Visual formats in risk preference elicitation: What catches the eye?

Segovia, Michelle and Palma, Marco and Lusk, Jayson L. and Drichoutis, Andreas

University of Missouri, Columbia, United States, Texas AM University, College Station, United States, Purdue University System, West Lafayette, United States, Agricultural University of Athens, Athens, Greece

8 December 2022

Visual formats in risk preference elicitation: What catches the eye?*

Michelle Segovia†1, Marco A. Palma‡2, Jayson L. Lusk§3, and Andreas C. Drichoutis¶4

[1]University of Missouri
[2]Texas A&M University
[3]Purdue University
[4]Agricultural University of Athens

Abstract: We explore the effect of different presentation formats on elicitation of risk preferences using a popular probability-varying task (Holt and Laury, 2002) and a payoff-varying task (Drichoutis and Lusk, 2016). The presentation formats use horizontal bars that vary either the width or height of the bars (or both at the same time) to potentially help subjects in judging how large or small probabilities and monetary amounts are in a given choice task. These graphical formats are compared to a text only format. We complement our data collection with eye-tracking data that enriches our structural models with additional information regarding how visual attention and engagement vary with the presented information. While we find no statistically significant effects of presentation formats on elicited parameters for risk preferences, we find that eye-tracking information not only is associated with preference parameters, but it also changes the inferences with respect to which decision theory better fits our data.

Keywords: Risk, Individual decision making, Visual attention, Eye tracking

JEL codes: D81, D83, C91

---

*Part of this work was completed while Andreas Drichoutis was a Fulbright Visiting Scholar at Texas A&M University under the Greek Scholarship program 2021-2022. Data and codes to replicate the analysis have been deposited with the Open Science Framework.

†Assistant Professor, Department of Agricultural and Applied Economics, University of Missouri, e-mail:segoviacoronelm@missouri.edu.

‡Professor and Director Human Behavior Laboratory, Department of Agricultural Economics, Texas A&M University, College Station, TX 77843 USA, tel:+1-9798455284 e-mail: mapalma@tamu.edu.

§Distinguished Professor and Head, Department of Agricultural Economics, Purdue University, 403 W. State St, West Lafayette, IN 47907-2056, USA, e-mail: jlusk@purdue.edu.

¶Associate Professor, Department of Agricultural Economics & Rural Development, School of Applied Economics and Social Sciences, Agricultural University of Athens, Iera Odos 75, 11855, Greece, e-mail: adrihout@aua.gr.

1 Introduction

Risk is an inherent part of life and a central aspect in all domains of economic analysis that study choices between alternatives yielding uncertain outcomes. For example, decisions about occupation, education, finances or health behavior, regularly involve at least some degree of risk. The extant literature on risk preference elicitation has been using a variety of methods in order to measure risk and multiple price lists (MPLs) are likely one of the most popular approaches in experimental economics (see Charness et al. (2013) or Hey and Zhou (2014) for reviews of the literature).

In an MPL, individuals make a series of choices between a safe and a risky option. Risk preferences can then be determined by the switching point from the safe to the risky option (Andersen et al., 2006) or more nuanced methods can be used that allow identifying parameters of various theories of risk (e.g., Harrison and Rutström, 2009).[1] MPLs are appealing because they are simple and easy for subjects to understand, but they also have disadvantages. First, the behavioral responses to the MPL task may be sensitive to the presentation format, framing, and ordering (Harrison et al., 2005; Andersen et al., 2006). Second, an MPL could be susceptible to multiple switching behavior (potentially inconsistent preferences), as subjects switch from the safe to the riskier option and switch back to a safe option in a subsequent decision (Deck et al., 2014; Hirschauer et al., 2014; Charness et al., 2016).

Previous literature provides several possible explanations for the inconsistent behavior including participants' lack of comprehension of the elicitation method (Bruner, 2011; Reynaud and Couture, 2012), boredom and fatigue (Lévy-Garboua et al., 2012), confusion due to context framing (Rommel et al., 2017) and consequentiality of low monetary incentives (Holt and Laury, 2002), among others.[2] Third, depending on the MPL type (i.e., whether the MPL varies the monetary payoff or the probability across choices), researchers are more likely to capture information on either the curvature of the utility function or the curvature of the probability weighting function (Drichoutis and Lusk, 2016). In fact, Drichoutis and Lusk (2016) (DL) show that the Holt and Laury (2002) MPL is likely more accurate at eliciting the shape of the probability weighting function while a payoff-varying MPL, constructed by the authors, is likely more accurate at eliciting the shape of the utility function. Among the different types of MPLs, the Holt and Laury (2002) (HL) MPL with varying probabilities and fixed monetary amounts is likely one of the most used ones in the economics literature.[3] Perhaps because of the method's popularity, it has been heavily scrutinized, and in many cases, found lacking. We contribute

[1] See Andersen et al. (2006) for a discussion on the advantages and drawbacks of the use of MPL designs to measure risk aversion.

[2] Multiple switching behavior may also imply thick indifference curves and structural econometric methods offer ways to account for it through noise or behavioral errors.

[3] Note however, that Holt and Laury (2002) also used scaled up versions of their main task (in terms of payoffs) so that across tasks, monetary amounts differ as well.

to this quest for refinement in risk preference elicitation by bringing eye-tracking technology to bear scrutiny to decision making processes associated with the presentation format of the lotteries.

The main objective of this article is to investigate the role of the presentation format of MPLs on elicited risk preferences. We build on the experimental findings of Harrison and Swarthout (2019) suggesting that decision-making processes regarding risk preference elicitation may be influenced by the attention subjects pay to information regarding the probabilities in choice tasks. By combining lottery choice tasks with process data from a laboratory experiment, Harrison and Swarthout (2019) show that the percentage of time subjects spend looking at probabilities is associated with greater decision-making using Expected Utility Theory (EUT) rather than Rank Dependent Utility (RDU). An immediate implication from this result is that using alternative designs that shift attention to probabilities, may encourage decision-making processes that mitigate probability weighting and generate choices that are consistent with EUT.

In this paper, we test for the effect of visual formats on risk preferences elicited through the original HL task and an equivalent payoff-varying MPL as in Drichoutis and Lusk (2016). We present subjects with graphical display formats that emphasize either monetary amounts or probabilities, or both and compare these treatments with a purely text format. In addition, we examine how eye-tracking data may augment conventional choice models by combining responses from both MPL types with eye-tracking measures of visual attention. Although a few studies have examined the effect of MPL formats on risk preferences, the use of eye-tracking to investigate decision-making processes under different display formats is limited. By capturing eye tracking data associated with different MPL formats, we are able to compare attention patterns in the processing of lottery attributes between a standard textual format and more rich visual format representations.

Relative to the standard MPL in textual format, visual display formats have been used when eliciting risk attitudes to facilitate subjects' understanding and reduce multiple switching behavior. For example, graphical or visual support in the display format of the lotteries has proven effective at improving participants' understanding of MPL tasks and thus reducing inconsistency rates (Charness et al., 2016). Lotteries are often presented to subjects in a textual format (using numbers), with few experiments adopting pictorial representations. To improve subjects understanding of the elicitation tasks, Zhou and Hey (2018) chose to visually display lotteries on the subjects' computer screens in two dimensions, with payoffs on the vertical axis and the probabilities on the horizontal axis. Therefore, changes in the length and width of vertical bars emphasized variations of payoff amounts and probabilities, respectively. Drichoutis and Lusk (2016) employed three types of MPLs in which lottery choices were displayed using pie charts, with different colors showing probabilities. However, the effect of display format of lotteries on risky choices goes beyond the purpose of the studies mentioned above.

Just a few studies in the economics literature have examined the impact of different MPL formats on risk preferences. Some preliminary evidence is provided by Habib et al. (2017) who compare risk choices made across five different MPL display tasks; an original text-only presentation and four (graphical) display tasks using rotatable three-dimensional pie charts to represent the gambles. The graphical display treatments vary on the type of text labels presented next to the pie charts to highlight price amounts, probabilities, both amounts and probabilities, or none. They find that graphical displays of lotteries reduce risk aversion (i.e., make subjects more risk-neutral). Although it is possible that most subjects are risk neutral towards small-stake gambles, some of the subjects may not be sufficiently numerate to calculate and compare expected values in text-based presentation formats.[4] The authors conjecture that by making the expected value of a lottery more salient through visual representations, subject's approximations of expected value would improve. Friedman et al. (2022) also examine the impact of text versus spatial representation of lotteries by comparing choices made under the HL MPL (text format) and the Budget Dots HL (spatial representation). They find less risk aversion in the Budget Dots HL task which suggests that presenting information via spatial representations shifts choice behavior towards risk neutrality.

Perhaps the closest to our study is the experiment by Bauermeister and Mußhoff (2019) which tests the effect of textual and visual display formats on two types of MPLs, a probability equivalence (PE) task and a certainty equivalence (CE) task. In the textual format, the authors found less multiple switching behavior in the CE task than the PE task; however, no difference across tasks was found in the visualized format. When comparing the display formats within MPL tasks, a reduction in multiple switching behavior was found when the PE task is displayed visually but no impact was found in the CE task. Two main differences between Friedman et al. (2022) and our study can be drawn. First, lottery options in their visual formal treatment were displayed using bags with ten colored balls in each. The balls varied in colors (and proportion by color) to represent changes in monetary outcomes or probabilities, depending on the MPL task.[5] Our treatments allow us to differentiate the effect of visual format when monetary outcomes, probabilities, or both are made salient to subjects in two MPL settings. Second, we record subjects' eye movements while performing the MPL tasks which provide us with insights on how their attention level and engagement vary with the format presented.

[4]Previous studies have shown that subjects with low numeracy tend to exhibit greater risk-aversion towards small-stake gambles (Cokely and Kelley, 2009; Benjamin et al., 2013; Schley and Peters, 2014); however, these studies rely on symbolic (e.g., with numbers) rather than visual lottery displays.

[5]The PE task with varying probabilities and fixed monetary outcomes is similar to the HL probability-varying task used in our experiment, while the CE task with fixed probabilities and varying payout amounts is representative of the DL payoff-varying task. For the PE task, different colors represented the various fixed monetary amounts. From one lottery decision (row) to the next, the composition of colored balls varied to represent changes in probabilities. For the CE task, the composition of colored balls remained fixed across lottery decisions to represent fixed probabilities.

In the economics literature, few studies use eye tracking to examine whether individuals' eye movement patterns are correlated with the choices they make. An early study by Arieli et al. (2011) employs a laboratory eye-tracking experiment to investigate if subjects' eye movements follow patterns consistent with EUT when choosing between two lotteries. They find that eye movements are more consistent with EUT when the expectations are relatively easy to calculate than when expectations are difficult to calculate. In the latter case, eye patterns indicate that subjects evaluate prizes and lotteries separately. Aimone et al. (2016) extend this work and find that subjects with decisions consistent with EUT tend to collect information in a manner consistent with calculating the expected value of each gamble. Subjects who do not collect information in this manner are more likely to choose the safer gamble. In both studies, the lotteries are presented in standard text format.

More recently, Barrafrem and Hausfeld (2020) use eye tracking to evaluate how individuals make risky decisions for themselves versus others. The results show that subjects spend less time, have less fixations, and inspect less information when deciding for others; that is, subjects employ less cognitive processing when deciding for other people. This is consistent with the assumption that cognitive effort is costly and utility maximizing agents reduce effort if there is no personal gain from it. Kee et al. (2021) test if the use of an eye tracking device itself induces changes in risk aversion behavior. Upon controlling for the quality of eye tracking data, the authors find no eye-tracking effect on elicited risk aversion. Previous studies in the psychology literature have also used eye movement data to understand the cognitive mechanisms underlying preference formation when making risky choices. Harrison and Swarthout (2019) review the literature on eye tracking studies in relation to risk preference elicitation from 1976 to 2016.

This paper is organized as follows. In Section 2, we describe the risk preference elicitation methods of our experiment and how the eye-tracking data were collected. As we use standard structural models to estimate risk preferences parameters, we specify, in Section 3, the theory and econometrics surrounding our estimations. Section 4 presents our results and we conclude in Section 5.

2 Methods

2.1 Incentivized elicitation of risk preferences

Subjects' risk preferences were elicited using Holt and Laury's (2002) probability-varying task and Drichoutis and Lusk's (2016) payoff-varying task. Drichoutis and Lusk (2016) have shown that greater predictive performance of choices can be achieved by combining information from the HL task and the DL task. This is because the HL task varies the probabilities of the lottery choices and provides a better approximation of the curvature of the probability weighting

Table 1: The Holt and Laury (2002) risk preference task

Lottery A				Lottery B				EV_A €	EV_B €	EV difference
p	€	p	€	p	€	p	€			
0.1	10	0.9	8	0.1	19.25	0.9	0.5	8.2	2.38	5.83
0.2	10	0.8	8	0.2	19.25	0.8	0.5	8.4	4.25	4.15
0.3	10	0.7	8	0.3	19.25	0.7	0.5	8.6	6.13	2.48
0.4	10	0.6	8	0.4	19.25	0.6	0.5	8.8	8.00	0.80
0.5	10	0.5	8	0.5	19.25	0.5	0.5	9.0	9.88	-0.88
0.6	10	0.4	8	0.6	19.25	0.4	0.5	9.2	11.75	-2.55
0.7	10	0.3	8	0.7	19.25	0.3	0.5	9.4	13.63	-4.23
0.8	10	0.2	8	0.8	19.25	0.2	0.5	9.6	15.50	-5.90
0.9	10	0.1	8	0.9	19.25	0.1	0.5	9.8	17.38	-7.58
1	10	0	8	1	19.25	0	0.5	10.0	19.25	-9.25

Notes: EV stands for Expected Value.

function (if subjects weigh probabilities non-linearly), while the DL task varies the monetary amounts, providing better approximation of the curvature of the utility function. In the HL task, individuals are asked to make a series of 10 decisions between two lottery options (see Table 1). Table 2 shows the DL payoff varying task that keeps the probabilities constant across the 10 decision sets and instead changes the monetary payoffs across the 10 choice sets. Both tasks are constructed in a way that the expected value of lottery A exceeds the expected value of lottery B for the first four decision tasks. Thus, under Expected Utilty Theory (EUT), a risk neutral person should prefer lottery A for the first four decision tasks and then switch to lottery B for the remainder of the decision tasks. For both tasks, administered payoffs were five times the standard payoffs normally used in these tasks and each decision task was presented on a separate screen (Brown and Healy, 2018). The order of the tasks was varied across subjects; that is, half of the subjects completed the HL task first, followed by the DL task, and the other half completed the two tasks in the opposite order. At the end of the session, one of the 20 choice sets was randomly selected for payment using a bingo cage containing 20 numbered balls. Then, a bingo cage containing 100 balls, numbered 1-100, was used to determine the event in the binding choice set.

Table 2: The Drichoutis and Lusk (2016) task

Lottery A				Lottery B				EV_A €	EV_B €	EV difference
p	€	p	€	p	€	p	€			
0.5	8.40	0.5	8	0.5	10.05	0.5	5	8.20	7.53	0.67
0.5	8.80	0.5	8	0.5	10.85	0.5	5	8.40	7.93	0.48
0.5	9.20	0.5	8	0.5	11.60	0.5	5	8.60	8.30	0.30
0.5	9.60	0.5	8	0.5	12.40	0.5	5	8.80	8.70	0.10
0.5	10.00	0.5	8	0.5	13.25	0.5	5	9.00	9.13	-0.13
0.5	10.40	0.5	8	0.5	14.30	0.5	5	9.20	9.65	-0.45
0.5	10.80	0.5	8	0.5	15.70	0.5	5	9.40	10.35	-0.95
0.5	11.20	0.5	8	0.5	17.70	0.5	5	9.60	11.35	-1.75
0.5	11.60	0.5	8	0.5	22.50	0.5	5	9.80	13.75	-3.95
0.5	12.00	0.5	8	0.5	23.50	0.5	5	10.00	14.25	-4.25

Notes: EV stands for Expected Value.

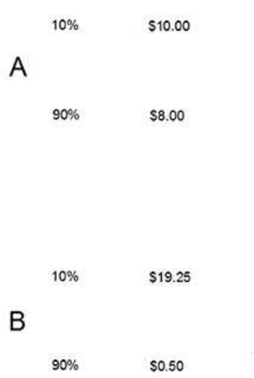
2.2 Experimental design and procedure

Our experiment consisted of a between-subject design where the presentation format of the lottery choices in the HL and DL tasks was the manipulating factor. Participants randomly received one of four presentation format treatments: i) Text format or control, ii) Emphasis on probabilities, iii) Emphasis on monetary amounts, and iv) Emphasis on monetary amounts and probabilities. In the 'Emphasis on probabilities' format treatment, lotteries were visually displayed using horizontal graphic bars that varied in height to emphasize the probability of the lottery options. In the 'Emphasis on monetary amounts' format treatment, the length of the horizontal bars varied to highlight changes in the monetary amounts of the lottery options across choice sets. Both the height and length of the horizontal bars were modified in the 'Emphasis in monetary amounts and probabilities' format treatment to make changes in probabilities and monetary amounts salient. No graphs were used in the text format treatment which serves as our control. Figures 1 and 2 present samples of the presentation format treatments for the HL task and DL task, respectively. Experimental instructions are available in the Electronic Supplementary Material (Section 5).

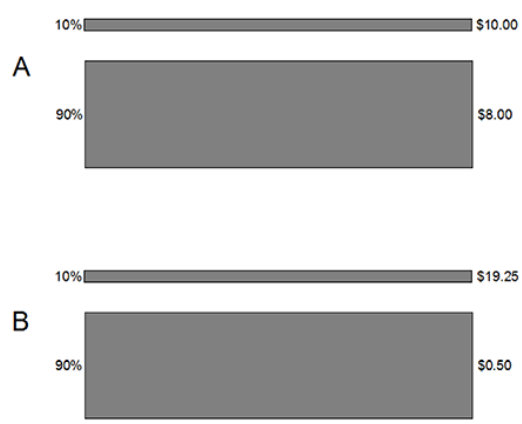
The experiment was combined with eye tracking and computerized in iMotions (iMotions, 2014). In total, 206 undergraduate students from a large university in the South region of the U.S. completed the experiment albeit one subject was excluded from all further analysis because s/he did not exhibit any variation in any of their choices (i.e., s/he always chose lottery B). To qualify for the study, participants had to be at least 18 years old, without an eye corrective surgery. The experimental sessions lasted approximately 30 minutes and were held individually (one subject at the time) at different times in the day (from 8 am to 6 pm) in order to randomize any time of the day effects. The experimental earnings were described as a $10 show-up fee

Figure 1: Example of first lottery choice set by treatment (Holt and Laury, 2002, task)

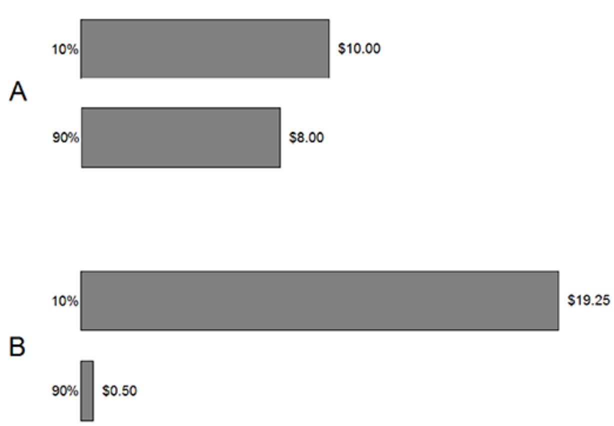
(a) Text format



(b) ‘Emphasis on probabilities’ format



(c) ‘Emphasis on monetary amounts’ format

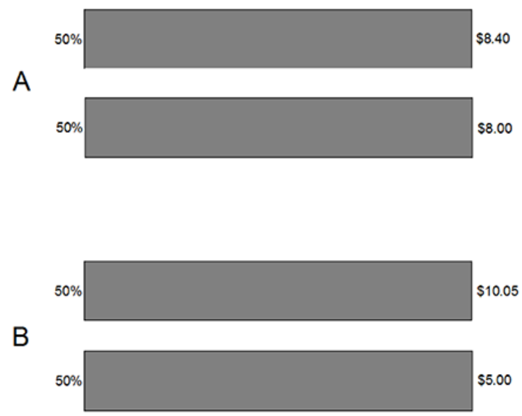


(d) ‘Emphasis on both monetary amounts and probabilities’ format

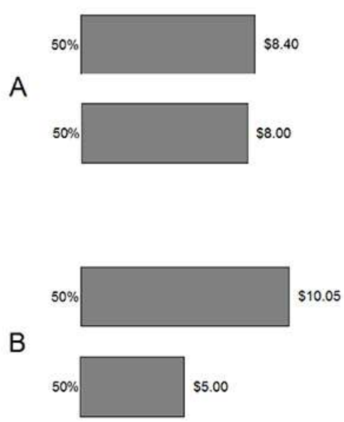
Figure 2: Example of first lottery choice set by treatment (Drichoutis and Lusk, 2016, task)

(a) Text format

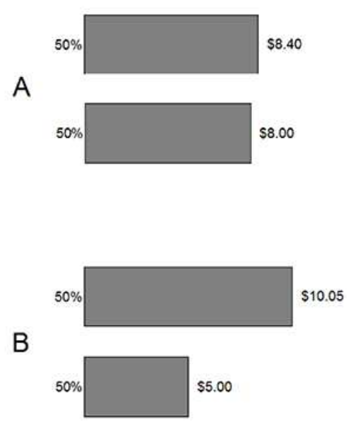
(b) 'Emphasis on probabilities' format



(c) 'Emphasis on monetary amounts' format



(d) 'Emphasis on both monetary amounts and probabilities' format



plus the potential to earn extra money depending on the decisions taken during the experiment. Cash payments were received in coded envelopes at the end of the experiment. Average total payoffs including lottery earnings were \$20.63 (S.D. = 6.34). The study received ethical approval from the University's Institutional Review Board.

2.3 Eye tracking

Subjects' eye movements were recorded with a remote (screen-based) Tobii TX300 eye tracking device (Tobi, 2014). The device utilizes near-infrared technology in combination with a high-resolution camera to track gaze direction at a sampling rate of 120 Hz (i.e., 120 observations per second) and gaze accuracy of 0.4°.[6] The screen-based eye tracker required the participant to sit in front of the computer screen with the embedded eye tracker, keeping a distance between the participant's eyes and the eye tracker of 50-80 cm. The technology is non-intrusive (nothing to attach to the participant) and freedom of movement was allowed within the eye tracker's limit. Subjects were told that their eye movements would be tracked during the experiment, however they did not know its purpose. The stimuli were presented using the iMotions platform on a 23" monitor with a screen resolution of 1920 x 1080 pixel.

To measure subjects' visual attention toward specific lottery attributes, we created Areas of Interest (AOIs) by defining subregions of the displayed stimuli. This allowed us to extract eye tracking metrics for separate AOIs such as probabilities, monetary amounts, and graphic horizontal bars. We use time dwell (in milliseconds) to quantify the amount of time that respondents spent looking at an AOI. Our analysis includes AOIs for probabilities, monetary amounts, and graphic bars for each lottery option, for a total of 12 AOIs per choice decision (with the exception of the text-only format where no graphical displays were used). In addition, we used a second eye tracking metric, pupil size, to measure the amount of emotional arousal or engagement subjects exhibited towards the lottery stimuli.[7]

3 Theory and econometrics of risk preferences

We use standard structural models to estimate risk preferences parameters (Andersen et al., 2008, 2014, 2013). Let the utility function be the constant relative risk aversion (CRRA) specification[8]: $U(M) = \frac{M^{1-r}}{1-r}$, where r is the relative risk aversion (RRA) coefficient, $r = 0$

[6] The mechanism behind the eye tracking technology is often referred to as Pupil Center Corneal Reflection (PCCR), as the light reflecting from the cornea and the center of the pupil are used to inform the device on the eye movement and direction (citation).

[7] Although pupillary responses are often used as a measure for emotional arousal, they do not provide an indication of whether arousal arises from negative or positive reactions toward the stimulus.

[8] Constant relative risk aversion, rather than increasing or decreasing relative risk aversion, is a realistic assumption given the narrow range of prizes paid out in the lottery choice tasks (Holt and Laury, 2002).

denotes risk neutral behavior, $r > 0$ denotes risk aversion behavior and $r < 0$ denotes risk loving behavior. If we assume that Expected Utility Theory (EUT) describes subjects' risk preferences, then the expected utility of lottery i can be written as:

$$EU_i = \sum_{j=1,2} p_i(M_j)U(M_j) \tag{1}$$

where $p(M_j)$ are the probabilities for each outcome M_j that are induced by the experimenter as per Tables 1 and 2. A popular alternative to EUT is Rank Dependent Utility (RDU) developed by Quiggin (1982), which was incorporated into Tversky and Kahneman's (1992) cumulative prospect theory. RDU extends the EUT model by allowing for non-linear probability weighting associated with lottery outcomes.

To calculate decision weights under RDU, one replaces expected utility in equation (1) with:

$$RDU_i = \sum_{j=1,2} w_i[p(M_j)]U(M_j) = \sum_{j=1,2} w_{ij}U(M_j) \tag{2}$$

where $w_{i2} = w_i(p_2 + p_1) - w_i(p_1) = 1 - w_i(p_1)$ and $w_{i1} = w_i(p_1)$ with outcomes ranked from worst to best and $w(\cdot)$ is the probability weighting function. We use Tversky and Kahneman's (1992) (TK) probability weighting function: $w(p) = \frac{p^\gamma}{(p^\gamma+(1-p)^\gamma)^{\frac{1}{\gamma}}}$ (if $\gamma = 1$ it collapses to $w(p) = p$).

We assume subjects have some latent preferences over risk which are linked to observed choices via a probabilistic model function of the general form:

$$Pr(B) = \Lambda\left(\mu\frac{(V_B - V_A)}{D}\right) \tag{3}$$

where $Pr(B)$ is the probability of choosing lottery B (the right hand side lottery), μ is a structural 'noise parameter' (sometimes called a scale or precision parameter) used to allow some errors from the perspective of the deterministic model and V_A, V_B are the decision-theoretic representations of values associated with lotteries A and B. That is, $V_j = EU_j$ for $j = A, B$ if the theory is EU or $V_j = RDU_j$ for $j = A, B$ if the theory is RDU. D reflects a 'contextual utility' error specification which adjusts the scale parameter by $D = V_{max} - V_{min}$, to account for the range of possible outcome utilities (Wilcox, 2008, 2011). D is defined as the maximum utility V_{max} over all prizes in a lottery pair minus the minimum utility V_{min} over all prizes in the same lottery pair and because it changes from lottery pair to lottery pair, it is said to be contextual. $\Lambda : R \rightarrow [0, 1]$ is the standard logistic distribution function with $\Lambda(\zeta) = 1/(1+e^{-\zeta})$, which is to say that this function takes any argument between $\pm\infty$ and transforms it to a number between 0 and 1 (i.e., a probability).

The log-likelihood function can then be written as:

$$\ln L(y) = \sum_{i=1}^{N} \left[(\ln Pr | y_i = 1) + (\ln(1 - Pr) | y_i = -1) \right] \tag{4}$$

where $y_i = 1$ denotes the choice of lottery B and $y_i = -1$ denotes the choice of the A lottery in the risk preference task i.

Equation (4) 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 at the individual level (i.e., it relaxes the independence assumption and requires only that the observations be independent across the clusters). The robust estimator of variance that relaxes the assumption of independent observations involves a slight modification of the robust (or sandwich) estimator of variance which requires independence across all observations (StataCorp, 2013, pp. 312).

4 Results

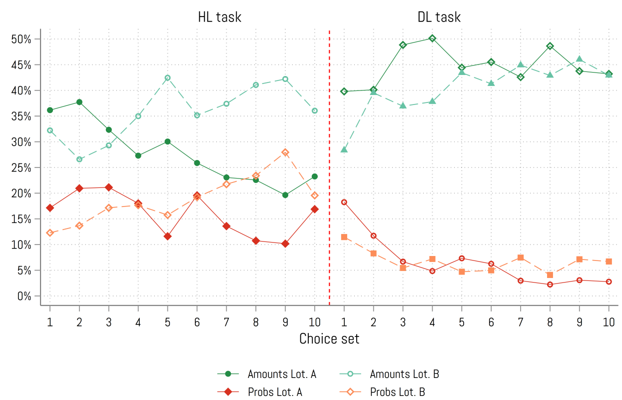
4.1 Eye tracking data

Figure 3 shows visit duration times by Area of Interest (AOI), task and treatment as a percentage of total time spent on any screen. One particular feature that is common across treatments and tasks, is a cross-over pattern where attention is gradually shifted from Lottery A to Lottery B. This process coincides with a typical choice pattern where subjects choose lottery A for the first few choice tasks and then switch to lottery B. The pattern differs between treatments with the text format treatment lines shifted upwards due to the absence of a graphical display.

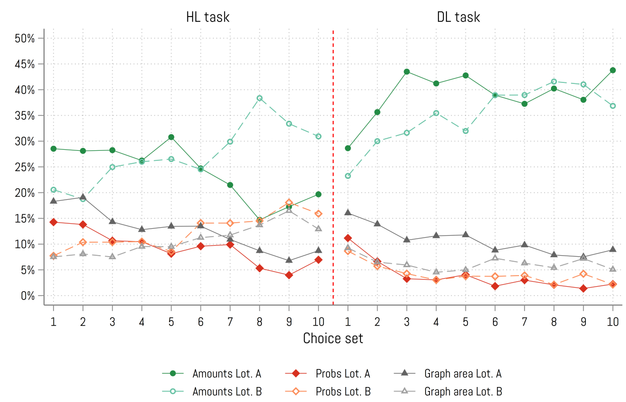
Subjects spend more time looking at the monetary amounts than they do for probabilities and graphical displays (all differences are statistically significant at the 5% level according to Wilcoxon signed rank sum tests). Moreover, subjects spend more time looking at the monetary amounts in the DL task as compared to the HL task (differences are statistically significant at the 5% level according to Wilcoxon-Mann-Whitney tests) which may be explained by the fact that the DL task shows larger monetary amounts particularly for later choice sets. The pattern reverses for probabilities i.e., subjects spend less time looking at the monetary amounts in the DL task as compared to the HL task (differences are statistically significant at the 5% level according to Wilcoxon-Mann-Whitney tests). Visual attention for the monetary amounts follows a decreasing trend in the HL task and an increasing trend in the DL task which may be explained by the fact that monetary amounts stay constant in the HL task (i.e., learning) and they increase in the DL task. The opposite pattern applies for probabilities between tasks i.e.,

Figure 3: Fraction of visual time spent per Area of Interest and choice task

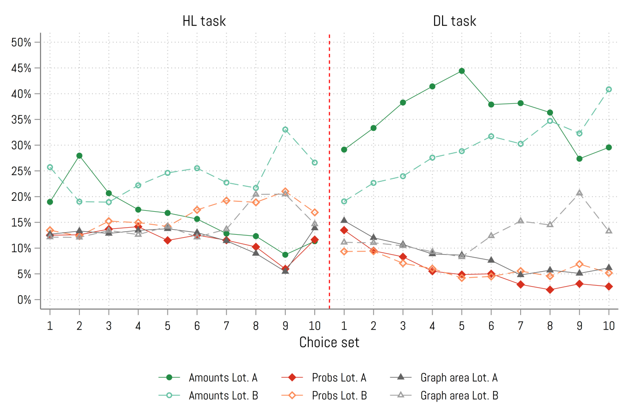
(a) Text format



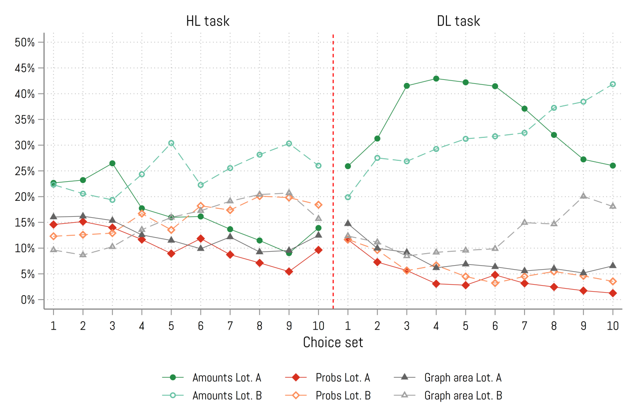
(b) 'Emphasis on probabilities'



(c) 'Emphasis on monetary amounts'



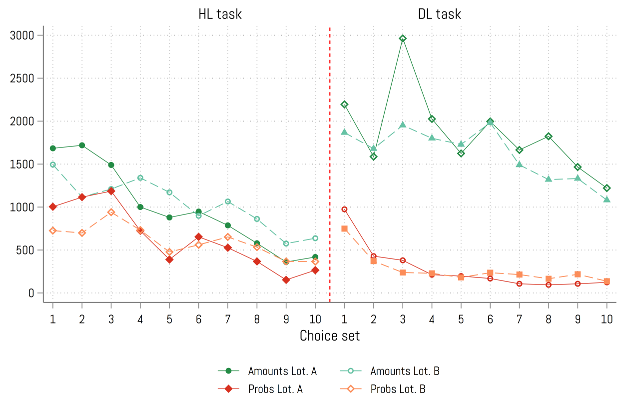
(d) 'Emphasis on monetary amounts and probabilities'



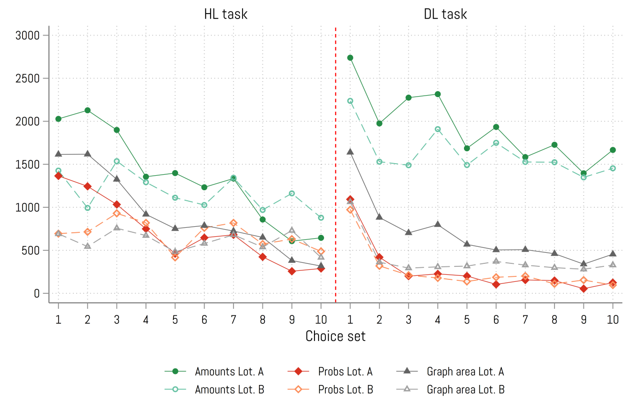
Notes: HL task: Holt and Laury's (2002) probability varying task; DL task: Drichoutis and Lusk's (2016) payoff varying task

Figure 4: Visual time visit duration per Area of Interest and choice task

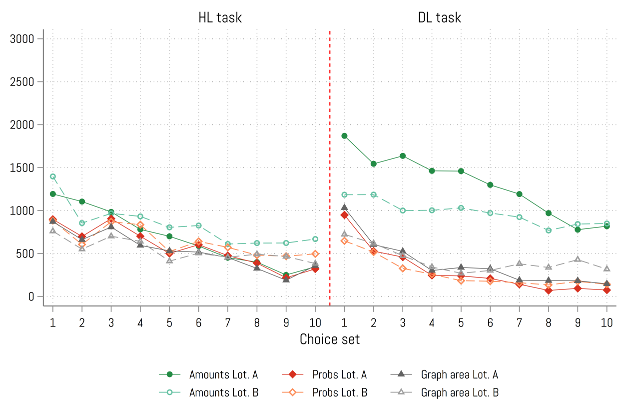
(a) Text format



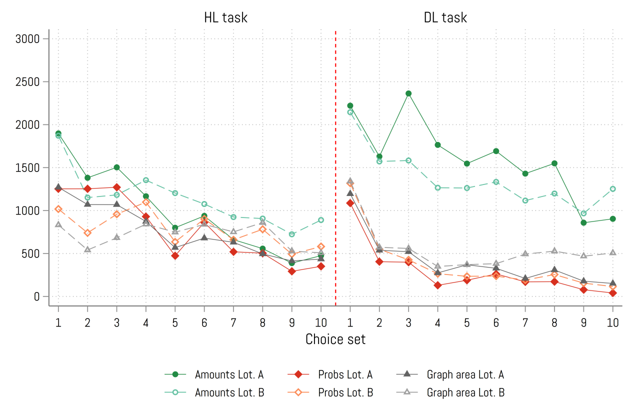
(b) 'Emphasis on probabilities'



(c) 'Emphasis on monetary amounts'



(d) 'Emphasis on monetary amounts and probabilities'



Notes: HL task: Holt and Laury's (2002) probability varying task; DL task: Drichoutis and Lusk's (2016) payoff varying task

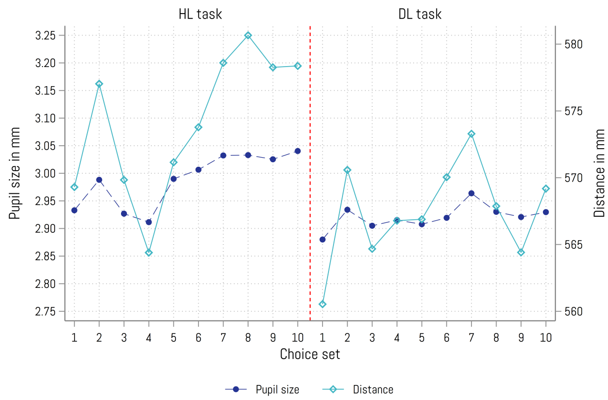
attention decreases as subjects move from the first to the last choice set in the DL task.

Figure 4 shows absolute dwell time visit duration per choice task and treatment for the respective AOIs. Dwell times generally decrease over choice sets within a task (i.e., within the HL or the DL task) and are significantly larger for monetary amounts than the probabilities or graphs. The gap between the amount of time subjects spent looking at the monetary amounts and the probabilities is much larger in the DL task than the HL task and subjects spend more time looking at monetary amounts in the DL task than in the HL task.

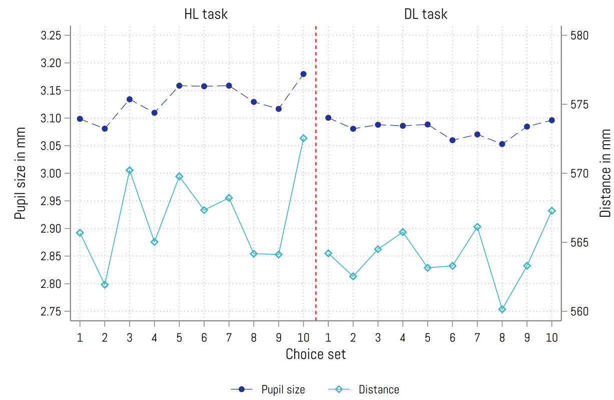
Figure 5 shows pupil size dilation and distance from the screen. Pupil size is useful to understand the decision making process and it has been shown to be a good predictor of choice (de Gee et al., 2014; Sirois and Brisson, 2014). Pupil size is generally higher in the graphical formats compared to the text-only format and differences between presentation formats

Figure 5: Pupil size and distance from the screen by task and treatment

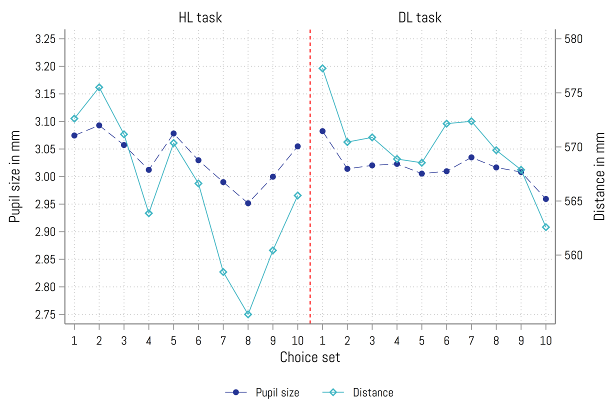
(a) Text format



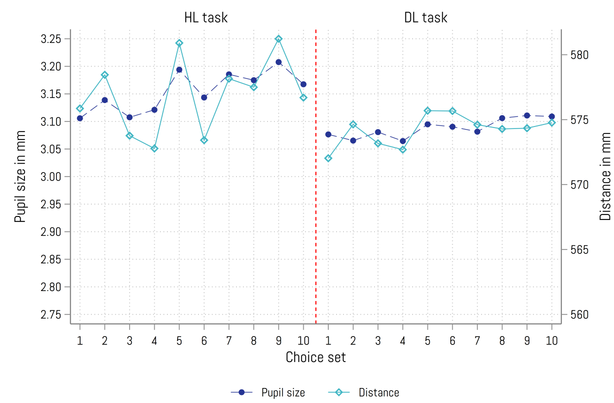
(b) ‘Emphasis on probabilities’



(c) ‘Emphasis on monetary amounts’



(d) ‘Emphasis on monetary amounts and probabilities’



Notes: HL task: Holt and Laury’s (2002) probability varying task; DL task: Drichoutis and Lusk’s (2016) payoff varying task

are statistically significant according to a Kruskal-Wallis test ($\chi^2 = 78.556$, p-value= 0.0001). This result provides an indication that participants are more responsive to the reward cues in graphical formats (Chiew and Braver, 2013).

4.2 Estimation results

We first estimate basic models of EUT and RDU and then progressively add choice process data from the eye-tracking equipment. A constants only model for EUT returns $r = 0.343$ and $\mu = 7.619$, both being significantly different from zero at the 5% level indicating moderate risk aversion for the subjects in our sample. The corresponding values for RDU are $r = 0.275$, $\gamma = 0.799$ and $\mu = 8.426$ with all estimates being significantly different from zero and γ being significantly different from 1 at the 5% level, indicating that risk aversion and probability weighting are better characterizations of subjects' choices than EUT.

Model (1) in Table 3 shows estimated parameter values for EUT with the treatment variables and basic demographic characteristics. Since our basic premise for the treatments in our experiment was that graphical displays will help subjects to better understand how monetary values and probabilities vary by choice set, we also allow the treatment variables to enter as covariates of the noise parameter. The results show that none of the variables significantly affects risk aversion. Model (1) in Table 4 show estimates for RDU where we allow r and γ to be a function of the treatment variables and demographics. The bottom part of the table also shows Wald test of $\gamma = 1$ for the various coefficient combinations, calculated at the means of the continuous variables for all the relevant models of Table 4.

Table 4 shows that under RDU the visual format giving emphasis on probabilities has a positive impact on r and the visual format giving emphasis on the monetary amounts has a negative impact on the probability weighting parameter. However, we fail to reject the null that $\gamma = 1$ indicating that for the basic model, RDU does not provide a better characterization of the data than EUT.

Next, we ask whether eye-tracking data can be more informative than the standard set of information available to the experimenter. Models (2) in Tables 3 and 4 use the percent of time a subject spent on AOIs such as the monetary amounts (separate for each lottery), probabilities and the graphical areas. We find that for both EUT and RDU the percentage of time spent looking at the various AOIs associated with lottery A (the 'safe' lottery) has a positive impact on the risk aversion coefficient r. We don't find similar evidence for the γ parameter.

Another way to use the eye tracking information is to use the differences between time spent looking at lottery B versus lottery A (recall the respective gap in attention as shown in Figures 3 and 4) for the various AOIs. These differences can be interpreted as the relative importance participants place on each piece of information. Model (3) in Tables 3 and 4 uses these differences and model (4) augments the set of covariates using pupil size and distance from the screen. Interestingly, the differences between lottery B and A are significant determinants of both EUT and RDU, but more so for r rather than the γ parameter.

There is an important change in our results when including eye tracking information. The tests of whether RDU collapses to EUT favor RDU when including the eye tracking data. The bottom panel of Table 4 shows clear rejections of the null that $\gamma = 1$ for linear combinations of the various coefficients. Thus, we can conclude that ignoring eye tracking information or if eye-tracking data were not available, we would have erroneously concluded that EUT is a better characterization of subjects choices than RDU.

Table 3: Estimates for Expected Utility Theory

	(1)		(2)		(3)		(4)		(5)		(6)	
r												
Constant	0.345***	(0.110)	0.015	(0.229)	0.364***	(0.119)	0.418	(0.515)	0.414	(0.507)	0.433	(0.521)
trt_2: Emphasis on Probs	0.147	(0.112)	0.193	(0.155)	0.134	(0.131)	0.132	(0.134)	0.140	(0.133)	0.125	(0.136)
trt_3: Emphasis on $	0.116	(0.109)	0.237	(0.144)	0.140	(0.123)	0.140	(0.125)	0.143	(0.123)	0.138	(0.125)
trt_4: Emphasis on Probs & $	-0.248*	(0.132)	-0.139	(0.169)	-0.227	(0.145)	-0.227	(0.149)	-0.222	(0.148)	-0.226	(0.149)
3rd year student	-0.052	(0.106)	-0.006	(0.121)	-0.009	(0.121)	-0.009	(0.121)	-0.015	(0.120)	-0.007	(0.122)
4th year student	0.093	(0.103)	0.110	(0.118)	0.116	(0.119)	0.116	(0.120)	0.110	(0.118)	0.116	(0.120)
Gender: Male	-0.089	(0.086)	-0.072	(0.099)	-0.077	(0.099)	-0.076	(0.103)	-0.083	(0.102)	-0.076	(0.103)
AOI: amounts Lot. A			0.985***	(0.230)								
AOI: amounts Lot. B			-0.141	(0.234)								
AOI: graph Lot. A			0.679*	(0.411)								
AOI: graph Lot. A			-0.549	(0.349)								
AOI: prob Lot. A			0.797**	(0.353)								
AOI: prob Lot. B			-0.399	(0.288)								
AOI: Monetary amounts diffs					-0.553***	(0.149)	-0.555***	(0.151)	-0.515***	(0.151)	-0.580***	(0.165)
AOI: Graphs diffs					-0.598**	(0.264)	-0.601**	(0.269)	-0.537**	(0.270)	-0.644**	(0.286)
AOI: Prob, diffs					-0.609***	(0.202)	-0.606***	(0.201)	-0.590***	(0.199)	-0.597***	(0.202)
Pupil size							0.003	(0.143)	-0.010	(0.142)	0.004	(0.143)
Distance							-0.0001	(0.001)	-0.00003	(0.001)	-0.0001	(0.001)
μ												
Constant	8.115***	(0.739)	7.877***	(0.726)	7.875***	(0.729)	7.877***	(0.728)	7.753***	(0.734)	8.003***	(0.767)
Emphasis on Probs	0.538	(1.061)	-0.434	(1.025)	-0.534	(1.027)	-0.547	(1.034)	-0.464	(1.055)	-0.567	(1.032)
Emphasis on $	-0.812	(1.095)	-0.745	(1.052)	-0.757	(1.067)	-0.754	(1.072)	-0.783	(1.075)	-0.751	(1.059)
Emphasis on Probs & $	-0.915	(1.002)	-0.690	(0.999)	-0.691	(0.990)	-0.692	(1.004)	-0.735	(0.997)	-0.672	(0.993)
Inattention to Lot. A									1.344	(1.117)		

Inattention to Lot. B									1.261	(1.809)		
Partial inattention to Lot. A											-0.690	(0.698)
Partial inattention to Lot. B											0.161	(0.902)
N	3980		3980		3980		3980		3980		3980	
LogL	-2055.381		-1988.725		-1992.560		-1992.543		-1990.971		-1991.945	
AIC	4132.761		4011.450		4013.121		4017.085		4017.942		4019.890	
BIC	4201.941		4118.364		4101.167		4117.710		4131.145		4133.092	

Notes: Standard errors in parentheses. * $p<0.1$, ** $p<0.05$ *** $p<0.01$

Table 4: Estimates for Rank Dependent Utility Theory

	(1)		(2)		(3)		(4)		(5)		(6)	
r												
Constant	0.164	(0.136)	0.052	(0.246)	0.278*	(0.153)	0.133	(0.595)	0.145	(0.592)	0.153	(0.594)
trt_2: Emphasis on Probs	0.256**	(0.121)	0.028	(0.205)	0.008	(0.188)	0.081	(0.171)	0.093	(0.173)	0.044	(0.174)
trt_3: Emphasis on $	0.206	(0.138)	0.097	(0.178)	0.039	(0.156)	0.169	(0.133)	0.177	(0.134)	0.157	(0.134)
trt_4: Emphasis on Probs & $	-0.215	(0.182)	-0.253	(0.206)	-0.300	(0.189)	-0.275*	(0.165)	-0.270	(0.165)	-0.285*	(0.164)
3rd year student	0.014	(0.148)	0.002	(0.130)	-0.002	(0.131)	-0.012	(0.123)	-0.017	(0.123)	-0.011	(0.123)
4th year student	0.085	(0.175)	0.132	(0.134)	0.135	(0.137)	0.064	(0.126)	0.059	(0.127)	0.069	(0.128)
Gender: Male	-0.094	(0.085)	-0.040	(0.105)	-0.037	(0.106)	-0.110	(0.104)	-0.114	(0.104)	-0.112	(0.103)
AOI: amounts Lot. A			0.635**	(0.305)								
AOI: amounts Lot. B			-0.201	(0.260)								
AOI: graph Lot. A			0.573	(0.406)								
AOI: graph Lot. A			-0.372	(0.395)								
AOI: prob Lot. A			0.780**	(0.380)								
AOI: prob Lot. B			-0.260	(0.314)								
AOI: Monetary amounts diffs					-0.421**	(0.192)	-0.462***	(0.154)	-0.440***	(0.157)	-0.503***	(0.169)
AOI: Graphs diffs					-0.449*	(0.258)	-0.513**	(0.257)	-0.482*	(0.262)	-0.588**	(0.276)
AOI: Prob, diffs					-0.496**	(0.213)	-0.449**	(0.207)	-0.445**	(0.204)	-0.437**	(0.207)
Pupil size							-0.192	(0.128)	-0.197	(0.128)	-0.187	(0.130)
Distance							0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
γ												
Constant	1.135***	(0.242)	0.929**	(0.396)	0.775***	(0.233)	0.496	(0.661)	0.528	(0.671)	0.462	(0.664)
Emphasis on Probs	-0.260	(0.231)	0.829**	(0.378)	0.775**	(0.345)	0.817***	(0.313)	0.810**	(0.316)	0.817***	(0.298)
Emphasis on $	-0.424**	(0.198)	-0.136	(0.279)	-0.147	(0.271)	0.048	(0.135)	0.057	(0.141)	0.035	(0.144)
Emphasis on Probs & $	-0.215	(0.362)	-0.177	(0.324)	-0.189	(0.326)	-0.105	(0.149)	-0.101	(0.147)	-0.122	(0.157)
3rd year student	0.415*	(0.221)	0.053	(0.098)	0.049	(0.098)	0.067	(0.106)	0.059	(0.109)	0.076	(0.106)

4th year student	0.619**	(0.301)	0.107	(0.200)	0.105	(0.192)	0.001	(0.119)	-0.007	(0.123)	0.013	(0.125)
Gender: Male	-0.136	(0.199)	0.125	(0.095)	0.133	(0.112)	-0.045	(0.135)	-0.045	(0.134)	-0.051	(0.140)
AOI: amounts Lot. A			-0.461	(0.287)								
AOI: amounts Lot. B			-0.003	(0.261)								
AOI: graph Lot. A			-0.496*	(0.280)								
AOI: graph Lot. A			0.182	(0.340)								
AOI: prob Lot. A			-0.215	(0.389)								
AOI: prob Lot. B			0.215	(0.327)								
AOI: Monetary amounts diffs					0.287**	(0.125)	0.191*	(0.109)	0.192*	(0.108)	0.197*	(0.109)
AOI: Graphs diffs					0.291**	(0.145)	0.239	(0.232)	0.247	(0.243)	0.239	(0.219)
AOI: Prob, diffs					0.168	(0.153)	0.172	(0.107)	0.165	(0.111)	0.179*	(0.106)
Pupil size							-0.382***	(0.118)	-0.378***	(0.118)	-0.396***	(0.116)
Distance							0.003	(0.002)	0.003	(0.002)	0.003*	(0.002)
μ												
Constant	6.978***	(0.701)	8.035***	(1.123)	8.081***	(1.130)	8.601***	(0.982)	8.555***	(0.987)	8.776***	(0.965)
Emphasis on Probs	2.114*	(1.132)	-1.121	(1.268)	-1.109	(1.246)	-1.637	(1.213)	-1.640	(1.223)	-1.575	(1.176)
Emphasis on $	0.306	(1.126)	-0.563	(1.196)	-0.567	(1.198)	-1.197	(1.215)	-1.238	(1.230)	-1.166	(1.179)
Emphasis on Probs & $	-0.529	(1.003)	-0.109	(1.273)	-0.066	(1.293)	-0.429	(1.345)	-0.456	(1.347)	-0.414	(1.288)
Inattention to Lot. A									0.831	(1.169)		
Inattention to Lot. B									0.364	(1.943)		
Partial inattention to Lot. A											-1.264*	(0.720)
Partial inattention to Lot. B											0.285	(0.970)
	χ^2	p-value	χ^2	p-value	χ^2	p-value	χ^2	p-value	χ^2	p-value	χ^2	p-value
$\gamma_{cons} = 1$	1.96	(0.162)	0.03	(0.855)	0.02	(0.900)	0.02	(0.888)	0.01	(0.917)	0.09	(0.769)
$\gamma_{cons} + \gamma_{trt_2} = 1$	0.01	(0.939)	4.68**	(0.031)	4.74**	(0.029)	5.03**	(0.025)	4.76**	(0.029)	5.89**	(0.015)
$\gamma_{cons} + \gamma_{trt_3} = 1$	0.40	(0.525)	0.27	(0.604)	0.40	(0.529)	0.14	(0.710)	0.15	(0.701)	0.15	(0.701)
$\gamma_{cons} + \gamma_{trt_4} = 1$	0.003	(0.953)	0.35	(0.552)	0.45	(0.501)	0.39	(0.535)	0.38	(0.537)	0.41	(0.522)
N	3980		3980		3980		3980		3980		3980	

LogL	-2046.124	-1967.512	-1970.770	-1964.240	-1963.782	-1962.303
AIC	4128.248	3995.023	3989.540	3984.480	3987.563	3984.605
BIC	4241.450	4183.694	4140.477	4160.573	4176.234	4173.276

Notes: Standard errors in parentheses. * p<0.1, ** p<0.05 *** p<0.01

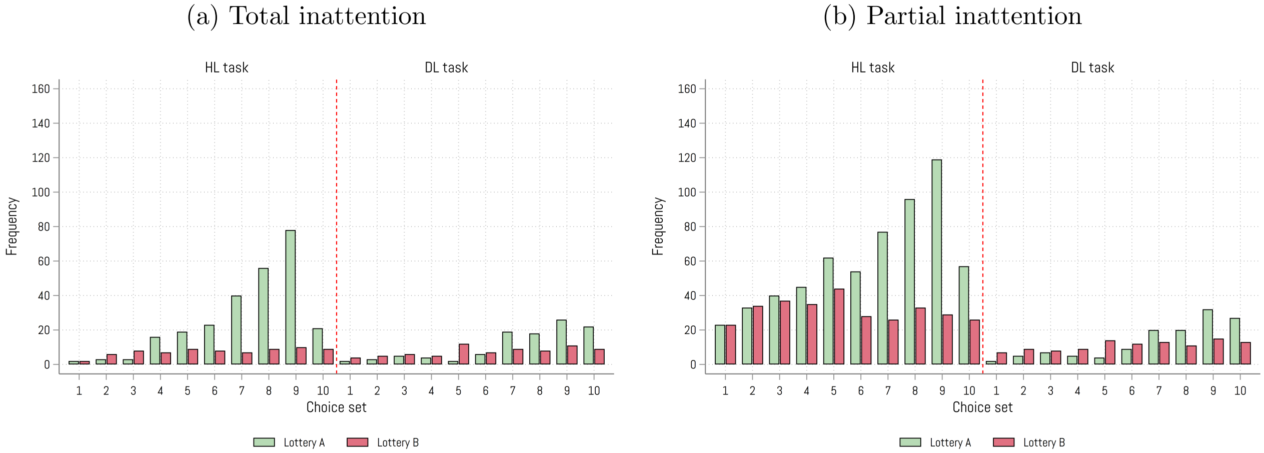
4.3 Inattention

Figure 6 presents frequency of total inattention and partial inattention per choice set and choice task. Total inattention is defined as failure to look at any of the areas of interest for lottery A or B (which includes monetary amounts, probabilities and graph areas). The left part of Figure 6 shows that frequency of total inattention increases as subjects progress in a choice task, but it is more prevalent in the HL task and almost null in the DL task. Inattention is also more prevalent for lottery A than lottery B.

Because as subjects progress through choice sets, some information remains constant (e.g., the monetary amounts in the HL task and probabilities in the DL task) and subjects get accustomed to that information, they are less likely to look at the information that they expect to remain constant as they advance in choice sets. However, some information changes between choice sets so we define partial inattention when a subject does not spend time looking at the probabilities in the HL task or in the monetary amounts in the DL task in a given choice set. The graph in the right panel of Figure 6 shows that subjects exhibit greater partial inattention as compared to total inattention and that this comes predominantly from lottery A.

Models (5) and (6) in Tables 3 and 4 add total and partial inattention as covariates in the noise parameter μ. As shown, our results are robust to inattention.

Figure 6: Fraction of inattentive choices by task



Notes: HL task: Holt and Laury's (2002) probability varying task; DL task: Drichoutis and Lusk's (2016) payoff varying task

4.4 Out-of-sample predictions

The out-of-sample log likelihood (OSLLF) criterion evaluates models by their fit out of sample. In essence, the OSLLF approach uses one set of data to estimate the parameters of the model, and then, given these parameters, calculates the likelihood function values observed for the out-of-sample observations. The OSLLF value is calculated by using out-of sample observations to calculate the likelihood function:

$$\ln L(y) = \sum_{i=1}^{N} \left[(\ln Z | y_i = 1, \hat{\theta}_{f,-i}) + (\ln(1-Z) | y_i = -1, \hat{\theta}_{f,-i}) \right] \tag{5}$$

where $\hat{\theta}_{f,-i}$ is the parameter vector estimated without the ith set of observations. The OSLLF value can be calculated in several ways (Norwood et al., 2004). The estimate $\hat{\theta}_{f,-i}$ can be calculated using cross-validation where $\hat{\theta}_{f,-i}$ is estimated using every observation except i. This is referred to as "leave one out at a time forecasting." Alternatively, one could partition the observations into groups where each group is iteratively omitted and $\hat{\theta}_{f,-i}$ is estimated. Then, the omitted group of observations can be used to calculate the OSLLF. This procedure is known as grouped-cross-validation. In what follows, we carry out group-cross validation with individuals being the partitions, where each partition contains 20 observations. Essentially, we leave one subject (and their associated 20 choices) out at a time, estimate the model, and calculate equation (5) for the subject. The process is repeated for every subject in the sample and repeat this exercise for all models of Tables 3 and 4.

Table 5 reports OSLLF values for EUT and RDU for models (1) to (6) of Tables 3 and 4.

As shown better fit is produced with the AOI variables and RDU wins by this metric as well indicating it is a better characterization of subjects' choices.

Table 5: Out-of-sample Log-Likelihoods

	(1)	(2)	(3)	(4)	(5)	(6)
EUT	-2055.381	**-1988.72**	-1992.561	-1992.543	-1990.971	-1991.945
RDU	-2046.124	-1967.512	-1977.863	-1964.240	-1963.782	**-1962.303**

5 Discussion and Conclusions

Our study shows that complementing structural estimates of theories of choice under risk with eye-tracking data, allows a better characterization of the theory that governs particular decision making processes. We find that ignoring information provided by the eye-tracking data can lead to erroneous conclusions as per whether EUT or RDU are a better characterization of subjects' choices. An immediate implication of our results is that any study on choice under risk should be routinely collecting eye-tracking data. Inasmuch as eye-tracking data are not cheap to collect, our suggestion may seem impractical but with recent advances in online eye-tracking methods (e.g., Papoutsaki et al., 2017, 2016), it might be a matter of time before researchers start collecting choice process data en masse.

References

Aimone, J. A., S. Ball, and B. King-Casas (2016). It's not what you see but how you see it: Using eye-tracking to study the risky decision-making process. *Journal of Neuroscience, Psychology, and Economics 9*(3-4), 137.

Andersen, S., G. W. Harrison, M. Lau, and E. E. Rutström (2013). Discounting behavior and the magnitude effect. *Economica 80*(320), 670–697.

Andersen, S., G. W. Harrison, M. I. Lau, and E. E. Rutström (2006). Elicitation using multiple price list formats. *Experimental Economics 9*(4), 383–405.

Andersen, S., G. W. Harrison, M. I. Lau, and E. E. Rutström (2008). Eliciting risk and time preferences. *Econometrica 76*(3), 583–618.

Andersen, S., G. W. Harrison, M. I. Lau, and E. E. Rutström (2014). Discounting behavior: A reconsideration. *European Economic Review 71*, 15–33.

Arieli, A., Y. Ben-Ami, and A. Rubinstein (2011). Tracking decision makers under uncertainty. *American Economic Journal: Microeconomics 3*(4), 68–76.

Barrafrem, K. and J. Hausfeld (2020). Tracing risky decisions for oneself and others: The role of intuition and deliberation. *Journal of Economic Psychology 77*, 102188.

Bauermeister, G.-F. and O. Mußhoff (2019). Multiple switching behaviour in different display formats of multiple price lists. *Applied Economics Letters 26*(1), 58–63.

Benjamin, D. J., S. A. Brown, and J. M. Shapiro (2013). Who is 'behavioral'? cognitive ability and anomalous preferences. *Journal of the European Economic Association 11*(6), 1231–1255.

Brown, A. L. and P. J. Healy (2018). Separated decisions. *European Economic Review 101*, 20–34.

Bruner, D. M. (2011). Multiple switching behaviour in multiple price lists. *Applied Economics Letters 18*(5), 417–420.

Charness, G., U. Gneezy, and A. Imas (2013). Experimental methods: Eliciting risk preferences. *Journal of Economic Behavior & Organization 87*, 43–51.

Charness, G., A. Viceisza, et al. (2016). Three risk-elicitation methods in the field: Evidence from rural senegal. *Review of Behavioral Economics 3*(2), 145–171.

Chiew, K. S. and T. S. Braver (2013). Temporal dynamics of motivation-cognitive control interactions revealed by high-resolution pupillometry. *Frontiers in psychology 4*, 15.

Cokely, E. T. and C. M. Kelley (2009). Cognitive abilities and superior decision making under risk: A protocol analysis and process model evaluation.

de Gee, J. W., T. Knapen, and T. H. Donner (2014). Decision-related pupil dilation reflects upcoming choice and individual bias. *Proceedings of the National Academy of Sciences 111*(5), E618–E625.

Deck, C., J. Lee, and J. Reyes (2014). Investing versus gambling: experimental evidence of multi-domain risk attitudes. *Applied economics letters 21*(1), 19–23.

Drichoutis, A. C. and J. L. Lusk (2016). What can multiple price lists really tell us about risk preferences? *Journal of Risk and Uncertainty 53*(2), 89–106.

Friedman, D., S. Habib, D. James, and B. Williams (2022). Varieties of risk preference elicitation. *Games and Economic Behavior 133*, 58–76.

Habib, S., D. Friedman, S. Crockett, and D. James (2017). Payoff and presentation modulation of elicited risk preferences in mpls. *Journal of the Economic Science Association 3*(2), 183–194.

Harrison, G. W., E. Johnson, M. M. McInnes, and E. E. Rutström (2005). Risk aversion and incentive effects: Comment. *The American Economic Review 95*(3), 897–901.

Harrison, G. W. and E. E. Rutström (2009). Expected utility theory and prospect theory: One wedding and a decent funeral. *Experimental Economics 12*(2), 133–158.

Harrison, G. W. and J. T. Swarthout (2019). Eye-tracking and economic theories of choice under risk. *Journal of the Economic Science Association 5*(1), 26–37.

Hey, J. and W. Zhou (2014). Do past decisions influence future decisions? *Applied Economics Letters 21*(3), 152–157.

Hirschauer, N., O. Musshoff, S. C. Maart-Noelck, and S. Gruener (2014). Eliciting risk attitudes–how to avoid mean and variance bias in holt-and-laury lotteries. *Applied Economics Letters 21*(1), 35–38.

Holt, C. A. and S. K. Laury (2002). Risk aversion and incentive effects. *The American Economic Review 92*(5), 1644–1655.

Kee, J., M. Knuth, J. N. Lahey, and M. A. Palma (2021). Does eye-tracking have an effect on economic behavior? *Plos one 16*(8), e0254867.

Lévy-Garboua, L., H. Maafi, D. Masclet, and A. Terracol (2012). Risk aversion and framing effects. *Experimental Economics 15*(1), 128–144.

Norwood, B. F., M. C. Roberts, and J. L. Lusk (2004). Ranking crop yield models using out-of-sample likelihood functions. *American Journal of Agricultural Economics 86*(4), 1032–1043.

Papoutsaki, A., J. Laskey, and J. Huang (2017). Searchgazer: Webcam eye tracking for remote studies of web search. In *Proceedings of the ACM SIGIR Conference on Human Information Interaction & Retrieval (CHIIR)*. ACM.

Papoutsaki, A., P. Sangkloy, J. Laskey, N. Daskalova, J. Huang, and J. Hays (2016). Webgazer: Scalable webcam eye tracking using user interactions. In *Proceedings of the 25th International Joint Conference on Artificial Intelligence (IJCAI)*, pp. 3839–3845. AAAI.

Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior & Organization 3*(4), 323–343.

Reynaud, A. and S. Couture (2012). Stability of risk preference measures: results from a field experiment on French farmers. *Theory and decision 73*(2), 203–221.

Rommel, J., D. Hermann, M. Müller, and O. Mußhoff (2017). Comprehension in risk elicitation experiments. *Applied Economics Letters 24*(9), 627–634.

Schley, D. R. and E. Peters (2014). Assessing "economic value" symbolic-number mappings predict risky and riskless valuations. *Psychological science 25*(3), 753–761.

Sirois, S. and J. Brisson (2014). Pupillometry. *Wiley Interdisciplinary Reviews: Cognitive Science 5*(6), 679–692.

StataCorp (2013). *Stata user's guide release 13.* College Station, Texas, USA: Stata Press.

Tversky, A. and D. Kahneman (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty 5*(4), 297–323.

Wilcox, N. (2008). Stochastic models for binary discrete choice under risk: A critical primer and econometric comparison. In J. C. Cox and G. W. Harrison (Eds.), *Research in Experimental Economics Vol 12: Risk Aversion in Experiments*, pp. 197–292. Bingley, UK: Emerald Group Publishing Limited.

Wilcox, N. T. (2011). 'Stochastically more risk averse:' A contextual theory of stochastic discrete choice under risk. *Journal of Econometrics 162*(1), 89–104.

Zhou, W. and J. Hey (2018). Context matters. *Experimental economics 21*(4), 723–756.

Electronic Supplementary Material of

Visual formats in risk preference elicitation: What catches the eye?

Michelle Segovia*, Marco A. Palma†, Jayson L. Lusk‡, and Andreas C. Drichoutis§,

*Assistant Professor, Department of Agricultural and Applied Economics, University of Missouri, e-mail:segoviacoronelm@missouri.edu.

†Professor and Director Human Behavior Laboratory, Department of Agricultural Economics, Texas A&M University, College Station, TX 77843 USA, tel:+1-9798455284 e-mail: mapalma@tamu.edu.

‡Distinguished Professor and Head, Department of Agricultural Economics, Purdue University, 403 W. State St, West Lafayette, IN 47907-2056, USA, e-mail: jlusk@purdue.edu.

§Associate Professor, Department of Agricultural Economics & Rural Development, School of Applied Economics and Social Sciences, Agricultural University of Athens, Iera Odos 75, 11855, Greece, e-mail: adrihout@aua.gr.

Experimental instructions

WELCOME!

Thank you for participating in our study. The session will proceed in two stages.

Stage 1: Gamble Task
Stage 2: Questionnaire

Gamble Task

You have the chance to earn a cash prize today. You will be presented with **20 choices**.
For each choice, you must select one of two Gambles: A or B.

Each gamble has two **monetary** amounts and a **probability** to win each amount of money.

Gamble Task

You have the chance to earn a cash prize today. You will be presented with **20 choices**.
For each choice, you must select one of two Gambles: A or B.

Each gamble has two **monetary** amounts and a **probability** to win each amount of money. The **probability** to win each amount of money is shown by the **height** of the bars.

Gamble Task

You have the chance to earn a cash prize today. You will be presented with **20 choices**.
For each choice, you must select one of two Gambles: A or B.

Each gamble has two **monetary** amounts and a **probability** to win each amount of money. The **monetary amounts** are shown by the **length** of the bars.

Gamble Task

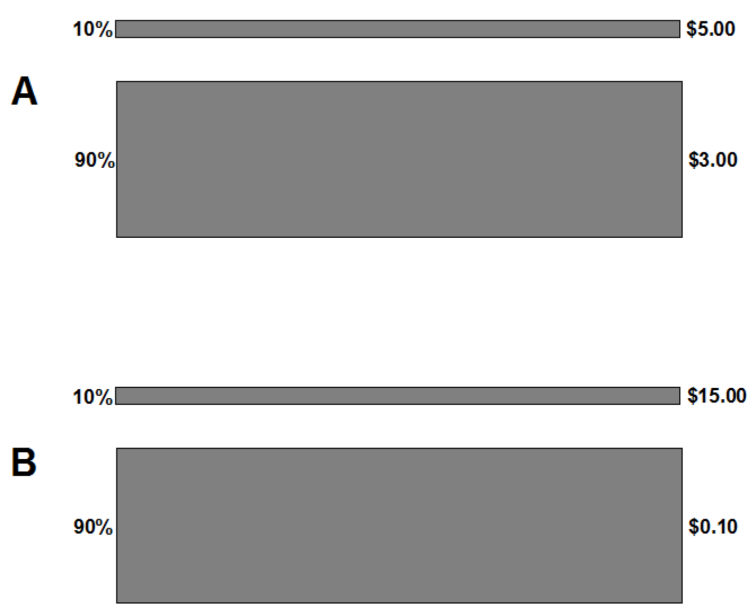
You have the chance to earn a cash prize today. You will be presented with **20 choices**.
For each choice, you must select one of two Gambles: A or B.

Each gamble has two **monetary** amounts and a **probability** to win each amount of money. The **monetary amounts** are shown by the **length** of the bars and the **probability** to win each monetary amount is shown by the **height** of the bars.

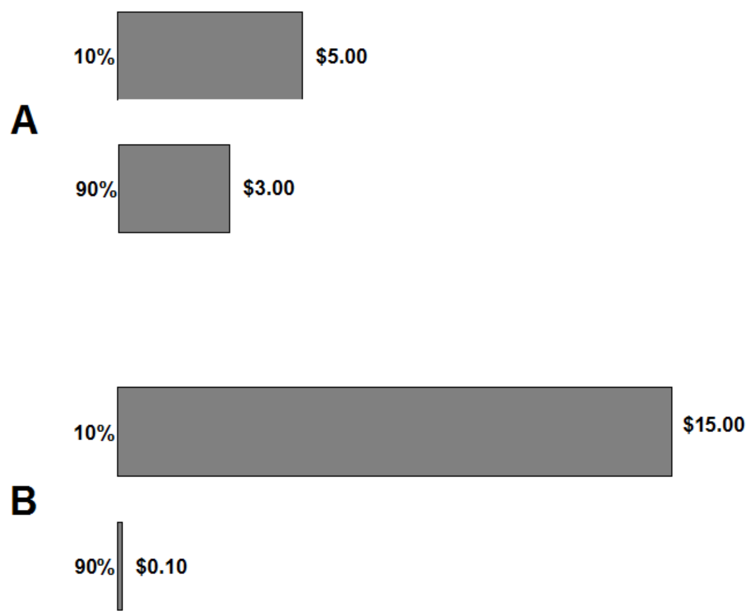
For example, if you select Gamble A, you will have 10% probability (1 out of 10 chances) of winning $5.00 and 90% probability (9 out of 10 chances) of winning $3.00. If you select Gamble B, you will have 10% probability of winning $15.00 and 90% of winning $0.10. You must select Gamble A **or** B according to your preferences.

	10%	$5.00
A		
	90%	$3.00
	10%	$15.00
B		
	90%	$0.10

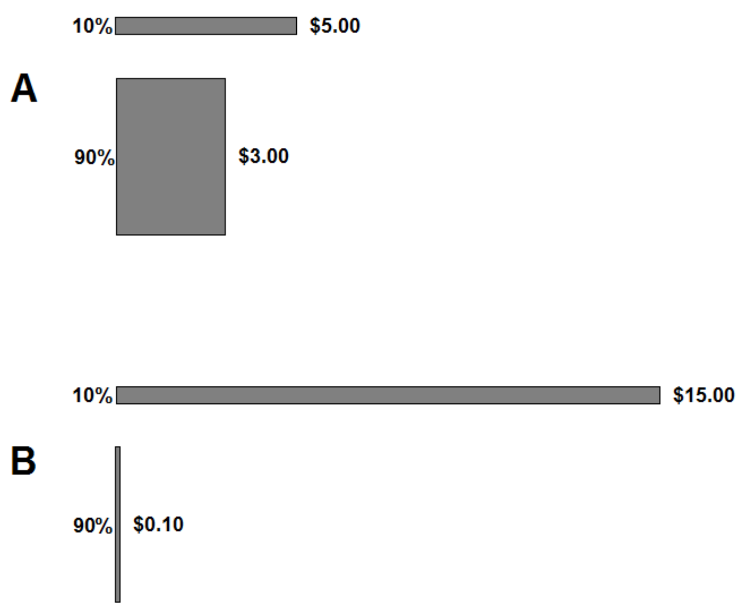
For example, if you select Gamble A, you will have 10% probability (1 out of 10 chances) of winning $5.00 and 90% probability (9 out of 10 chances) of winning $3.00. If you select Gamble B, you will have 10% probability of winning $15.00 and 90% of winning $0.10. You must select Gamble A **or** B according to your preferences.



For example, if you select Gamble A, you will have 10% probability (1 out of 10 chances) of winning $5.00 and 90% probability (9 out of 10 chances) of winning $3.00. If you select Gamble B, you will have 10% probability of winning $15.00 and 90% of winning $0.10. You must select Gamble A **or** B according to your preferences.



For example, if you select Gamble A, you will have 10% probability (1 out of 10 chances) of winning $5.00 and 90% probability (9 out of 10 chances) of winning $3.00. If you select Gamble B, you will have 10% probability of winning $15.00 and 90% of winning $0.10. You must select Gamble A **or** B according to your preferences.



The gambles are presented so that the highest monetary amount is on the top and the lowest monetary amount is on the bottom. Each choice differs from the previous and the next one with respect to monetary amounts or with respect to probabilities of monetary amounts. Your task is to choose the gamble you prefer the most.

After choosing one of the two gambles (the respective circle will be colored black as a confirmation of what you chose), you click on the <Next> button to move on to the next choice. In all, you will make **20** such **choices**.

Given your choices in the gambling task, you will receive extra earnings. At the end of the session, **you will randomly choose one of these choices** to be realized. You will learn which choice will be realized only after you choose your preferred gamble for all 20 choices. Therefore, your best strategy is to think of every choice as if it is the binding choice that will count toward your earnings.

Your earnings from the gamble task will be determined by:

- Which of the two gambles you selected in the binding choice; and
- Which of the two possible payoffs occurred.

A bingo cage containing 20 balls will be used to determine which of the 20 choices will be binding.

Since each gamble has two possible events, each event will occur with its indicated probability. A bingo cage containing 100 balls will be used to determine which event will occur in the gamble you chose. To make this clear, lets review an example shown in the picture below. Gamble A pays the amount of $5 with probability 10% and the amount of $3 with probability 90%. If the drawn number is between 1 and 10 you will earn $5. If the drawn number is between 11 and 100 you will earn $3.

	10%	**$5.00**
A		
	90%	**$3.00**

Your compensation for this part of the study will be determined by:

- Which of the two gambles you selected in the binding choice; and
- Which of the two possible payoffs occurred.

A bingo cage containing 20 balls will be used to determine which of the 20 choices will be binding.

Since each gamble has two possible events, each event will occur with its indicated probability. A bingo cage containing 100 balls will be used to determine which event will occur in the gamble you chose. To make this clear, lets review an example shown in the picture below. Gamble A pays the amount of $5 with probability 10% and the amount of $3 with probability 90%. If the drawn number is between 1 and 10 you will earn $5. If the drawn number is between 11 and 100 you will earn $3.

Your compensation for this part of the study will be determined by:

- Which of the two gambles you selected in the binding choice; and
- Which of the two possible payoffs occurred.

A bingo cage containing 20 balls will be used to determine which of the 20 choices will be binding.

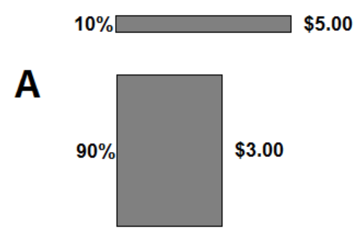
Since each gamble has two possible events, each event will occur with its indicated probability. A bingo cage containing 100 balls will be used to determine which event will occur in the gamble you chose. To make this clear, lets review an example shown in the picture below. Gamble A pays the amount of $5 with probability 10% and the amount of $3 with probability 90%. If the drawn number is between 1 and 10 you will earn $5. If the drawn number is between 11 and 100 you will earn $3.

Your compensation for this part of the study will be determined by:

- Which of the two gambles you selected in the binding choice; and
- Which of the two possible payoffs occurred.

A bingo cage containing 20 balls will be used to determine which of the 20 choices will be binding.

Since each gamble has two possible events, each event will occur with its indicated probability. A bingo cage containing 100 balls will be used to determine which event will occur in the gamble you chose. To make this clear, lets review an example shown in the picture below. Gamble A pays the amount of $5 with probability 10% and the amount of $3 with probability 90%. If the drawn number is between 1 and 10 you will earn $5. If the drawn number is between 11 and 100 you will earn $3.



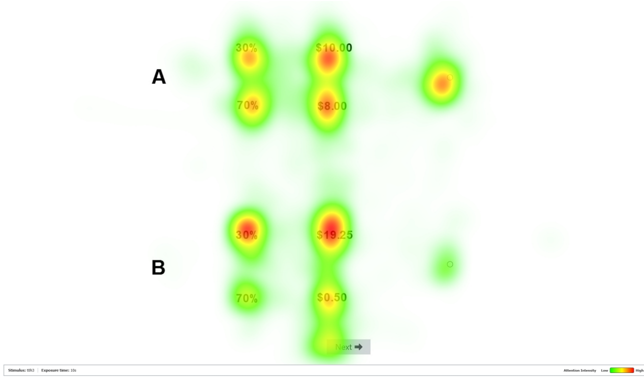
After completing the gamble task you will be asked to fill in a questionnaire.

Next, your earnings from the gambling task will be determined and finally you will receive an envelope with your payment.

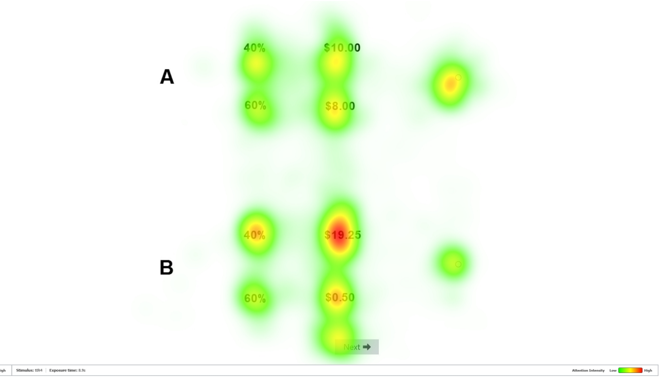
Additional Figures

(a) Choice task 1

(b) Choice task 2

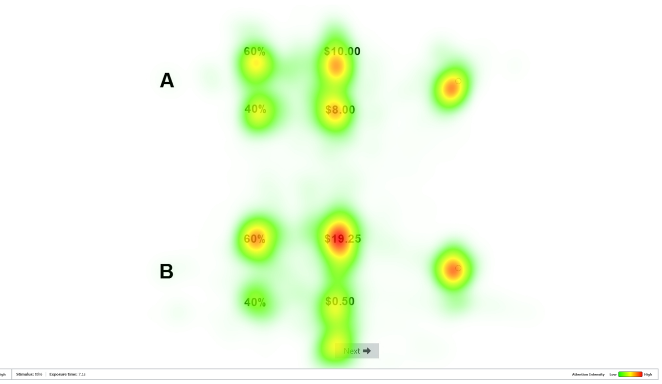


(c) Choice task 3

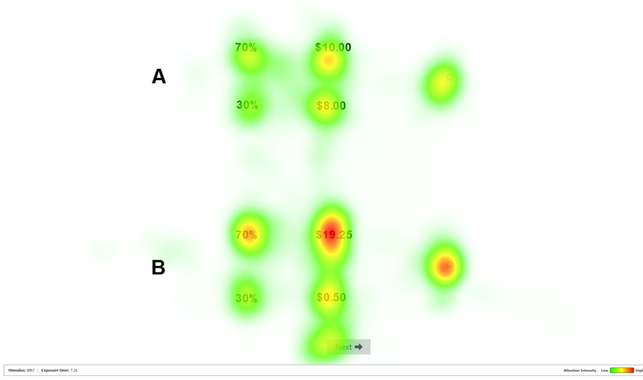


(d) Choice task 4

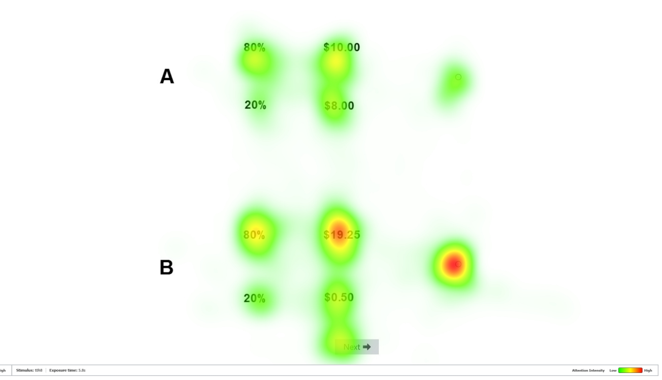
(e) Choice task 5



(f) Choice task 6



(g) Choice task 7



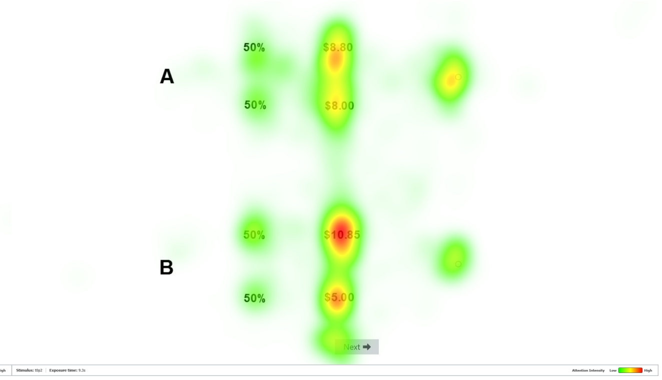
(h) Choice task 8

(i) Choice task 9

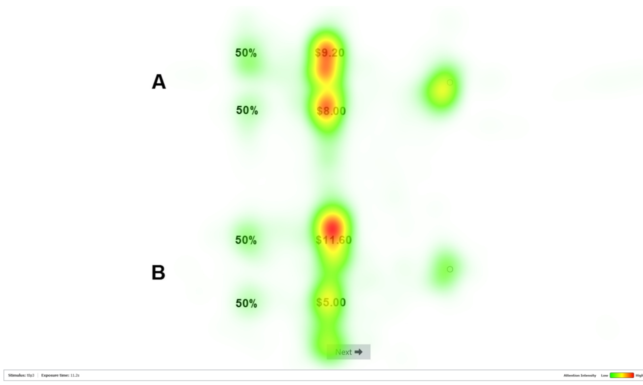
(j) Choice task 10

Figure A1: Heatmaps for the Text format treatment (Holt and Laury, 2002, task)

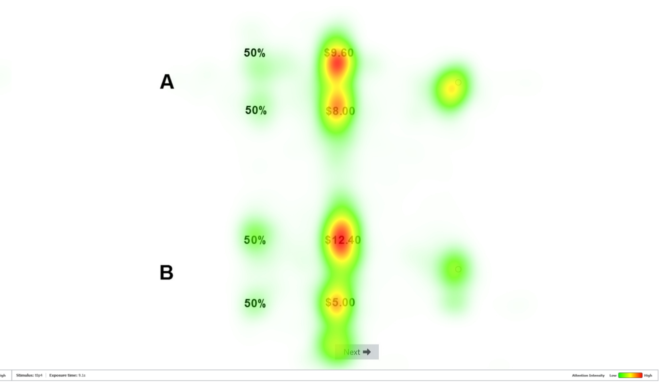
(a) Choice task 1



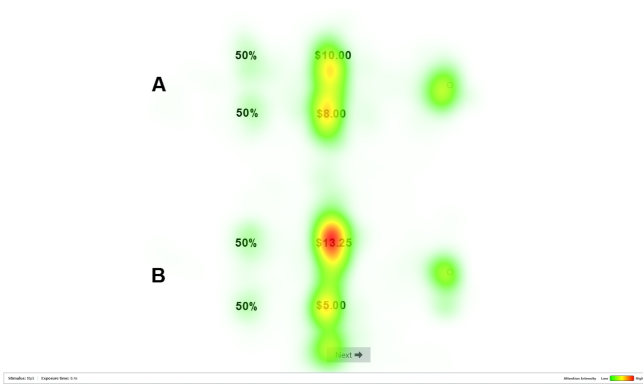
(b) Choice task 2



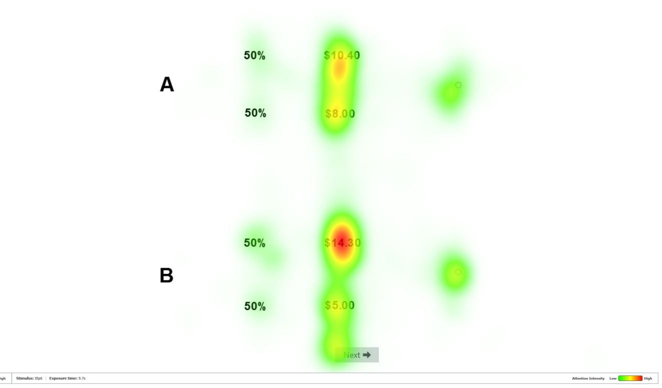
(c) Choice task 3



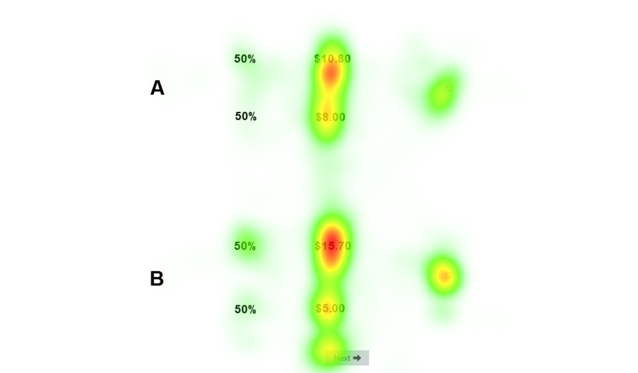
(d) Choice task 4



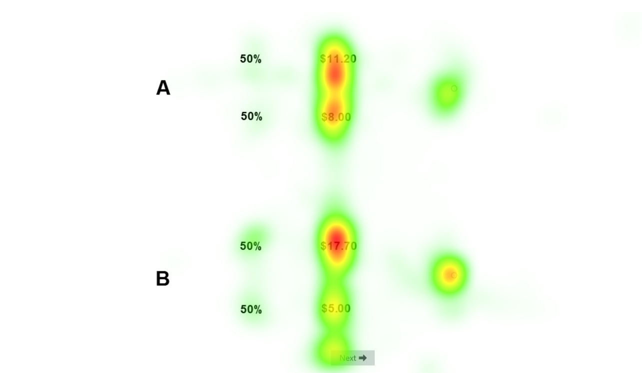
(e) Choice task 5



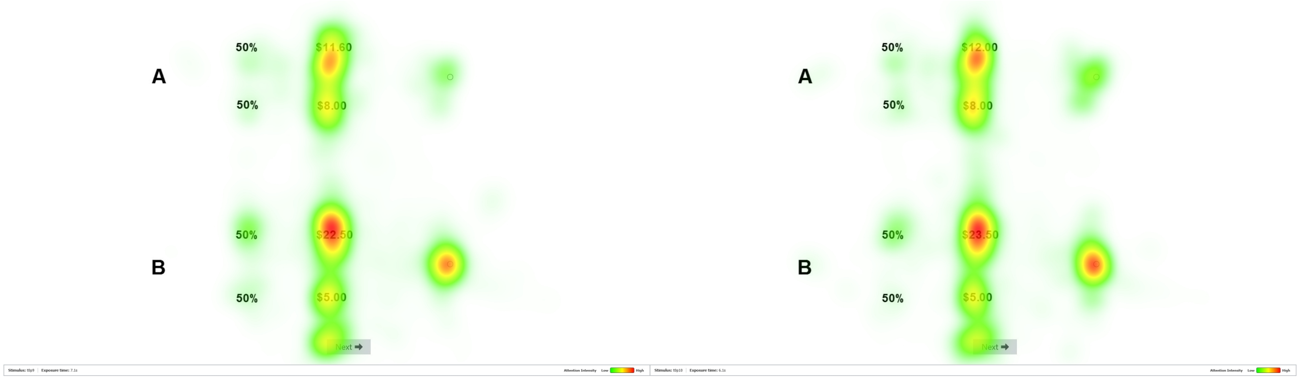
(f) Choice task 6



(g) Choice task 7



(h) Choice task 8



(i) Choice task 9

(j) Choice task 10

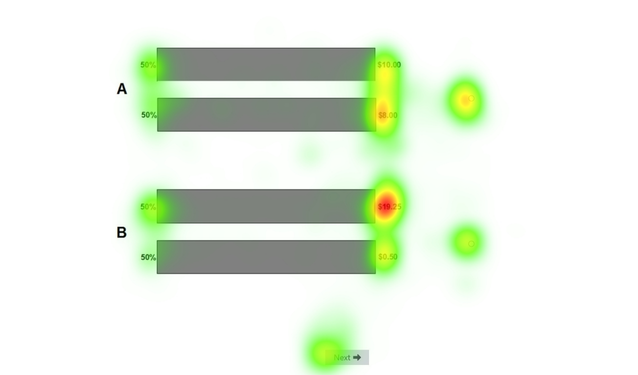
Figure A2: Heatmaps for the Text format treatment (Drichoutis and Lusk, 2016, task)

(a) Choice task 1

(b) Choice task 2

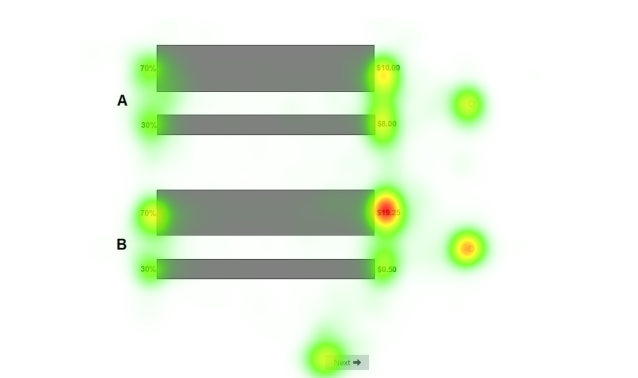
(c) Choice task 3

(d) Choice task 4



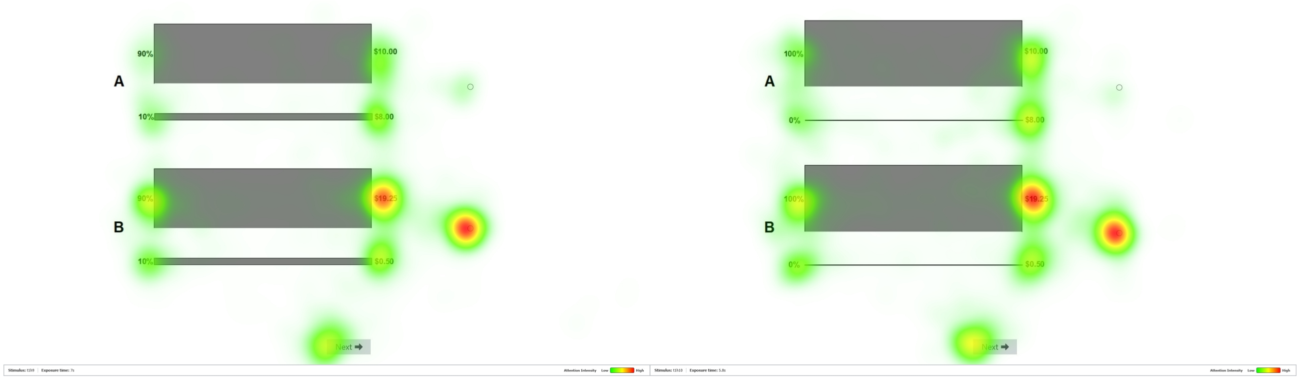
(e) Choice task 5

(f) Choice task 6



(g) Choice task 7

(h) Choice task 8



(i) Choice task 9

(j) Choice task 10

Figure A3: Heatmaps for the 'Emphasis on probabilities' format treatment (Holt and Laury, 2002, task)

(a) Choice task 1

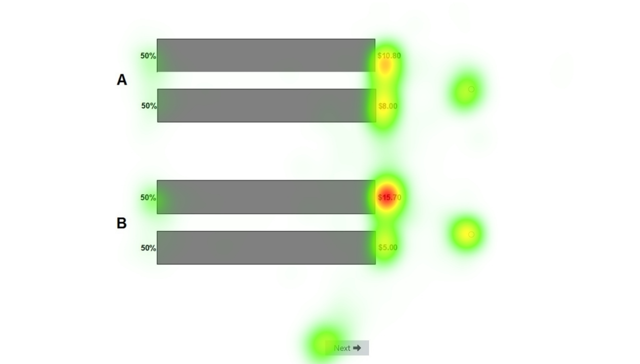
(b) Choice task 2

(c) Choice task 3

(d) Choice task 4

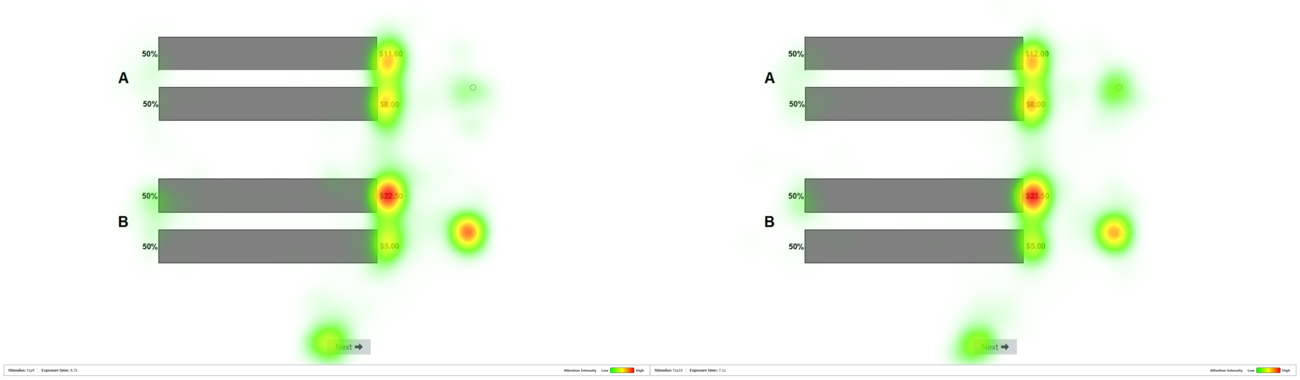
(e) Choice task 5

(f) Choice task 6



(g) Choice task 7

(h) Choice task 8



(i) Choice task 9 (j) Choice task 10

Figure A4: Heatmaps for the 'Emphasis on probabilities' format treatment (Drichoutis and Lusk, 2016, task)

(a) Choice task 1

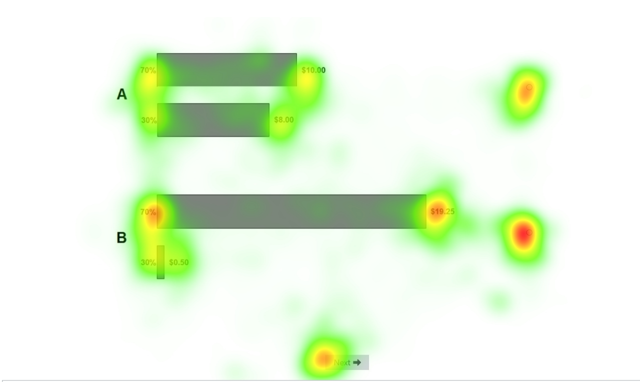
(b) Choice task 2

(c) Choice task 3

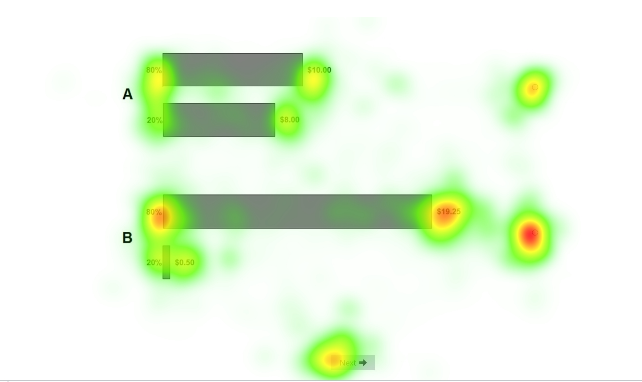
(d) Choice task 4

(e) Choice task 5

(f) Choice task 6



(g) Choice task 7



(h) Choice task 8

(i) Choice task 9

(j) Choice task 10

Figure A5: Heatmaps for the 'Emphasis on monetary amounts' format treatment (Holt and Laury, 2002, task)

(a) Choice task 1

(b) Choice task 2

(c) Choice task 3

(d) Choice task 4

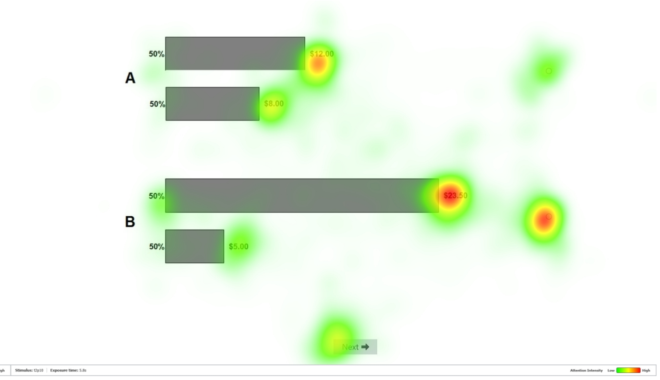
(e) Choice task 5

(f) Choice task 6

(g) Choice task 7

(h) Choice task 8

(i) Choice task 9



(j) Choice task 10

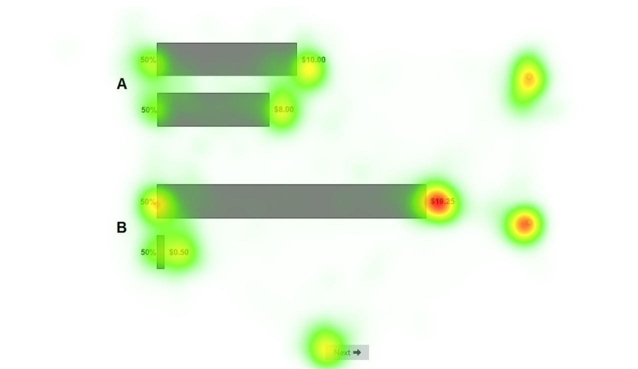
Figure A6: Heatmaps for the 'Emphasis on monetary amounts' format treatment (Drichoutis and Lusk, 2016, task)

(a) Choice task 1

(b) Choice task 2

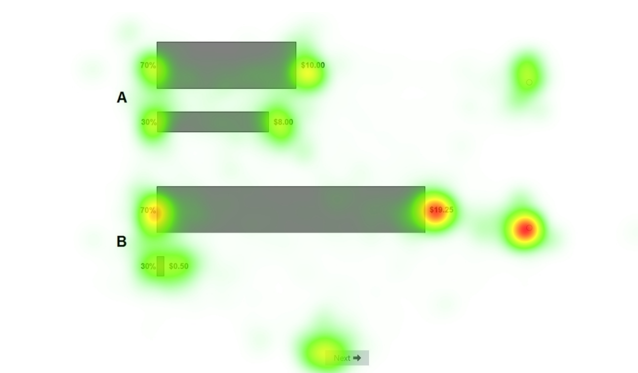
(c) Choice task 3

(d) Choice task 4



(e) Choice task 5

(f) Choice task 6



(g) Choice task 7

(h) Choice task 8

(i) Choice task 9

(j) Choice task 10

Figure A7: Heatmaps for the ‘Emphasis on both monetary amounts and probabilities’ format treatment (Holt and Laury, 2002, task)

(a) Choice task 1

(b) Choice task 2

(c) Choice task 3

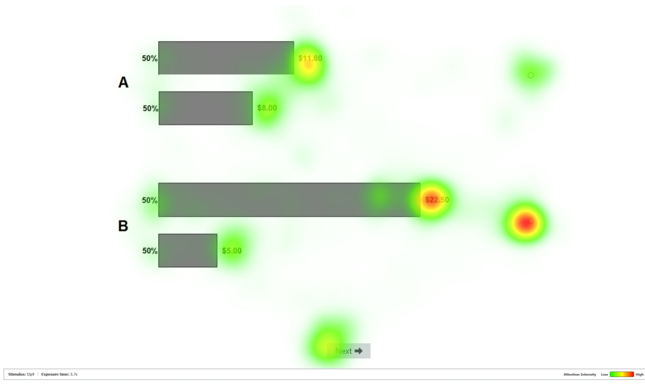
(d) Choice task 4

(e) Choice task 5

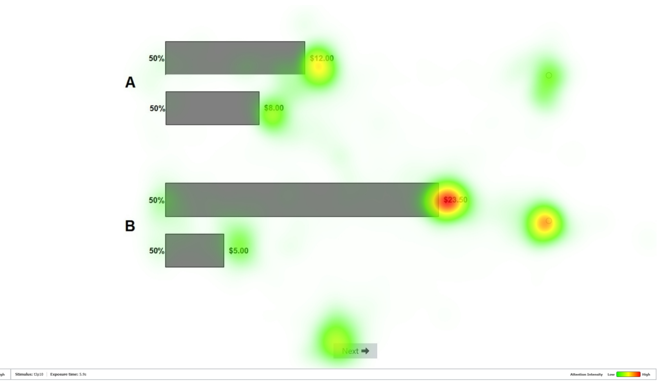
(f) Choice task 6

(g) Choice task 7

(h) Choice task 8



(i) Choice task 9



(j) Choice task 10

Figure A8: Heatmaps for the 'Emphasis on both monetary amounts and probabilities' format treatment (Drichoutis and Lusk, 2016, task)