Risk preference elicitation without the confounding effect of probability weighting

Drichoutis, Andreas and Lusk, Jayson

University of Ioannina, Department of Economics, Oklahoma State University

27 March 2012

Risk Preference Elicitation without the Confounding Effect of Probability Weighting

Andreas Drichoutis[†] and Jayson L. Lusk[‡]

[†] Department of Economics, University of Ioannina, Greece, email: adrihout@cc.uoi.gr

[‡] Department of Agricultural Economics, Oklahoma State University, USA, email: jayson.lusk@okstate.edu

Abstract: In this paper we show that the wildly popular Holt and Laury (2002) risk preference elicitation method confounds estimates of the curvature of the utility function, the traditional notion of risk preference, with an estimate of the extent to which an individual weights probabilities non-linearly. We show that a slight modification to their approach can remove the confound while preserving the simplicity of the method which has made it so popular. Data from a laboratory experiment shows that our new method yields significantly different levels of implied risk aversion than the Holt and Laury task even after econometrically controlling for probability weighting in the latter. Implied risk aversion from the traditional Holt and Laury task is relatively insensitive to payout amount, but our new method reveals increasing relative risk aversion and risk neutrality at low payout amounts.

JEL codes: C91, D81

Keywords: expected utility theory, experiment, probability weighting, rank dependent utility, risk

1. Introduction

The abundance of uncertainty in life has prompted a great many investigations into humans' response to risk. The interest in understanding risk preferences has created a latent demand for effective, easy-to-use risk preference elicitation devises. Following a long line of previous research by Becker, DeGroot, and Marshak (1964), Binswanger (1980; 1981), and others, in 2002 Holt and Laury (H&L) introduced a risk preference elicitation method that has subsequently become a mainstay. In a testament to the general interest in risk preference elicitation and to the specific appeal of the approach introduced by H&L, their work has been cited more than 1,500 times according to Google Scholar and is the third most highly cited paper published by the *American Economic Review* since 2002 according to ISI's Web of Knowledge.

Although there have been a few quibbles over some of the details of original study (e.g., see Harrison *et al.*, 2005; Holt & Laury, 2005), there has heretofore been little doubt expressed that the basic approach introduced by H&L can cleanly identify risk preferences. In this paper, we show that the H&L approach is subject to Wakker and Deneffe's (1996) insight that many risk preference elicitation methods confound estimates of the curvature of the utility function (i.e., the traditional notion of risk preference) with an estimate of the extent to which an individual weights probabilities non-linearly. These are two conceptually different constructs that have different implications for individuals' behavior under risk, and without controlling for one, biased estimates of the other are obtained.

While it is possible to use data from the H&L technique to estimate these two constructs *ex post*, such econometric approaches require a number of implicit and explicit assumptions (including assumptions about the functional form of the utility and probability weighting functions, error structure, and extent of preference heterogeneity), any of which might produce misleading inferences about risk preferences. We show that with a slight modification to the original H&L method, one can remove the confound between risk preferences and probability weighting while preserving the simplicity of the method which has made it so useful and popular. Using results from laboratory experiments, we show that at low payout amounts, the original H&L method suggests individuals are more risk averse than our new method, which removes probability weighting as a determinant of choice. In fact, the new approach shows that people are essentially risk neutral over low payout amounts. When payouts are scaled up, we find increasing relative risk aversion in our new task, but constant relative risk aversion with the traditional H&L task. Attempting to econometrically control for probability weighting in the H&L task does *not* yield the same implied risk aversion as our new method.

In the next section, we illustrate why the existence of probability weighting could lead to misleading inferences about risk preferences using the H&L approach, and reveal our solution to the problem. Then, we discuss the psychological literature which suggests incentive-effects might affect probability weighting. The following section outlines our new method and the experimental design. We discuss our results in the penultimate section and then conclude.

2. Effect of Probability Weighting on Choice

In the base-line treatment used by H&L, individuals were asked to make a series of 10 decisions between two options: A and B (see Table 2). In option A, the high payoff amount is fixed at $2 and the low payoff amount is fixed at $1.60 across all 10 decision tasks. In option B, the high payoff amount is fixed at $3.85 and the low payoff amount is fixed at $0.10. The only thing changing across the 10 decisions are the probabilities assigned to the high and low payoffs. Initially the probability of receiving the high payoff is 0.10 but by the tenth decision task, the probability is 1.0. The expected value of lottery A exceeds the expected value of lottery B for the first four decision tasks. Thus, someone who prefers lottery A for the first four decision tasks and then switches and prefers lottery B for the remainder is often said to have near-risk neutral preferences. Analysts often use the number of "safe choices" (e.g., the number of times option A was chosen) or the A-B switching point to describe risk preferences and to infer the shape of an assumed utility function (e.g., Bellemare & Shearer, 2010; Bruner *et al.*, 2008; Eckel & Wilson, 2004; Glöckner & Hochman, 2011; Lusk & Coble, 2005 just to name a few).

For simplicity and consistency with the H&L experiment, let p represent the probability receiving the higher payoffs in lottery options A and B, which are \$2 and \$3.85, respectively. The probability of receiving the lower monetary outcomes, \$1.60 and \$0.10 for options A and B, is thus (1-p). Given the ample evidence (and theory) of non-linear probability weighting, e.g., Quiggin (1982) and Tversky and Kahneman (1992), we write the weighted utility of option A as: $EU_A = w(p)\cdot U(2) + (1- w(p))\cdot U(1.6)$ and option B as: $EU_B = w(p)\cdot U(3.85) + (1- w(p))\cdot U(0.1)$. The likelihood an individual chooses option A over B (i.e., the measure of the degree of risk aversion) is monotonically related to the difference in weighted utilities: $EU_A - EU_B = w(p)\cdot U(2) + (1- w(p))\cdot U(1.6)- w(p)\cdot U(3.85) - (1- w(p))\cdot U(0.1)$.

Because analysts typically use the number of A choices an individual makes as they move down the H&L table as a measure of the degree of risk aversion, and the probability of receiving the higher payout linearly increases as one moves down the table, we can ask how the likelihood of choosing option A over B changes with p:

(1) $\partial(EU_A - EU_B)/\partial p = \partial w(p)/\partial p\cdot[U(2)-U(3.85)]+ \partial w(p)/\partial p\cdot[U(0.1)-U(1.6)]$.

Because, for any well behaved utility function, $U(3.85)>U(2)$ and $U(1.6)>U(0.1)$, the above derivative must be negative, which means that as one moves down the H&L table, they are less likely to choose option A and are more likely to choose option B.

The key observation we make here is that the choice between options A and B in the ten H&L decision tasks, which is driven by the derivative in (1), is influenced by how people weight probabilities: $\partial w(p)/\partial p$. A number of experimental studies have estimated the shape of w(p), using functional forms such as $w(p) = p^\gamma/[p^\gamma + (1-p)^\gamma]^{1/\gamma}$. Estimates of γ typically fall in the range of 0.56 to 0.71 (e.g., see Camerer and Ho (1994), Tversky and Kahneman (1992), or Wu and Gonzalez, (1996)), which implies an S-shaped probability weighting function that over-weights low probability events and under-weights high probability events. Only under the case where $\gamma = 1$ does $w(p) = p$, and it is only here that the derivative in (1), i.e., the switching point, is uninfluenced by probability weighting. Stated differently, the extent to which an individual weights probabilities non-linearly will, as shown in equation (1), drive when they choose to switch between options A and B, which is the key measure researchers typically use to make inferences about the curvature of the function $U(x)$. Not controlling for $w(p)$ may, therefore, provide misleading estimates of the curvature of $U(x)$.

To illustrate the problem more precisely, consider a simple example where individuals are risk neutral: i.e., $U(x) = x$. With the traditional H&L task, a risk neutral person with $\gamma = 1$ would switch between options A and B between the fourth decision task, where $EU_A - EU_B = 0.4 \cdot [2-3.85]+0.6 \cdot [1.6-0.1] = 0.16$ and the fifth decision task, where $EU_A - EU_B = 0.5 \cdot [2-3.85]+0.5 \cdot [1.6-0.1] = -0.175$. However, if the person weights probabilities non-linearly, say with a value of $\gamma = 0.6$, then they would instead switch from option A to B between the fifth decision task, where $EU_A - EU_B = w(0.5) \cdot [2-3.85]+(1-w(0.5)) \cdot [1.6-0.1] = 0.108$, and the sixth decision task, where $EU_A - EU_B = w(0.6) \cdot [2-3.85]+(1-w(0.6)) \cdot [1.6-0.1] = -0.066$. Here is the key result: in the original H&L decision task, an individual with $\gamma = 0.6$, will *appear* risk averse *even though* they have a linear utility function, $U(x) = x$. The problem is further exasperated as gamma diverges from one. Of course in reality, people may weight probabilities non-linearly and exhibit diminishing marginal utility of earnings, but the point remains: simply observing the A-B switching point in the H&L decision task is insufficient to identify the shape of $U(x)$ and the shape of $w(p)$. The two are confounded.

Given the above set-up, one might ask if there is a simple way to avoid the confound. With a slight modification to the H&L task, one can eliminate probability weighting as an explanation for the switch between options A and B. Indeed, looking back at equation (1), if probabilities do not change across decision tasks, then probability weighting cannot possible explain the switch. This is, in effect, our simple solution. We modify the H&L task such that probabilities remain constant across the ten decision tasks and instead change the dollar payoffs so that the switch from A to B can only be explained by the shape of $U(x)$.

3. Experimental procedures

3.1. Description of the experiment

A conventional lab experiment was conducted using z-Tree software (Fischbacher, 2007). Subjects consisted of undergraduate students at the University of Ioannina, Greece and were recruited using the ORSEE recruiting system (Greiner, 2004). During the recruitment, subjects were told that they would be given the chance to make more money during the experiment.[1] Stochastic fees have been shown to be able to generate samples that are less risk averse than would otherwise have been observed (Harrison et al., 2009).

Subjects participated in sessions of group sizes that varied from 9 to 11 subjects per session (all but two sessions involved groups of 10 subjects). In total, 100 subjects participated in 10 sessions that were conducted between December 2011 and January 2012. Each session lasted about 45 minutes and subjects were paid a €10 participation fee. Subjects were given a power point presentation explaining the risk preferences tasks as well as printed copies of instructions. They were also initially given a five-choice training task to familiarize them with the choice screens that would appear in the real task. Subjects were told that choices in the training phase would not count toward their earnings and that this phase was purely hypothetical.

Full anonymity was ensured by asking subjects to choose a unique three-digit code from a jar. The code was then entered at an input stage once the computerized experiment started. The experimenter only knew correspondence between digit codes and profits. Profits and participation fees were put in sealed envelopes (the digit code was written on the outside) and were exchanged with digit codes at the end of the experiment. No names were asked at any point of the experiment. Subjects were told that their decisions were independent from other subjects, and that they could finish the experiment at their own convenience. Average total payouts including lottery earnings were 15.2€ (S.D.=4.56).

[1] Subjects were told that "In addition to a fixed fee of 10€, you will have a chance of receiving additional money up to 25€. This will depend on the decisions you make during the experiment."

3.2. Risk preference elicitation

Our experiment entailed a 3x2 within-subject design, where each subject completed three different multiple price lists (MPL) at two payout (low vs. high) amounts. As shown in Table 1, the baseline (or control) involved the original H&L task at their low payoff amounts.

Table 1. Treatments in experiment

	Payout	
Multiple Price List	**low(x1)**	**high (x5)**
H&L	Control	Treatment 1
Modified H&L with constant probabilities	Treatment 2	Treatment 3
Modified H&L with non-linear probabilities	Treatment 4	Treatment 5

The baseline H&L MPL presented subjects with a choice between two lotteries, A or B, as illustrated in Table 2. In the first row, the subject was asked to make a choice between lottery A, which offers a 10% chance of receiving €2 and a 90% chance of receiving €1.6, and lottery B, which offers a 10% chance of receiving €3.85 and a 90% chance of receiving €0.1. The expected value of lottery A is €1.64 while for lottery B it is €0.475, which results in a difference of €1.17 between the expected values of the lotteries. Proceeding down the table to the last row, the expected values of both lotteries increase, but the rate of increase is larger for option B. For each row, a subject choose A or B, and one row was randomly selected as binding for the payout. The last row is a simple test of whether subjects understood the instructions correctly.[2] The first treatment (Treatment 1) is identical to the control (shown in table 2) except that all payouts are scaled up by a magnitude of five.

[2] 16 out of 100 subjects failed to pass this test concerning comprehension of lotteries and were omitted from our sample.

Table 2. Original H&L Multiple Price List

Lottery A				Lottery B				EV^A (€)	EV^B (€)	Difference (€)	Open CRRA interval if subject switches to Lottery B (assumes EUT)	
p	€	*p*	€	*p*	€	*p*	€					
0.1	2	0.9	1.6	0.1	3.85	0.9	0.1	1.640	0.475	1.17	-∞	-1.71
0.2	2	0.8	1.6	0.2	3.85	0.8	0.1	1.680	0.850	0.83	-1.71	-0.95
0.3	2	0.7	1.6	0.3	3.85	0.7	0.1	1.720	1.225	0.50	-0.95	-0.49
0.4	2	0.6	1.6	0.4	3.85	0.6	0.1	1.760	1.600	0.16	-0.49	-0.15
0.5	2	0.5	1.6	0.5	3.85	0.5	0.1	1.800	1.975	-0.18	-0.15	0.14
0.6	2	0.4	1.6	0.6	3.85	0.4	0.1	1.840	2.350	-0.51	0.14	0.41
0.7	2	0.3	1.6	0.7	3.85	0.3	0.1	1.880	2.725	-0.85	0.41	0.68
0.8	2	0.2	1.6	0.8	3.85	0.2	0.1	1.920	3.100	-1.18	0.68	0.97
0.9	2	0.1	1.6	0.9	3.85	0.1	0.1	1.960	3.475	-1.52	0.97	1.37
1	2	0	1.6	1	3.85	0	0.1	2.000	3.850	-1.85	1.37	+∞

Note: Last four columns showing expected values and implied CRRA intervals were not shown to subjects.

The second MPL used in the experiment involved a modification of the H&L task to remove non-linear probability weighting as an explanation for the switch between options A and B. Table 3 shows the modified price list used in treatment 2 (treatment 3 was identical with dollar amounts scaled up by five). In the modified H&L task, the probabilities of all payouts are held constant at 0.5, and as such, choices between lotteries *cannot* be explained by non-linear probability weighting. We constructed the modified H&L task shown in table 3 so that it matched the original H&L task in terms of the coefficient of relative risk aversion (CRRA) implied by a switch between choosing option A and option B. For example, if an individual switched from choosing option A to option B on the sixth row of the original H&L task, it would imply a CRRA between 0.14 and

0.41. Likewise, in the modified H&L task with constant probabilities, a switch from choosing option A to option B on the sixth row would also imply a CRRA between 0.14 and 0.41.

Table 3. Modified H&L with Constant Payoffs

Lottery A				Lottery B				EV^A (€)	EV^B (€)	Difference (€)	Open CRRA interval if subject switches to Lottery B	
p	€	*p*	€	*p*	€	*p*	€					
0.5	1.68	0.5	1.60	0.5	2.01	0.5	1.00	1.640	1.506	0.13	-∞	-1.71
0.5	1.76	0.5	1.60	0.5	2.17	0.5	1.00	1.680	1.583	0.10	-1.71	-0.95
0.5	1.84	0.5	1.60	0.5	2.32	0.5	1.00	1.720	1.658	0.06	-0.95	-0.49
0.5	1.92	0.5	1.60	0.5	2.48	0.5	1.00	1.760	1.738	0.02	-0.49	-0.15
0.5	2.00	0.5	1.60	0.5	2.65	0.5	1.00	1.800	1.827	-0.03	-0.15	0.14
0.5	2.08	0.5	1.60	0.5	2.86	0.5	1.00	1.840	1.932	-0.09	0.14	0.41
0.5	2.16	0.5	1.60	0.5	3.14	0.5	1.00	1.880	2.068	-0.19	0.41	0.68
0.5	2.24	0.5	1.60	0.5	3.54	0.5	1.00	1.920	2.272	-0.35	0.68	0.97
0.5	2.32	0.5	1.60	0.5	4.50	0.5	1.00	1.960	2.748	-0.79	0.97	1.37
0.5	2.40	0.5	1.60	0.5	4.70	0.5	1.00	2.000	2.852	-0.85	1.37	+∞

Note: Last four columns showing expected values and implied CRRA intervals were not shown to subjects.

For a more robust investigation into the issue, we constructed another MPL that modified the original H&L design such that the probability of receiving the higher payout option increased nonlinearly down the list (see table 4). This task does *not* remove probability weighting as a factor explaining the choices between option A and B, but it is constructed so that the switching point is adjusted for the likely fact that individuals likely weight probabilities non-linearly. In particular, we constructed the modified H&L task shown in table 4 so that it matched the original H&L task in terms of the coefficient of relative risk aversion (CRRA) implied by a switch between choosing option A and option B under the assumption that an individual weighted probabilities nonlinearly with $w(p) = p^{0.6}/[\, p^{0.6} + (1\text{-}p)^{0.6}]^{1/0.6}$.

Table 4. Modified H&L with Non-Linear Probabilities

Lottery A				Lottery B							Open CRRA interval if subject switches to Lottery B (assumes probability weighting)	
p	€	p	€	p	€	p	€	EV^A (€)	EV^B (€)	Difference (€)		
0.03	2.00	0.97	1.60	0.03	3.85	0.97	0.10	1.610	0.194	1.42	-∞	-1.71
0.09	2.00	0.91	1.60	0.09	3.85	0.91	0.10	1.636	0.439	1.20	-1.71	-0.95
0.20	2.00	0.80	1.60	0.20	3.85	0.80	0.10	1.678	0.835	0.84	-0.95	-0.49
0.34	2.00	0.66	1.60	0.34	3.85	0.66	0.10	1.735	1.365	0.37	-0.49	-0.15
0.50	2.00	0.50	1.60	0.50	3.85	0.50	0.10	1.800	1.975	-0.17	-0.15	0.14
0.66	2.00	0.34	1.60	0.66	3.85	0.34	0.10	1.865	2.585	-0.72	0.14	0.41
0.80	2.00	0.20	1.60	0.80	3.85	0.20	0.10	1.922	3.116	-1.19	0.41	0.68
0.91	2.00	0.09	1.60	0.91	3.85	0.09	0.10	1.964	3.512	-1.55	0.68	0.97
0.97	2.00	0.03	1.60	0.97	3.85	0.03	0.10	1.990	3.756	-1.77	0.97	1.37
1.00	2.00	0.00	1.60	1.00	3.85	0.00	0.10	2.000	3.850	-1.85	1.37	+∞

Note: Last four columns showing expected values and implied CRRA intervals were not shown to subjects.

Instead of providing a table of choices arrayed in an ordered manner all appearing at the same page as in H&L, each choice was presented separately showing probabilities and prizes (as in Andersen *et al.*, 2011)). Subjects could move back and forth between screens in a given table but not between tables. Once all ten choices in a table were made, the table was effectively inaccessible. The order of appearance of the treatments for each subject was completely randomized to avoid order effects (Harrison et al., 2005). An example of one of the decision tasks is shown in figure 1. Because each subject completed three MPLs (with 10 choices each) at two payouts, they each made 60 binary choices. For each subject, one of the 60 choices was randomly chosen and paid out.

Figure 1. Example Decision Task

4. Data analysis and results

4.1. Descriptive analysis

Figure 2 illustrates the proportion of subjects choosing option A over B across the three risk preference tasks for small payoff (x1) amounts. Note that all three tasks were designed to elicit the same switching point for a given risk aversion coefficient but under different assumptions about probability weighting. The standard H&L task assumes that EUT holds and that individuals linearly weight probabilities. The results imply significant risk averse behavior for the traditional H&L task as subjects switch, on average, far after task four. Similar results are obtained from the H&L task that employs non-linear probabilities. However, in our modified task, where probabilities are held constant to avoid the confound of probability weighting, a different picture emerges. Subjects appear less risk averse in the constant-probability task than in the conventional H&L task.

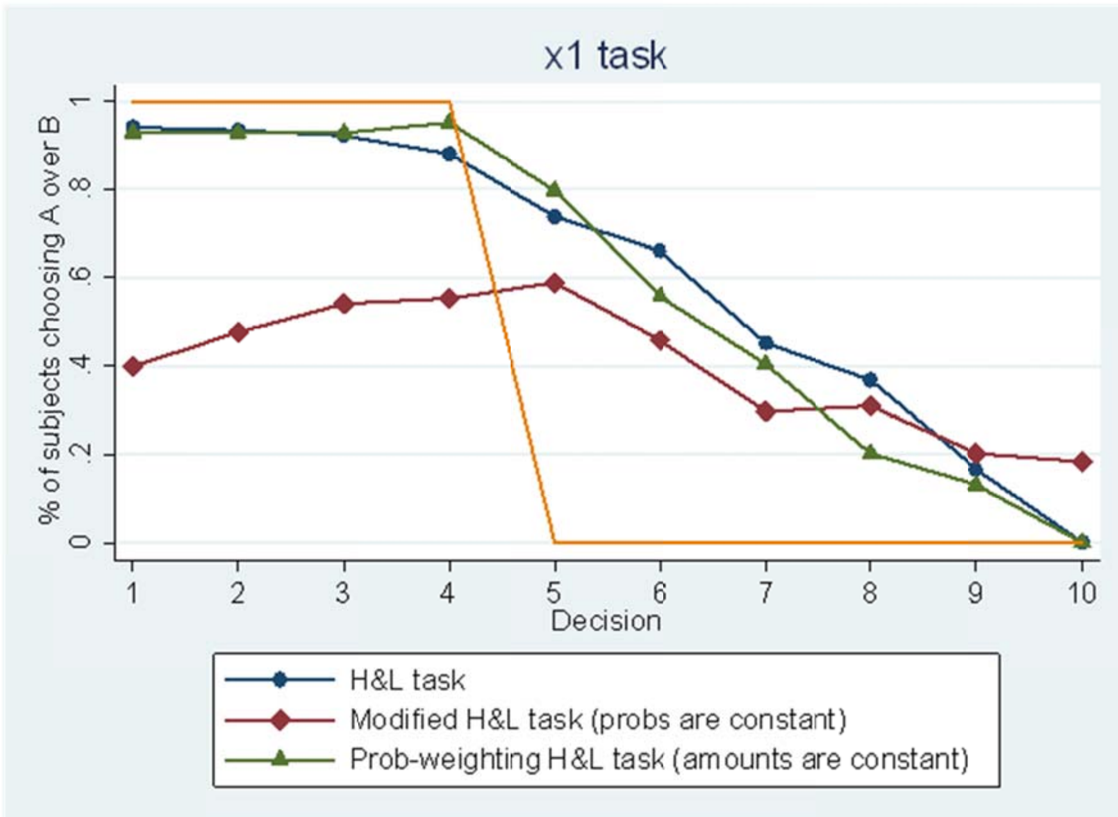

Figure 2. Proportion of choices in each decision for the x1 task (solid line without markers represents risk neutrality under EUT)

One striking difference in the new constant-probability task is the fact that the percent choosing option A over B remains at about 50% for the first five decision task, and, in fact, slightly increases over this range. One explanation for this trend is that the new task generated more multiple switching points than the standard H&L task.[3] If we calculate the number of choices that violate monotonicity, we find that the average

[3] In our experiment, we did not impose monotonicity on choices or provide warnings when monotonicity was violated. Although such a procedure could be implemented it is unclear if it is superior to simply observing how people behave when unconstrained.

subject made 0.21 and 0.11 such violations in the original H&L task at low and high payouts, respectively. By contrast, in our modified H&L task with constant probabilities, the average subject made 0.85 and 0.69 such violations in the low and high payout tasks, respectively. Over the first few choices in the new decision task, the difference in the expected values between lottery options A and B were relatively small, and this might partially explain why the constant probability tasks generated more switching behavior. However, it should be noted that such small differences in expected values were *required* to generate the same implied CRRA intervals as the original H&L task given the overall payout magnitudes. Thus, this is not a feature of our task *per se* but rather a feature of constant relative risk aversion and expected utility theory applied to lotteries with payouts of the magnitude considered in the original H&L task but with constant probabilities. Importantly, we have analyzed our data removing individuals that significantly violated monotonicity (i.e., made three or more inconsistent choices), and our econometric estimates (discussed momentarily) are virtually unchanged, suggesting that it is not this particular feature of the new task that is driving the differences in implied CRRA across tasks.

Figure 3 illustrates the proportion of subjects choosing option A over B for the three tasks that involve higher payoff prizes. As expected, risk aversion increases with payoff sizes. The modified constant-probability task initially shows fewer "safe" choices than the conventional H&L task, but after the eighth task shows more "safe" choices. The issue of monotonicity does not appear as problematic in the modified constant-probability task when payouts are scaled up. This might be because the expected value differences between options A and B (shown in table 3) are also scaled up by a factor of five in this task.

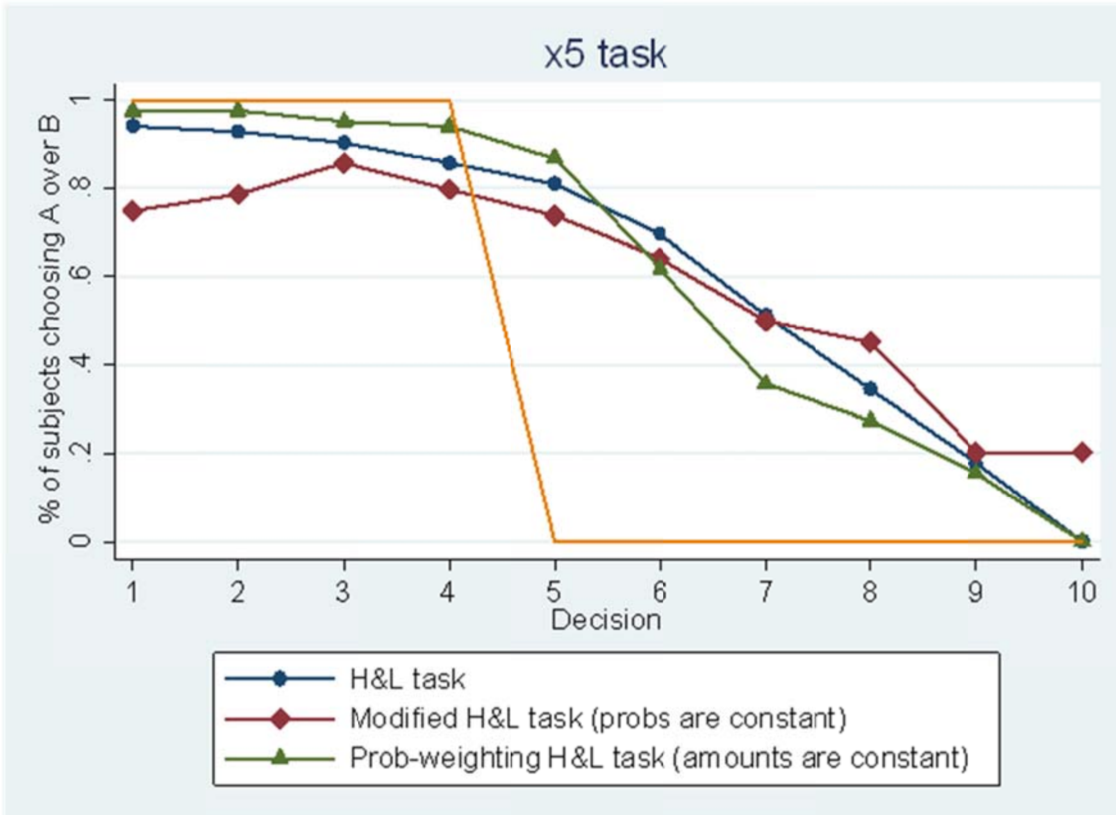

Figure 3. Proportion of choices in each decision for the x5 task

4.2. Structural estimation of risk preferences

To estimate the effect of the three tasks and two payout levels on implied levels of risk aversion, we follow the framework of Andersen et al. (2008). Let the utility function be the CRRA specification:

(2) $$U(M) = \frac{M^{1-r}}{1-r}$$

where r is the CRRA coefficient and where $r=0$ denotes risk neutral behavior, $r>0$ denotes risk aversion behavior and $r<0$ denotes risk loving behavior.

To describe subjects' risk preference tasks, let the expected utility (EU) of lottery i be written as:

(3) $EU_i = \sum_{j=1,2} \left(p\left(M_j\right) \cdot U\left(M_j\right) \right)$

where $p\left(M_j\right)$ are the probabilities for each outcome M_j that are induced by the experimenter (i.e., columns 1, 3, 5 and 7 in Tables 2, 3 and 4). To explain choices between lotteries, we utilize the stochastic specification originally suggested by Fechner and popularized by Hey and Orme (1994). In particular, the following index:

(4) $\nabla EU = \left(EU_B - EU_A \right) / \mu$

is then calculated where EU_A and EU_B refer to expected utilities of options A and B (the left and right lottery respectively, as presented to subjects), and where μ is a noise parameter that captures decision making errors. The latent index is linked to the observed choices using a standard cumulative normal distribution function $\Phi\left(\nabla EU\right)$, which transforms the argument into a probability statement. We modified equation (2) to include Wilcox's (2011) proposed "contextual utility" specification:

(5) $\nabla EU = \left(\left(EU_B - EU_A \right) / c \right) / \mu$

In (5), c is a normalizing term, defined as the maximum utility over all prizes in a lottery pair minus the minimum utility over all prizes in the same lottery pair. It changes from lottery pair to lottery pair, and thus it is said to be contextual.

The conditional log-likelihood can then be written as:

(6) $\ln L\left(r, \mu; y, \mathbf{X}\right) = \sum_i \left(\left(\ln \Phi\left(\nabla EU\right) \mid y_i = 1 \right) + \left(\ln\left(1 - \Phi\left(\nabla EU\right)\right) \mid y_i = -1 \right) \right)$

where $y_i = 1(-1)$ denotes the choice of the option B (A) lottery in the risk preference task i. Subjects were allowed to express indifference between choices and were told that if that choice was selected to be played out, the computer would randomly choose one of the two options for them and that both choices had equal chances of being selected. The likelihood function for indifferent choices is constructed such that it implies a 50/50 mixture of the likelihood of choosing either lottery:

(7) $$\ln L(r,\mu;y,\mathbf{X}) = \sum_i \begin{pmatrix} \left(\ln \Phi(\nabla EU) \mid y_i = 1\right) + \left(\ln\left(1-\Phi(\nabla EU)\right) \mid y_i = -1\right) \\ + \left(\frac{1}{2}\ln \Phi(\nabla EU) + \frac{1}{2}\ln\left(1-\Phi(\nabla EU)\right) \mid y_i = 0\right) \end{pmatrix}$$

The parameter *r* in equation (7) can be allowed to be a linear function of treatment variables, namely the three risk aversion tasks as well as the payoff size variable and the respective interactions. Equation (7) is maximized using standard numerical methods. The statistical specification also takes into account the multiple responses given by the same subject and allows for correlation between responses by clustering standard errors, which were computed using the delta method.

For the original H&L task and the non-linear probability H&L task, we can extend the analysis by accounting for probability weighting. Rank Dependent Utility (Quiggin, 1982) extends the EUT model by allowing for decision weights on lottery outcomes. To calculate decision weights under RDU, one replaces expected utility in equation (3) with:

(8) $$EU_i = \sum_{j=1,2}\left(w\left(p\left(M_j\right)\right)\cdot U\left(M_j\right)\right) = \sum_{j=1,2}\left(w_j \cdot U\left(M_j\right)\right)$$

where $w_2 = w(p_2 + p_1) - w(p_1) = 1 - w(p_1)$ and $w_1 = w(p_1)$, with outcomes ranked from worst (outcome 2) to best (outcome 1) and $w(\cdot)$ is the weighting function. We assume $w(\cdot)$ takes the form proposed by Tversky and Kahneman (1992):

(9) $$w(p) = p^{\gamma} \Big/ \left[p^{\gamma} + (1-p)^{\gamma}\right]^{1/\gamma}$$

When $\gamma = 1$, it implies that $w(p) = p$ and this serves as a formal test of the hypothesis of no probability weighting.

As with the CRRA parameters, we can condition γ on a vector of treatment variables. However, because γ is – by definition – unidentified in the modified constant probability H&L task, γ is set to one for these treatments, and these treatment variables do not enter the γ function.

4.3. Results

Table 5 shows the estimates of the model when it is assumed that EUT explains observed choices (i.e., there is no probability weighting). The constant term, 0.571, represents the CRRA for the conventional H&L task at the low-payoff amounts, and it is generally consistent with prior estimates of CRRA obtained in other experimental studies. Results show that the constant probability H&L task suggests significantly lower CRRA (0.687 lower to be precise) for subjects in the x1 Task as compared to the standard H&L task. The interaction term *Constant prob H&L · x5Task* is positive and statistically significant, implying that our modified task elicits higher risk aversion than the H&L task when lottery prizes are scaled up. The constant probability task implies slightly risk loving preferences in the x1 task (0.571-0.687= -0.116) and risk aversion in the x5 task (0.571-0.687+0.027+0.897=0.808), implying increasing relative risk aversion. That the *x5Task* task variable is insignificant suggests the conventional H&L task was invariant to scale of payoffs.

Table 5. CRRA estimates assuming EUT

	Estimate	Std. Error	95% Confidence Interval	
Constant prob H&L	-0.687**	0.214	-1.107	-0.267
Non-linear prob H&L	-0.002	0.063	-0.126	0.121
x5Task	0.027	0.068	-0.106	0.159
Constant prob H&L · x5Task	0.897**	0.230	0.447	1.347
Non-linear prob H&L · x5Task	0.094	0.085	-0.073	0.260
Constant	0.571**	0.066	0.441	0.701
μ	0.249**	0.019	0.211	0.286
N=5040, Log-pseudolikelihood= -2413.535				

Note: **, * = Significance at 5%, 10% level.

In Table 6, we allow for probability weighting. A Wald test of whether $\gamma = 1$ rejects the null, implying that probability weighting better characterizes subject's choices. The constant term in the γ function corresponds to the degree of probability weighting for the low-payout, conventional H&L task. Unlike many previous estimates in which γ is estimated in the 0.5 to 1.0 range, we find $\gamma = 3.1$. Such an estimate implies significant under-weighting of all probabilities. In our case, we define $w(p)$ as the weight attached to the high-payout outcome and $1\text{-}w(p)$ as the weight attached to the low-payout outcome. Thus, the results imply people under-weight the likelihood of receiving the high payouts and over-weight the likelihood of receiving the low payouts. Given the magnitude of γ, the results imply that unless the probability of receiving the high payout is at least p=0.2, it is virtually ignored (i.e., subjects act as if receiving the high payoff was impossible for p<0.2 in which case $w(p) \approx 0$). In fact, the results are entirely consistent with an attitude of pessimism in that subjects discount the likelihood of receiving the better payout.

Although our findings regarding γ, are a bit unusual, they are not totally unrealistic. In particular, as shown in figure 4, even at conventional estimates of γ, say γ=0.6, individuals also under-weight probabilities at probabilities greater than about 0.35. Given that the conventional H&L does not entail choices over very low probability risks (i.e., $p < 0.05$), where heavy over-weighting is thought to exist, it may not be particularly well suited to estimate γ, which is another reason to support the use of our modified constant probability task. Nevertheless, we should note that our estimate of γ is influenced by modeling choices. In particular, if we ignore the "contextual utility" specification suggested by Wilcox (2011), our estimate of γ in the control condition is 0.79, which is more similar to previous estimates. If we keep the "contextual utility" specification but instead specify the weighting function, $w(p)$, to apply to the lower payoff events (rather than the higher payoff events), the estimate of γ in the control condition is 0.82. Nevertheless, neither of these alternative specifications provide a better fit to the data. They do, however, highlight the challenges in trying to control for probability weighting with the conventional H&L task; a task that is unnecessary with our new modified task.

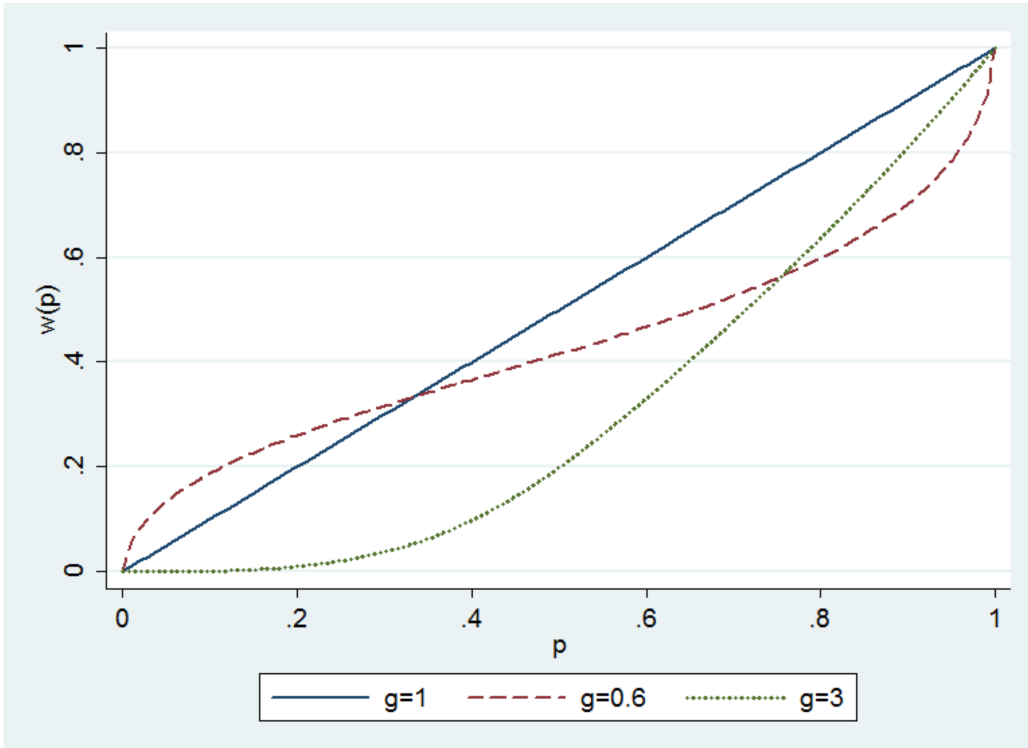

Figure 4. Comparison of probability weighting functions for three gamma (g) values

The important point is that regardless of the model specification, individuals appear to weight probabilities non-linearly; a fact that could produce misleading estimates of CRRA in the traditional H&L task. Moreover, with all specifications we have considered, when one accounts for such probability weighting, the estimate of the CRRA in the traditional H&L task *falls* related to the EUT specification that assumes linear probability weighting.

Table 6 also reports the effects of the various treatment combinations on the CRRA. Note that the estimated constant is 0.009, implying that the H&L task elicits approximately risk neutral preferences under RDU. The *Constant prob H&L · x5Task* interaction term is significant and positive implying risk averse behavior in the modified HL when we scale up payoffs. The *Non-linear prob H&L · x5Task* is also statistically significant which implies that risk aversion increases in the non-linear probability H&L

task along with payoff prizes, although the magnitude of increasing relative risk aversion is far less than that implied by the constant-probability task.

Table 6. CRRA and probability weighting function curvature estimates

	Estimate	Std. Error	95% Confidence Interval	
r				
Constant prob H&L	-0.197	0.247	-0.681	0.288
Non-linear prob H&L	0.088	0.133	-0.173	0.349
x5Task	-0.064	0.105	-0.270	0.143
Constant prob H&L · x5Task	1.076**	0.274	0.540	1.612
Non-linear prob H&L · x5Task	0.290*	0.173	-0.049	0.629
Constant	0.009	0.106	-0.200	0.218
γ				
Non-linear prob H&L	0.141	0.496	-0.830	1.113
x5Task	0.390	0.379	-0.353	1.133
Non-linear prob H&L · x5Task	-0.828	0.596	-1.997	0.340
Constant	3.116**	0.374	2.383	3.848
μ	0.278**	0.015	0.248	0.307
N=5040, Log-pseudolikelihood= -2368.143				

Note: **, * = Significance at 5%, 10% level.

To flesh out the implications of our findings, Table 7 shows predicted mean CRRA's and confidence intervals (implied by the models in tables 5 and 6) by treatment under the assumptions of EUT and RDU. As expected, and by construction, our constant probability task generates virtually identical estimates of CRRA regardless of whether EUT or RDU is assumed. In the constant probability task, the estimated CRRA implies risk neutrality for low payoffs and risk aversion for higher payoffs, r =0.81.

Table 7. Predicted Coefficients of Relative Risk Aversion by Treatment

		x1 Task			*x5 Task*		
		CRRA	95% Confidence Interval		RRA	95% Confidence Interval	
H&L	*EUT*	0.571	0.441	0.701	0.598	0.457	0.738
	RDU	0.009	-0.200	0.218	-0.055	-0.283	0.174
Constant prob H&L	*EUT*	-0.116	-0.535	0.302	0.807	0.533	1.081
	RDU	-0.188	-0.641	0.265	0.825	0.525	1.125
Non-linear prob H&L	*EUT*	0.569	0.408	0.729	0.689	0.545	0.833
	RDU	0.097	-0.160	0.355	0.324	0.111	0.536

Table 7 reveals that without accounting for non-linear probability weighting, the conventional H&L task implies risk aversion, r = 0.57. It is only when one estimates a RDU model that risk neutrality is implied – a finding which matches with our constant probability task. The conventional H&L task suggests constant CRRA across low and high-payouts, however, our constant probability task implies increasing relative risk aversion. The non-linear probability H&L task shows falls between these two with evidence of slightly increasing relative risk aversion.

5. Conclusions

Although H&L introduced a useful tool for characterizing risk taking behavior, their approach is not able to identify why a particular behavior under risk was observed. Risk averse behavior could result from curvature of the utility function, curvature of the probability weighting function, or both. The obvious implication is that caution should be taken in directly using behavior from H&L's risk preference elicitation method to infer curvature of the utility function, the theoretical concept that is often of interest, because risk averse behavior may be driven by probability weighting.

We introduced a modified version of the H&L task which, by construction, rules out probability weighting as a driver of lottery choice. At low payoff amounts, we find approximate risk neutral behavior in our new task – a finding only implied by the conventional H&L task after an econometric model allowing for probability weighting is fit to the conventional H&L data. At high payoff amounts, we find significant levels of risk aversion in our modified decision task, with an estimate of the coefficient of relative risk aversion of about 0.8. However, once one accounts for non-linear probability weighting via an econometric model, the conventional H&L task suggests approximate risk neutral preferences at high payouts.

The advantage of the experimental approach is the ability to isolate the causal effects of factors of interest. Our new approach allows one to isolate the effects of key variables, such as the scale of payoffs, on the curvature of the utility function without having to make any assumptions about the extent to which people weight probabilities non-linearly.

References

Andersen, S., G.W. Harrison, M.I. Lau, & E.E. Rutstrom. (2008). Eliciting risk and time preferences. *Econometrica 76*:583-618.

Andersen, S., G.W. Harrison, M.I. Lau, & E.E. Rutström. (2011). Discounting behavior: A reconsideration. *Center for the Economic Analysis of Risk, Working Paper 2011-03*.

Becker, G.M., M.H. Degroot, & J. Marschak. (1964). Measuring utility by a single-response sequential method. *Behavioral Science 9*:226-232.

Bellemare, C., & B. Shearer. (2010). Sorting, incentives and risk preferences: Evidence from a field experiment. *Economics Letters 108*:345-348.

Binswanger, H.P. (1980). Attitudes toward risk: Experimental measurement in rural India. *American Journal of Agricultural Economics 62*:395-407.

Binswanger, H.P. (1981). Attitudes toward risk: Theoretical implications of an experiment in rural India. *The Economic Journal 91*:867-890.

Bruner, D., M. McKee, & R. Santore. (2008). Hand in the cookie jar: An experimental investigation of equity-based compensation and managerial fraud. *Southern Economic Journal 75*:261-278.

Camerer, C.F., & T.-H. Ho. (1994). Violations of the betweenness axiom and nonlinearity in probability. *Journal of Risk and Uncertainty 8*:167-196.

Eckel, C.C., & R.K. Wilson. (2004). Is trust a risky decision? *Journal of Economic Behavior & Organization 55*:447-465.

Fischbacher, U. (2007). z-Tree: Zurich Toolbox for Ready-made Economic Experiments. *Experimental Economics 10*:171-178.

Glöckner, A., & G. Hochman. (2011). The interplay of experience-based affective and probabilistic cues in decision making. *Experimental Psychology 58*:132-141.

Greiner, B. (2004). An Online Recruitment System for Economic Experiments. In: Kurt Kremer, Volker Macho (Hrsg.): Forschung und wissenschaftliches Rechnen. GWDG Bericht 63. Ges. für Wiss. Datenverarbeitung, Göttingen, 79-93.

Harrison, G.W., E. Johnson, M.M. McInnes, & E.E. Rutström. (2005). Risk aversion and incentive effects: Comment. *The American Economic Review 95*:897-901.

Harrison, G.W., M.I. Lau, & E.E. Rutström. (2009). Risk attitudes, randomization to treatment, and self-selection into experiments. *Journal of Economic Behavior & Organization 70*:498-507.

Hey, J.D., & C. Orme. (1994). Investigating generalizations of expected utility theory using experimental data. *Econometrica 62*:1291-1326.

Holt, C.A., & S.K. Laury. (2002). Risk aversion and incentive effects. *The American Economic Review 92*:1644-1655.

Holt, C.A., & S.K. Laury. (2005). Risk aversion and incentive effects: New data without order effects. *The American Economic Review 95*:902-904.

Lusk, J.L., & K.H. Coble. (2005). Risk perceptions, risk preference, and acceptance of risky food. *American Journal of Agricultural Economics 87*:393-405.

Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior & Organization 3*:323-343.

Tversky, A., & D. Kahneman. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty 5*.
Wakker, P., & D. Deneffe. (1996). Eliciting von Neumann-Morgenstern utilities when probabilities are distorted or unknown. *MANAGEMENT SCIENCE 42*:1131-1150.
Wilcox, N.T. (2011). 'Stochastically more risk averse:' A contextual theory of stochastic discrete choice under risk. *Journal of Econometrics 162*:89-104.
Wu, G., & R. Gonzalez. (1996). Curvature of the Probability Weighting Function. *MANAGEMENT SCIENCE 42*:1676-1690.