Inconsistent Choices in Lottery Experiments: Evidence from Rwanda

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Abstract: Lottery experiments have been performed in many contexts to test theories of risk aversion and to measure risk preferences. People are typically offered a series of lotteries with increasing expected payoffs and variances. A person with a concave utility function should switch from risky bets to safer bets at some point and never switch back. Switching back implies preferences inconsistent with a concave utility function. Our experiment, conducted with a population of adults in Rwanda, presents respondents with a series of binary-choice lotteries over gains and losses. We observe that 54-55% of subjects made at least one inconsistent choice over gains or losses, and 7-13% made at least two inconsistent choices. This holds for both hypothetical and real lottery payoffs. Inconsistent choices were less common when stakes were higher, and women are more likely to be inconsistent. While risk aversion alone is not correlated with actual economic outcomes, such as membership in savings (tontines) and insurance groups and holding a larger number of bank accounts, inconsistency is.

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Introduction

There is an intriguing disconnect in the literature on individuals' decisions under risk. On the one hand, theoretical constructs in nearly all areas of microeconomics rely on parameters that describe risk preferences. On the other hand, attempts to estimate risk preferences with lotteries, although simple and quite convincing in their design, often generate results that are unsatisfactory in explaining actual economic outcomes.[1]

The results correlating risk preferences elicited using lottery experiments with real-world risky choices or economic outcomes are mixed. For example, Eckel, Johnson, Montmarquette, and Rojas (2005) find no link, while Binswanger (1980) does find a modest link. Bellemare and Shearer (2006) find a link between risk aversion measures and sorting into jobs. Additionally, it has been found that the institution in which risk preferences are elicited can have a strong effect on the risk preferences that are observed, even changing risk aversion rankings across people (Isaac and James, 1999 and 2000; Berg, Dickhaut, and McCabe, 2005). We use a lottery choice experiment with certain monetary payoffs to investigate inconsistency in risk choices and examine whether that inconsistency is linked to demographic variables and to economic outcomes.

Using an adult population in Rwanda, we perform binary-choice lotteries with increasing stakes and variances. The procedure is similar to Holt and Laury (2002), but our method differs from theirs in several important ways. First, our lotteries were presented sequentially, rather than all at once. Second, instead of fixing payoffs and changing probabilities, we fix probabilities at 50-50 and change payoffs. These methods are theoretically equivalent. The sequential binary-choice lotteries were also designed to be equivalent to presenting six lotteries at the same time

[1] Harrison, List and Towe's (2006) research suggests that some of this disconnect between risk preferences measured with lotteries and actual outcomes may well do with ignored background risk. They find that subjects are more risk averse when background risk is introduced in a binary-choice lottery experiment.

and having the subject choose one (as in Binswanger, 1980; Eckel, Johnson, Montmarquette, and Rojas, 2005). Finally, in addition to lotteries over gains, we also present lotteries over losses.

In the sequential binary-choice lottery procedure, each lottery pair consists of an "A" (risky) choice and a "B" (safe) choice. The A lottery always has a higher expected payoff and variance than does the B lottery. In the next lottery in the sequence, the A lottery from the previous pair becomes the B choice and a new, riskier lottery is presented as the A lottery.

A person who is risk-neutral or risk-loving should always choose the A lottery because the expected payoff is higher.[2] However, a risk-averse person, one with concave preferences, should choose the riskier A lottery for lower stakes, and then the safer B lottery for higher stakes.[3] The switching point from risky to safe lotteries depends on how risk-averse the person is and can be used as a risk aversion measure. Finally, a risk-averse individual should switch from risky to safe lotteries earlier over losses than over gains.

If a person violates this pattern by switching from a safe to a risky lottery, that individual did not choose in a pattern consistent with concave preferences, or even convex preferences. This kind of switch would imply the presence of an inflection point right in the middle of this lottery's wealth range. In these cases, people may be making "mistakes" (e.g. noisy choice or some systematic error), or they may be making intentional choices that are still rational (e.g. they may be intentionally "testing the waters" or their preferences are time-inconsistent or not concave over all lotteries). Since subjects do not know the outcome of their choices until all decisions have been made, these inconsistencies cannot be due to wealth effects. An alternative

[2] Note that this is also an important difference between our design and that of Holt and Laury (2002). While a risk-neutral person would switch from choosing the risky to the safe lottery somewhere in the middle of the range of lottery choices in Holt and Laury, in our design a risk-neutral subject would always choose the risky lottery.

[3] The true switching point for some risk-averse individuals may fall outside the range of wealth of our lotteries; thus, some risk-averse people will always choose the safe lotteries while others will always choose the risky lotteries. This design does not allow "mildly risk averse" individuals to be distinguished from risk neutral and risk loving individuals, as all of these will choose only risky lotteries.

explanation is that subjects make these unexpected decisions because they view the lotteries as a risk portfolio instead of as independent decisions. Our experiment is not designed to isolate such effects, and we therefore assume that such effects are negligible. Finally, a systematic error in lottery choice could occur due to the compounding of lotteries that occurs in a randomly-paid experiment. However, that should simply make people behave in a consistent, but more risk-averse, fashion in this experiment (Holt, 1986).

Previous research has found varying degrees of inconsistent behavior using lotteries to measure risk preferences. Indeed, some research does not observe inconsistency because, by design of the experiment, subjects are forced to choose consistently. For example, in a simultaneous lottery presentation experiment (e.g. Binswanger, 1980 and 1981), the subject picks just one from an array of lotteries. Using the sequential binary-choice lottery, some research has avoided the inconsistency issue by asking the subject to choose a switching point rather than choose an option for each lottery (e.g. Tanaka, Camerer, and Nguyen 2006). Harrison, Lau, Rutstrom and Sullivan (2005) have an iterative method that allows them to hone in on a particular switching point, rather than allowing a subject to switch back and forth. Other inconsistent behavior has been found in the form of preference reversals, where the lottery valued at a lower price is chosen, using lottery auctioning tools such as the Becker-DeGroot-Marshak mechanism.[4]

Among research that does not force a switching point, there is evidence that people do make inconsistent choices. Holt and Laury (2002) present a series of binary lotteries to students and find inconsistencies in 5% to 13% of decisions in real and hypothetical treatments. Stockton

[4] Some relevant research includes, Ballinger and Wilcox (1997), discussing probabilistic choice; Holt (1986), discussing the pitfalls of the "random lottery" payoff mechanism in light of violations of the independence axiom; Grether and Plott (1979) on preference reversals in which the lottery not chosen is given a higher reservation price; Cox and Epstein (1989), in which it is determined that subjects violate the asymmetry axiom.

(2006) studied binary-choice risk preferences over hypothetical health outcomes with adults, and found that 11% of people make inconsistent choices. A similar "switching back" has also been observed in decisions relating to time preferences. Castillo, Ferraro, Jordan, and Petrie (2006) found that 42% of eighth-grade students demonstrated an inconsistent choice with real payments. Meier and Sprenger (2006) performed real payment time preference experiments with adults and found that 12% of the data show an inconsistent choice. This literature suggests that inconsistent behavior in binary-choice experiments is not uncommon, and it is observed in both real and hypothetical payment situations.[5]

In our experiment, we found that 54-55% of subjects made at least one inconsistent choice, switching from the safe to the risky lottery, in each set of lotteries, and 7-13% made at least two inconsistent choices. We investigate the nature of this inconsistency and relate it to economic outcomes. We find that inconsistency is a better predictor of outcomes than the risk aversion parameter derived from the lotteries.

Experiment

The experiments were conducted in conjunction with a 2002 World Council of Credit Unions survey on the economic activities and household characteristics of credit union members and non-members in seven locations across Rwanda. In each location, fifty members and fifty non-members were interviewed, for a total of 700 survey respondents. Interviewed members were randomly selected from lists of active credit union members. Interviewed non-members

[5] There is a debate in the experimental literature as to whether real monetary payoffs are necessary to incentivize "realistic" behavior in experimental settings. Largely, the conclusion has been that real, rather than hypothetical, payoffs are essential for believable results. Ortmann and Hertwig (2006) summarize the recent debate, concluding that financial incentives *may* be important in motivating economic behavior, particularly in some settings. Importantly, they emphasize the importance of a "do-it-both-ways" rule, so that experimenters can compare results of financially motivated and non-motivated treatments. Although our setting is one of those that Ortmann and Hertwig (2001 and 2006) find particularly compelling for the use of financial incentives, we note that we did try both monetary and hypothetical payments. We do not see a significant behavioral difference in our context between the real and hypothetical treatments at a given level of payoffs.

were randomly selected from neighborhoods served by the credit union. Survey respondents were at least 18 years old and were asked questions about household demographics, the economic activities of household members, and credit use. Interviews were conducted in Kinyarwanda, the primary Rwandan language, by Rwandan enumerators.[6]

At the end of the survey, each survey respondent was asked to complete two lottery experiments, one with only positive earnings (the gain lotteries) and one with both positive and negative earnings (the loss lotteries). Of the 700 respondents, 15 received test treatments that were not designed to generate usable data, another 62 were unable or unwilling to complete the full lottery experiment, so 623 individuals provided risk preference data. Of those 623, 442 received a treatment that presented five lottery pairs at once and asked the subject to choose one of those lottery pairs (as in Binswanger, 1980). This five-pair simultaneous presentation treatment, by design, did not allow the subjects to choose inconsistently. The remaining 181 subjects received sequential binary-choice treatments that did permit inconsistent choices. Eighty-two subjects participated in a treatment with low payoffs (55 with hypothetical and 27 with real payoffs) and 99 had a treatment with high payoffs (all hypothetical). All 181 of these subjects lived either in the capital Kigali or in Gitarama or Butare, towns in the south of Rwanda.

In the experiment, subjects face a series of five pairs of lotteries, each with 50-50 odds, and asked to choose one lottery (A or B) in each pair. The lottery pairs are shown in

[6] For a complete description of the data and survey design, refer to Petrie (2002).

Table 1. Before making their decisions, subjects are told that one of the five lotteries will be randomly chosen for payment by pulling a number between one and five from a hat. Then, a coin will be flipped to determine payment. After the procedures are explained, the subject is allowed to practice briefly with a sample lottery pair. Then, all lottery pairs are presented one at a time and in the same order for all subjects. For example, in the gain lottery, subjects are first presented with the payoffs for G1 and are asked if they would prefer lottery A or lottery B. Next, they are presented the payoffs for G2 and asked to choose between A and B, and so on. Once subjects have made their decisions for the gain lotteries, they are presented the loss lotteries one by one and in the same order. When all lotteries have been completed, a lottery is randomly chosen for payment from the gain sequence and another from the loss sequence. A coin is flipped for the chosen lottery in the gain sequence. There is another coin toss for the chosen lottery in the loss sequence. If the coin turns up heads, the subject earns the first number in the payoff pair for the chosen lottery. For example, if lottery G3 was randomly chosen in the low payoff treatment and the subject chose option A for G3, then if the coin flip turned up tails, the subject would earn 200 RWF.

The gain and loss lotteries are increasing in expected payoff and variance, and in each pair, lottery B has a lower expected payoff and variance. Also, in each subsequent pair, option B has the same payoffs as option A in the previous pair. If choices are consistent, this lottery exercise is equivalent to presenting subjects six lotteries simultaneously and asking them to choose one. An individual with a concave utility function would start with option A and switch to lottery B as expected payoffs and variance increases and continue to choose option B. Since the subject's "switching point" may occur above or below the wealth range of the lotteries presented to the subjects, strongly risk-averse subjects may always choose option B, while less risk-averse subjects may always choose option A.

Table 1: Lottery Treatment Payoffs (in Rwandan Francs, 500 RWF = $1 US[7])

Low Payoffs (real and hypothetical)

	A	B
G1	(700, 400)	(500, 500)
G2	(900, 300)	(700, 400)
G3	(1100, 200)	(900, 300)
G4	(1300, 100)	(1100, 200)
G5	(1500, 0)	(1300, 100)

	A	B
L1	(700, -100)	(500, 0)
L2	(900, -200)	(700, -100)
L3	(1100, -300)	(900, -200)
L4	(1300, -400)	(1100, -300)
L5	(1500, -500)	(1300, -400)

High Payoffs (hypothetical only)

	A	B
G1	(1650, 1000)	(1250, 1250)
G2	(2050, 750)	(1650, 1000)
G3	(2450, 500)	(2050, 750)
G4	(2850, 250)	(2450, 500)
G5	(3250, 0)	(2850, 250)

	A	B
L1	(1650, -200)	(1250, 0)
L2	(2050, -400)	(1650, -200)
L3	(2450, -600)	(2050, -400)
L4	(2850, -800)	(2450, -600)
L5	(3250, -1000)	(2850, -800)

Subjects in the real-payment treatment were given 500 RWF as a show-up fee and paid the outcomes of the coin tosses over gains and over losses. They were paid in cash. Subjects in the hypothetical treatments were not paid. They were not given 500 RWF, and after the two coin flips, they were told their total hypothetical earnings, or what they would have earned had they been paid.

[7] At the time of this research, median per capita annual income in Rwanda was 118,000 RWF, according to the US Department of State, so 500 RWF was roughly equivalent to a day's wage. From our survey data, median monthly per capita income and expense measures were between 15,000 – 18,000 RWF, and this would imply a daily wage (based on 5 working-days a week) of 691- 830 RWF in our sample.

The 181 participants of the sequential-choice lottery game are similar to the larger survey population (of 700 individuals). Both have similar gender ratios (39.0% female for the sequential-choice lottery participants and 39.4% for the survey population), average ages (36.6 and 37.2, respectively), and average monthly per capita incomes (30,897 RWF and 34,520 RWF, respectively). Like the survey population, 93% of the sequential-choice lottery participants are literate. Compared to the 2002 official Rwandan national census, the survey population is similar on many demographic dimensions. However, the survey population is slightly richer and more literate than the national average in Rwanda. This may be because credit union members, who made up 2% of the Rwandan population at the time of the survey, were over sampled.

Results

We look first at inconsistent choices. Then, we examine measurements of risk aversion. Finally, we relate risk aversion measures, inconsistency and real-life outcomes.

Inconsistent Choices

Of the 181 people who completed the sequential binary lottery treatment, 54-55% made at least one inconsistent choice over gains or losses.

Table 2 illustrates the distribution of lottery choices across categories of consistency. The percentage of inconsistent choices made was not significantly different between gain-only lotteries, where 53.6% made at least one inconsistent choice, and lotteries that allowed a loss, where 54.7% made at least one inconsistent choice. Between 8-27% of subjects could be classified as consistent strong risk averse over gains or losses, and 9-13% could be classified as consistent risk loving or as only very mildly risk averse.

Table 2: Percent of Lottery Choices Over All Sequential-Choice Lottery Treatments

Type	Gains	Losses
Consistent Strong Risk Averse (always chose safe)	7.7	27.1
Consistent Risk Averse (chose risky, then switched to safe)	26.0	9.4
Consistent Risk Loving (always chose risky)	12.7	8.8
Inconsistent, One Switch	47.0	42.0
Inconsistent, Two Switch	6.6	12.7

We define an inconsistent choice as a switch from a safe lottery to a risky lottery, so in our five lotteries, an individual can make at most two inconsistent choices each over gains and over losses. Of the subject population, 6.6% made two inconsistent choices over gains, and 12.7% made two inconsistent choices over losses.

There are other possible categorizations that could capture people who are consistent with some other decision mechanism. For example, people may use a "rule of thumb" wherein a subject chose all A's or all B's but could deviate once (to test the waters). Using this categorization only helped explain 30 more choices (16.6%) over gains and 37 (20.4%) more choices over losses, leaving 67 (37.0%) choices over gains and 62 (34.3%) over losses still classified as inconsistent. While this is one more possible categorization of the data, we do not pursue this further as it would still collapse into an inconsistent choice for the purpose of our analysis.

How do subjects' choices change between gain and loss lotteries? The shaded region of Table 3 shows consistent choices over gains and losses. Of those choosing consistently, most are strongly risk-averse in the loss lottery. Conditioning on having made a consistent choice over gain and loss, 10% were more risk-averse over gain than over loss, 38% were equally risk-averse over gain and loss, and 52% were more risk-averse over loss than over gain. This means that of the subjects that made consistent choices, a little over half made choices consistent with a concave utility function over gains and losses. In terms of inconsistencies, roughly half of the subjects made the same number of inconsistent choices over gain as over losses. More people made two inconsistent switches over losses than over gains.

Table 3: Choices over Gain and Loss – Numbers of Subjects

		Choices over loss					
		Consistent strong risk-averse	Consistent risk-averse	Consistent risk-loving	Inconsistent one-switch	Inconsistent two-switch	Total
Choices over gain	Consistent strong risk-averse	9	1	0	3	1	14
	Consistent risk-averse	14	6	4	21	2	47
	Consistent risk-loving	9	3	4	5	2	23
	Inconsistent one-switch	16	6	8	40	15	85
	Inconsistent two-switch	1	1	0	7	3	12
	Total	49	17	16	76	23	181

Looking at real versus hypothetical payments, there is no discernable difference in the distribution of inconsistent choices for low stakes payments. This gives us confidence that the inconsistency we observe in choices is not due to hypothetical payments. Table 4 shows the distribution of lottery choices by treatment. Here, we collapse the consistent categories, strong risk averse, risk averse and risk loving, into a single category, labeled Consistent. The difference in distribution of classifications for low payoffs across real and hypothetical payments is insignificant (chi-squared test p-value = 0.896).[8] However, people tended to choose more consistently in the high-payoff hypothetical treatment as compared to the low-payoff real or hypothetical treatment (chi-squared test p-value = 0.000). This increase in consistency with high

[8] There is also no significant difference in distributions when the Consistent category is further disaggregated into Strong Risk Averse, Risk Averse, and Strong Risk Loving.

payoffs could be explained by increased focus due to larger payoffs, or by the larger differential that exists between the A and B lotteries in the high-stakes treatment.

Table 4: Percent of Lottery Choices by Treatment

	Low Hypo		Low Real		High Hypo	
Consistency Category	**Gains**	**Losses**	**Gains**	**Losses**	**Gains**	**Losses**
Consistent	24.3	32.7	25.9	22.2	62.6	58.6
Inconsistent one-switch	61.8	43.6	51.8	59.3	37.4	36.4
Inconsistent two-switch	10.9	23.6	22.2	18.5	0	5.1
Number of observations	55	55	27	27	99	99

Measurement of Risk Aversion

The overwhelming presence of inconsistent choices makes a risk measure based on a switching point from risky lotteries to safe lotteries in our data problematic, as many subjects have multiple switching points. We can, however, still look at a naïve measure of risk aversion (as in Holt and Laury, 2002) by counting the number of B (safe) choices the person made. This gives us a risk-aversion rating between 0 and 5 for each set of lotteries for each person. The higher this rating, the more risk-averse the person is.

We would like to compare this naïve measure for the sequential-choice lottery to the five-pair simultaneous lottery risk aversion measure. Recall that 442 survey respondents were asked to choose one of five possible lotteries over gains and one over losses. Because these subjects had to choose one lottery, the risk aversion measure ranges from 1 to 5, with one indicating one safe choice and five indicating five safe choices. We normalized both to a common scale of 0-1. The five-pair risk-aversion measures were normalized by subtracting one and dividing by four. The sequential-choice risk-aversion measures were normalized by dividing by five.[9]

Table 5 shows the mean risk aversion values over gains and losses by lottery treatment for this naïve measure. The average measure for sequential-choice lotteries over gains is 0.44,

[9] Since the original risk measures took on only integer values on different scales, the adjusted measures share the same scale but do not take on coincident values within the range.

while that over losses is 0.59. For the five-pair lotteries, the average risk-aversion measure is 0.56 over gain and 0.53 over loss. Across these two treatments, there is a significant difference in the average over gains (t-test for difference in means p-value = 0.000), over losses (p-value = 0.076), but not over a combined measure of gains and losses (p-value = 0.189).[10]

Table 5: Mean Naïve Risk Aversion Measures by Lottery Treatment

	Sequential-Choice Lotteries	Simultaneous Five-Pair Lotteries
Risk aversion over gain	0.44 (0.29)	0.56 (0.37)
Risk aversion over loss	0.59 (0.33)	0.53 (0.37)
Overall measure of risk aversion (gain + loss)	0.51 (0.22)	0.54 (0.32)

Standard deviations in parentheses

The inconsistent choices we observed may actually represent the individual's preferences or may be mistakes. If they are mistakes, can we measure the severity of those mistakes? We considered three methods for reclassifying an inconsistent choice as a consistent choice the subject may have really preferred. For the first two methods, we first change each inconsistent pattern to the consistent pattern that is closest to it by choosing the pattern that is the smallest number of changes away. For example, the inconsistent pattern BBABB could be reclassified to BBBBB with one change or to AAABB with two changes. Thus, we would choose to change it to BBBBB.

In some cases, this reclassification by the fewest changes does not uniquely identify a consistent choice. For example, the pattern ABABB could be reclassified to AAABB with one change or ABBBB with one change. For these cases, in the second step, we create two

[10] The distributions of the risk measures for the sequential-choice and five-pair lotteries yield similar results. Over both gains and losses, the distributions are significantly different across treatment types (chi-squared test p-value = 0.000). For the sequential-choice lotteries, more people choose the most extremely risk-averse option (BBBBB) over losses than over gains.

reclassified risk aversion measures. The first, called the “safe rebin,” always chooses the safer lottery. The second, called the “risky rebin,” always chooses the riskier lottery.[11] The latter method yields a lottery choice pattern with higher expected payoffs and higher variances than the former. Each such reclassification is assigned a change cost. This is the absolute value of the difference in expected value between the safe and risky choices.

Note that the safe and risky rebin cost measures are identical because there is only one reclassification cost. The difference between the expected payoffs of the A and B lotteries had a single value for each set of lottery pairs. This per-change cost was 50 for the gain and loss lotteries for the real and hypo-low treatments, 75 for the gain lotteries for the high treatments, and 100 for the loss lotteries for the high treatments.

The third method, called the “first switch rebin,” does not reclassify lottery choices based on the fewest number of changes. It assumes that the first time an individual chooses a safe choice is the person’s actual desired switching point. For example, a choice of ABAAA would be classified as ABBBB. We also calculate the costs of making these changes.

The first-switch rebin, by design, is the most costly. Average cost for the low-payoff treatment is 144-158 RWF (min of 0, max of 350). For the high-payoff treatment, the average cost is 128 RWF (min of 0, and max of 700). For the safe/risky rebin, the average cost for the low-payoff treatments is 87-96 RWF (min of 0, max of 200). The average cost for the high-payoff treatment is 75 RWF (min of 0, max of 275). Recall that there were fewer inconsistent choices in the high-payoff treatment, so costs should be lower.

For each method of reclassification, new risk aversion measures were constructed just as they were constructed for the original raw lottery choices: the number of safe choices was

[11] For example, the pattern ABABB would be reclassified as ABBBB for the safe rebin and as AAABB for the risky rebin.

counted, and the measure was then adjusted to be on the 0-1 range. Combining all three treatments together, Table 6 shows the average risk measures over gains and losses and the distribution of risk classifications with our three methods of making choices consistent.[12] As with the risk measure in Table 5, the risk aversion measures in Table 6 are higher for losses than for gains. Also, we see that the risky and safe rebin methods tend to distribute subjects similarly across all the three classifications for gains and losses. The first-switch method makes people more risk averse.

Table 6: Risk Measures and Distribution After Choices are Made Consistent
Sequential-Choice Lotteries
(percentages, unless noted otherwise)

	Risky Rebin	Safe Rebin	First Switch Rebin
Risk Aversion Over Gains (mean)	0.37	0.46	0.65
Risk Aversion Over Losses (mean)	0.56	0.64	0.81
Gains			
Consistent Strong Risk Averse	11.0	17.7	32.0
Consistent Risk Averse	57.0	55.4	55.2
Consistent Risk Loving	32.0	25.9	12.7
Losses			
Consistent Strong Risk Averse	37.6	44.2	59.1
Consistent Risk Averse	42.6	32.6	32.0
Consistent Risk Loving	29.8	23.2	8.8
Gains and Losses			
More risk averse over gain than loss	24.9	25.4	20.4
Equally risk averse over gain and loss	27.1	22.1	29.8
More risk averse over loss than gain	48.1	52.5	49.4

Looking at the distribution of people over gains and losses in Table 6 (the last three rows in the table), we see that, after "fixing" mistakes, about half of all subjects would be classified as more risk averse over losses than over gains. This is consistent with a concave utility function.

[12] We show the distribution of risk aversion measures combining all treatments for ease of presentation. When disaggregated, the rebinned distributions for the hypothetical treatments yield slightly more risk-averse subjects than the real treatment.

About 25% are more risk averse over gains than over losses. This is consistent with a convex utility function.

Risk Aversion, Inconsistency and Real-Life Outcomes

Given the prevalence of inconsistent choices, we want to know if this has implications for understanding real-life decisions. First, who is making these inconsistent choices? Ordinary least squares regressions were used to see if inconsistencies could be explained by demographic and household variables.[13] These variables include a dummy variable for being female, a dummy for being married, the subject's age in years, the number of years of education the subject has completed, the subject's per capita household monthly expenses, number of children (18 years and younger), the number of elderly (60 years and older), and a dummy variable for whether the treatment was low-stakes. The variables are summarized in Table 7. Because no difference was noted between real and hypothetical treatments for low stakes, these results are grouped together.[14]

Table 7: Summary Statistics

Variable	Mean	Std Dev
Female	0.39	0.49
Married	0.64	0.48
Age	36.58	11.23
Education – years[a]	8.84	3.78
Per Capita Monthly Expenditures[b]	30.90	62.34
Number of Children (<= 18 years)	2.97	2.15
Number of Elderly (>= 60 years)	0.26	0.95
Number of Financial Accounts	1.22	1.15
Member of Savings Group (Tontine)	0.18	0.39
Member of Insurance Group	0.20	0.40
Number of Observations	623	

[a] There are 14 missing observations on education, so this is based on n=609.
[b] Household per-capita monthly expenses in Rwandan Francs divided by 1000, range was 0 to 1007.

[13] Logit regressions were also tried for all binary dependent variables, and Tobit and Ordered Logit regressions were tried for the number of inconsistencies. All alternative specifications yielded qualitatively similar results. OLS results are reported for ease of interpretation of coefficients.
[14] If a dummy variable for the real payment treatment is included, it is not significant, and the results do not change.

Table 8 shows the results. As the dependent variable, we use a dummy variable if the person made an inconsistent choice over gain, a dummy if he made an inconsistent choice over loss, and the total number of inconsistent choices the person made over gains and losses (an integer between zero and four).[15]

Table 8: OLS Regressions of Inconsistency Measures

Variable	Inconsistent over gain	Inconsistent over loss	Number of total inconsistencies
Female	0.095 (0.240)	0.157 (0.050)	0.318 (0.032)
Married	0.038 (0.656)	0.034 (0.702)	-0.062 (0.705)
Age	-0.001 (0.869)	-0.004 (0.250)	-0.000 (0.894)
Education (years)[a]	0.016 (0.099)	-0.000 (0.966)	0.018 (0.282)
Monthly expenses	-0.000 (0.557)	-0.001 (0.044)	-0.002 (0.061)
Number of children (<= 18 years)	0.004 (0.853)	0.015 (0.453)	0.044 (0.269)
Number of elderly (>=60 years)	-0.029 (0.132)	-0.042 (0.047)	-0.079 (0.037)
Low stakes treatment	0.406 (0.000)	0.276 (0.000)	1.005 (0.000)
Constant	0.156 (0.423)	0.541 (0.006)	0.506 (0.152)
R^2	0.173	0.167	0.282
N*	178	178	178

Note: p-values reported in parentheses. Robust standard errors are used. All regressions include village-level fixed effects.

[a] There were missing values on education for three observations, so those observations are dropped.

The variable that controls for low-stakes treatments was always significant and large. This fits well with previous theoretical and empirical work showing that individuals' risk preferences are sensitive to the institution in which the preferences are elicited (Berg, Dickhaut,

[15] The same results hold if we regress the switch cost in the safe/risky rebin or the first-switch rebin cost, in lieu of the total number of inconsistent choices.

and McCabe, 2005; Isaac and James, 2000; Holt and Laury, 2002; Harrison, List and Towe, 2006). The strongest and most consistent demographic result across all specifications was that females are significantly more likely to make inconsistent choices than are males. This is not significant in gain lotteries.

Ultimately, we would like to know how risk and inconsistency measures relate to economic outcomes. Outcomes tested included whether the subject had taken a formal or informal loan, the number of financial accounts the subject had, whether the subject was a member of a savings group (a tontine), a credit union or an insurance group, whether the subject was a business owner, and whether the subject had a checking account. We show results from the outcome variables that show a relationship with our inconsistency measure. These are membership in a savings group, membership in an insurance group, and the number of financial accounts. We start first by examining how outcomes are explained by risk aversion alone, ignoring any measures of inconsistency. We use the naïve risk aversion measure (without correcting for inconsistencies). We compare outcomes where choices were forced to be consistent to those that could be made inconsistently.

Table 9 shows results from the outcome regressions, ignoring inconsistency.[16] The top panel shows results for the five-pair lottery, where people were forced to choose consistently, and the bottom panel shows results from the sequential-choice lotteries, where people could choose inconsistently. To make these two sets of regressions comparable, we restrict the sample to areas where both types of lotteries were randomly administered. This occurred in two of the

[16] Results were similar if we used the first-switch rebin cost, instead of the safe/risky rebin cost. Results are also robust to alternative specifications, such as Logit for binary outcome variables and Tobit and Ordered-Logit for truncated, count outcome variables.

seven survey locations.[17] There is no significant relationship between risk aversion and any outcome. This is consistent with much of the previous research using risk measures alone.

Table 9: OLS Results of Economic Outcome Regressions Without Inconsistency Measures

Five-Pair Lotteries						
	Savings Group		Insurance Group		Number of Financial Accounts	
Risk Aversion (gain)	-0.014 (0.898)		-0.106 (0.446)		-0.038 (0.914)	
Risk Aversion (loss)		0.073 (0.419)		-0.108 (0.401)		-0.092 (0.785)
R^2	0.063	0.069	0.074	0.074	0.493	0.494
N	83	83	83	83	83	83
Sequential-Choice Lotteries						
	Savings Group		Insurance Group		Number of Financial Accounts	
Risk Aversion (gain)	0.274 (0.162)		0.189 (0.308)		0.138 (0.679)	
Risk Aversion (loss)		0.124 (0.426)		-0.067 (0.649)		0.231 (0.517)
R^2	0.224	0.205	0.322	0.312	0.538	0.540
N	90	90	90	90	90	90

Note: p-values reported in parentheses. Robust standard errors are used. All regressions include the following control variables: gender, married, age, education, monthly per-capita expenses, children age 0-5, children age 6-10, children age 11-15, children age 16-18, adults age 60 and older, and village-level fixed effects. There were missing values on education for 14 observations (3 from the Sequential-Choice Lotteries and 11 from the Five-Pair Lotteries), so those observations are dropped.

Table 10 shows the outcome regressions if we include measures of inconsistency. The additional variables are the presence of inconsistency, an interaction term of the risk-aversion measure and the presence of inconsistency, and the safe/risky rebin cost to reclassify the subject. The regressions use the risk and inconsistency measures over gains and the risk and inconsistency measures over losses – these are shown separately in the table. Once these measures are included, some risk aversion and inconsistency measures are related to outcomes.

[17] The two groups are similar on most demographic and outcome variables. The only exception is that the participants in the five-pair lottery have higher monthly expenditures and were less likely to belong to a savings group than participants in the sequential-choice lottery.

Table 10: OLS Results of Economic Outcome Regressions Using Inconsistency Measures

	Savings Group		Insurance Group		Number of Financial Accounts	
Risk Aversion (gain)	0.338 (0.142)		-0.048 (0.818)		0.564 (0.115)	
Inconsistent dummy (gain)	0.428 (0.061)		-0.296 (0.119)		0.653 (0.244)	
Risk aversion (gain) * Inconsistent dummy (gain)	-0.485 (0.191)		0.814 (0.014)		-1.559 (0.071)	
Risk Aversion (loss)		0.460 (0.001)		0.034 (0.836)		0.440 (0.258)
Inconsistent dummy (loss)		0.545 (0.007)		0.144 (0.414)		0.335 (0.428)
Risk aversion (loss) * Inconsistent dummy (loss)		-1.152 (0.000)		-0.221 (0.500)		-1.116 (0.135)
Cost to safe/risky rebin	-0.002 (0.088)	-0.000 (0.647)	-0.000 (0.991)	-0.000 (0.716)	-0.001 (0.606)	0.000 (0.919)
R^2	0.272	0.304	0.376	0.319	0.567	0.560
N	90	90	90	90	90	90

Note: p-values reported in parentheses. Robust standard errors are used. All regressions include the following control variables: gender, married, age, education, monthly per-capita expenses, children age 0-5, children age 6-10, children age 11-15, children age 16-18, adults age 60 and older, and village-level fixed effects. There were missing values on education for 3 observations, so those observations are dropped.

Risk aversion and inconsistency interact in important ways. As risk aversion over losses increases, people who chose consistently are significantly more likely to belong to a savings group, while those who chose inconsistently are less likely. This relationship also holds for other outcomes but not significantly. The only exception to this general trend is for belonging to an insurance group and risk measures over gains. In this case, an inconsistent person is significantly more likely to belong to an insurance group as risk aversion over gains increases.

In theory, a risk-averse individual would prefer to reduce variance in income and would be willing to pay a higher premium to avoid risk. Our results suggest that inconsistency in choices may lead to suboptimal behavior. As an individual becomes more risk averse, he should be more likely to insure against fluctuations in income that could produce losses (i.e. through a savings or insurance group), not less likely.

The coefficient magnitudes on the inconsistency measures over losses are economically large. A person with a risk aversion measure of 0.5 would be 3 percentage points more likely to belong to a savings group if he chose consistently than if he chose inconsistently. For someone with a risk aversion measure of 1.0, he would be 60 percentage points more likely to join a savings group if he chose consistently than if he chose inconsistently.

Our results show that knowing whether people make mistakes is informative. Table 10 shows that there are significant differences between those that make consistent choices from those that do not. Indeed, comparing the results of Table 9 and Table 10, we can say that knowing whether people can make consistent decisions is important in understanding the relationship between risk preferences and economic behavior.

Conclusions

We use lottery experiments over gains and losses to examine consistency in risky choices and how that explains outcomes. Adults in Rwanda are presented a series of sequential binary-choice lotteries, first over gains only and then over gains and losses. The lotteries are designed to measure risk aversion by finding the switch point that a person with concave preferences would chose. A more risk-averse person would switch from risky to safe lotteries earlier.

People make choices inconsistent with a concave utility function and it is this inconsistency, not the risk measure alone derived from the lottery choices, which is related to outcomes. Over half of all subjects display this type of inconsistency. Women and people in low-stakes treatments are more likely to be inconsistent.

What if the inconsistent choices are just mistakes? We consider three methods to correct for these mistakes. We do so by finding the fewest number of changes to make the subject's choices consistent with a concave utility function and calculate a cost for changing choices around. Once these “mistakes” are fixed, we find that about half of all subjects display concave utility functions over gains and losses.

Relating the risk measures to outcomes, we find no evidence that risk measures alone explain outcomes. This has also been found in previous research. However, by incorporating inconsistency measures, we find that inconsistency and risk measures can explain some outcomes. A person who is inconsistent in risk choices over losses is more likely be in a savings group (a tontine) over low levels of risk aversion, but becomes less likely to belong as risk aversion increases. Inconsistency in choices seems to lead to sub-optimal decisions.

These results raise into question whether people have a smooth utility functions that can be characterized by a unique switch point. Experiments that are designed to elicit one switch point may be missing important, time-inconsistent information on behavior. Knowing if risk measures are generated by consistent choices may help explain some economic outcomes.

The way we measure risk many times takes for granted that preferences are well-behaved and subjects are able to express them. Drawing from a heterogeneous sample of decision makers we find that this might not be the case. Therefore, we might need to think how to collect and understand the way people make mistakes before conclusions about attitudes towards risk are possible.

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