WINPEC Working Paper Series No.E1609
June 2017

# Monetary Incentives and Eye Movements

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**Abstract**

Providing monetary incentives to each participant according to his or her payoff in an experiment is an important procedure for experimental economics. Nowadays, eye tracking has become an effective method to investigate economic decision making. However, whether incentives affect eye movements remains an unresolved question. This study explores this unaddressed question in the case of a risky choice experiment. Two experimental treatments are used regarding the incentive: real incentive (RI) treatment and hypothetical incentive (HI) treatment. Participants' eye movements, choices, and decision time are recorded and compared. The results are as follows. First, the choice distributions between the two treatments are almost identical. Second, the decision time is longer for RI than HI. Third, participants' eye movement pattern is different between two treatments even though the choices are identical. Finally, the relationship between eye movements and choices becomes stronger in the presence of monetary incentives. The findings suggest that it is appropriate to provide monetary incentives for eye tracking experiment.

Keywords: Eye movements, Eye-tracking experiments, Monetary incentives, Risky choice

JEL Classification Numbers: B4, C9, D0

## 1 Introduction

It is generally accepted that providing monetary incentives to each participant according to his or her performance in an experiment is one of the most important procedures in experimental economics. This procedure is typical among other experimental sciences, such as experimental psychology. Almost all economic experiments involve monetary incentives (Camerer and Hogarth 1999; Davis and Holt 1993; Roth 1995). The reasons for the importance of providing incentives in economic experiments are explained as follows.[1] First, most economic experiments test economic theories based on maximization assumptions (Hertwig and Ortmann 2001; Roth 1995). Secondly, it is widely believed by experimental economists that salient monetary payoffs reduce decision error variance (Camerer and Hogarth 1999; Davis and Holt 1993; Smith 1976, 1982, 1991; Smith and Walker 1993a, 1993b). Finally, they typically aim to observe participants' actual reaction to monetary incentives. Therefore, other procedures such as questionnaires or other devices based on hypothetical stimuli do not satisfy their requirement (Wallis and Friedman 1942). Therefore, experimental economists design experiments with careful attention to the relationship between incentives and participants' choices.

There is ample literature on the relationship between incentives and participants' decision making in experimental economics. Surveys conducted by Camerer and Hogarth (1999) and Smith and Walker (1993a) that reviewed the relationship between participants' choices and incentives are well known.[2] Camerer and Hogarth (1999) conducted a survey using 74 experimental studies and concluded that

*This work was supported by JSPS KAKENHI (Grant-in-Aid for Research Activity Start-up) Grant Numbers JP15H06685.

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[1] See Hertwig and Ortmann (2001) for detailed discussion on the reasons.

[2] See Hertwig and Ortmann (2001) for broad review and comparison on the practice of providing incentives in economics and psychology. They concluded that incentives (in many cases) bring decisions closer to the predictions of the normative models and that incentives can reduce variability substantially, and suggested that psychologists also consider using incentives. See also Camerer and Hogarth (1999) for the aspects of using monetary incentives by economists and psychologists.

providing incentives reduces the noisy response, but does not change the average behavior. They also showed that providing incentives improves the performance most reliably in judgment and decision making, while it is immaterial when tasks are quite easy or difficult. Smith and Walker (1993a) reviewed 31 experimental studies reporting the incentive effect. They showed that if incentives are provided, participants' decisions show a central tendency toward theoretical predictions in several experimental studies, and that the incentives reduce the data variance around the predicted outcome in all cases. The relationships between respective economic issues and incentives were also studied. Beattie and Loomes (1997) investigated the random problem selection procedure where participants' monetary reward depended on only one problem randomly selected from a series of problems. They found that when the problem was simple, incentives made little difference to performance. Kühberger et al. (2002) compared the framing effect between hypothetical and real decisions. Although the framing effect depended on the payoff size, real and hypothetical treatments resulted in a similar choice pattern. Holt and Laury (2002) explored the incentive effect on risky choices. They found that incentives did not make a difference in choices and risk attitudes when payoffs were low. However, when payoffs increased, participants became more risk averse only when incentives were real. Gächter and Renner (2010) investigated the effects of incentivized belief elicitation in a public good experiment. They found that incentives improved the belief accuracy and that incentivized beliefs led to a higher contribution level of public goods than non-incentivized beliefs.

Obviously, choice data recorded in traditional economic experiments is one of the most important information to test an economic theory. All choices are the outcome of decision-making process. However, observed choice itself does not always indicate its underlying decision-making process. Moreover, different decision-making processes can lead to identical choices. Therefore, non-choice data underlying decision-making processes is also important. With such information, decision-making process can be understood more precisely. Technological progress has developed methods to measure non-choice data. In recent years, an eye-tracking method has become an effective technique. By using an eye tracker, we can track participants' information acquisition process before making choices. Such processes provide deeper insights into economics theories.

One example is about decision making under risk (Arieli et al. 2011; Fiedler and Glöckner 2012; Glöckner and Herbold 2011; Stewart et al. 2015; Su et al. 2013). Although whether choices are based on expected utility theory has been a central question in this field, it is difficult to answer the question with only choice data. Eye movements provide deeper insights into decision making under risk and provide some hints to the question. For example, Arieli et al. (2011) conducted choice experiments between two lotteries and recorded participants eye movements when they compared two lotteries. They explored the visual transition data between attributes of risky options (i.e., two outcomes and two probabilities) and examined whether the decision-making process under risk was based on the expected-utility-like model. Their data indicated that decision making was based on comparison of two prizes and of two probabilities. Therefore, evidence for expected utility theory was insufficient. Another example is about strategic decision making. Although player's choice is observable in traditional game experiment, whether participants strategically play a game remain unproved. Devetag et al. (2016) analyzed participants' eye movements when they played a series of two-person 3 x 3 normal form games. The eye movement data indicated that participants did not analyze the payoff matrix strategically (as game theory assumes), ignoring their opponents' payoff or rarely eliminating the dominated strategy. In this way, eye tracking provides unobservable information in ordinal experiments, and such information can contribute development in economics.[3]

However, compared to the developed literature on the relationship between incentives and participants' decision making, the corresponding literature on the relationship between incentives and participants' eye movements has been scarce.[4] The practice of providing incentives differs with the study. Arieli et al. (2011) did not provide incentives because Camerer and Hogarth (1999) showed that the

[3]Other studies using an eye-tracking method in experimental economics include information acquisition in games (Hristova and Grinberg 2005), learning in games (Knoepfle et al. 2009), social preference (Jiang et al. 2015), and decision making under time pressure (Reutskaja et al. 2011).

[4]Studies on the relationship between incentives and other characteristics related to the decision-making process include incentive effects on working memory capacity (Heitz et al. 2008), neural mechanisms (Kang et al. 2011; Morgenstern et al. 2013; Small et al. 2005), decision time (Wilcox 1993), and pupil dilation (Heitz et al. 2008; Kahneman et al. 1968; Kahneman and Peavler 1969).

absence of incentives does not significantly affect participants' *choices*. However, whether the lack of incentives affects participants' *eye movements* has not been investigated and the relationship between incentives and eye movements is still an open question.[5] Considering the capability of the eye-tracking method in experimental economics, an attempt to explore the relationship between incentives and eye movements is required.

This paper reports the results of an experiment designed to address this basic methodological question and contributes to the literature on the relationship between incentives and eye movements. In the experiment, participants choose one of two risky options. The experiment consists of two treatment methods of providing monetary incentives: (i) RI treatment, where each participant is paid a monetary reward according to his or her own earnings in the experiment, and (ii) HI treatment, where each participant is paid a fixed show-up fee only. Participants' eye movements, their choices, and decision time are recorded and compared. Moreover, the relationship strengths between eye movements and choices are explored using a logistic regression to predict choices from eye movements, and prediction accuracies are compared.

It is found that incentives do not affect participants' choices but affect their decision time. With incentives, participants take a longer time to make decisions. Therefore, people invest cognitive effort to choose appropriately. This is consistent with previous studies, where incentives lead participants to invest cognitive effort to make decisions. Regarding the relationship between incentives and eye movements, there is a remarkable difference in the visual transition pattern between attributes, probabilities, and outcomes. Visual transitions within one risky option, which is consistent with the expected-utility-like model, are more frequent under a hypothetical setting. However, it is not the case with RI treatment. This implies that not only eye movements but also decision-making processes can be biased in the absence of incentives. The choice prediction accuracy using some eye-movement information is improved by providing incentives. Therefore, the relationship between participants' choices and their eye movements becomes more direct by providing incentives.

To our knowledge, this is the first study to explore the relationship between incentives and eye movements. This study does not test particular theories regarding the consistency of visual transition with the expected-utility-like model. Essentially, our contribution focuses on the fundamental and methodological issue in experimental economics using the eye-tracking method. We highlight the importance of providing monetary incentives when conducting an eye-tracking experiment, as is usually done in ordinal economic experiments.

This paper is organized as follows: Section 2 explains the experimental design and procedure. Section 3 presents the experimental results and their implications. Section 4 concludes the paper and discusses the contribution and limitation of the study.

## 2 Experiment

The purpose of this study is to address the fundamental and methodological question when conducting an eye-tracking economic experiment, which is about the relationship between incentives and eye movements. To shed light on the relationship, an economic experiment using the eye-tracking method was conducted with two treatments about incentives: RI and HI treatments. The experiment was a choice experiment between two risky options, as risky choice experiments using the eye-tracking method have been studied extensively. When participants were comparing two risky options, their eye movements were recorded and compared along with their choices and decision time.

In each choice task, each participant was presented with a series of choice tasks between two risky options, and was asked to choose one of the two options by clicking the mouse button. No time restriction was imposed. A risky option was a simple binary lottery that yielded a certain amount of money with a probability $P$ or nothing with $1 - P$. The two lotteries are represented in Fig.1. The attributes defining the two lotteries were aligned vertically so that one lottery was on the left and the other on the right. The outcomes were at the top of the screen and the probabilities were at the bottom. The left lottery

[5] One relevant study is a dissertation by Taylor (2012). He compared participants' information acquisition under real and hypothetical incentives by using Mouselab, but did not analyze their eye movements. He found that the information acquisition on incentives was similar across two settings.

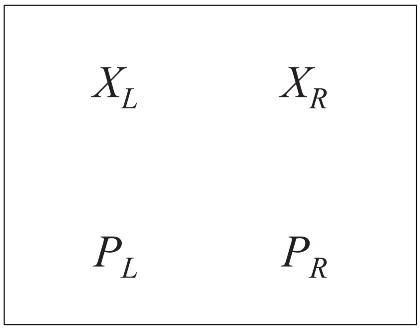


Fig. 1. Representation of two lotteries in the experiment.

yielded $X_L$ with probability $P_L$ and the right lottery yielded $X_R$ with probability $P_R$. The parameters of outcome and probability are presented in Table 1. For convenience, lotteries with higher (lower) expected values were denoted as lottery A (B) in each task. These were identical to Arieli et al.'s (2011) experiment, except that the outcome values were about one-thousandth of those according to their study and that their experiment did not provide incentives. The location of the lotteries (on the left or right side of the screen) and the sequence of choice tasks were counterbalanced. Four choice tasks, U1-U4, were also analyzed in Arieli et al. (2011). U1 and U2 were the choice problems, wherein calculating the expected values of both lotteries was easy. In U3 and U4, it was relatively difficult to accurately calculate the expected values. In these four tasks, the differences in the expected values between two lotteries were small—from ¥0.31 to ¥3. U5 and U6 were the easiest choice tasks among all tasks because lottery A had a larger outcome with a higher probability than those of lottery B. For U7, it was difficult to accurately calculate the expected values, but it was easy to judge the lottery with a higher expected value.

Table 1. Choice tasks for analysis. Lottery A has a higher expected value than lottery B. Each lottery was placed on the right or left side of the screen.

| Task | A | B |
|---|---|---|
| U1 | ¥300<br>15% | ¥400<br>11% |
| U2 | ¥170<br>40% | ¥130<br>50% |
| U3 | ¥64<br>64.9% | ¥55<br>73.2% |
| U4 | ¥136<br>31% | ¥155<br>27% |
| U5 | ¥528<br>27% | ¥527<br>26.9% |
| U6 | ¥583<br>80% | ¥510<br>60% |
| U7 | ¥666<br>60% | ¥444<br>80% |

The experiment was conducted under two kinds of treatment procedures for providing incentives. In RI treatment, an incentive was provided for making choices. Each participant played one lottery that had been chosen in the experiment. After all tasks were completed, one of the choice tasks was selected at random and each participant played the lottery chosen by him or herself in the selected task. Participants' payment depended on the result of the lottery played. However, in HI treatment, the monetary reward did not depend on the participants' choices. In the choice tasks, participants were asked which lottery they would choose if they could choose and play just one, and would be paid accordingly. Therefore, incentives were hypothetical in HI treatment. The experiment had a between-participants design: each participant could take part only once and for one treatment.

In this study, participants' eye movements were recorded by an eye tracker. We defined areas of interest (AOI) around each information (i.e., $X_L$, $X_R$, $P_L$, and $P_R$) with the size of 300 x 300 pixels.

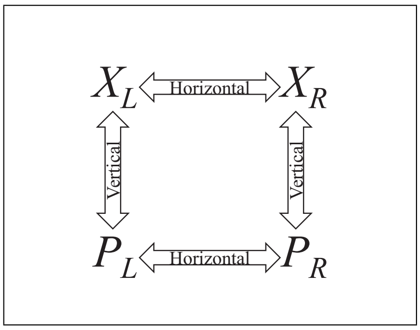


Fig. 2. Two visual transitions, vertical and horizontal transitions.

We particularly focused on participants' visual transition between four attributes: $X_L$, $X_R$, $P_L$, and $P_R$. Visual transition provides insights into how participants collect and process information to make decisions. Therefore, it is possible to investigate the decision-making process with visual transition. In risky choice experiments, visual transitions are frequently used to explore the decision-making process (e.g., Arieli et al. 2011; Fiedler and Glöckner 2012; Glöckner and Herbold 2011; Stewart et al. 2015; Su et al. 2013). Here, two kinds of visual transitions were focused: *vertical* and *horizontal* transitions (see Fig.2). Vertical transition is a visual transition within one lottery, that is, a transition between an outcome and a probability of an identical lottery. To calculate the value of a lottery based on expected-utility-like models, such as expected value model, expected utility model, and prospect theory, information acquisition should mainly be vertical. Therefore, vertical transition is consistent with the expected-utility-like models. Horizontal transition is a visual transition between two lotteries, that is, a transition between two outcomes or two probabilities. This kind of visual transition is consistent with alternative models of the expected-utility-like models, such as heuristic models. For instance, the priority heuristic model assumes that people compare the minimum outcomes of two lotteries, then the probabilities of the minimum outcomes, and finally the maximum outcomes (Brändstatter et al. 2006; Brändstatter and Körner 2014).

In addition to participants' eye movements, participants' decision time was also recorded to investigate the incentive effect on cognitive effort. Decision time is the time elapsed between the onset of a choice task and a decision. This variable is used to measure the cognitive effort of participants when they are making choices (Wilcox 1993).[6] Cognitive effort is believed to be a scarce resource for appropriate decision making. If participants are provided incentives, they will invest cognitive effort for better decisions (Camerer 1995). Consequently, the decision variance will be reduced (Camerer and Hogarth 1999; Hertwig and Ortmann 2001; Smith and Walker 1993a). For example, Wilcox (1993) incorporated cognitive effort (decision cost) into a decision-making model and showed that the increased incentive levels raise participants' willingness to incur cognitive effort. He measured the cognitive effort by decision time and found that the decision time increased with the incentive level. Therefore, the decision time of this experiment was expected to be higher under RI treatment.

Participants' choice distribution for lottery A and B was analyzed. In this experiment, the incentive level was at an ordinal economic experiment level. Hence, the choice distribution was expected to be the same in both treatments (Camerer and Hogarth 1999; Holt and Laury 2002).

All experiments were conducted at Waseda University, and the entire processes of participants' eye movements were recorded by the eye tracker, Tobii Technology T-120.[7] The eye tracker recorded the positioning of the participants' gaze on the screen every 8 milliseconds (120 Hz sampling rate) with a resolution of 1280 x 1024 pixels. Participants comprised 182 undergraduate students from various majors in Waseda University. Ten participants were excluded because of their low quality of eye tracking[8] and

[6]Cognitive effort can also be measured by galvanic skin response (Shi et al. 2007; Nourbakhsh et al. 2012) and pupil dilation (Beatty 1982; Kahneman and Peavler 1969; Kahneman et al. 1968; Wang 2011).

[7]The eye tracker can track participants' eye movements without a chinrest in front of the eye tracker. The distance between the screen and the participants' head was about 60 cm.

[8]The quality of eye tracking was evaluated by the percentage calculated by dividing the number of correctly identified gaze samples by the number of attempts to identify; 100% means that eye movements were identified perfectly, and 50%

two participants were excluded because they could not understand the method of choice task. Thus, the total number of observations was 88 (38 females, average age 20.22, S.D. 1.53) in RI treatment and 82 (24 females, average age 20.11, S.D. 1.45) in HI treatment.

At the beginning of the experiment, participants were randomly assigned to booths in the laboratory. The instructions were read aloud. Then, the eye tracker was calibrated using a 9-point calibration procedure. Subsequently, participants performed each choice task. The experiments lasted for 40 minutes on average, and participants received about ¥900 on average in RI treatment and fixed ¥1000 in HI treatment. Although rewards were slightly larger in HI, these were twice higher than the ordinal hourly wage of a typical student job.

# 3 Results

In this section, participants' choices, decision time, and visual transitions were analyzed and compared. Moreover, the relationship strengths between eye movements and choices were also compared across treatments using a logistic regression. Except for the analysis of choices, in each task and treatment, trials with decision times longer or shorter than 3 standard deviations from the mean decision time were excluded from the analysis (29 trials, approximately 2.4%).

Table 2. Numbers and proportions of choices in each task and treatment.

| Task | RI | | HI | | Fisher's exact test |
|---|---|---|---|---|---|
| | A | B | A | B | $p$ value |
| U1 | 40<br>45.5% | 48<br>54.6% | 36<br>43.9% | 46<br>56.1% | 0.878 |
| U2 | 41<br>46.6% | 47<br>53.4% | 53<br>64.6% | 29<br>35.4% | 0.021 |
| U3 | 27<br>30.7% | 61<br>69.3% | 29<br>35.4% | 53<br>64.6% | 0.624 |
| U4 | 45<br>51.1% | 43<br>48.9% | 33<br>40.2% | 49<br>59.8% | 0.168 |
| U5 | 86<br>97.7% | 2<br>2.3% | 78<br>95.1% | 4<br>4.9% | 0.431 |
| U6 | 87<br>98.9% | 1<br>1.1% | 79<br>96.3% | 3<br>3.7% | 0.354 |
| U7 | 31<br>35.2% | 57<br>64.8% | 32<br>39.0% | 50<br>61.0% | 0.636 |
| Pooled | 357<br>58.0% | 259<br>42.0% | 340<br>59.2% | 234<br>40.8% | 0.680 |

## 3.1 Choice

**Result 1:** *Incentives did not affect choices.*

Support: Table 2 shows the number and proportion of choices for each task and treatment. In tasks U1, U3, U5, U6, and U7, the choice proportions were similar between treatments. In tasks U1, U3, and U7, the majority chose lottery B in both treatments. In tasks U5 and U6, almost all participants in both treatments chose lottery A, as they had a larger outcome with a higher probability than lottery B. The statistical tests showed that the difference was not significant (Fisher's exact test, U1: $p = 0.878$, U3: $p = 0.624$, U5: $p = 0.431$, U6: $p = 0.354$, U7: $p = 0.636$). In task U2, the choice for lottery B was more frequent under RI treatment (53.4%) than under HI treatment (35.4%). The distribution of choices in the task was significantly different (Fisher's exact test, $p = 0.021$). Lottery A was risky in that the variance of the lottery was higher than that of lottery B in task U2. This result implies that participants under HI treatment showed more risk-taking behavior because their choices did not affect their own monetary rewards. Compared to HI treatment, participants under RI treatment made a

means that half of the eye movements were not identified. In this study, participants lower than 50% were excluded from the analysis.

more careful choice because their choices could affect their own monetary rewards; thus, they tended to choose a lottery with more certain but lower outcome. In task U4, participants under HI treatment also showed more risk-taking behavior and preference for lottery B (59.8%) than those of participants under RI treatment (48.9%). However, the statistical test did not show the difference (Fisher's exact test, $p =$ 0.168). Overall, the choice distributions were almost identical in both treatments (Fisher's exact test, $p$ = 0.680). This is consistent with Holt and Laury's (2002) results. Choice invariance with incentives is confirmed by this result.

Table 3. Average decision time (millisecond).

| Task | RI | HI |
|---|---|---|
| U1 | 6811.38 | 5105.99 |
| U2 | 5787.52 | 4926.33 |
| U3 | 6865.95 | 5371.93 |
| U4 | 6740.40 | 5254.36 |
| U5 | 5942.63 | 5273.64 |
| U6 | 4015.70 | 3561.94 |
| U7 | 9400.56 | 5463.48 |
| Pooled | 6504.64 | 4993.11 |

## 3.2 Decision Time

**Result 2:** *Participants took longer time to make a decision under RI treatment.*

Support: Table 3 depicts the average decision time (millisecond) in each task and treatment. Overall, participants under RI treatment took as much as 1.5 seconds longer to reach a decision compared to HI treatment. Considering the differences separately, the decision time under RI treatment was longer in all tasks. Providing incentives made participants take a longer time to decide.

The difference in decision time was small (approximately 450-700 milliseconds) in tasks U5 and U6. There was no tradeoff between probability and outcome in these tasks. Therefore, tasks U5 and U6 were the easiest tasks in the sense that lottery A was advantageous in terms of both probability and outcome. It is known that the difficulty in choice is positively proportional to decision time (Fiedler and Glöckner 2012; Glöckner and Betsch 2008; Glöckner and Herbold 2011; Krajbich et al. 2010). Moreover, it is also known that an incentive is immaterial when a task is quite easy (Camerer and Hogarth 1999). In tasks U5 and U6, participants could find an optimal lottery quickly. Therefore, an incentive might be immaterial for decision time.

To investigate the above observations statistically, decision time was regressed on *tradeoff*, *treatment*, and their interactions. *Tradeoff* is a dummy variable that takes the value of 0 when the task is U5 or U6. *Treatment* is also a dummy variable that takes the value of 1 when the treatment is RI. Table 4 shows the results of the regression. Participants were clustered and robust standard errors were computed for the repeated measurement designs. Each coefficient indicates the average change in decision time from the base level, tradeoff = 1 and treatment = 0. All three coefficients—tradeoff, treatment, and their interactions—were significant. The coefficient of tradeoff was -806.60. This indicates that if the task becomes a no-tradeoff situation, that is U5 or U6, decision time will shorten by approximately 0.8 seconds. Similarly, if incentives are provided, decision time will increase by 1.9 seconds. From the coefficient of interaction, although incentives are provided, decision time will shorten by 1.3 seconds in a no-tradeoff task. The regression results support the above observations. To summarize, except for the tasks for which it was easy to find an optimal option, participants who were provided incentives took a longer time to reach decisions. As mentioned in Hertwig and Ortmann (2001), economists think of cognitive effort as a scarce resource that people invest strategically to reduce the decision error. When payments satisfy saliency and dominance requirement (Smith 1976, 1982), people are believed to invest cognitive effort to make better choices (Camerer and Hogarth 1999). Previous experimental studies showed that people invest cognitive effort to make better decisions when incentives are provided. For example, Wilcox (1993) measured the cognitive effort by decision time and found that participants took a longer time to make a choice when incentives were high. Furthermore, Kahneman et al. (1968) and Kahneman and Peavler (1969) measured the cognitive effort by pupil dilation. They showed that when

Table 4. Results of regressing decision time on tradeoff, treatment, and their interactions. The base level is tradeoff = 1 and treatment = 0. Order effects are included as control factors in the regression (not reported). t-statistics are in parentheses. *, **, and *** indicate significance levels at $p<0.05$, $p<0.01$, and $p<0.001$, respectively.

| | Decision time |
|---|---|
| Tradeoff (base level = 1) | -806.60 *** |
| | (-3.68) |
| Treatment (base level =0) | 1881.37 *** |
| | (3.85) |
| Interaction | -1345.05 ** |
| | (-3.53) |
| Intercept | 5450.68 *** |
| | (15.69) |
| Observation | 1161 |

Table 5. Average numbers and proportions of visual transition in each task and treatment.

| Task | RI | | HI | |
|---|---|---|---|---|
| | Vertical | Horizontal | Vertical | Horizontal |
| U1 | 5.88 | 5.50 | **5.15** | 4.40 |
| | 51.7% | 48.3% | **53.9%** | 46.1% |
| U2 | 5.16 | 5.30 | **5.18** | 4.63 |
| | 49.3% | 50.7% | **52.8%** | 47.2% |
| U7 | 6.73 | 6.83 | **5.52** | 4.29 |
| | 49.7% | 50.3% | **56.3%** | 43.7% |
| U3 | 5.38 | **6.24** | 4.84 | **5.15** |
| | 46.3% | **53.7%** | 48.4% | **51.6%** |
| U4 | 5.71 | **7.11** | 4.89 | **5.58** |
| | 44.5% | **55.5%** | 46.7% | **53.3%** |
| U5 | 4.43 | **7.37** | 4.29 | **6.40** |
| | 37.5% | **62.5%** | 40.1% | **59.9%** |
| U6 | 3.91 | **4.40** | 3.60 | **4.15** |
| | 47.0% | **53.0%** | 46.5% | **53.6%** |

participants were provided with incentives, their pupil dilated and that the higher the incentives, the larger were the dilation. Result 2 is consistent with these previous studies. Therefore, Result 2 indicates that participants invest cognitive effort when incentives are provided.

## 3.3 Visual Transition

**Result 3:** *Vertical transitions within a lottery were significantly more frequent under HI treatment in tasks where the calculation of expected values of each lottery was relatively easy. In the tasks with more difficult calculation of expected values, there was no difference in visual transition pattern between two treatments.*

Support: Table 5 shows the average numbers and proportions of three visual transitions in each task and treatment. We call tasks U1, U2, and U7 *simple* tasks, as it is easy to calculate their expected values or to judge a lottery with a higher expected value. Tasks U3 and U4 are called *hard* tasks, as it is difficult to calculate their expected values. Tasks U5 and U6 are called *dominance* tasks, as lottery A has a larger outcome with higher probability than lottery B. In the simple tasks, the vertical transitions were more than 50% and they were more frequent by 6-13% than the horizontal transitions under HI treatment. Meanwhile, under RI treatment, the vertical and horizontal transitions were almost equal in the simple tasks. The visual transition distribution in the simple tasks was significantly different between treatments (Fisher's exact test, $p = 0.003$). However, in the hard tasks, the visual transition pattern had a similar feature: horizontal transitions were more frequent than vertical transitions. In the hard tasks, the distribution of treatments was not significantly different between treatments (Fisher's exact test, $p = 0.197$). In the dominance tasks, the horizontal transitions were a majority in both treatments. The distribution was not significantly different (Fisher's exact test, $p = 0.473$). To find an advantageous lottery, it was enough to process the information horizontally. Therefore, the horizontal transitions were more frequent.

As the outcomes in this experiment were about one-thousandth of the respective values in Arieli et al.'s (2011) experiment, the experimental designs were almost the same, except that they did *not* provide monetary incentives for participants' choices. The result of our experiment under both treatments was consistent with that of Arieli et al. (2011):[9] when it was difficult to calculate the expected values, horizontal transitions were more frequent. However, when it was relatively easy to calculate the expected values, vertical transitions were more frequent only under HI in our experiment.

Table 6. Average numbers and proportions of visual transitions with respect to participants' choices

Participants who chose higher expected value (Lottery A)

| Task | RI | | HI | |
|---|---|---|---|---|
| | Vertical | Horizontal | Vertical | Horizontal |
| U1 | 5.56 | 4.59 | **6.11** | 4.17 |
| | 54.8% | 45.2% | **59.4%** | 40.6% |
| U2 | 5.85 | 5.74 | **5.50** | 4.69 |
| | 50.4% | 49.6% | **54.0%** | 46.0% |
| U7 | 7.97 | 8.07 | **7.33** | 4.83 |
| | 49.7% | 50.3% | **60.3%** | 39.7% |

Participants who chose lower expected value (LotteryB)

| Task | RI | | HI | |
|---|---|---|---|---|
| | Vertical | Horizontal | Vertical | Horizontal |
| U1 | 6.15 | 6.26 | 4.40 | 4.58 |
| | 49.6% | 50.4% | 49.0% | 51.0% |
| U2 | 4.60 | 4.94 | 4.57 | 4.50 |
| | 48.2% | 51.8% | 50.4% | 49.6% |
| U7 | 6.07 | 6.16 | 4.41 | 3.96 |
| | 49.6% | 50.4% | 52.7% | 47.3% |

To investigate the difference in the frequency of vertical transitions between two treatments in simple tasks, the average numbers and proportions of visual transitions in the simple tasks were analyzed with respect to participants' choices (Table 6 and Fig. 3). Under HI treatment, participants tended to mainly collect information vertically only when they chose lotteries with higher expected values (lottery A). Their vertical transitions were among 54-60% and were more frequent than horizontal transitions by 8-20%. Meanwhile, under RI treatment, participants' vertical and horizontal transitions did not show such large differences; two visual transitions were almost equal when they chose lotteries with higher expected values. The visual transition distributions were significantly different between two treatments when participants chose lotteries with higher expected values (Fisher's exact test, $p = 0.003$). However, when participants chose lotteries with lower expected values (lottery B), their vertical and horizontal transitions were almost equal in both treatments. No significant differences in visual transition distributions were observed when participants chose lotteries with lower expected values (Fisher's exact test, $p = 0.459$).

Suppose a decision maker evaluates lotteries by calculating expected values and choosing the highest one, their information acquisition should be mainly a vertical one. The fact that participants showed more frequent vertical transitions under HI treatment and that this was observed only when they chose lotteries with higher expected values suggests that the hypothetical intervention can induce participants to calculate the expected values. In other words, by not providing incentives, participants' decision-making process and information acquisition can be altered even though the choices are identical. The differences between RI and HI treatments in visual transition imply that hypothetical incentives can affect decision-making processes as well as eye movements.

## 3.4 Prediction of Choices

If eye movements are related to choices, it will be expected that the eye movement information can predict choices. Participants' choices were predicted by a logistic regression. Tasks U5 and U6 were excluded from this regression because almost all participants in both treatments chose the same lottery. The dependent variable was the choice in a task, while the independent variables varied across the model.

[9] Arieli et al. (2011) analyzed the visual transition for only tasks U1, U2, U3, and U4, but not for U5, U6, and U7.

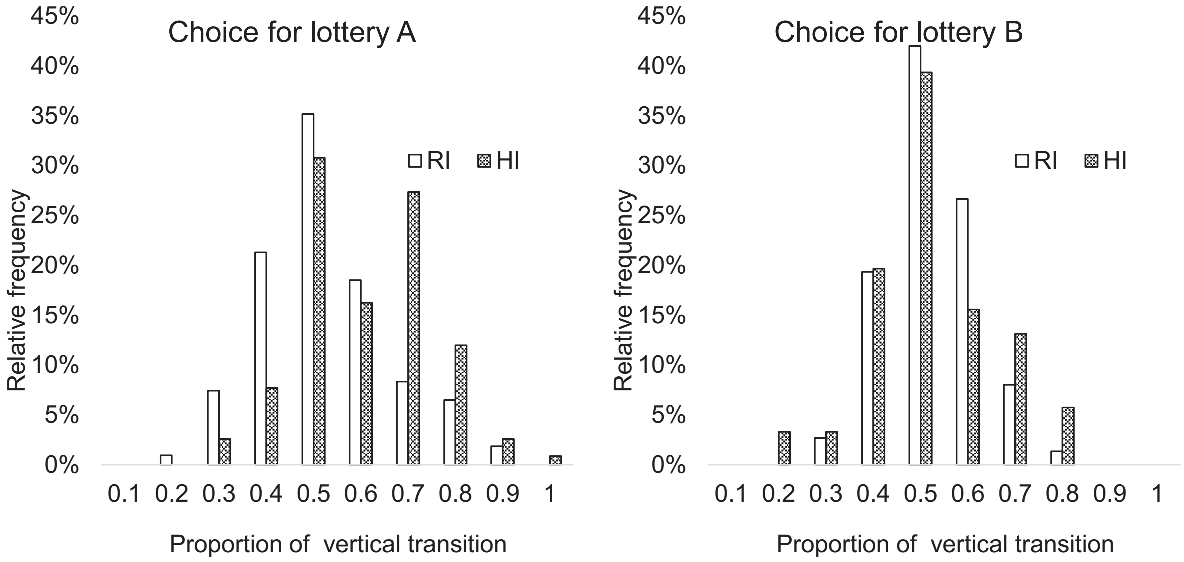


Fig. 3. Proportions of vertical transition (within lotteries) with respect to participants' choices.

In this analysis, three models predicted participants' choices: (i) final fixation model, (ii) fixation on lottery model, and (iii) visual transition model. In the first two models, the dependent variable was choice for the lottery on the left or right side (choice for lottery on the right side = 1). In the last model, the dependent variable was choice for the lottery A or B (choice for lottery A = 1).

The final fixation model uses the independent variable, which indicates whether the final fixation is to the lottery on the left or right side. It is known that people tend to choose the option that is fixated at the point they make a decision (Fiedler and Glöckner 2012; Glaholt and Reingold 2009b; Krajbich et al. 2010; Stewart et al. 2015). Therefore, it is expected that the coefficient of final fixation is significant and the model predicts choices well. The fixation on lottery model uses the relative fixation duration on both lotteries. The fixation duration is interpreted as an indicator of a participant's valuation or importance of an option (Russo 2011).[10] Hence, the chosen lottery is expected to be focused upon. The visual transition model uses the number of vertical and horizontal transitions. From Result 3, it is expected that the coefficients of transitions are significant only in HI treatment.

**Result 4:** *When an incentive was provided, the prediction accuracy improved in models using final fixation and fixation duration. The model using the number of transitions was a better fit in HI treatment.*

Support: Table 7 depicts the summary of each model and prediction accuracy. Two models using eye movements predicted better in RI treatment. In the final fixation model, participants' final fixation predicted their choices better in RI treatment (RI: 71.3%, HI: 65.7%). In the fixation on lottery model, the coefficient of fixation duration on right lottery was positive and significant under RI treatment. This means that the more participants pay attention to the lottery on the right side, the more liable they are to choose that lottery. However, this fixation bias was not observed under HI treatment. No coefficients were significant. Again, the prediction accuracy was higher under RI treatment (RI: 65.0%, HI: 61.7%). Therefore, this model was also better under RI treatment. To summarize, in these two models, the prediction accuracies under RI treatment outperformed by about 3-6%. The choice prediction accuracy was improved by providing incentives. This suggests that the relation between choice and eye movements becomes clearer by providing incentives. The observed strong relations between choices and fixation duration or final fixation in RI treatment are consistent with studies that explore the relation between choices and eye movements (Fiedler and Glöckner 2012; Glaholt and Reingold 2009a, 2009b; Glöckner and Herbold 2011; Krajbich et al. 2010; Shimojo et al. 2003; Stewart et al. 2015).

[10]Because the decision times are not the same in all trials, we use the relative fixation duration in which fixation durations are divided by decision times.

Table 7. Results of logistic regressions and prediction accuracy. Logistic regressions predicting choices. Order effects are included as control factors in the regression (not reported). Observations were corrected for clusters, and robust standard errors were computed. Z-statistics are in parentheses. *, **, and *** indicate significance levels at the $p<0.05$, $p<0.01$, and $p<0.001$, respectively.

| | Final Fixation | | Fixation on Lottery | | Visual Transition | |
|---|---|---|---|---|---|---|
| | Choice for right lottery = 1 | | | | Choice for A = 1 | |
| | RI | HI | RI | HI | RI | HI |
| Final Fixation | 1.83 *** | 1.32 *** | | | | |
| (Right=1,Left=0) | (7.52) | (5.24) | | | | |
| Fixation on Left | | | -2.23 | -1.77 | | |
| | | | (-1.35) | (-0.92) | | |
| Fixation on Right | | | 5.35 *** | 3.90 | | |
| | | | (3.60) | (1.92) | | |
| Vertical | | | | | 0.05 | 0.22 *** |
| | | | | | (1.72) | (4.02) |
| Horizontal | | | | | -0.04 | -0.17 ** |
| | | | | | (-1.15) | (-2.94) |
| Intercept | -0.73 *** | -0.39 * | -1.05 | -0.57 | -0.22 | -0.48 |
| | (-3.77) | (-2.13) | (-0.89) | (-0.35) | (-1.10) | (-1.76) |
| Observation | 429 | 399 | 429 | 399 | 429 | 399 |
| AIC | 506.10 | 514.40 | 548.45 | 533.52 | 582.51 | 529.26 |
| Prediction Accuracy | 71.3% | 65.7% | 65.0% | 61.7% | 61.3% | 63.7% |

However, the visual transition model showed the opposite result. In the model, the coefficient of vertical transition was positively significant, and that of the horizontal transition was negatively significant under HI treatment. This implies that the more participants process information vertically (horizontally), the more (less) liable they are to choose the lottery with a higher expected value. However, it was not the case with RI treatment, as the two coefficients were not significant. The prediction accuracy was higher under HI treatment (RI: 61.3%, HI: 63.7%). This tendency indicates that people can calculate the expected values of lotteries and choose lotteries with higher expected values only when monetary incentives are hypothetical.

# 4 Concluding remarks

Despite the importance of using an eye-tracking method and providing an incentive to participants in experimental economics, little has been understood about the relationship between monetary incentives and participants' eye movements. This study addressed the basic methodological question and contributed to the literature on the relationship by conducting a risky choice experiment with Real Incentive (RI) and Hypothetical Incentive (HI) treatments. In the experiment, participants chose between two lotteries. Their eye movements, decision time, and choices were recorded and compared across two treatments. The relationship strengths between eye movements and choices were also compared using a logistic regression to predict choices.

It was found that participants took a longer time to decide under the RI treatment. This result supports the idea of cognitive effort, where it is assumed that people invest cognitive effort to make better choices. Participants' eye movement pattern was also different between two treatments even though the choices were identical. This implies that providing no incentives can affect eye movements and decision-making processes. In particular, an analysis of whether risky choices are based on the expected-utility-like model has mixed results, because the proportions of visual transition differ across studies. In some prior works on risky choice experiments using an eye-tracking method, a high visual transition frequency within attributes of single option was observed (e.g., Glöckner and Herbold 2011). In other previous works, the visual transition within one option was moderate (e.g., Stewart et al. 2015). The results of our study will provide a clue to address these mixed results. The prediction accuracy of choices was improved by providing incentives in the final fixation model and the fixation on lottery model, and thus choices and eye movements can be related more strongly as a result of incentives. However, in the model using visual transitions, the prediction accuracy was better in HI treatment. This indicates that people can calculate the expected values and make a choice.

The finding that visual transition distributions were different between two treatments suggests that the implication or interpretation of the decision-making process can differ, and thus we should pay careful attention to incentives. For example, if incentives are hypothetical, the decision-making process will be consistent with expected-utility-like models; however, if incentives are provided, the process can be considered as alternative to the expected-utility-like models. In general, experimental economics aim at observing peoples' actual reactions to monetary incentives. Therefore, it is appropriate to provide real incentives to conduct an eye-tracking experiment when conducting ordinal economic experiments.

To our knowledge, this is the first study to explore the relationship between incentives and eye movements. However, there are some drawbacks to this study. First, the experiment conducted was a basic risky choice experiment, as a simple binary lottery was used. In some prior works, more complicated options were used. Therefore, there is room to explore the relationship in more complicated circumstances. Second, only a risky choice experiment was conducted. Currently, the eye-tracking method is used in experiments for game theory, social preference, etc. Thus, the relationship should be studied in a broader economic context. However, this study does contribute to the basic methodological question when conducting an eye-tracking economic experiment

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