by their choice (again assuming a CRRA utility function and labeling the categories following HL). Each bar represents one participant and the vertical axis represents the task numbers, standardized to “revised forward order” in Table 1. A bar that is only one vertical unit tall represents a participant who switched only once. A bar that is more than one vertical unit tall means the participant switched more than once; the bar represents the range over which the participant was indifferent or uncertain (above the bar they always chose Lottery A, below the bar they always chose Lottery B, and within the bar they switched back and forth). The upper-left panel shows the 90 participants who switched over an interval of greater than 4 tasks. It seems likely that these participants did not understand the tasks because the implied indifference range for *r* is implausibly wide (in some cases ranging from “risk-loving” to “highly risk averse”). Of the remaining 234 participants, 166 switched once, 25 switched twice, and 42 participants did not switch at all (29 preferred the safe lottery in all ten choice tasks, and 13 preferred the risky lottery in all ten tasks).

We estimated three probit models to explore in more detail who made a mistake or misunderstood the task, one model for each of three definitions of misunderstanding (Figure 6). The first, broadest definition of misunderstanding excludes participants from the sample who did not answer the “certainty” task correctly or could not fill out the answer form. A second definition excludes those using the first definition and also excludes participants who switched over intervals of 4 tasks or greater (the participants in the upper-left panel of Figure 5). The third definition excludes those using the first and second definitions and excludes any participants who switched more than once or who never switched at all. This third definition excludes over half of participants.

Table 3 reports the results of three probit models that explore the factors associated with misunderstanding using these three definitions. Not surprisingly, we find evidence that those with higher levels of education were less likely to make a mistake. Controlling for education, poorer participants were more likely to make a mistake, though the results were not uniformly significant across definitions. Compared to respondents aged 18-35, respondents aged 35-45 were more likely to make a mistake under the second and third definitions. Under the second definition, the person who agreed to be the volunteer was more likely to make a mistake, confirming in some regards our feeling that participants needed to see the whole exercise in order to understand it. The order that the tasks were shown to participants had the largest effect: those in groups in which the experiments were run in “reverse” order, or in the “revised forward" order, were more likely to understand the tasks using the first two definitions. (Again, this confirms our decision to revise the original "forward" order as described above).

Following Jacobson and Petrie (2009), we were also interested in whether the likelihood of making mistakes in the risk experiment was correlated with real decisions. We tested pairwise correlations of a dummy variable indicating whether the participant made a mistake and variables for whether they never boiled their water, ate street food more than three times per week (a risky proposition in Kolkata), or spent any money on the lottery in the past 30 days. Under all three definitions of mistakes, none of the correlation coefficients were above 0.10, and none were statistically significant.

For the remainder of the paper, we present results using only the third, most restrictive definition of understanding, though this reduces our sample size by half. We provide parallel results using the second definition of understanding in the supplementary appendix for interested readers.

5.3. What were the risk preferences of participants?

Among the 166 participants who switched only once, 84% would be classified as risk-averse based on the midpoint of their implied CRRA interval (shown in the bottom of Figure 1). Forty percent of participants exhibited "very" or "highly" risk-averse preferences ($r > 0.68$), but a sizeable fraction (16%) of participants indicated risk-seeking preferences. The average midpoint of the CRRA intervals among these participants was 0.53, or "risk-averse". The average midpoint among Binswanger's (1981) participants in rural India was 0.48 for an experiment with small payoffs, or 0.71 for experiments with larger payoffs. Our average risk aversion results are also roughly in line with those from Wik *et al*. (2004), Miyata (2003), Harrison *et al* (2010) and Tanaka *et al*. (2010).

Although it appears from the raw data in Figure 1 that the order in which the choice tasks were presented affected responses, the average midpoints of the CRRA interval, however, are not statistically different ($r=0.51$ for forward or "revised forward" and 0.55 for reverse order, $t = 0.36$).

If the volunteer who demonstrated the full experimental procedure in front of the group won the maximum of eight prizes, the remaining participants in that session showed less risk aversion. The midpoint of the CRRA interval for the 41 participants in these "volunteer luck" groups was 0.26 compared with 0.62 among the other 125 participants. This difference is statistically significant (two-sample t-test of difference in means, $t = 3.05$).

5.4. Are risk preferences associated with participants' socioeconomic characteristics?

Table 2 lists the variables that we hypothesize may be associated with risk aversion, their summary statistics, and their one-way correlation coefficient with the number of safe choices using the second exclusion definition.[12] Most correlation coefficients are low (less than 0.10) and not statistically significantly different from zero. Illiterate participants, participants in groups where the volunteer won the maximum number of prizes, participants who classify their economic status relative to neighbors as below average, and more present-oriented participants made fewer safe choices. Participants with more rooms in their house (an income proxy) made more safe choices, although income itself is not statistically significant.

Following HL, we regress experimental and socioeconomic characteristics on the number of safe choices made using an OLS framework (Table 4). As suggested by the pairwise correlations, lucky volunteers seem to have induced more risky choices in the remaining participants. This is similar to the "good luck" effect found by Binswanger (1980), Wik *et al*. (2004), and Yesuf and Bluffstone (2009): when participants realized the outcome of one risky choice before making another choice, participants who were lucky in earlier rounds began making more risky choices in later rounds.

Game order is weakly statistically-significant in two of the three models, but of an economically-important magnitude. Like a number of studies, we find that men were less risk-averse, as were present-oriented participants. Both literacy and levels of formal education are not associated with choices in the experiment. Although Tanaka et al (2010) find that participants with higher education were more risk

[12] In this analysis of the number of safe choices, we collapse the first and last categories. All participants who made 0-2 safe choices are recoded as having made two safe choices, and all participants who made 9-11 safe choices are recoded as having made 9 safe choices.

averse, most studies do not find robust education effects.[13] Binswanger (1980), Miyata (2002), Wik *et al*. (2003), and Tanaka *et al*. (2010) all found that participants with higher incomes were less risk-averse. Among our participants, income is not statistically-significant (in models not shown, we also tested electricity bills as an income proxy). In fact, one income proxy - whether the house has a ceiling fan – was statistically significant but of an unexpected sign,[14] indicating that wealthier participants made more safe choices and were *more* risk-averse.

We also include a number of additional analyses in the supplementary appendix for interested readers. First, we report similar model results using the less restrictive definition of mistakes. Second, we test the effect of experimental and socioeconomic characteristics in both an interval regression model and in the maximum likelihood framework of Harrison et al (2009). We find the same pattern of results broadly speaking, though the maximum likelihood approach produces higher overall estimates of risk aversion. Third, we present results from a double-selection model following Tunali (1986) which accounts for selection both at the participation level (who among the full sample showed up?) and the level of who understood the task.

6. Discussion

Using a novel adaptation of the HL multiple price list format in an urban area of a developing country, we find average risk preferences among the individuals in our sample that is similar to other studies in rural areas ($r \sim 0.5$). We also find, however, several results that researchers in the field may find somewhat troubling. First, participants were influenced by the context of the experiments, including game order (though only weakly significant and not robust across specifications) and whether a volunteer won the maximum number of prizes. Second and most importantly, nearly half of our participants may not

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[13] In a related vein, though, Dohmen et al (2010) find that people with lower cognitive ability (as measured by standard IQ tests) were more risk averse and less patient. Cognitive ability, however, should not be confused with education.

[14] Air conditioners were, of course, virtually non-existent in our study site. Ceiling fans were a fairly uncommon but undeniably positive asset. The correlation coefficient between household income and ownership of a ceiling fan is 0.15.

have understood the task, despite considerable effort by the research team to make the protocol as easy to understand as possible.

A reader might dismiss our findings because they were “contaminated” by having participants watch a volunteer. Researchers who are concerned that participants with low levels of formal education understand the protocol face a dilemma. In particular, to ensure incentive compatibility, participants must understand that one of the tasks will be randomly selected to play for real winnings. In group settings, having a volunteer run through the entire exercise including the payout would increase the chances that the remaining participants will understand the experiment and its payout structure. We find some evidence for this, as people who were the volunteers were more likely to make some types of mistakes. If participants play individually and do not see the entire sequence of events, they will not be biased by a volunteer but may not fully grasp the exercise. Alternately, participants could complete practice or “warm-up” rounds, though their prior luck in these warm-up rounds may then affect behavior in subsequent games.

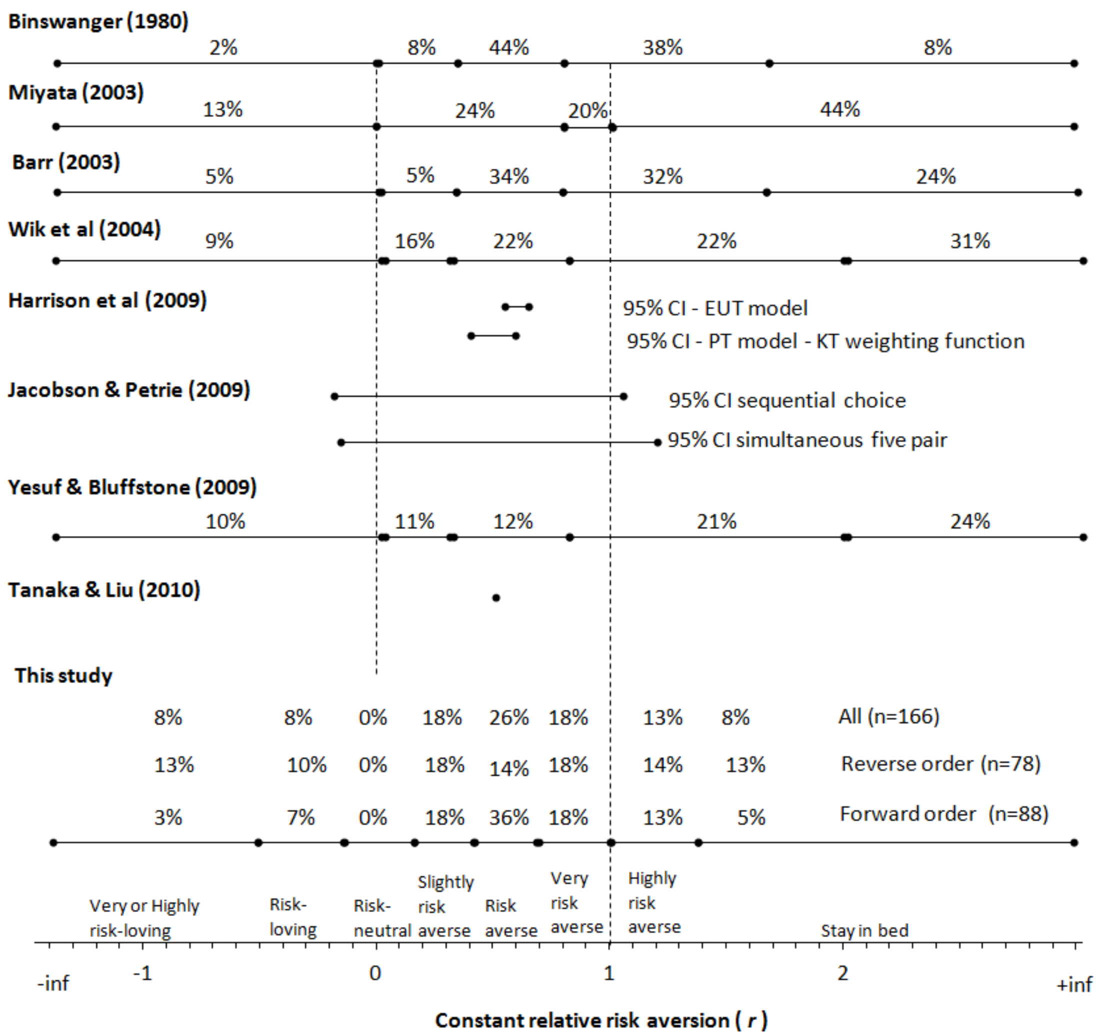
One might ask, though, is this such a bad thing? As Yesuf and Bluffstone argue, the fact that prior game winnings affect behavior is in fact policy relevant. Path dependence matters, and (they argue) policymakers might do well to focus initially on projects or interventions that have only slightly higher expected values for very moderate increases in risk. Only after initial successes with these projects will risk-averse farmers feel more confident about planting high expected value/high variance varieties. Our results push this argument further. In rural areas of poor countries, people will not necessarily make decisions in isolation and without knowledge of how that new and risky seed variety worked out for their neighbors. Focusing on adoption of lower risk policies among village leaders or community members with large social networks might help other farmers make better decisions under uncertainty.

A reader might also think that our experimental approach was unhelpfully different than existing studies (Why give poor people probabilities of 10%? Why use colored spinners?). “Clearly the approach did not work”, the reader may think, “because so many people did not answer the questions in a sensible way”. We would again note that our study was in the field roughly at the same time as studies which have since appeared in the literature, so we did not have the benefit of learning from the experience of these other teams. Furthermore, we are far from alone in finding confused participants among those who have designed their experiments to allow for mistakes. As described earlier, 55% of the participants in Jacobson and Petrie's study in Rwanda made inconsistent choices, and probabilities in their studies were presented as 50-50 coin tosses. Galarza (2009) found 40% of 410 rural farmers in Peru in a similar HL-style sequential binary choice research design switched multiple times, and 28% answered a certain question incorrectly (a higher fraction that among our participants). Binswanger himself found 2.5% - 9.3% of subjects made "inefficient" choices, though as we noted earlier his design has considerably less power in detecting confusion.

We would echo Jacobson and Petrie in arguing that there is much to be learned about decision-making under uncertainty from those people who are confused by risky situations. Risk parameters alone have not generally been shown to correlate well with real-world decisions, though Jacobson and Petrie show risk aversion is much more explanatory when coupled with information on mistakes. Future experiments should be designed both to maximize the chance that participants will understand (by tailoring language and materials to local customs, as Barr (2003) does in Zimbabwe) and to detect if they in fact still do not understand. We can then have more confidence in knowing what we are learning from the experimental gamble studies that are proliferating around the globe.

TABLES AND FIGURES

Figure 1. Review of risk preferences in developing countries



Notes: Constant relative risk aversion based on $U(x) = x^{1-r}/(1-r)$. Verbal descriptions at bottom based roughly on those given by Holt and Laury (2002). Most studies cited here had participants complete multiple tasks with multiple payoff levels. The figure reports results from tasks that were broadly representative of the authors' results. Results shown here respond to Binswanger's Task 12 (Rs.50); Miyata's Task 3 (10,000Rp); Wik *et al*.'s 10,000Kw real gain (no losses) with real payment; Yesuf & Bluffstone's Set 3 gains-only; and Jacobson and Petrie gain only. We report point estimates for the south from Tanaka & Liu (see Fig 1 in their paper for the distribution). For Binswanger, 10% of participants chose an "inefficient" lottery; these results re-code the percentages from his Table 3 to include only those who did not make an inefficient choice. Results shown from Harrison *et al*. (2010) correspond to models with no covariates.

Table 1. The ten binary choice tasks used in the experiments, patterned after Holt and Laury (2002)

Order in which tasks were shown						
Forward Order	Revised Forward Order	Reverse Order	**Lottery A** – "Safe" choice[a]	**Lottery B** – "Risky" choice[a]	EV(A) – EV(B)	Implied CRRA if switch to B[b]
	1		$1.11 with **p=0** , $0.67 with **p=1.0**	$1.78 with **p=0**, $0.22 with **p=1.0**	$0.44	n/a [c]
1	**2**	10	$1.11 with **p=0.1** , $0.67 with **p=0.9**	$1.78 with **p=0.1**, $0.22 with **p=0.9**	$0.33	(<-1.54)
2	**3**	9	$1.11 with **p=0.2** , $0.67 with **p=0.8**	$1.78 with **p=0.2**, $0.22 with **p=0.8**	$0.22	(-1.54, -0.83)
3	**4**	8	$1.11 with **p=0.3** , $0.67 with **p=0.7**	$1.78 with **p=0.3**, $0.22 with **p=0.7**	$0.11	(-0.83, -0.37)
4	**5**	7	$1.11 with **p=0.4** , $0.67 with **p=0.6**	$1.78 with **p=0.4**, $0.22 with **p=0.6**	**$0.00**	(-0.37, 0)
5	**6**	6	$1.11 with **p=0.5** , $0.67 with **p=0.5**	$1.78 with **p=0.5**, $0.22 with **p=0.5**	-$0.11	**(0.00, 0.33)**
6	**7**	5	$1.11 with **p=0.6** , $0.67 with **p=0.4**	$1.78 with **p=0.6**, $0.22 with **p=0.4**	-$0.22	(0.33, 0.65)
7	**8**	4	$1.11 with **p=0.7** , $0.67 with **p=0.3**	$1.78 with **p=0.7**, $0.22 with **p=0.3**	-$0.33	(0.65, 1.0)
8	**9**	3	$1.11 with **p=0.8** , $0.67 with **p=0.2**	$1.78 with **p=0.8**, $0.22 with **p=0.2**	-$0.44	(1.0, 1.41)
9	**10**	2	$1.11 with **p=0.9** , $0.67 with **p=0.1**	$1.78 with **p=0.9**, $0.22 with **p=0.1**	-$0.56	(1.41, 2.0)
10	**(11)**[d]	1	$1.11 with **p=1.0** , $0.67 with **p=0**	$1.78 with **p=1.0**, $0.22 with **p=0**	-$0.67	>2.0

Notes: [a] Winnings were not cash; participants won "1-prize" notes and selected from prizes worth approximately Rs. 10 (US$0.22). [b] The interpretation here is for participants who choose Lottery A in all rows above and continues choosing Lottery B in all subsequent games. As discussed in the text, this interval is more difficult to interpret for participants who switch multiple times. [c] A participant who chooses Lottery B in this row has misunderstood the task, since it involves no uncertainty and the prize in A is larger. [d] Participants were not presented with this task in "revised forward" order. It is labeled as Task 11 because all tasks were standardized to this order for analysis.

Table 2. Socioeconomic and attitudinal characteristics of participants and correlation with number of safe choices.

Variable	Definition	Stated preference participants (n=959)[a] Mean (S.D.)	All risk experiment participants (n=404) Mean (S.D.)	Pair-wise correlation with number of "safe" choices (Exclusion Def. C)[b]
Male	=1 if participant is male	49%	38%	-0.13
Age	Participant age (continuous)	35 (7.8)	35 (7.7)	0.012
AgeMid	=1 if age 35-45	46%	46%	-0.0007
AgeOlder	=1 if age >45	10%	9%	0.062
Edu2	=1 if participant completed 1- 9 years of school	43%	51%	-0.12
Edu3	=1 if participant completed 12 years of school or vocational school	32%	29%	0.037
Edu4	=1 if participant completed university, post-graduate or prof. course	16%	10%	0.13
Illiterate	=1 if participant said they could not read a newspaper	12%	15%	-0.15*
Income	Per capita monthly household income (US$)	$28 ($38)	$20 ($18)	0.13
Elecbill	Per capita electricity bill (US$)	$2.0 ($2.8)	$1.5 ($0.4)	0.095
NumAdult	Number of adults (age≥16) in household	3.8 (1.9)	3.6 (1.8)	0.083
NumChild	Number of children (age≤15) in household	1.4 (0.9)	1.4 (0.8)	-0.039
Reverse	=1 if reverse order	n/a	46%	-0.029
VolunteerLuck	=1 if in group where volunteer won maximum number of prizes	n/a	27%	-0.24*
PlayLottery	=1 if spent any money on lottery in past 30 days	5%	6%	-0.060
Volunteer	=1 if volunteer for group	n/a	8%	0.052
NeverBoil	=1 if never boil drinking water	61%	62%	-0.12
StreetFood	=1 if eat food from street vendors 3 or more times per week	23%	21%	-0.053
EconDecline	=1 if participant reported household's economic situation will "probably decline somewhat" or "certainly get much worse"	9%	9%	-0.039
WorseOthers	=1 if participant classifies economic status relative to neighbors as "below average" or "much worse than average"	27%	37%	-0.17*
TimePref	Continuous rate of time preference	19 (24)	17 (23)	-0.16*
NumRooms	Number of rooms in house	2.7 (2.0)	2.2 (1.3)	0.21*
DifficCredit	= 1 if "somewhat difficult" or "very difficult" or "impossible" to borrow Rs. 1000	63%	70%	-0.061
NoWindow	=1 if participant's home has no windows	3%	5%	-0.026
CeilFan	=1 if participant has ceiling fan	34%	22%	0.12
Car	=1 if participant has car	7%	3%	0.023

Notes: [a]Stated preference participants only in Beliaghata neighborhood; [b]Excludes participants who answered the certainty question incorrectly or switched more than once or never switched at all. * indicates that the correlation coefficient is significantly different from zero at the 5% level or better.

Figure 2. Spinner used to represent a coin toss.

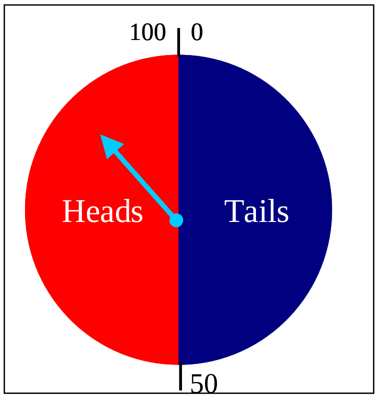


Figure 3. Subject spinning the wheel to determine his prize winnings.

Figure 4. Practice task: Choosing between two lotteries where the prize is the number of bars of soap.

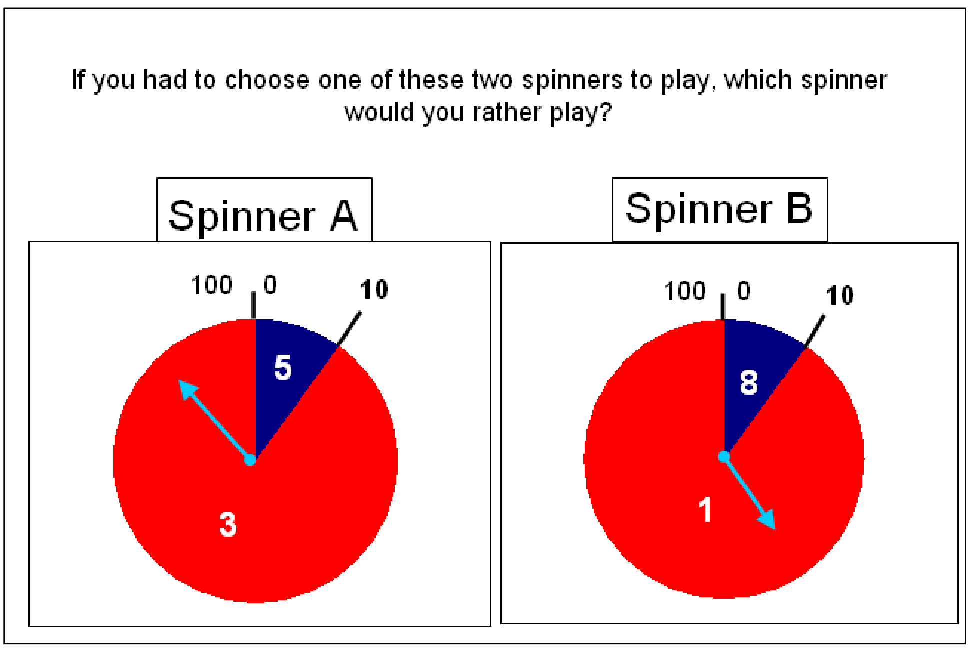
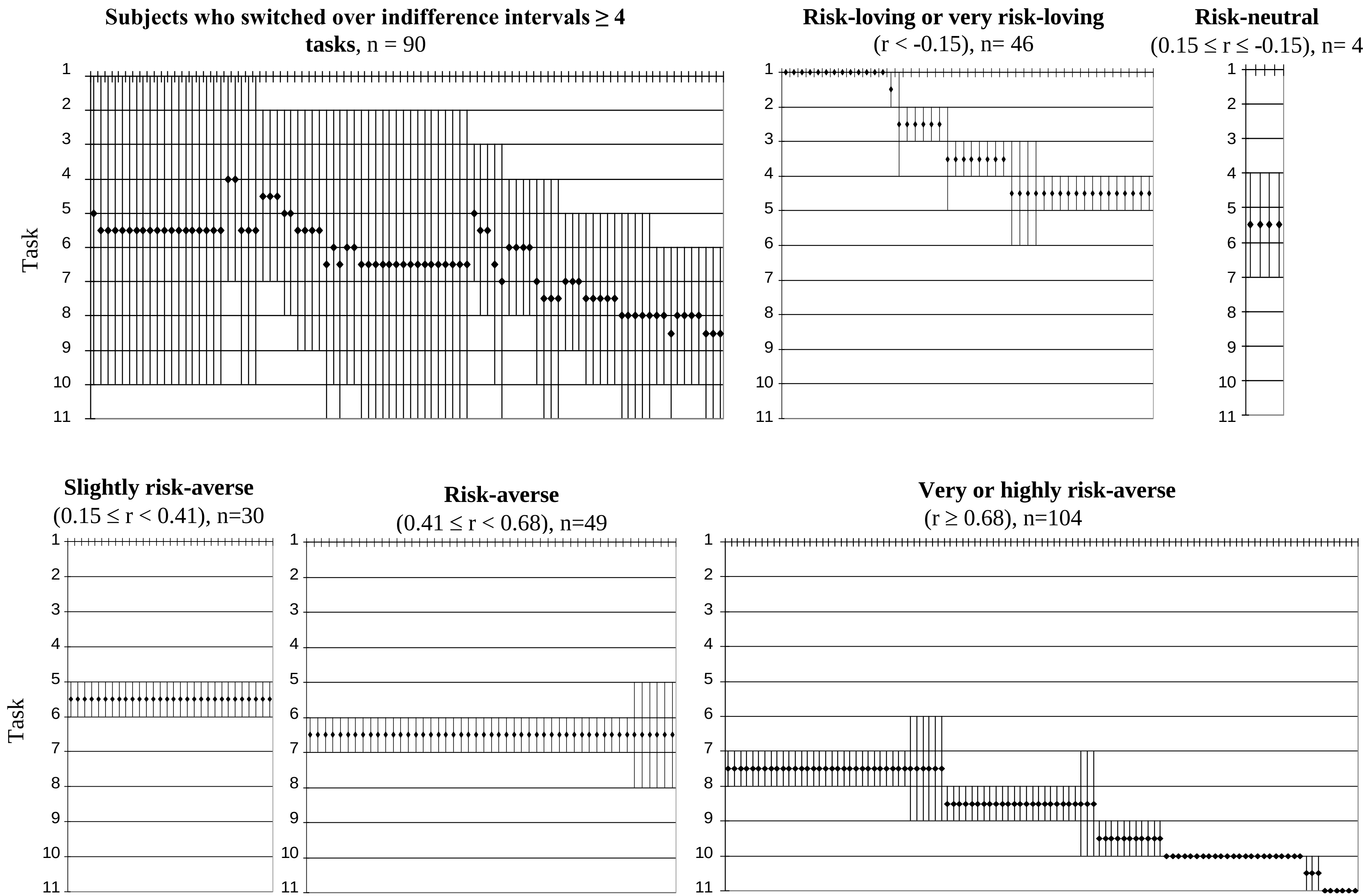


Figure 5. Distribution of risk responses classified by <u>midpoint</u> of implied CRRA interval



Notes: 82 participants who got the certainty question wrong or could not complete the form are not shown.

Figure 6. Summary of three definitions of whether participants made a mistake or misunderstood the task

Total Excluded Responses	Total Useable Responses	**n = 404**
n = 81	*n* = 323	**Definition A**: Exclude participants who could not complete form or answered certainty question incorrectly (exclude 81 participants)
n = 170	*n* = 234	**Definition B**: Also exclude participants who switched over intervals of four or more tasks (exclude an additional 89 participants)
n = 238	*n* = 166	**Definition C**: Also exclude participants who switched more than once or who never switched at all (exclude an additional 67 participants)

Table 3. Multivariate probit models of whether participant made a "mistake" or misunderstood task, using three definitions

	Definition A: *Exclude incorrect "certainty" question or bad form*		Definition B: *Def. A + exclude indifference interval ≥ 4 tasks*		Definition C: *Def. B + exclude those who switch more than once or never switched*	
Male	-0.076	(0.18)	-0.082	(0.15)	-0.25	(0.15)
AgeMid	0.14	(0.18)	0.29**	(0.14)	0.48***	(0.15)
AgeOlder	-0.16	(0.33)	-0.069	(0.27)	0.21	(0.28)
Education						
1-8 yrs education	-0.080	(0.25)	0.27	(0.23)	-0.20	(0.24)
9-12 yrs education or vocational	-0.40	(0.29)	-0.056	(0.25)	-0.67**	(0.26)
University or post-grad education	-1.05**	(0.48)	-0.13	(0.32)	-0.74**	(0.33)
Income (US$ per cap)[a]	$-3.0e^{-2}$***	($9.0\ e^{-3}$)	$-8.8\ e^{-3}$*	($5.1\ e^{-3}$)	$-7.1e^{-3}$	($4.6\ e^{-3}$)
Subject was volunteer	0.31	(0.32)	0.51**	(0.25)	0.26	(0.26)
"Reverse" order[b]	0.21	(0.19)	0.049	(0.14)	-0.18	(0.14)
Revised "forward" order[b]	1.41***	(0.23)	1.00***	(0.20)	0.72***	(0.21)
Constant	-0.58**	(0.30)	-0.47*	(0.25)	0.56**	(0.26)
Number of participants making mistakes	81		170		238	
Total N for regression	403		403		403	
Pseudo R^2	0.19		0.08		0.09	

Notes: Standard errors are in parenthesis. * indicates statistical significance at the 10% level, ** at the 5% level, *** at the 1% level. Convenience sample participants for whom we have no socioeconomic data are excluded from regressions. [a] Total household income reported by the participant divided by the number of household members, and converted to US$ at the Aug. 2004 exchange rate of Rs.45 = 1US$. [b] original "forward" order is excluded category

Table 4. OLS model of the number of safe choices

	Model 1		Model 2		Model 3	
	Est	se	Est	se	Est	se
“Reverse” order	0.88*	(0.52)	0.85*	(0.51)	0.83	(0.51)
Revised “forward” order	0.89	(0.55)	0.84	(0.53)	0.81	(0.54)
VolunteerLuck	-0.73**	(0.33)	-0.81**	(0.33)	-0.84**	(0.33)
Volunteer	0.18	(0.49)				
Male	-0.63**	(0.28)	-0.67**	(0.27)	-0.73***	(0.28)
AgeMid	-0.080	(0.28)	0.026	(0.27)	-0.056	(0.28)
AgeOlder	0.90*	(0.52)	0.73	(0.49)	0.92*	(0.51)
Education						
1-8 yrs education	0.11	(0.57)			-0.48	(0.59)
9-12 yrs education or vocational	0.35	(0.57)			-0.44	(0.60)
University or post-grad education	0.84	(0.67)			-0.026	(0.67)
Income (US$ per cap)	2.5e^{-3}	(6.6 e^{-3})				
TimePref	-0.013**	(5.6 e^{-3})	-0.015***	(5.4 e^{-3})	-0.016***	(5.5 e^{-3})
Illiterate			-0.51	(0.45)		
NumRooms			0.15	(0.092)	0.11	(0.099)
CeilFan			0.90*	(0.52)	1.16**	(0.52)
NoWindow			-0.38	(0.55)	-0.41	(0.56)
PlayLottery					0.055	(0.64)
NeverBoil					-0.43	(0.27)
StreetFood					-0.012	(0.16)
Constant	5.24***	(0.97)	4.55***	(0.94)	4.93***	(1.15)
Observations	166		164		164	
R-squared	0.164		0.217		0.234	

Notes: Standard errors are in parenthesis. * indicates statistical significance at the 10% level, ** at the 5% level, *** at the 1% level. Includes only participants who switched once and only once between rows (Exclusion definition C). Excluded categories are original “forwards” order and no formal education.

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