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Do Changing Probabilities or Payoffs in Lottery-Choice Experiments Affect Risk Preference Outcomes? Evidence from Rural Uganda

Hanna Julia Ihli, Brian Chiputwa, and Oliver Musshoff

This study compares risk preferences elicited from two different methods and the resulting inconsistency rates in response behavior. We also identify and compare how demographic and socioeconomic characteristics influence risk preferences elicited from the two methods. We use experimental and survey data collected from 332 randomly selected smallholder coffee farmers in Uganda. We find relatively low inconsistency rates in the response behavior and that both methods classify most farmers as risk averse. However, a closer inspection reveals significantly different risk results. Specific demographic and socioeconomic characteristics affect farmers' risk preferences but are not stable across elicitation methods.

Key words: elicitation of risk preferences, inconsistency rates, laboratory experiment in the field, Uganda

Introduction

The majority of the poor in developing countries live in rural areas and depend on agriculture for food and as their main source of livelihood. Agricultural production in these areas is often characterized by precarious and risky conditions. Farmers' crop yields and incomes are dependent on marginal land prone to the vagaries of nature such as droughts or floods and market conditions like price fluctuations. Risk and uncertainty become central to farmers' decision making (Menapace, Colson, and Raffaelli, 2013). Ultimately, risk plays a considerable role in almost every important economic farm decision, such as crop selection (Price and Wetzstein, 1999), technology adoption (Purvis et al., 1995), soil and water conservation practices (Winter-Nelson and Amegbeto, 1998), and participation in crop insurance markets (Hill and Viceisza, 2012). However, individuals naturally differ in the ways they make decisions involving risk and uncertainty due to differences in risk preferences. Therefore, understanding the risk preferences of economic agents provides useful insights to their economic behavior (Reynaud and Couture, 2012).

Understanding risk preferences of economic agents is pertinent to gaining insights into behavioral decisions under risk and uncertainty and, more importantly, to be able to predict this behavior under different policy interventions (Bhattamishra and Barrett, 2010). Harrison (2011) contends that welfare evaluation of any proposed policy with outcomes involving risk should consider individuals' risk preferences. This requires collecting comprehensive risk preference data; if these data are imprecise or biased, incorrect inferences and ineffective policies can emerge. As a result, many researchers have used some standardized lottery games to elicit risk preferences in both laboratory and field settings.

Hanna Julia Ihli is a post-doctoral fellow and Oliver Musshoff is a professor in the Department of Agricultural Economics and Rural Development at Georg-August-University of Goettingen in Germany. Brian Chiputwa is a post-doctoral fellow in the Research Methods Group at the World Agroforestry Centre in Kenya.
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There is an extensive body of empirical studies using different elicitation methods to measure individuals' risk preferences in the context of developed countries (e.g., Holt and Laury, 2002; Eckel and Grossman, 2002, 2008; Dave et al., 2010; Reynaud and Couture, 2012) as well as developing countries (e.g., Binswanger, 1980; Humphrey, 2004; Jacobson and Petrie, 2009; Yesuf and Bluffstone, 2009). Similarly, a variety of methods have emerged for testing these preferences, including lottery choice task decisions (e.g., Holt and Laury, 2002), self-assessment questions (e.g., Dohmen et al., 2011), hypothetical gambles (e.g., Anderson and Mellor, 2009), and willingness-to-pay elicitation methods (e.g., Kahneman, Knetsch, and Thaler, 1990).

A common approach to characterize individual risk preferences is to use the expected utility (EU) theory, in which risk aversion is the sole parameter for determining the curvature of the utility function (von Neumann and Morgenstern, 1947; Liu, 2013; Bocquého, Jacquet, and Reynaud, 2014).[1] One advantage of the EU theory is that risk exposure and risk preferences can be explicitly distinguished through the use of probabilities and a utility function (Chavas, Chambers, and Pope, 2010). In this case, constant relative risk aversion (CRRA) is a convenient assumption to impose because of the simplicity of the implied utility function (de Brauw and Eozenou, 2011).

Little attention has been focused on comparing the consistency and risk results obtained from commonly used methods of risk preference elicitation under different environments. This is especially true for within-subject designed experiments in developing countries. Furthermore, explanatory factors of risk preferences may vary depending on the elicitation method (Nielsen, Keil, and Zeller, 2013).

The specific objectives of this paper are twofold. First, we empirically assess the comparability of risk preferences and inconsistency rates of two commonly applied risk elicitation methods: the Holt and Laury (HL) (2002) and Brick, Visser, and Burns (BVB) (2012) lottery tasks,[2] which are used in a within-subject designed experiment among Ugandan farmers. The HL lottery involves keeping payoffs constant while varying probabilities, whereas the BVB lottery keeps probabilities constant and varies payoffs.

Second, we identify and compare how various demographic and socioeconomic factors influence risk preferences between the two elicitation methods. To our knowledge, this study is the first to compare risk preference outcomes, explaining factors affecting these preferences and inconsistency rates based on elicitation methods applied by Holt and Laury (2002) and Brick, Visser, and Burns (2012) in a within-subject designed experiment in a developing country. Furthermore, examining determinants of risk preferences across elicitation methods allows us to check the robustness of explanatory factors and examine whether explanatory factors of risk preferences vary by elicitation method.

The intention of this work is neither to provide conclusive evidence on the comparative performance of the HL and BVB lotteries nor is to suggest a superior theory to replace EU theory. Rather, we seek to build on existing risk elicitation methods and offer preliminary insights on the comparability and consistencies of the two methods in order to stimulate follow-up work on ways to better adapt different techniques used in assessing risk preferences in developing countries.

Holt and Laury (2002) propose a specific lottery-choice experiment in which subjects are presented with a menu comprising consecutive choices between paired lotteries. In the last decade, the HL lottery has virtually become the standard method to elicit subjective risk preferences and has been used in a great variety of contexts and with different subject groups (e.g., Harrison, Lau, and Rutström, 2007; Anderson and Mellor, 2009; Masclet et al., 2009; Tanaka, Camerer, and Nguyen, 2010).

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[1] This paper focuses on EU theory, since farmers are usually assumed to be expected EU maximisers (Bocquého, Jacquet, and Reynaud, 2014). However, we are aware of alternatives to EU theory such as cumulative prospect theory (CPT), in which the shape of the utility function is jointly determined by risk aversion, loss aversion, and nonlinear probability weighting (Kahneman and Tversky, 1979). CPT has the potential to offer new insights into farmers' behaviors in a risky environment.

[2] See Holt and Laury (2002) and Brick, Visser, and Burns (2012) for more details.

Brick, Visser, and Burns (2012) apply a theoretically similar design to that of Holt and Laury (2002). Instead of changing probabilities and fixing payoffs, probabilities are fixed and payoffs change. They claim that their method has an advantage because subjects, who might struggle with descriptions of lotteries involving varying probabilities, are likely to more easily understand structures of lotteries with the same probabilities (Brick, Visser, and Burns, 2012). Subjects tend to switch back and forth between lotteries as they progress down the choice tasks. This may indicate that they fail to understand the procedure, which reduces the reliability of the risk preference measure and can potentially bias the results (e.g., Starmer and Sugden, 1989; Harless and Camerer, 1994; Wu, 1994).

Such inconsistent behavior has been reported in many studies but is especially prevalent in the context of developing countries (e.g., Galarza, 2009; Jacobson and Petrie, 2009; Engle-Warnick, Escobal, and Laszlo, 2011). This poses an obvious problem since the inference of risk preferences and, in turn, parameter estimation requires a unique switch point. Such inconsistent behavior is difficult to rationalize under standard assumptions on preferences. Andersen et al. (2006) suggest that multiple switching behaviors might reflect indifference between the two lottery options. Other researchers view such behavior as indicative of a lack of comprehension, suggesting that the HL lottery, although widely used, might not be the most appropriate elicitation tool in the context of a developing country; these data are often removed from the analysis to avoid biases (e.g., Holm, Opper, and Nee, 2013). The proportion of individuals making inconsistent choices may significantly hinder the usability of any elicitation method.

In order to make our experiments easily understood by rural farmers in Uganda (many of whom are illiterate) and mitigate inconsistent behavior, we modify the two original lottery-choice experiments. Instead of trying to verbally explain probabilities and payoffs to subjects, we used images of bags of colored balls to represent probabilities of different payoffs. Based on these changes, we describe our experiments as the modified HL and modified BVB lotteries. The modified versions aim to reduce inconsistency rates and provide more reliable measures of risk preferences.

Literature Review and Hypotheses

An interesting result that emerges from existing experimental literature on risk preference elicitation is that an individual's risk preference may vary across elicitation methods. Binswanger (1980) measures the risk preferences of Indian farmers using two different methods, a hypothetical questionnaire and an experimental gambling method with real payoffs, and discovers inconsistencies in the measures of risk aversion in the two methods. Reynaud and Couture (2012) compare the Holt and Laury (2002) and the Eckel and Grossman (2008) lottery tasks using a sample of French farmers. They find that risk preferences are affected by the type of method used and show that risk preference instability can be related to nonexpected utility preferences and context dependency. However, neither of the applied lotteries were incentivized.

Charness and Viceisza (2016) compare three distinct nonincentivized elicitation methods—the Holt and Laury (2002) lottery tasks, an adaptation of a simple binary method initially proposed by Gneezy and Potters (1997), and a willingness-to-risk scale pioneered by Dohmen et al. (2011)—using a sample drawn from the rural population in Senegal. The results indicate that the simple binary method has substantially more predictive power compared to the HL lottery, which reveals a relatively low level of understanding. The willingness-to-risk question generated results that were unlikely to be accurate according to patterns in other risk preference elicitation studies.

In a Danish sample, Andersen et al. (2006) examine the properties of the multiple price list method as well as some variants on the basic design and find that the elicitation of risk preferences was sensitive to procedures, subject pools, and the format of the multiple price list tables.[3] Maart-

[3] The multiple price list (MPL) method confronts subjects with a series of consecutive choices between two outcomes, where the expected value of one outcome increases at a higher rate than the other. The point at which an individual switches from choosing one outcome to the other is often used as a measure of risk aversion.

Noelck and Musshoff (2014) apply incentivized Holt and Laury (2002) lottery tasks and two psychometric methods based on Dohmen et al. (2011) on a sample of German students and German and Kazakh farmers. They find that students responded consistently across all three elicitation methods, whereas German and especially Kazakh farmers were more inconsistent.

Thus far, no research has investigated how risk preferences assessed by the Holt and Laury (2002) and Brick, Visser, and Burns (2012) lotteries compare to each other in a within-subject designed experiment. Therefore, we analyze the consistency of risk measures across the two different elicitation methods, which we have adapted to individuals in a rural, developing setting. We formulate the following hypothesis: *H1 'Consistency of risk preferences': There is a consistency between the risk preferences determined in the modified HL and BVB lotteries*.

Holt and Laury (2002) proposed a specific lottery-choice experiment in which subjects are presented with a menu that comprises consecutive choices between paired lotteries. Among this sequence of choices, the transition from the less risky ("safe") lottery A to the more risky lottery B is rewarded by an increasing risk premium. While subsequently being transformed into a risk-aversion coefficient, risk preferences are initially measured by an individual's "number of safe choices" before crossing over to the riskier lottery B. Making random choices between lotteries A and B represents an inconsistent response behavior because the risk premium offered in the HL lottery increases monotonically along the sequence of the paired lottery choices. If this choice represents true preferences and utility is increasing over money, there must be an inflection point in the wealth range of these lotteries. Such a pattern of choices is inconsistent with EU theory, which assumes subjects to be EU maximisers (von Neumann and Morgenstern, 1947; Jacobson and Petrie, 2009).

The problem of inconsistent behavior has been noted in many studies using the HL lottery but is especially prevalent in a developing country context. Galarza (2009) report an inconsistency rate of 52% in a study conducted with Peruvian cotton farmers. Jacobson and Petrie (2009) find that approximately 55% of Rwandan participants made at least one inconsistent switch. Brick, Visser, and Burns (2012) find that about 41% of the sample of South African fishers showed multiple switching behaviors, and Charness and Viceisza (2016) find that 51% of participating farmers in Senegal switched lotteries at least twice. Examples of studies that report lower inconsistency rates in developed countries include Holt and Laury (2002), who find 13% inconsistent behavior from students in the United States, and Dave et al. (2010), who find 8.5% inconsistent behavior from an adult population in Canada. In developing countreies, only de Brauw and Eozenou (2011) report a relatively lower inconsistency rate of 14% among farmers in Mozambique.

While multiple switching behavior might reflect indifference between the two lottery options, as suggested by Andersen et al. (2006), it is more likely to be a product of lack of comprehension. The relatively large proportion of participants in developing countries making inconsistent choices in lottery choice task decisions could indicate that the HL lottery, although widely used, may not be the most appropriate elicitation tool within this setting. An interesting question in this context is whether some subjects always make inconsistent choices or whether subjects make inconsistent choices given one method but more consistent choices under another method. Therefore, we analyze the inconsistency rates of the modified HL and BVB lotteries and assess whether the two elicitation methods were well understood by the subjects. Our second hypothesis is *H2 'Inconsistency rates of elicitation methods': Both methods are equally consistent regarding the inconsistency rates in subjects' response behavior*.

Individuals' characteristics naturally vary and may also have an impact on risk preferences (Doss, McPeak, and Barrett, 2008). We focus on variables for subjects' characteristics, which may influence individual risk preferences: age (e.g., Nielsen, Keil, and Zeller, 2013), gender (e.g., Croson and Gneezy, 2009), education (e.g., Harrison, Lau, and Rutström, 2007), household size (e.g., Miyata, 2003), number of dependents (e.g., Hallahan, Faff, and Mckenzie, 2004), wealth (e.g., Cohen and Einav, 2007), farm size (e.g., Wik et al., 2004), access to a savings account (e.g., Jacobson and Petrie, 2009), and access to credit (e.g., Eswaran and Kotwal, 1990). However, to this date, comparison of the stability of explanatory factors of risk preferences across different elicitation

Table 1. Payoff Matrix of the HL Lottery

Task	Option A	Option B	EV^A	EV^B	CRRA Ranges	Risk Aversion Class
1	With 10% prize of 6,000	With 10% prize of 11,550	4,920	1,425	$r < -1.71$	Extremely RL
	With 90% prize of 4,800	With 90% prize of 300				
2	With 20% prize of 6,000	With 20% prize of 11,550	5,040	2,550	$-1.71 < r < -0.95$	Highly RL
	With 80% prize of 4,800	With 80% prize of 300				
3	With 30% prize of 6,000	With 30% prize of 11,550	5,160	3,675	$-0.95 < r < -0.49$	Very RL
	With 70% prize of 4,800	With 70% prize of 300				
4	With 40% prize of 6,000	With 40% prize of 11,550	5,280	4,800	$-0.49 < r < -0.14$	RL
	With 60% prize of 4,800	With 60% prize of 300				
5	With 50% prize of 6,000	With 50% prize of 11,550	5,400	5,925	$-0.14 < r < 0.15$	RN
	With 50% prize of 4,800	With 50% prize of 300				
6	With 60% prize of 6,000	With 60% prize of 11,550	5,520	7,050	$0.15 < r < 0.41$	Slightly RA
	With 40% prize of 4,800	With 40% prize of 300				
7	With 70% prize of 6,000	With 70% prize of 11,550	5,640	8,175	$0.41 < r < 0.68$	RA
	With 30% prize of 4,800	With 30% prize of 300				
8	With 80% prize of 6,000	With 80% prize of 11,550	5,760	9,300	$0.68 < r < 0.97$	Very RA
	With 20% prize of 4,800	With 20% prize of 300				
9	With 90% prize of 6,000	With 90% prize of 11,550	5,880	10,425	$0.97 < r < 1.37$	Highly RA
	With 10% prize of 4,800	With 10% prize of 300				
10	With 100% prize of 6,000	With 100% prize of 11,550	6,000	11,550	$1.37 < r$	Extremely RA
	With 0% prize of 4,800	With 0% prize of 300				

Notes: Prizes are displayed in Ugandan shillings (UGX). At the time of the experiments, the exchange rate was approximately \$1 to UGX 3,000, so prizes range from approximately \$0.10 to \$3.85. The fourth and fifth columns show the expected values (EV) of the respective option. Constant relative risk aversion coefficient assumes a power risk utility function. Risk aversion classes are risk loving (RL), risk neutral (RN), and risk averse (RA).
Source: Author's own illustration, following Holt and Laury (2002).

methods has been largely neglected in the literature. There are only a handful of studies that have elicited risk preferences using more than one elicitation method (e.g., Anderson and Mellor, 2009; Dohmen et al., 2011) and even fewer studies that have examined whether explanatory factors of risk preferences are stable across different elicitation methods (e.g., Dave et al., 2010; Nielsen, Keil, and Zeller, 2013). Therefore, we construct several variables to explore whether estimated risk preferences vary by experimental measure and by subjects' characteristics. Our last hypothesis is *H3 'Stability of explanatory factors': Explanatory factors of risk preferences are stable across elicitation methods*.

Experimental Design and Implementation

The Holt and Laury Lottery and its Modification

In the Holt and Laury (2002) lottery-choice experiment, subjects make ten choices between two systematically varied options: option A (the relatively safer option) or option B (the relatively riskier option). The safer option A has less variability in the payoffs than the riskier option B. In our design, option A offers the chance to either receive UGX 6,000 or UGX 4,800 with a certain probability, while option B offers the chance to receive UGX 11,550 or UGX 300 with the same probability (table 1).[4] We use the rate of 1:3,000 (which corresponds to the exchange rate) to get the equivalent payoffs in Ugandan shillings compared to the HL lottery baseline treatment. The payoffs are held constant across the choice tasks, whereas the probabilities of the payoffs vary in intervals of 10% between the choice tasks. The expected values of the options change as participants move from one to the next choice task.

The switch point from the safer to the riskier option can be used to classify subjects' risk aversion level. Depending on the HL value (i.e., the number of safe choices), an individual can be classified into three categories of risk behavior: (i) risk seeking, if the HL value lies between one and three;

[4] A complete set of instructions for the experiment is included in the appendix (see supplementary material available online at JARE website).

Table 2. Payoff Matrix of the BVB Lottery

Task	Option A	Option B	EV^A	EV^B	CRRA Ranges	Risk AversionClass
1	With 100% prize of 10,000	With 50% prize of 10,000 With 50% prize of 0	10,000	5,000	r < −1.41	Highly RL
2	With 100% prize of 7,500	With 50% prize of 10,000 With 50% prize of 0	7,500	5,000	−1.41 < r < −0.36	Very RL
3	With 100% prize of 6,000	With 50% prize of 10,000 With 50% prize of 0	6,000	5,000	−0.36 < r < 0	RL
4	With 100% prize of 5,000	With 50% prize of 10,000 With 50% prize of 0	5,000	5,000	0 < r < 0.24	RN
5	With 100% prize of 4,000	With 50% prize of 10,000 With 50% prize of 0	4,000	5,000	0.24 < r < 0.42	Slightly RA
6	With 100% prize of 3,000	With 50% prize of 10,000 With 50% prize of 0	3,000	5,000	0.42 < r < 0.57	RA
7	With 100% prize of 2,000	With 50% prize of 10,000 With 50% prize of 0	2,000	5,000	0.57 < r < 0.70	Very RA
8	With 100% prize of 1,000	With 50% prize of 10,000 With 50% prize of 0	1,000	5,000	r < 0.70	Highly RA

Notes: Prizes are displayed in Ugandan shillings (UGX). At the time of the experiments, the exchange rate was approximately \$1 to UGX 3,000, so prizes range from approximately \$0.35 to \$3.50. The fourth and fifth columns show the expected values (EV) of the respective option. Constant relative risk aversion coefficient assumes a power risk utility function. Risk aversion classes are risk loving (RL), risk neutral (RN), and risk averse (RA).
Source: Author's own illustration according to Brick, Visser, and Burns (2012).

(ii) risk neutral, if the HL-value is equal to four; and (iii) risk averse, if the HL value is between five and ten. Following Holt and Laury (2002), a power risk utility function with a constant relative risk aversion (CRRA) defined over the lottery prize can also be used to calculate the implied bounds of an individual's CRRA coefficient. The CRRA function is of the form

$$U(x) = (x^{1-r})/(1-r), \tag{1}$$

where x is the lottery prize and r is the coefficient of relative risk aversion. For instance, a subject choosing option A four times before switching to option B reveals a CRRA coefficient interval between 0.49 and 0.14. The lower and upper bound of the risk aversion parameter is determined by solving for r:

$$0.3\frac{6,000^{1-r}}{1-r} + 0.7\frac{4,800^{1-r}}{1-r} = 0.3\frac{11,550^{1-r}}{1-r} + 0.7\frac{300^{1-r}}{1-r} \Leftrightarrow r \equiv -0.49; \tag{2}$$

$$0.4\frac{6,000^{1-r}}{1-r} + 0.6\frac{4,800^{1-r}}{1-r} = 0.4\frac{11,550^{1-r}}{1-r} + 0.6\frac{300^{1-r}}{1-r} \Leftrightarrow r \equiv -0.14; \tag{3}$$

The exact value of this subject's risk aversion parameter lies in the range from 0.49 to 0.14. Values of $r > 0$ indicate risk seeking preferences, $r = 0$ indicates risk neutrality, and values of $r < 0$ indicate risk aversion.

In order to develop an easily applicable and effective method to elicit risk preferences, we modify the standard HL lottery by replacing probabilities expressed in percentages with images of bags of colored balls representing the probabilities of different payoffs (option A: blue ball UGX 4,800, red ball UGX 6,000; option B: green ball UGX 300, yellow ball UGX 11,550) (figure 1). Each ball corresponds to a 10% probability and each bag includes ten balls. The different payoffs are represented by different colors. Apart from using images of bags and balls, the experiment was identical to the standard HL lottery.

The Brick-Visser-Burns Lottery and its Modification

The experimental design used in Brick, Visser, and Burns (2012) is similar to that of Holt and Laury (2002), with one notable difference. Instead of keeping payoffs constant and varying the probabilities

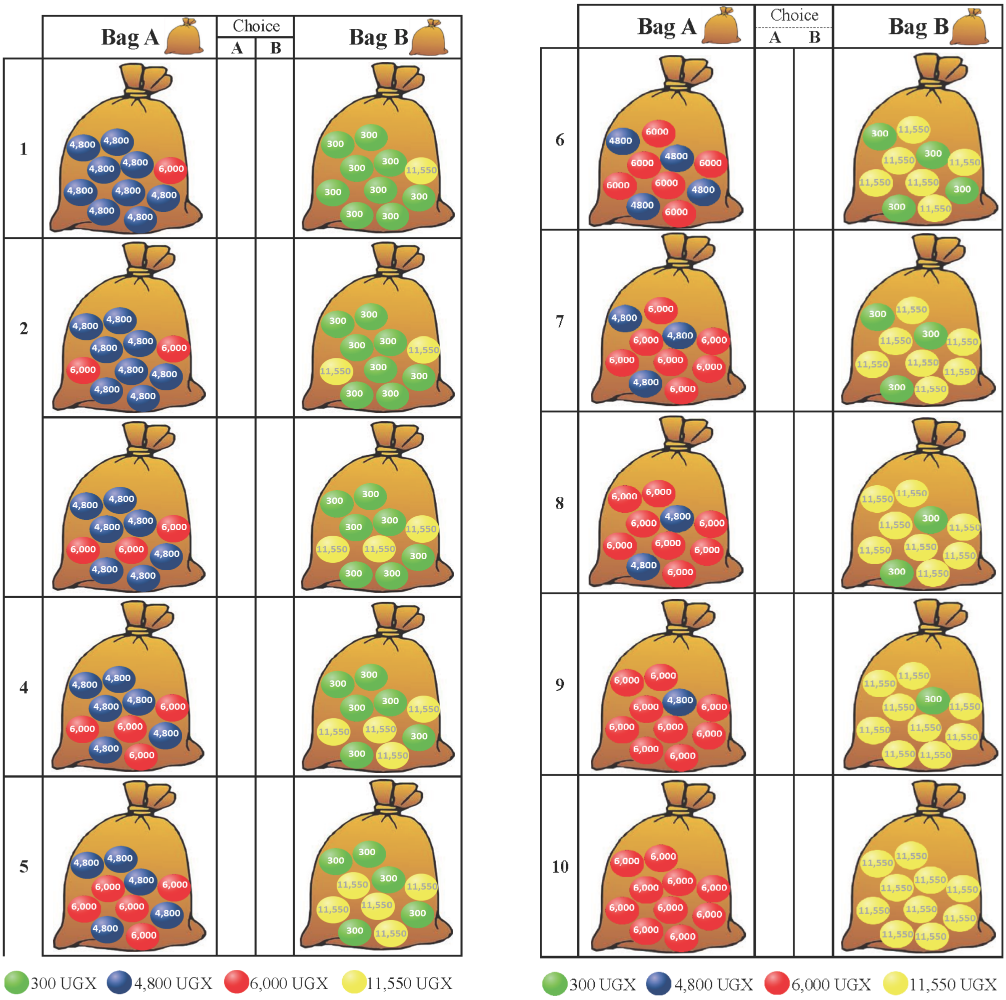

Figure 1. Graphical Display of the Modified HL Lottery

of receiving the high and low outcomes, probabilities are constant and payoffs are varied. We use the rate of 1:500 to get the equivalent payoffs in Ugandan shillings compared to the BVB lottery baseline treatment and to adjust to the payoffs of the HL lottery. For each choice task, subjects have to choose between options A (relatively safer) and B (relatively riskier). Option A involves a 100% chance of receiving a payoff (between UGX 10,000 and UGX 1,000), while option B involves a 50% chance of receiving a payoff (UGX 10,000) and a 50% chance of receiving no payoff (UGX 0) (table 2). The payoff associated with option A declines systematically through the eight choice tasks, while the payoff for option B remains unchanged. The switch point is used as the measure of the individual's risk preference. Furthermore, choices in the experiment can also be used to define a range of values for each subject's risk-aversion parameter.

As in the modified HL lottery, we use images of bags of colored balls to represent probabilities of different payoffs (option A: green ball between UGX 10,000 and UGX 1,000; option B: red ball UGX 0, blue ball UGX 10,000) (figure 2). Each bag contains up to two balls with each ball representing either a 50% or 100% probability. The different payoffs are represented in a different color, except for the varying value of the green ball. Apart from using images of bags and balls, the experiment was identical to the standard BVB lottery.

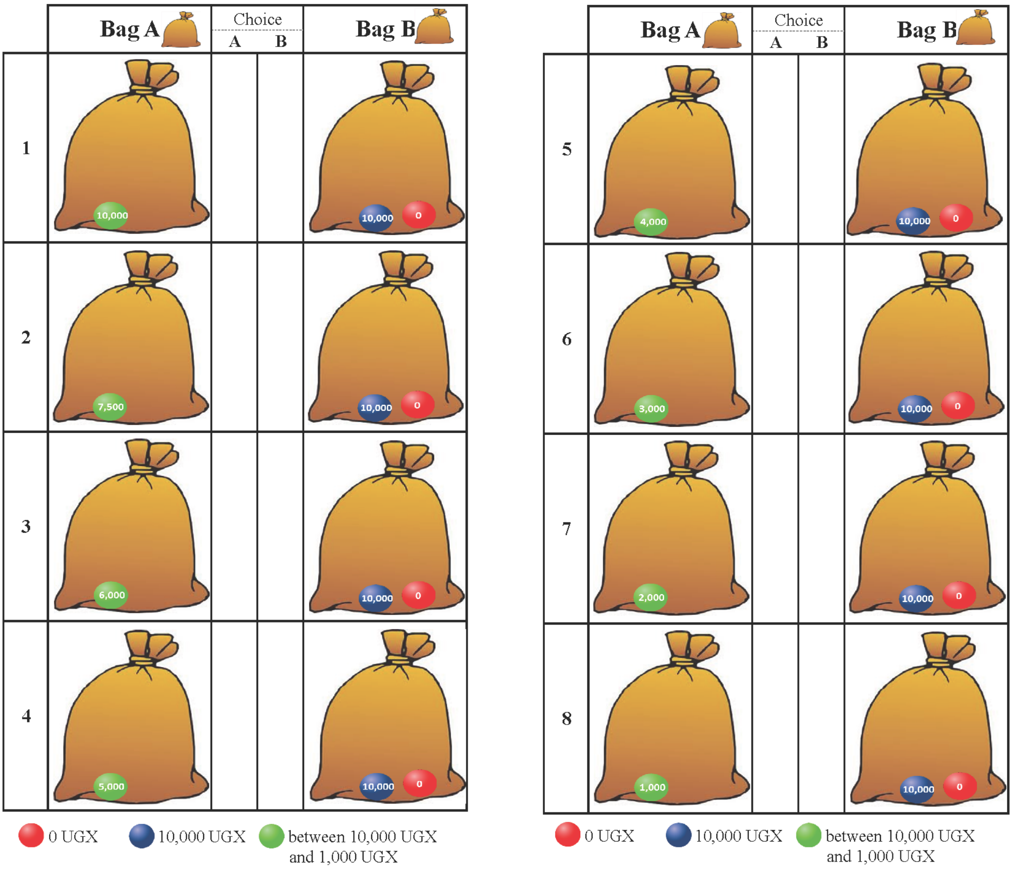

Figure 2. Graphical Display of the Modified BVB Lottery

Household Survey and Mathematical Literacy Task

In addition to the lottery-choice experiments, we also conducted a structured household survey in which we captured various information including household demographics, farm factors, and all economic activities pertaining to agricultural production decisions of the participants. Some of the variables collected and used in this paper are age, gender, education, household size, number of dependents, district, per capita household expenditure (as a proxy variable for wealth), total land owned, access to savings account, and access to credit.[5] Furthermore, we include the variable "probability test score" because a participant's ability to reason with numbers and probabilities may affect his or her understanding and choice of risky lotteries and, hence, give us the opportunity to obtain an accurate measurement of risk preference (Dave et al., 2010). This has to be considered when eliciting risk preferences of individuals in developing countries where task complexity may be more critical due to individuals' potentially limited mathematical skills (Charness and Viceisza, 2016). Therefore, we include an assessment that measures the ability to process percentage and probabilistic information adapted from Viceisza (2011) and Charness and Viceisza (2016). The assessment consists of three tasks, and the results provide an indicator of an individual's competencies.[6]

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[5] For full information on the details of the household survey, see Chiputwa, Spielman, and Qaim (2015) and Chiputwa and Qaim (2016).

[6] See Appendix in supplementary material online available at JARE website.

Experimental Implementation

Data used in this study were obtained from experiments and household surveys conducted in July and August 2012 of 332 smallholder coffee farmers randomly selected from two districts, Masaka and Luwero, located in the Central Region of Uganda. These districts have been broadly classified as having similar agro-climatic conditions and farming systems. To select smallholder coffee farmers to be interviewed, we used a multi-stage sampling procedure. At first, we randomly selected parishes and villages. Within each selected village, smallholder farmers were then randomly selected using updated, village-level household lists. The farmers were then recruited via the local extension service to participate in a household survey and an experiment. The invitation to attend our experiment was provided orally by the recruiters and included the date, time, and place of the study; a brief and general purpose of the study; and the type of compensation that could be expected. The household survey took place one day prior to the actual experiments. Participants were limited to either the household head or the spouse, those individuals most likely to be faced with choices involving risk and important economic decisions.

The 332 smallholder coffee farmers were allocated randomly to groups for the experimental sessions.[7] In total, we conducted fifty-six sessions during the course of thirty days. Two sessions of sixty to ninety minutes were held each day, and each session involved a group of six farmers. All participants played both lottery-choice experiments and the order in which they were faced with the two experiments was randomly determined. In the experiment, choices made by participants were not time constrained. The experimental sessions were held in several villages and conducted in classrooms of local schools or in the meeting rooms at the main gathering places of farmers' groups. A team of seven local enumerators were carefully selected, trained, and supervised by the researchers and conducted all of the experimental sessions. For easy interpretation, all of the experimental sessions were conducted in Luganda, the main local language.

Each experiment session consisted of registration, instruction, practice, decision making, and payment. The experiment instructions were read aloud to all participants as a group by the experimenter and supported by posters of graphical examples displayed on a large board at the front of the room. To further facilitate comprehension, we used real bags of colored balls representing probabilities of the different payoffs. Participants were informed about all parameters and assumptions underlying the experiment, and they had to answer some control questions to ensure that they entirely understood the instructions. Our overall impression was that the instructions were well understood by the participants because of the visual, oral, and written explanations as well as the practical implementation with real bags and colored balls.

Incentive Design

Financial incentives in experiments have been subject to controversial discussions in the literature. Though psychologists believe that experimental subjects usually have sufficient intrinsic motivation to work hard even in the absence of financial rewards, economists presume that experimental subjects will work harder and more effectively if they earn more money for better performances (Camerer and Hogarth, 1999). To ensure incentive compatibility of our experiments and motivate subjects to consider each decision carefully, the decisions were related to an actual payment. Participants were informed at the beginning of the experiment that, when they had completed all decision tasks in the respective lottery-choice experiment, one task would be selected at random and played out for real money.

It has become increasingly common in economics experiments to elicit a series of choices from subjects and then pay for only one, selected at random, after all have been made (Andreoni and Miller, 2002; Goeree, Holt, and Laury, 2002; Holt and Laury, 2002; Humphrey, 2004). This random-

[7] However, four farmers were excluded from the analysis. One farmer left before completing all tasks, and three farmers participated in the household survey but were not able to undertake (or arrived too late to participate in) the experiment.

Table 3. Descriptive Statistics of Respondent Characteristics (N = 332)

Variable	Definition	Mean	Std. Dev.
Age	Age in years	50.21	14.28
Gender	= 1 if female, 0 otherwise	0.39	–
Education	Years of formal schooling	6.67	3.60
Household size	Number of household members	6.56	3.10
Dependency ratio	Ratio of dependent (less than 15 years of age or greater than 64) to nondependent household members	1.51	1.18
District	=1 if from Masaka, 0 = Luwero	0.57	–
Probability test score	Number of probability questions correctly answered	2.05	0.78
Household expenditure	Annual per capita household expenditure in UGX	516,855.00	392,949.00
Total land owned	Total land owned in acres[a]	5.73	4.53
Access to a savings account	= 1 if access to a savings account, 0 otherwise	0.28	–
Access to credit	= 1 if access to credit, 0 otherwise	0.43	–

Notes: At the time of the experiments, the exchange rate was approximately $1 to UGX 3,000.
Source: Survey data.
[a] 1 acre = 0.40 hectare.

choice payment method allows a large number of individual decisions to be observed without the high transaction cost that would be associated with paying for all choices and without scaling down payoffs to a level that subjects may not take seriously. The assumption is that subjects will consider each choice at its stated value and consider all scenarios carefully, because any one of them could be used in the end to determine payoffs for the entire experiment (Laury, 2005). By not paying subjects for all choices they make, the random-choice payment method also controls for any income effects (Humphrey, 2004). Camerer and Hogarth (1999) also find that higher incentives often improve subjects' performance during the experiment. Furthermore, they show that participants often overestimate their chance to be selected for a cash premium, so that it seems to be more advantageous and even more motivating to hold out the prospect of a high cash premium for one participant instead of a low cash premium for all participants. Bolle (1990) explicitly compares the two alternatives in an experiment and shows that participants' decision behavior does not differ significantly in the two payment systems.

Therefore, we decided to choose one participant at random for payment for each lottery-choice experiment of our payment design; hence we had two winners per session. The earning of the participant was based on his/her choices in the respective lottery-choice experiment. The average payoffs of the two lotteries were UGX 6,674 (approximately $2.30) and UGX 5,687 (approximately $2.00), respectively. Furthermore, all participants received a show-up fee of UGX 5,000 (approximately $1.70) as a compensation for their time, comparable to the wages for one day of casual farm labor in this area.

Experimental Results

Descriptive Statistics

Table 3 presents descriptive statistics on demographic and socioeconomic characteristics of the participants. On average, participants were 50.21 years of age. Of all participants, 39% were female. Household heads had an average 6.67 years of schooling. The average household size and dependency ratio were 6.56 and 1.51, respectively. Of all participants, 57% were from Masaka District and 43% were from Luwero District. In order to assess whether farmers have a basic comprehension of probabilities, we conducted a short probability test composed of three simple questions before the experimental session started. On average, each farmer correctly answered two

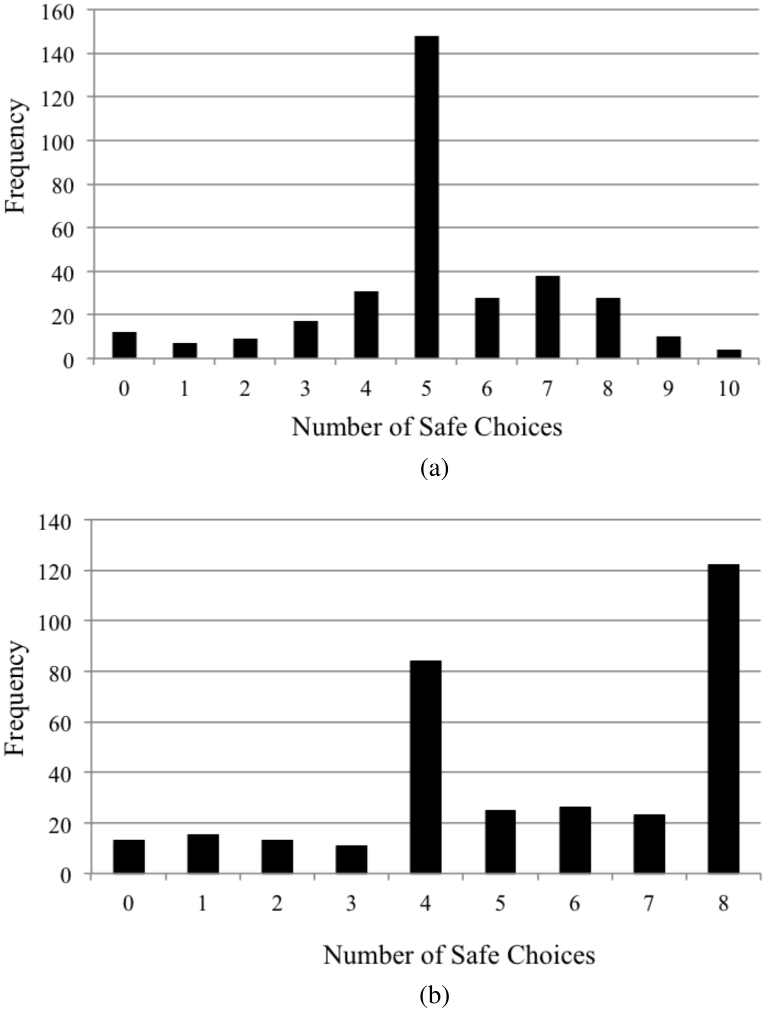

Figure 3. Distribution of Safe Choices in the Modified HL Lottery (a: N= 332) and the Modified BVB Lottery (b: N = 332)

Source: Survey data.

(a) 0–3 represent "risk seeking" (CRRA range: −1.71 to −0.14), 4 represents "risk neutral" (CRRA range: −0.14 to 0.15), and 5–10 represent "risk averse" (CRRA range: 0.15 to 1.37).

(b) 0–3 represent "risk seeking" (CRRA range: −1.41 to 0), 4 represents "risk neutral" (CRRA range: 0 to 0.24), and 5–8 represent "risk averse" (CRRA range: 0.24 to 0.70).

of the three questions. The average annual per capita household expenditure was approximately UGX 516,855.00. The mean farm size for each farmer was about 5.73 acres. Of all participants, 28% indicated having access to a savings account, while 43% claimed to be able to access financial credit for agricultural activities whenever they needed it.

Validity Test of Hypotheses

Test of H1 'Consistency of Risk Preferences'

Responses from the modified HL and BVB lotteries are shown in figure 3. Individual risk preference varies between risk seeking and strong risk aversion. The panel of the modified HL lottery shows a

Table 4. Summary Statistics of the Two Risk Preference Elicitation Methods in a 'Within-Analysis' and 'Between-Analysis' (N = 332)

	Within Analysis (All)			Between Analysis (First: HL)			Between Analysis (First: BVB)		
Risk Category	Modified HL	Modified BVB	Test of Significance	Modified HL	Modified BVB	Test of Significance	Modified HL	Modified BVB	Test of Significance
				Risk Category (%)					
Risk seeking	13.55	15.66		16.46	10.98		10.71	20.24	**a
Risk neutral	9.34	25.3	***a	9.15	25.61	***a	9.52	25	***a
Risk averse	77.11	59.04	***a	74.39	63.41	*a	79.76	54.76	**a
				Distribution of Safe Choices[b] (%)					
Mean	52.04	68.83	$Z^c = -1.75^*$	50.73	71.11	$Z^c = -2.3^{**}$	52.33	66.59	$Z^c = -0.73$
Std. dev.	19.58	30.27		20.14	27.88		19.01	32.36	
Median	50	75		50	75		50	68.75	
Skewness	−0.37	−0.55		−0.24	−0.59		−0.49	−0.48	
Kurtosis	3.85	2.27		3.50	2.48		4.32	2.04	

Notes: Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.
Source: Survey data.
[a]Based on the chi-square test.
[b]Due to the difference in scale value, the number of safe choices in the modified HL lottery (range of 0–10) and the modified BVB lottery (range of 0–8) are converted into percentages of safe choices for comparison.
[c]Based on the Wilcoxon rank-sum (Mann-Whitney) test.

high peak at 5 (the average value in the range), while there is a high peak at 4 (the average value in the range) and a very high peak at 8 in the histogram of the modified BVB lottery. One explanation for the difference between risk preferences elicited through the modified HL and BVB lotteries could be aversion to uncertainty. Option A of the modified BVB lottery involves a 100% chance of receiving a payoff, while option B involves a 50% chance of receiving a payoff and a 50% chance of receiving no payoff. Subjects may have chosen the safer option A eight times rather than taking the risk of receiving no payoff.

Table 4 presents within-analysis and between-analysis summary statistics of the two risk preferences elicitation methods to check how consistent the results are depending on the order of how the game was played. The within-analysis considers the pooled data, while the between-analysis considers two cases: when the subjects started with the modified HL lottery and when the subjects started with the modified BVB lottery. The relative proportions of farmers in each of the three categories for the two lotteries are generally similar across the within-analysis and between-analysis. Both analyses reveal high proportions of farmers classified as risk averse. However, the results of the chi-square tests show that there is a significant difference in the proportions of the categories of risk neutral ($p < 0.01$) and risk averse participants ($p < 0.01$) in the two elicitation methods, while there is no significant difference in the category of risk-seeking participants. Due to the nonnormal distribution[8] of the data, it is more appropriate to use the Wilcoxon rank-sum test to examine whether there is a statistically significant difference between the two methods. The results reveal that there is a statistically significant difference ($p < 0.10$).[9] The results of the between-analysis qualitatively confirm those of the within-analysis, although there is a significant difference of the risk-seeking category (first: modified BVB lottery).

An additional analysis, which excludes subjects who behave inconsistently and switch back and forth, generates qualitatively similar results.[10] We exclude nineteen participants of the modified HL lottery and twenty-five participants of the modified BVB lottery. Even though the inconsistency rate of both risk elicitation methods in our study is relatively low compared to other studies in this field, there are some subjects that are noisy in their responses. This behavior may indicate that they failed to understand the procedure, which reduces the reliability of the risk preference measure and can potentially bias the results. However, since only few subjects show an inconsistent response behavior, the bias regarding the average number of safe choice is negligible. Thus, inconsistent subjects are included in the further analysis, which does not change the conclusions of the paper (e.g., Holt and Laury, 2002; Houser, Schunk, and Winter, 2010; Abdellaoui, Driouchi, and L'Haridon, 2011). Based on the overall results, we reject *H1* 'Consistency of risk preferences.' Essentially, this means that the type of method used affects risk preferences. Although we find inconsistencies in the individual risk preferences across the two elicitation methods, the tendency of participants to be risk averse is the same, which corroborates empirical findings of other studies conducted in developing countries (e.g., Jacobson and Petrie, 2009; Yesuf and Bluffstone, 2009; Harrison, Humphrey, and Verschoor, 2010).

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[8] In order to test whether the distribution of the safe choices is normally distributed and to check robustness, we conduct three different tests: the Shapiro Francia, the Shapiro Wilk, and the Skewness Kurtosis. All three tests show that the distribution of safe choices in the modified HL and BVB lotteries are nonnormally distributed ($p < 0.05$). This finding compels us to use nonparametric test statistics to compare whether the two distributions are significantly different from each other (Gardner, 1975).

[9] Given the differences in the number of tasks in each method and the implied CRRA ranges, the number of safe choices are converted into percentages of safe choices in order to make the comparison between the two risk elicitation methods possible.

[10] Hirschauer et al. (2014) show that including inconsistent subjects in a Holt-and-Laury analysis will bias the mean as well as the variance of the risk attitudes of the subject group of interest to an extent that cannot be determined *a priori* and that must not be neglected.

Table 5. Classification of Groups by Consistency and Inconsistency Rate (N = 332)

	Group	Description	Modified HL lottery
Consistent	1	Switch once	303
	2	Always choose option B	10
Inconsistent	3	Always choose option A	4
	4	Switch at least twice	15

	Group	Description	Modified BVB lottery
Consistent	1	Switch once	185
	2	Always choose option A	122
Inconsistent	3	Always choose option B	10
	4	Switch at least twice	15

Source: Survey data.

Test of H2 'Inconsistency Rates of Elicitation Methods'

We analyze the inconsistency rates by monitoring the switching behavior of subjects across different options, which is a good indicator of whether subjects actually understood the lotteries. We do this by grouping individuals into four groups, as shown in table 5. With respect to the modified HL lottery, the first group consists of participants that initially chose option A and at some point switched to option B. The second group comprises participants who always chose option B. Participants in these two groups made logical and consistent decisions in playing the games and hence are assumed to have understood the lottery. The third group comprises participants who always chose option A. This group is considered inconsistent in that participants would not have completely understood the lottery. A participant who fully understood the game would be expected to logically switch to option B in decision task 10 at the latest. The fourth group comprises participants who switched at least twice.

With respect to the modified BVB lottery, the first group also encompasses participants who first chose option A and at some point switched to option B. The second group comprises participants who always chose option A, and the third group comprises participants who always chose option B. Although the third group was consistent in their response behavior, we think that participants did not completely understand the lottery, since they should have chosen option A at least in the first decision task. Hence, this group is considered to be inconsistent. The last group comprises participants who switched at least twice.

According to this classification scheme, 313 of 332 participants (94.3%) appear to have understood the modified HL lottery. Another 4 participants (1.2%) always chose option A, and 15 participants (4.5%) switched at least twice. In the modified BVB lottery, 307 of 332 participants (92.5%) appear to have understood the lottery. Another 10 participants (3.0%) always chose option B, and 15 participants (4.5%) switched at least twice. In both risk preferences elicitation methods, the inconsistency rates of 5.7% in the modified HL lottery and 7.5% in the modified BVB lottery are relatively low compared to other studies in this field (Galarza, 2009; Jacobson and Petrie, 2009; Charness and Viceisza, 2016; Brick, Visser, and Burns, 2012). The relatively low rates of inconsistency may be an indication that our design of the modified HL and the BVB lotteries were well understood by the participants. The results of a t-test reveal that there is no statistically significant difference between the inconsistency rates of the two methods ($p < 0.25$). On this basis, we fail to reject *H2 'Inconsistency rates of elicitation methods'*.

Test of H3 'Stability of Explanatory Factors'

Interval and Poisson regression models are estimated to analyze the relationship between risk preferences and demographic and socioeconomic factors and to test whether these factors are stable

Table 6. Results of the Interval and Ordered Probit Regression with the Individual Risk Preference as the Dependent Variable (N = 332)

	Interval Regression		Poisson Regression	
Variable	Modified HL	Modified BVB	Modified HL	Modified BVB
Age (*years*)	0.003	0.001	0.002	−0.001
	(0.003)	(0.005)	(0.002)	(0.002)
Gender (*1= female*)	0.009	0.014	−0.001	0.013
	(0.078)	(0.143)	(0.52)	(0.051)
Education (*years*)	0.008	−0.045**	0.001	−0.018**
	(0.012)	(0.023)	(0.008)	
Household size (*number*)	−0.001	−0.021	−0.001	−0.004
	(0.013)	(0.024)	(0.009)	(0.008)
Age dependency ratio[a]	−0.008	−0.069	0.001	−0.029
	(0.034)	(0.062)	(0.023)	(0.022)
District (*1 = Masaka*)	−0.220***	0.027	−0.120***	0.017
	(0.078)	(0.144)	(0.052)	(0.051)
Probability test score (*number*)	0.111**	0.200**	0.061**	0.060*
	(0.049)	(0.092)	(0.034)	(0.033)
Per capita household expenditure	$7.64e-08$	0.001**	$4.33e-08$	0.001**
(annual) in UGX[b]	(0.001)	(0.001)	($6.80e-08$)	($6.36e-08$)
Total land owned (*acres*)[c]	0.007	−0.005	0.003	−0.001
	(0.008)	(0.016)	(0.005)	(0.006)
Access to a savings account (*dummy*)	0.012	0.179	0.013	0.068
	(0.088)	(0.164)	(0.059)	(0.057)
Access to credit (*dummy*)	−0.016	0.019	−0.018	0.003
	(0.076)	(0.140)	(0.051)	(0.050)
Order of experiment (*1 = first*	0.053	−0.151	0.025	−0.061
modified BVB)	(0.076)	(0.142)	(0.051)	(0.051)
Winner modified BVB (*dummy*)	0.255*		0.141	
	(0.153)		(0.097)	
Winner modified HL (*dummy*)		0.249		0.074
		(0.255)		(0.086)
Constant	−0.422*	0.124	1.440***	1.689***
	(0.223)	(0.413)	(0.152)	(0.147)
Observations	332	332	332	332
Chi-square test	23.43	19.18	15.62	17.53
Log likelihood	−698.0	−621.7	−714.8	−786.0
Interval observations	290	169		
Right-censored observations	14	122		
Left-censored observations	19	41		
Uncensored observations	9	0		

Notes: : Standard errors in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level. The dependent variable for the interval regression comes from the midpoint CRRA coefficients from the modified HL and BVB lotteries. The dependent variable used for the poisson regression is the number of safe choices in the modified HL and BVB lotteries.
Source: Survey data.
[a]A measure showing the number of dependents (age 0–14 and over the age of 65) to the number of people (age 15–64).
[b]At the time of the experiments, the exchange rate was approximately $1 to UGX 3,000.
[c]1 acre = 0.40 hectare.

across elicitation methods. Estimation results from the Interval and Poisson models are shown in table 6. Education is statistically significant and negatively correlated with risk preferences in the modified BVB lottery but show no significant effect in the modified HL lottery. Subjects who correctly answered more questions in the probability test are significantly more risk averse in both elicitation methods. Subjects from the Masaka District are substantially less risk averse in the modified HL lottery than subjects from the Luwero District.[11] Per capita household expenditure

[11] A disaggregated analysis by district level reveals qualitatively similar results. Similarities between the two districts are based on climatic and agro-ecological zoning, cropping patterns of coffee-based systems, market access conditions, and proximity to the capital city, Kampala, which also to the decision to pool the data for the analysis. However, regional variation in measured risk preferences may be explained by the fact that the Luwero District was affected more by war than the Masaka District, which might have an effect on risk preferences.

Table 7. Results of the Logit Regression with Certification Adoption as the Dependent Variable

Variable	Logit Regression	
Risk aversion in HL (*dummy*)	0.133	(0.576)
Risk loving in HL (*dummy*)	0.176	(0.684)
Risk aversion in BVB (*dummy*)	−1.012***	(0.392)
Risk loving in BVB (*dummy*)	−0.722	(0.501)
Male household head (*dummy*)	−0.373	(0.382)
Age of household head (*years*)	0.017	(0.014)
Education of household head (*years*)	0.075	(0.052)
Cellphone ownership (*dummy*)	0.248	(0.434)
Man Equivalent Unit (*MEU*)	0.235**	(0.092)
Years resident in village	−0.000422	(0.005)
Number of rooms (*5 years ago*)	0.424***	(0.121)
Years growing coffee	0.038***	(0.014)
Leadership position (*dummy*)	0.990***	(0.366)
Access to credit (*dummy*)	1.074***	(0.333)
Total land owned 5 years ago (*acres*)	−0.028	(0.037)
Farm altitude in (*m*)	−0.017***	(0.003)
Distance to input market (*km*)	−0.078**	(0.031)
Distance to output market (*km*)	0.045	(0.037)
Distance to all-weather road (*km*)	−0.070***	(0.015)
Constant	17.750***	(3.419)
Observations	332	
Chi-square test	160.5	
Log likelihood	−220.4	

Notes: Standard errors in parentheses. Single, double, and triple asterisks (*, **, ***) indicate significance at the 10%, 5%, and 1% level.
Sources: Survey data.

has a positive impact on risk aversion in the modified BVB lottery but shows no significant effect in the modified HL lottery. The binary indicator for winning in the first lottery-choice experiment shows that a subject who first played the modified BVB lottery and won is more risk averse in the subsequent modified HL lottery.[12] This indicates that conducting various successive experiments should be done with caution, as prior experience with one task affects behavior in a subsequent task. Although we find some significant effects of explanatory factors of risk preferences, these factors are not consistent across the two elicitation methods.[13] On this basis, we fail to reject *H3 'Stability of explanatory factors'*.

An additional analysis examines the explanatory power of risk preferences in observed actual economic behavior in order to test the validity of the applied elicitation methods. We estimate the impact of risk preferences on technology adoption (i.e., certification adoption).[14] Risk preferences may influence a household's ability and willingness to adopt certification. There is a rich literature on the dynamics of technology adoption in the developing world, in which risk is one of several important factors (e.g., Feder, Just, and Zilberman, 1985; Marra, Pannell, and Abadi Ghadim, 2003; Hurley, 2010). A key finding from this literature is that risk aversion slows the adoption

[12] We also included the variables "order of experiment," "winner modified BVB lottery," and "winner modified HL lottery" in the analysis. These variables are used to test whether the order of the two lottery-choice experiments and winning in the first lottery-choice experiment has an effect on the risk preferences elicited in the subsequent lottery-choice experiment.

[13] The low explanatory power of respondent characteristics in explaining risk preferences indicates that the examined factors can only partly account for risk preferences and that other factors may explain more variance.

[14] Since the experiments were linked to another project on linking farmers to certified markets, we have access to comprehensive survey data that allowed us to link risk preferences to certification adoption. For a detailed explanation of the explanatory variables included in the regression analysis, see Chiputwa, Spielman, and Qaim (2015).

of new technology because a lack of familiarity can lead farmers to view it as more risky. Furthermore, certification adoption decisions may be influenced by individual characteristics of the farm household head and farm characteristics. Hence, we include a broad range of explanatory variables.

Estimation results from a logit model are shown in table 7. Risk aversion in the modified BVB lottery decreases the likelihood of certification, while there is no significant effect of risk aversion in the modified HL lottery. This finding shows that the use of different risk attitude measures in explaining actual economic behavior leads to diverging results, thus, conclusions should be made with caution. Nevertheless, the finding supports Brick, Visser, and Burns (2012), who show that a greater degree of risk aversion translates into a reduction in standard compliance. Furthermore, the negative impact of risk aversion on certification adoption supports findings in other technology adoption studies.

Conclusions

The majority of poor people in developing countries live in rural areas, where agricultural production (under very risky conditions) constitutes a significant part of their livelihoods. The role of risk is particularly important in developing countries due to incomplete or nonexistent strategies or markets designed to cushion farmers from risk (e.g., through insurance and safety-net mechanisms). Thus, there has been a growing interest among researchers to better understand how risk and uncertainty affect smallholder farmers' behavioral decisions. This is an important step in guiding policy in better predicting the likely effects of certain policy changes and designing effective programs that help farmers deal with risk.

However, several studies quantifying individual risk preference have shown that results of different elicitation methods may vary and reported relatively high inconsistency rates in individuals' response behavior, which may indicate a low level of comprehension. Comparison of different risk preferences elicitation methods allows insights into which method may be better adapted to assess risk preferences of farmers in developing countries. Taking the case of smallholder coffee farmers in Uganda, this study compares the risk outcomes elicited from using two commonly used methods, the Holt and Laury (2002) and Brick, Visser, and Burns (2012) lottery tasks, that differ in that one varies probabilities while keeping the payoffs fixed and the other keeps probabilities fixed as payoffs vary. We also evaluate inconsistency rates in response behavior and whether explanatory factors of risk preferences are consistent across elicitation methods.

Empirical results show that, first, the inconsistency rates of both elicitation methods are relatively low compared to other studies in this field. This may be an indication that our versions and implementation of the modified HL and modified BVB lotteries were well understood by the subjects and were thus appropriate elicitation methods in a developing country context. It also shows that, in our case, people do not have more difficulties with varying probabilities than with varying amounts of payoffs, given the low inconsistency rates in both lottery-choice experiments. Second, most of the sampled farmers are classified as risk averse in both elicitation methods. However, the categories of risk preferences are statistically different across the two elicitation methods, implying that risk preference results may be affected by the elicitation method used. Third, explanatory factors of risk preferences are not consistent across the two elicitation methods.

Our results have several implications for policy makers. For example, our results show that most respondents are risk averse, which may indicate that smallholders may be unwilling to change their production systems by investing in new technology (e.g., certification adoption). The avoidance of investments involving risk, which could otherwise increase households' productive capacity, may keep the poor trapped in poverty (e.g., Rosenzweig and Binswanger, 1993). Our results also show that risk aversion decreases with education. Education measures may enable smallholder farmers to more realistically assess risks and make better-informed investment decisions. Furthermore, the results show that explanatory factors of risk preferences are not consistent across the two elicitation methods. This demonstrates that one has to be cautious in making meaningful conclusions about the impact of these factors on risk preferences and therefore policy recommendations.

When interpreting the results, it is important to take into account that our experimental design is abstracted from reality and is considerably simpler than situations involving risk that would occur in an actual setting. Subjects may act differently in the experimental situation than they do in a similar situation in the real world. A common criticism of laboratory experiments is that results are unlikely to provide reliable inferences outside the experimental environment (i.e., lack of external validity) and hence cannot be extrapolated to the real world (Levitt and List, 2007; Roe and Just, 2009). Plott and Zeiler (2007) argue that the purpose of the experiment becomes particularly important when choosing an experimental environment (e.g., laboratory versus field experiments). Most of the literature on risk preference elicitation relies on laboratory experiments. Andersen et al. (2006), however, have pointed out that field experiments are required to extrapolate findings from the laboratory to a population of interest. There has been some recent research to bring laboratory experiments to field subjects in order to complement the main conclusions obtained in traditional laboratory experiments. Although field experiments are less controlled than laboratory experiments, they may appear relevant for some research domains like elicitation of preferences. It can be important to have nonstandard subjects (e.g., farmers, etc.) because elicited preferences can then be compared to real choices made by individuals and also because nonstandard subjects may be endowed with past experiences affecting their preferences (Reynaud and Couture, 2012).

Some extensions of the present study might further verify the validity of our results. First, it would be interesting to analyze how the original lottery-choice experiment design with probabilities expressed in percentages and the modified lottery-choice experiment design with probabilities expressed in bags of colored balls compare to each other with regard to inconsistency rates in the response behavior. Second, additional research is needed to identify more explanatory factors of risk preferences. There may exist important, unidentified determinants of risk preferences apart from the factors included in this analysis. For example, the relation between risk preferences and social capital is particularly neglected in the literature. Previous studies on social capital suggest that households with more extensive networks and hence greater access to consumption credit, assistance in-kind, and capital markets are more able to cope with risks (Fafchamps and Lund, 2003; Steer and Sen, 2010; Attanasio et al., 2012). Thus, it would be worth exploring whether social capital influences an individual's risk preferences, since social capital is likely to be effective in risk sharing.

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