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ABSTRACT

Testing the Reference-Dependent Model: A Laboratory Search Experiment*

Our paper conducts laboratory experiments with the sequential search model to test whether participants engage in search activities in line with theoretical predictions derived from the expected utility model or the reference-dependent model, without assuming any specific formulation rule for a reference point. Our experimental results showed that the participants' search behavior did not align with the reference-dependent model. In addition, the correlation between individual preferences and search behavior reinforced our experimental results; that is, loss aversions were not significantly correlated with search behavior.

JEL Classification: D81, D83

Keywords: risk preference, loss aversion, sequential search

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1 Introduction

Our objective in this paper is to test whether individuals engage in sequential search activities on the basis of the expected utility model or the reference-dependent model in laboratory experiments with the individual sequential search model. Most of the existing literature on laboratory experiments with search models has focused on the standard sequential search model, in which an individual who has a preference for *risk aversion* optimally behaves to maximize her or his expected utility level, based on the expected utility model. The individual draws a point and then decides whether to accept the draw and stop searching or to reject the draw and continue the search activity by comparing the expected marginal benefit with the marginal cost of drawing an additional point in the next search round (Lippman and McCall, 1976).

However, the recent literature has considered a search model in which an individual who has a preference for *loss aversion* updates her or his reference point over the search based on the reference-dependent model. In the reference-dependent model, the individual's utility level can be expressed as the sum of standard consumption utility and the gain–loss utility, which describes the feeling of gain or loss that is determined by the extent to which the current level of consumption deviates from the reference level (Kahneman and Tversky, 1979: Tversky and Kahneman, 1991: Kőszegi and Rabin, 2006). Therefore, whether to accept or reject a draw in search activity is determined not only by a comparison of the marginal benefit and marginal cost of drawing an additional point in the next round of the search, but also by the expected extent to which a draw deviates from the reference point. Several previous studies have supported individuals engaging in search activities based on the reference-dependent model (Schunk, 2009: Schunk and Winter, 2009: Häubl et al., 2010: Koenig et al., 2016: DellaVigna et al., 2017). These studies found that participants' behaviors during a search are better explained by the reference-dependent model than by the expected utility model.

Despite the results from the above studies, the way that a reference point is formulated remains a topic of debate; in the existing literature, the reference points were arbitrarily determined; for example, based on the highest previous outcomes (Schunk, 2009: Schunk and Winter, 2009) and the average of recent outcomes (DellaVigna et al., 2017).

In this study, we propose a novel experimental design to test whether individuals engage in search activities on the basis of the expected utility model or the reference-dependent model, without assuming any specific formulation rule for a reference point. We designed laboratory search experiments with two treatments. In the first treatment, additional search behavior will be terminated coercively with some probability, but the drawn point does not result in the payoff to participants being discounted, regardless of the search duration (the *Termination* treatment); and in the second treatment, a draw in the next search round will result in the payoff being discounted by a fixed rate, but individuals can continue to search as long as they want (the *Discount* treatment). In the *Termination* treatment, individuals will experience a loss from the termination of search activity for any positive reference point if they behave on the basis of the reference-dependent model, but they do not incur such a loss if their search behavior is consistent with the expected utility model.

Given that the probability of surviving to the next round equals the discount factor, the effects of the discount factor and termination risk on search behaviors are different if an individual's search behavior is explained by the reference-dependent model. Under the expected utility model, in contrast, they would not differ. We predict that the reservation point will be lower in the case of the *Termination* treatment than in the *Discount* treatment if an individual behaves on the basis of the reference-dependent model, but that there will be no difference between the two treatments if the individual's behavior is explained instead by the expected utility model. Therefore, this design allows us to test which model better explains the individual's search behavior: the expected utility model or the reference-dependent model, simply by comparing the search behaviors between the two treatments.

It could be possible that an individual who behaves on the basis of the reference-dependent model chooses different reference points between the two treatments. In this case, a difference in search behavior is due not only to the change of treatments (direct change), but also to the change of the reference point through the channel of the different treatments (indirect change). Our concern is that the effect of the direct change on search behavior, which is the exact treatment effect focused on, is dominated by the one of the indirect change. To dispel this concern, we have conducted numerical exercises from the infinite-horizon sequential search model, and we show that the reservation point is strictly lower in the *Termination* treatment than in the *Discount* treatment within the framework of the reference-dependent model in Section 2.3, even though the individual is allowed to change her or his reference point between the treatments. This implies that the effect of the direct change of the treatments is not dominated by the one of the indirect change of reference points through the different treatments.

Our contributions to the literature are twofold. First, our approach does not require any specific formulation rule for a reference point, in contrast with the previous studies that tested the reference-dependent model in search activity (Schunk, 2009: Schunk and Winter, 2009: Häubl et al., 2010: Koenig et al., 2016: DellaVigna et al., 2017). Second, our approach does not require the individual heterogeneity of loss aversions to test the reference-dependent model because we use the within-subject differences between the two treatments. Our approach is different from those of Schunk (2009) and Schunk and Winter (2009), who conducted similar laboratory experiments to test the reference-dependent model by observing the correlation between the individual heterogeneity of search activity and loss aversions. They elicited the correlation from their questionnaire.

Our approach is tractable, but one condition has to be fulfilled for the validity of the experimental test; that is, it must be assumed that the utility function is linear. The experimental design is based on the standard model with sequential search, in which an individual discounts her or his utility. However, we designed the experiment in such a way that the points drawn over the search, but not the utility level, resulted in a discount of the payoffs to participants. The utility function must be linear to make the experimental design consistent with the implications from the standard search model. If an individual's utility function is linear, we can interpret this to mean that she or he is risk neutral. However, it does not necessarily mean that she or he behaves on the basis of the expected utility model. If the individual additionally has preferences for gain or loss that arises from deviation from the reference point, we conclude that she or he behaves on the basis of the reference-dependent model. We confirmed that this condition was fulfilled in Section 4.2. Therefore, our approach is sufficiently valid to test the hypothesis that individuals behave on the basis of the reference-dependent model.

The results from our experiments did not support the reference-dependent model better explaining participants' behavior in search activities. The search behavior of the participants did not significantly differ between the two treatments. We also elicited the degrees of risk aversion and loss aversion in a questionnaire conducted in the experiments. We found that the individual heterogeneity of search behavior was not significantly correlated with the degree of loss aversion, which was the key parameter in the reference-dependent model.

It should be noted that our result contrasts with those in Schunk (2009) and Schunk and Winter (2009), because we employed a different search setting. They conducted a laboratory search experiment in which a recall option of previous draws was allowed and the fixed cost of an additional search activity was explicitly incurred, but they did not incorporate a termination risk and a discount factor into their experimental design. They found a significant correlation between loss aversion and search behavior but not between risk preferences and search behavior. One possible interpretation is that individuals behave differently in a different search setting.

In addition, our method can be applied to a laboratory experiment with repeated games involving the random termination method frequently utilized in the literature. Our results supported the validity of this method.

There is a growing literature that uses a laboratory search experiment to test the theoretical predictions obtained from a sequential search model (Asano et al., 2015: Cagno et al., 2014: Brown et al., 2011: Häubl et al., 2010: Boone et al., 2009: Schunk, 2009: Schunk and

Winter, 2009: Friedman et al., 2007: Cox and Oaxaca, 1989 1992). Our study is in line with this literature.

The rest of our paper is organized as follows. The next section develops the infinite-horizon sequential search model used in our experiments and then specifies the identification strategy. Section 3 explains the experimental design, followed, in Section 4, by the summary statistics, a report on the validity of our approach, and the experimental results. Section 5 compares the experimental results with those from Schunk (2009) and Schunk and Winter (2009). Concluding remarks are provided in the final section.

2 Model

In this section, we explain an infinite-horizon sequential search model developed by Lippman and McCall (1976). The first subsection shows the search model in which an individual behaves on the basis of the expected utility model, and the subsequent subsection provides the search model in which an individual's behavior is determined by the reference-dependent model. The final subsection explains the identification strategy used in our laboratory experiment.

2.1 Expected Utility Model

A representative individual i engages in search activity. In the first round, individual i draws a point from a uniform distribution within the range between the lower bound, $m - a$, and the upper bound, $m + a$, thereby implying that the expected draw is m.

The individual decides whether to accept or reject the drawn point. If the individual accepts the point, then the search activity is ended, and the point becomes the individual's payoff. If the individual rejects the point, then the individual decides to continue to search and moves to the next round, drawing a new point from the same uniform distribution. However, the individual who rejects a point and decides to move to the next round is forced to end the search activity with the probability ρ, in which case the payoff to the individual is zero. Moreover, a point drawn in the next round is discounted by the discount factor δ. Therefore, the individual can continue to search for a higher point but, at the same time, she or he faces a risk of forced termination of search behavior and must accept the point and the payoff being discounted.

Additionally, in our laboratory experiment, we assume for simplicity that the individual's time preference does not affect the search activity because participants actually conduct this laboratory experiment in an hour or less in total. The individual can search as long as possible unless she or he stops searching or is forced to end the search activity. Therefore, this model describes the essence of the infinite-horizon sequential search activity.

In the expected utility model, the value function of individual i is given by:

$$V_i = \text{Emax}[u_i(x), (1-\rho)\delta V_i + \rho u(0)], \tag{1}$$

where V_i represents the present discount value of search for individual i, $u_i(x)$ is the utility function exhibiting $u_i' > 0, u_i(0) = 0$, x is a drawn point, ρ is the probability of termination, and δ is the discount factor. Equation (1) can be rewritten as:

$$(1-\delta+\rho\delta)V_i = \int_{R_i}^{m+a} [u_i(x) - (1-\rho)\delta V_i] \left(\frac{1}{2a}\right) dx, \tag{2}$$

where R_i represents individual i's reservation point.

The right-hand side of equation (2) represents the expected marginal gain of an additional search activity and the left-hand side indicates the marginal cost of an additional search activity. It should be noted that the reservation point does not become lower as the search duration increases in the infinite-horizon sequential search model. According to the reservation point property, the reservation point R_i is determinedly by $u_i(R_i) = (1-\rho)\delta V_i$.

Assuming that individual i is risk neutral, her or his utility function can be rewritten as $u_i(x) = p_i x$, where p_i is the individualistic parameter determining the utility from an accepted point.[1]

If individual i behaves on the basis of the expected utility model and has a preference for risk aversion, one of her or his utility functions can be formulated as $u_i(x) = \frac{x^{1-\theta_i-1}}{1-\theta}$, where θ_i represents individual i's degree of risk aversion. If $\theta_i = 0$, individual i is considered risk neutral, but if $\theta_i > 0$, she or he has a preference for risk aversion. As θ_i increases, she or he becomes more risk averse. According to Lippman and McCall (1976), the reservation point is lower for risk averse individuals than for risk neutral ones. Therefore, the average numbers of draws over a search is smaller for risk averse individuals than for risk neutral ones.

2.2 Reference-Dependent Model

Next, we shift our focus to the optimal search strategy within the framework of the reference-dependent model. We first consider the specification of a utility function developed by Kőszegi and Rabin (2006); that is:

$$u_i(x|r) = \begin{cases} v_i(x) + \eta_i(v_i(x) - v_i(r)) & \text{for } x \geq r \\ v_i(x) + \eta_i\lambda_i(v_i(x) - v_i(r)) & \text{for } x < r, \end{cases} \tag{3}$$

where r indicates the reference point of individual i, $v_i(\cdot)$ is the utility function exhibiting $v_i'(\cdot) > 0$ and $v_i(0) = 0$ and the deviation from the reference point $(v_i(x) - v_i(r))$ captures the gain–loss utility. η_i is individual i's weighting parameter of the gain–loss utility and λ_i is individual i's degree of loss aversion ($\lambda_i \geq 0$). It is noted that λ_i captures the asymmetric sensitivity of the gain–loss utility. Individual i is characterized as having a preference for loss

[1] In the case of the linear utility model, the individualistic parameter p_i appears on both sides of equation (2) and p_i can then be canceled out. Therefore, risk neutral individuals share the same reservation point, regardless of the heterogeneity of the individualistic parameter.

aversion if $\lambda_i > 1$.[2]

Behaving on the basis of the reference-dependent model, individual i feels loss when exogenous termination occurs after she or he decides to move to the next round. loss averse individuals are eager to exit earlier before termination occurs, which implies that the reservation point is lower for loss averse individuals than for loss neutral ones.

When $v_i(x) = p_i x$, where p_i represents the individualistic parameter, individual i is characterized as having a preference for risk neutrality. When $v_i(x) = \frac{x^{1-\theta_i - 1}}{1-\theta}$, where θ_i represents the degree of risk aversion, individual i instead has a preference for risk aversion if $\theta_i > 0$. Although individual i is risk neutral or averse, as well as loss averse, we treat her or him as behaving on the basis of the reference-dependent model. The reference-dependent model comprehensively includes preferences regarding risk embodied by the expected utility model. We test the null hypothesis that the weighting parameter of the gain–loss utility (η_i) is zero to confirm whether individual i engages in search activities on the basis of the expected utility model or the reference-dependent model.

In our experiment, our focus is not on whether participants are risk neutral or risk averse, but on whether they engage in search activities on the basis of the expected utility model or the reference-dependent model. As explained below, we suggest a unique identification strategy that is simple but valid if participants are risk neutral. We confirmed that the participants were risk neutral in Section 4.2 before conducting our main test.

2.3 Identification Strategy

This subsection provides a detailed explanation of the identification strategy to test which model better explains individuals' search behavior: the expected utility model or the reference-dependent model. To do so, we prepared two treatments, the *Termination* and *Discount* treatments.

In the *Termination* treatment, termination occurs with probability and coercively ends the

[2] The formal model developed by Kőszegi and Rabin (2006) can be expressed by $u_i(x|r) = v_i(x) + \mu_i(v_i(x) - v_i(r))$, where $\mu(\cdot)$ represents i's universal gain–loss utility function.

search activity, but drawn points are not discounted in terms of the payoff over the search ($\rho > 0$ and $\delta = 1$). In the *Discount* treatment, on the other hand, the drawn points are discounted in terms of the payoff received over the search, but the probability of termination is zero ($\rho = 1$ and $\delta < 1$).

If individual i behaves on the basis of the expected utility model, the value functions under the *Termination* and *Discount* treatments are, respectively:

$$V_{iT} = \mathrm{E}\max[u_i(x), (1-\rho)V_{iT} + \rho u_i(0)] = \mathrm{E}\max[u_i(x), (1-\rho)V_{iT}], \tag{4}$$

and

$$V_{iD} = \mathrm{E}\max[u_i(x), \delta V_{iD}]. \tag{5}$$

When $1 - \rho = \delta$ is fulfilled, there is no difference in the reservation point between the *Termination* and *Discount* treatments according to equations (4) and (5). The individual behaves in the same way over the search activity, regardless of the treatments.

On the other hand, if an individual's utility function is defined by the reference-dependent model, the treatments are not isomorphic. If a drawn point is larger than the reference point, then the individual feels gain; otherwise, she or he feels loss. The value functions given under the *Termination* and *Discount* treatments are, respectively:

$$V_{iT} = \mathrm{E}\max[u_i(x|r), (1-\rho)V_{iT} - \rho\eta_i\lambda_i v_i(r)], \tag{6}$$

and

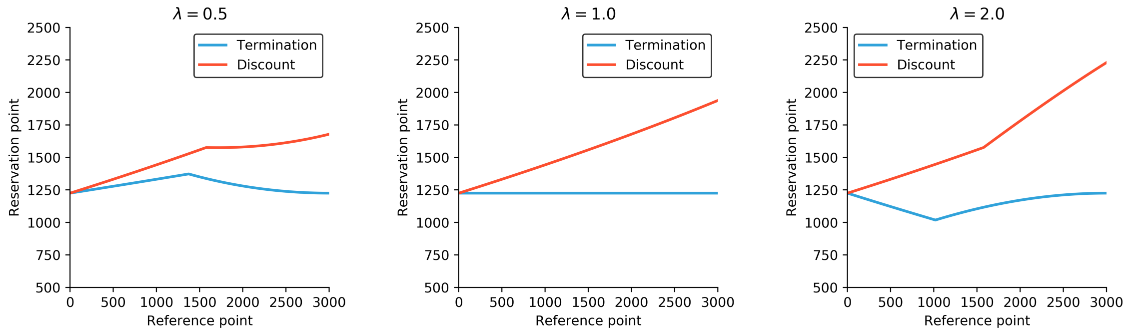
$$V_{iD} = \text{Emax}[u_i(x|r), \delta V_{iD}]. \tag{7}$$

In the *Termination* treatment, individual i, who has her or his reference point, feels loss when termination occurs after she or he decides to move to the next round in equation (6). However, in the *Discount* treatment, termination does not occur, and an individual is allowed to continue her or his search activity infinitely, although the draw accepted in later rounds is discounted in equation (7). Therefore, even though $1 - \rho = \delta$ is fulfilled, the value of continuing the search activity is lower in the *Termination* treatment than in the *Discount* treatment. This implies that the reservation point is lower in the *Termination* treatment than in the *Discount* treatment if individual i's behavior is explained by the reference-dependent model. If her or his search behavior can be explained by the expected utility model, individual i does not incur any loss when termination occurs, in which case the reservation point remains unchanged, regardless of the treatments.

It should be noted that the main source of the differences in search behavior between the two treatments is the presence of the term $(-\rho\eta_i\lambda_i v_i(r))$, or the loss utility, shown in parentheses on the right-hand side of equation (6). To make this identification strategy valid, we need to assume that the utility level, $u_i(x|r)$, shown in the parentheses on the right-hand sides of equations (6) and (7), remains unchanged, regardless of the two treatments. In other words, there is no difference in the reference point between the two treatments. However, we cannot ensure this, in which case this strategy cannot allow us to measure the exact effect of search behavior in the presence of loss utility.

To address concerns in regard to this, we show that the reservation point is lower for individual i, who behaves on the basis of the reference-dependent model in the *Termination* treatment, than it is in the *Discount* treatment, even if we relax the assumption that $u_i(x|r)$ does not change between the two treatments. Figure (1) displays numerical associations between the optimal reservation points and the reference points, using equations (6) and (7),

Figure 1: Optimal reservation points by reference points



The associations between the optimal reservation points and the reference points are calculated using equations (6) and (7).

assuming m and a are 1,500 and 500, respectively. Individuals draw a point from the uniform distribution within a range between the lower bound, 0, and the upper bound, 3,000, which is similar to our experimental design. When individual i is loss averse (λ= 2) or loss neutral (λ = 1), the optimal reservation point in the *Termination* treatment is equal to or lower than it is in the *Discount* treatment, regardless of any reference point. In other words, the maximum value of the optimal reservation point in the *Termination* treatment is strictly lower than its minimum value in the *Discount* treatment, except when r = 0 or 3,000.

When r=0, individual i's utility level depends only on x, and thus she or he does not incur any feeling of loss, which implies that her or his search behavior can be explained by the expected utility model. When r=3,000, the upper bound of the point distribution, individual i absolutely feels loss on drawing a point, to the extent that it discourages her or him from joining the search. Thus, we can rule out cases of r = 0 or 3,000 when comparing the two treatments from equations (6) and (7). Even though individual i chooses different reference points for the treatments, we can conclude that her or his reservation point is strictly lower in the *Termination* treatment than in the *Discount* treatment.

When individual i is gain seeking (λ = 0.5), the optimal reservation point in the *Termination* treatment is equal to or lower than it is in the *Discount* treatment for each reference point within the range between 0 and 3,000. We observe that the maximum value of the optimal reservation point in the *Termination* treatment is *not* strictly lower than its minimum value in the *Discount* treatment. This could indicate a result arising from our identification strategy that is different from our prediction of the treatment effect. However, we do not need to consider a rare case, such as this one in which an individual is gain seeking within the framework of the reference-dependent model.[3]

To summarize, when $1 - \rho = \delta$ is fulfilled, if there is no difference in individual i's reservation point between the *Termination* and *Discount* treatments, she or he behaves on the basis of the expected utility model. If the reservation point is higher under the *Discount* treatment than under the *Termination* treatment, her or his search behavior is based on the reference-dependent model.[4]

To make this identification strategy valid, participants' preferences must fulfill one condition; that is, the utility functions, $u_i(x)$ in the expected utility model and $v_i(x)$ in the reference-dependent model, must be linear. We constructed a standard sequential search model in which an individual discounts her or his *utility level* over the search. However, we designed the laboratory experiment in which *draws* over the search, but not the utility level, were discounted in terms of actual payoffs. Therefore, the utility functions ($u_i(x)$ in the expected utility model and $v_i(x)$ in the reference-dependent model) must be linear to make the experimental design consistent with implications from the standard search model. Even though an individual's utility function is linear, that is, risk neutral, it does not necessarily mean that she or he behaves on the basis of the expected utility model. If the individual's utility function includes the gain–loss utility term, we interpret this to mean that she or he engages in search activity on the basis of the reference-dependent model. We confirm the validity of this condition in Section 4.2.

[3]Our simulation exercise shows that the maximum value of the optimal reservation point in the *Termination* treatment is equal to or strictly lower than the minimum value of it in the *Discount* treatment if the degree of loss aversion (λ) is equal to or more than one.

[4]Our identification strategy only considers the fixed reference point. However, recent studies propose the stochastic reference point (Kőszegi and Rabin, 2006). We conjecture our identification strategy is also valid in the stochastic reference point.

3 Experimental Design

Our experiment consisted of three parts in each session, and we employed a within-subject design. Thus, all participants conducted all parts and treatments. The order of parts and treatments was randomly determined in each session. The instructions utilized in one session are provided in the Appendix.

In Part 1, participants conducted a search experiment. A computer allocated to each individual drew a point from a uniform distribution within the range between $m - a$ and $m + a$. As mentioned above, we prepared two treatments: a *Termination* and a *Discount* treatment, in our experimental design, and we set m and a as 1,500 and 1,500, respectively, noting that the expected value is $1,500$.

In the *Termination* treatment, we designed the experiment in such a way that termination occurred with probability and coercively ended the search activity, but that drawn points were not discounted in terms of the payoffs over the search activity. To focus on the effect of a preference for loss aversion on search behavior, we set the probability of termination as 30% (ρ). According to the prospect theory, individuals have preferences for loss aversion (reference-dependent model) and estimate the probability of outcomes based on their probability weighting function. Our objective is to test whether an individual's search behavior is determined by preferences for loss aversion and, therefore, we need to control the effect of probability weighting on search behavior. Individuals subjectively overestimate the probability of an occurrence when it is objectively low but underestimate it when it is objectively high. Abdellaoui (2000) shows that an individual's subjective probability of an occurrence equals the objective probability at the 30% level, according to the probability weighting function.

In the *Discount* treatment, we designed the experiment in such a way that drawn points were discounted in terms of the payoffs received over the search activity, but the probability of termination was zero. To make a direct comparison of the two treatments, we set the discount factor as 0.70 (δ). We set $1 - \rho = \delta$, as noted in Section 2.3.

Participants played our search games 15 times in both the *Termination* and the *Discount* treatments (resulting in a total of 30 trials per participant per session). The order of the two treatments was random to eliminate order bias.

In Part 2, participants responded to a monetary incentivized questionnaire concerning risk preferences. We utilized the multiple price list (MPL) method developed by Holt and Laury (2002). Table 1 displays an example of contents of the questionnaire. Participants chose either lottery A or lottery B for each row. If the participants chose lottery A, they received x_A with probability p or y_A with probability $1-p$; if they chose lottery B, they received x_B with probability p or y_B with probability $1-p$. We designed the experiment such that $x_A > y_A$, $x_B > y_B$, $x_A < x_B$ and $y_A > y_B$, which indicates that lottery A is regarded as a safe option, but lottery B is a risky option. We prepared four patterns of outcomes for (x_A, y_A) versus (x_B, y_B) as follows: (1) (2,000, 1,400) versus (3,000,0); (2) (1,600, 1,400) versus (2,500, 500); (3) (1,600, 1,400) versus (3,000, 0); and (4) (1,600, 1,400) versus (3,000, 500).

For each session, the participants conducted three of the four patterns of outcomes. The order of patterns was randomly determined in each session. As the row went down, p increased by 10 percentage points, and the increase in the expected value was larger for the risky options than for the safe options. We predicted that the participants would switch their choices from safe options to risky options as the row went down. We use the average number of safe options chosen from all the rows in the three patterns of outcomes as a measure of risk preferences. Note that an individual is more risk averse when she or he chooses a greater number of safe options.

In Part 3, participants responded to a nonmonetary incentivized questionnaire concerning loss aversion. We employed the certainty equivalent method (Wakker and Deneffe, 1996). Participants faced two options: A and B. If the participants chose option A, they received x or lost y, with both outcomes being equally likely. Otherwise, if the participants chose option B, they received 0. Given y, the participants were requested to answer x, that is, the minimum acceptance value to choose option A. We measure the extent of loss aversion as x/y

in Kahneman and Tversky (1979). This questionnaire could not be monetarily incentivized because the participants would have had incentives to reveal a higher x if the payoff was given on the basis of choosing option A.

Table 1: An example of the multiple price list

Choice number	Safe option (lottery A)	Risky option (lottery B)
1	1,500 (10%), 1,300 (90%)	2,000 (10%), 0 (90%)
2	1,500 (20%), 1,300 (80%)	2,000 (20%), 0 (80%)
3	1,500 (30%), 1,300 (70%)	2,000 (30%), 0 (70%)
4	1,500 (40%), 1,300 (60%)	2,000 (40%), 0 (60%)
5	1,500 (50%), 1,300 (50%)	2,000 (50%), 0 (50%)
6	1,500 (60%), 1,300 (40%)	2,000 (60%), 0 (40%)
7	1,500 (70%), 1,300 (30%)	2,000 (70%), 0 (30%)
8	1,500 (80%), 1,300 (20%)	2,000 (80%), 0 (20%)
9	1,500 (90%), 1,300 (10%)	2,000 (90%), 0 (10%)
10	1,500 (100%), 1,300 (0%)	2,000 (100%), 0 (0%)

After the three parts of the experiments were conducted, we randomly chose one decision that determined the reward for the experiments, based on the payoffs among 60 decision-making instances (15×2 trials in Part 1 and 10×3 choices in Part 2). If a decision in Part 1 was chosen, we converted 1 point to JPY 1.[5] Alternatively, if one row in Part 2 was chosen, we paid the money according to the distribution of occurrences in the lottery (A or B) selected by a participant. In addition, we paid all participants JPY 500 as a show-up fee.

4 Results

4.1 Experimental Procedures and Summary Statistics

The participants in our experiment were undergraduate students at Osaka University, Japan. The experiments were conducted on December 20, 2017. We recruited the participants by using the Online Recruitment System for Economic Experiments (ORSEE) (Greiner et al.,

[5] Using the exchange rate of JPY 100 to USD 0.90 for March 8, 2019, JPY 1,000 is equivalent to USD 9.0.

2004) and ran the experiments by using z-Tree (Fischbacher, 2007). In total, there were 51 participants, of whom 25 were male (over the three sessions). We dropped two participants from our sample. One participant should have switched from lottery A to lottery B only once in Part 2, when choosing from the top row to the bottom one, but actually made multiple switches between lotteries A and B. This means that she or he made inconsistent choices in the MPL method. Another participant chose an extremely high value for minimum acceptance (x) in Part 3. This implied such a high degree of loss aversion (more than 1,000) that this participant was treated as an outlier according to the certainty equivalent method. Therefore, the final sample size was 49.

Table 2 displays the summary statistics. The first column shows the means of the variables of interest, with the first two rows showing the mean proportions of participants accepting a draw in the *Termination* and *Discount* treatments, respectively. These proportions were calculated by dividing the number of draws accepted by participants by the total number of draws over the search activity in each of the two treatments. [6] The third row represents the mean degree of risk aversion obtained from the questionnaire in Part 2, calculated using the estimated results of the interval regressions from data collected by the MPL method.[7] The fourth row indicates the mean degree of loss aversion calculated from the questionnaire in Part 3. It was calculated by dividing the minimum acceptance value (x) by the amount of loss outcome from the result of option A (y) in the certainty equivalent method. The second column represents the standard deviations of the corresponding variables of the first column.

The first two rows of the third column show the theoretical predicted probabilities of an individual accepting a draw over the search activity, assuming that she or he is risk and loss neutral ($\theta = 0$ and $\lambda = 1$) in the two treatments. The fourth column shows the proportions of risk or loss averse participants based on experiments from Parts 1, 2, and 3. The first two rows of the fourth column represent the proportions of participants who accepted a draw earlier

[6] Because the participants conducted 15 trials of the *Discount* treatments, the numerator of the proportions was 15. There was possibility that the search activity was ended coercively in the *Termination* treatment, the numerator of the proportion was equal to or less than 15.

[7] The results are available upon request.

than did a risk and loss neutral individual in the *Treatment* and *Discount* treatments. The third row indicates the proportion of risk averse participants whose degrees of risk aversion (θ) are higher than the theoretical value for a risk neutral individual, using the data from the questionnaire in Part 2. In a similar manner, the fourth row displays the proportion of loss averse participants whose degrees of loss aversion (λ) are higher than the theoretical one for a loss neutral individual, using the data from the questionnaire in Part 3.

There are three findings to be reported from Table 2. First, we found that the mean proportions of participants accepting a draw (first column) were higher than the predicted ones for the risk and loss neutral individual (third column) in both treatments, which is consistent with the previous literature (Schunk (2009)). However, the mean-comparison tests significantly reject the null hypothesis that these proportions correspondingly equal the theoretical probabilities for the risk and loss neutral individual in the *Termination* treatment ($p = 0.019$), but not in the *Discount* treatment ($p = 0.359$). Second, according to the experiment from Part 2, we found that the participants were risk averse overall in the MPL method because the null hypothesis that the participants were risk neutral was rejected at the 1% level of significance ($p < 0.000$). Finally, experimental results from Part 3 show that the participants were loss averse overall according to the certainty equivalent method. We rejected the null hypothesis that the participants were loss neutral at the 1% level of significance ($p = 0.002$). According to the simple statistical description, our finding is that the participants were risk and loss averse overall.

Figure 2 displays histograms of the proportion of participants accepting a draw over the search in the *Termination* (right panel) and *Discount* (left panel) treatments. Although the mean-comparison test significantly rejected the null hypothesis of risk neutrality for the participants, we observed that the proportions of participants accepting a draw over the search were distributed around the theoretical predicted value chosen optimally by risk and loss neutral individuals ($p = 0.59$) in both treatments. We conclude that the participants were risk averse overall according to the statistical hypothetical testing, but that the extent

Table 2: Summary statistics

	$Mean$	$S.D.$	$Riskandlossneutral$	$Riskorlossaverse$
Termination	0.65	0.16	0.59	0.63
Discount	0.62	0.18	0.59	0.63
θ	1.03	0.61	0	0.98
λ	3.96	6.13	1	0.82
N	49			

[1] The first two rows of the first column show the mean proportions of participants accepting a draw in the *Termination* and *Discount* treatments, respectively. These proportions were calculated by dividing the number of draws accepted by participants by the total number of draws over the search activity in each of the two treatments.

[2] θ in the first column represents the within-mean of the expected degree of risk aversion. The expected degree of risk aversion is calculated by using estimated results of interval regressions from data collected using the MPL method (Part 2).

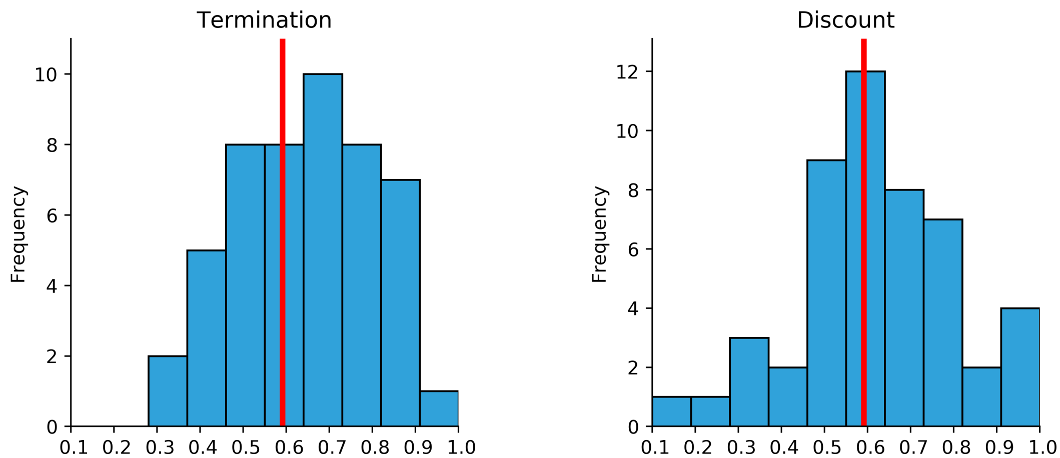
[3] λ in the first column represents the within-mean of the degree of loss aversion. The degree of loss aversion is calculated by dividing the minimum acceptance value (x) by the amount of the loss outcome (y) from the result of option A in the certainty equivalent method (Part 3).

[4] The first two rows of the third column show the theoretical predicted probabilities of an individual accepting a draw, assuming that she or he is risk and loss neutral in the *Termination* and the *Discount* treatments.

[5] The first two rows of the fourth column show the fractions of participants whose proportions of accepting a draw over the search activities (first column) are higher than the predicted probabilities of accepting (third column) in the *Termination* and the *Discount* treatments, respectively. The third row represents the proportion of risk averse participants whose degree of risk aversion (θ) is higher than the theoretical value for a risk neutral individual. The fourth row displays the proportion of loss averse participants whose degree of loss aversion (λ) is higher than the theoretical one for a loss neutral individual.

of risk aversion was negligible in size from Figure 2. In addition, we tested whether the distribution differed by treatments. The Kolmogorov–Smirnov test could not significantly reject the null hypothesis that the distributions of the proportions of participants accepting a draw over the search were similar between the two treatments ($p = 0.494$).

Figure 2: Histogram of acceptance probability



The red vertical lines show the theoretical acceptance probability of risk and loss neutral individual.

4.2 Model Fitting

As mentioned in Section 2.3, our approach for testing the reference-dependent model is valid under the assumption that the utility function is linear. To confirm the validity of this assumption, we check the model fitting to compare the linear utility with constant relative risk aversion (CRRA)-type nonlinear utility models. To do so, we calculate the goodness of fit (GoF) of the models. There are three steps to derive the GoF.

We first consider the case of the linear utility model with the reference-dependent framework (equation(3) in which $v_i(x) = p_i x$, where p_i represents the individualistic parameter). The first step is to calculate each participant's reservation point for each given reference point within the range between the lower bound 0 and the upper bound 3,000. For simplicity, the reference points were delimited by 1 points. The degree of loss aversion obtained from the questionnaire in Part 3 (λ) was extrapolated into the linear utility function to calculate each participant's reservation points corresponding to each reference point from 0 to 3,000. It is noted that differences of reservation points among the participants are attributable only to differences in their degrees of loss aversion (λ).

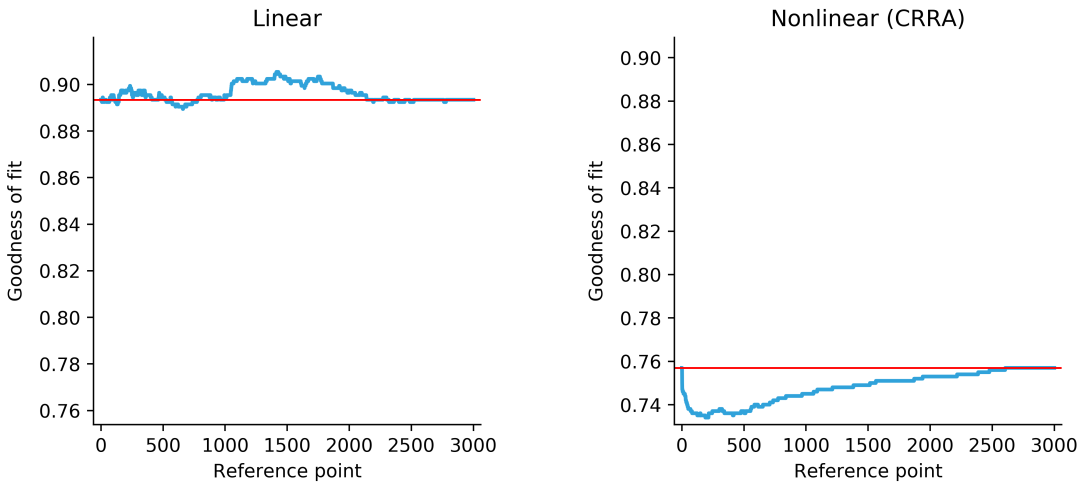
The second step is to check whether each participant properly accepted (rejected) a draw that was equal to or higher (lower) than her or his own reservation point according to the reservation point property. The third step is to calculate the GoF: the proportion of draws that the participants accepted or rejected properly for each given reference point.

Next, we execute the same steps to obtain the GoF in the case of the CRRA-type nonlinear model with the reference-dependent framework. The degree of risk aversion obtained from the questionnaire in Part 2 (θ) was used in the CRRA-type nonlinear utility function to calculate each participant's reservation point. It should be noted here that differences in the reservation points among the participants are attributable to differences in their degrees of risk aversion (θ) and loss aversion (λ).

Figure 3 displays the result of the model fitting. The vertical axis represents GoF, and the horizontal axis indicates the reference point, ranging from 0 to 3,000. The left panel shows the GoF of the linear utility model and the right panel shows the GoF of the nonlinear (CRRA-type) utility model. Based on a comparison of the two panels, there are two findings. First, despite the fact that we rejected the null hypothesis of risk neutrality according to the mean-comparison test shown in Section 4.1, the model fitting is better in the linear model than in the nonlinear model. Second, the GoF does not vary largely by the reference point, including $r = 0$ (The red horizontal lines shows the GoF at $r = 0$), in both panels. Therefore, it is not clear whether participants perceived feelings of gain or loss over their search; in other words, whether they engaged in search activities based on the reference-dependent model. In the left panel, the GoF is 0.89 at $r = 0$, and the highest GoF is 0.91 at $r = 1,427$.

Therefore, based on the model-fitting results, we concluded that our experimental data fitted better with the linear utility model than with the nonlinear utility model.

Figure 3: Model fitting of acceptance decision



The red horizontal lines shows the goodness of fit at $r = 0$.

4.3 Regression Analysis

From the results of the model-fitting exercises, we found that the linear utility model fitted better with the experimental data of the participants. Therefore, we conclude that our experimental design is sufficiently valid to test whether participants engaged in search activities on the basis of the reference-dependent model or whether participants had feelings of gain or loss over the search activity.

Next, we estimate the fixed effect linear probability model to explore differences in the probability of a participant accepting a draw between the two treatments. Recall that according to our hypothesis, if the search behaviors of the participants are explained better by the reference-dependent model, the mean of the probabilities of participants accepting a draw is lower in the *Discount* treatment than in the *Termination* treatment. As the independent variable, we use a dichotomous variable taking a value of one if a participant accepts a draw, but zero otherwise. We regress the independent variable with dummies indicating the treatments and search rounds.

As displayed in Table 3, in total, the coefficient of the *Discount* treatment is statistically insignificant and negligible in magnitude. The estimated results remain unchanged even by adding round dummies (column 2) or restricting the sub-sample covering the first three rounds (column 3). We cannot reject the hypothesis that the probability of a participant accepting a draw is lower in the *Discount* treatment than in the *Termination* treatment. Therefore, we conclude that the participants did not engage in the search activities set by our experimental design on the basis of the reference-dependent model.

Table 3: The probability of a participant accepting

Round	All (1)	All (2)	≤ 3 (3)
Discount	0.040	0.006	-0.001
	(0.034)	(0.024)	(0.025)
Round		-0.041^{***}	-0.194
		(0.006)	(0.127)
Round^2		0.001^{***}	0.055
		(0.000)	(0.034)
Constant	0.554^{***}	0.655^{***}	0.759^{***}
	(0.014)	(0.015)	(0.101)
R^2	0.002	0.034	0.002
N	2372	2372	2096

Cluster robust standard errors by individuals shown in parentheses.
* $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.
The third column restricts observations to the first three rounds.

So far, we have concluded that the participants in our experiments were risk and loss neutral overall; in other words, that they shared a linear utility function and did not have any feelings of gain or loss compared with the reference point. For the robustness checks, we next estimated the Cox hazard model to explore the effects on the number of search rounds of each participant's degrees of risk and loss aversion obtained from the questionnaire (Parts 2 and 3), which indicates how individual heterogeneity with respect to risk and the feelings of gain or loss affected search behaviors. To take into account the right-censoring of the number of search rounds in the *Termination* treatment, we ran a survival analysis.

Figure 4 shows the Kaplan–Meier survival function. It seems that the survival functions do not differ between the two treatments, and the Wilcoxon test cannot significantly reject the null hypothesis that these two survivor functions are similar ($p = 0.746$). This result reinforces our conclusion that the participants did not engage in search activities based on the reference-dependent model.

Figure 4: Kaplan–Meier survival functions of the Termination and Discount conditions

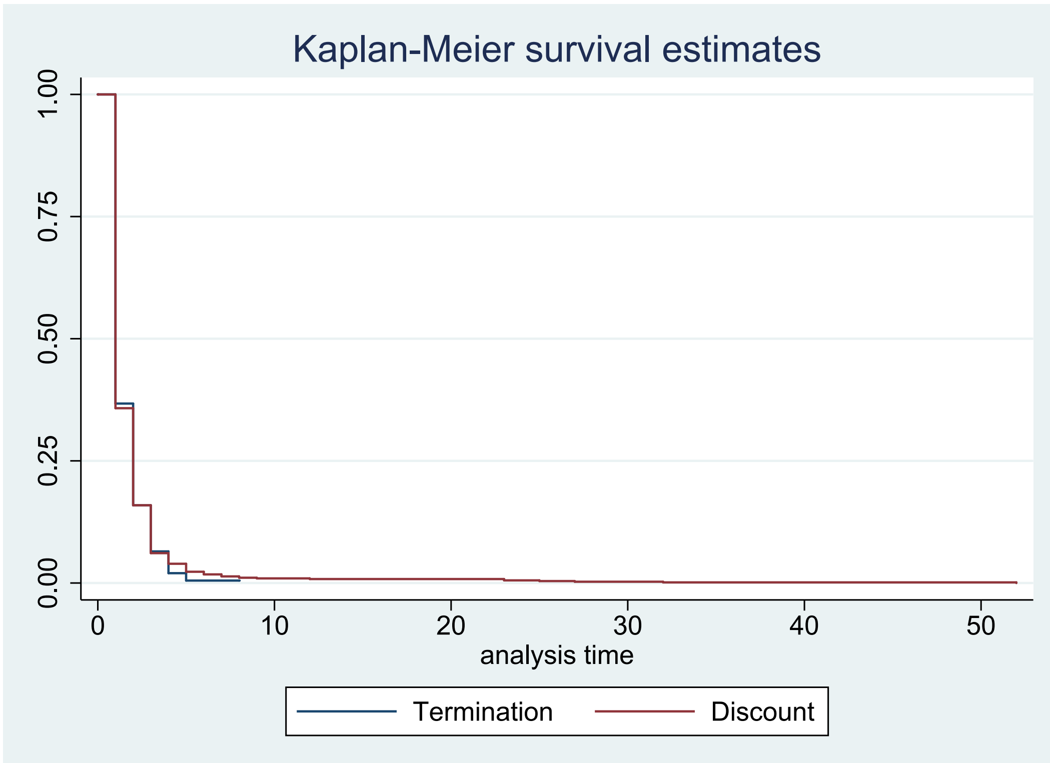


Table 4 shows the results obtained by estimating the Cox hazard model. The coefficient of *Discount* is statistically insignificant in all columns. In addition, the coefficient of the degree of loss aversion (λ) is insignificant. These two findings are consistent with the results from Table 3. Therefore, we can say that the participants' search behaviors were not explained by the reference-dependent model.

In contrast with our prediction, the coefficient of the degree of risk aversion (θ) is positive at the 1% level of significance, although we showed that the participants were risk neutral overall. This implies that more risk averse participants finished searching in early rounds, as shown in Lippman and McCall (1976). However, the degree of risk aversion is relatively weak. To show this, we calculate the standardized coefficient beta that measures the effect size of risk aversion and find that it is 0.04. According to the Cohen (2013), the effect size d is large if $d > 0.8$, medium if $0.3 < d \leq 0.8$ and small if $d \leq 0.3$. Therefore, even though the participants were risk averse overall, the effect size is so negligibly small that their risk preferences could be treated as risk neutrality.

Table 4: Correlation between individual preferences

	(1)	(2)	(3)	(4)
Discount	−0.00	−0.01	−0.01	−0.01
	(0.04)	(0.04)	(0.04)	(0.04)
θ		0.13***		0.13***
		(0.05)		(0.05)
λ			0.00	−0.00
			(0.00)	(0.00)
Male	−0.02	0.01	−0.02	0.02
	(0.06)	(0.05)	(0.06)	(0.06)
AIC	18254	18247	18255	18249
N	1470	1470	1470	1470

Cluster robust standard errors by individuals shown in parentheses.
* $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

5 Discussion

We tested whether the reference-dependent model better explained participants' search behaviors by using a novel experiment design. Comparing the effects of the *Discount* treatment with that of the *Termination* treatment on search behaviors (Table 3) and exploring the effects on the length of the search duration of individual heterogeneity with respect to risk and the feelings of gain or loss (Table 4), we concluded that the participants did not engage in search activities based on the reference-dependent model.

The motivation for our research is very similar to those of Schunk (2009) and Schunk and Winter (2009), who conducted search experiments to test the validity of the reference-dependent model in sequential search activities. In contrast with our result, they found a significant correlation between search behavior and the degree of loss aversion that was elicited from their questionnaire. However, they did not find a significant correlation between the degree of risk aversion and search behavior. Although we share the same motivation with Schunk (2009) and Schunk and Winter (2009), our experimental design differs from theirs in two ways. First, in Schunk (2009) and Schunk and Winter (2009), an additional draw in search activities required a participant to explicitly incur a fixed cost. Second, the participant was allowed to recall previous draws in a trial. In our study, an additional draw in search activities did not require a participant to pay a fixed cost, but the participants faced the search being coercively terminated with some probability or a discount of a drawn point. Additionally, our study did not allow the participants to recall previous draws. As pointed out by Kogut (1990), Sonnemans (1998) and Brown et al. (2011), participants might not feel the burden of the fixed cost they paid in a trial as a sunk cost. If the sunk cost effect is correlated with the degree of loss aversion, the differences in the results between their experiments and ours are attributable largely to the differences in the experimental designs.

Our method can be applied to the model with the infinitely repeated games because the explicit termination risk and discount factor were explicitly incorporated into our experiment. Similar to Zwick et al. (1992), which compared the difference between the effects of the termination risk and the discount factor by using an experiment with repeated games, our study supports the validity of the random termination method.[8]

6 Concluding Remarks

This paper tested whether an individual's behavior in sequential search activities was explained well by the reference-dependent model, and whether the individual had feelings of gain or loss when she or he drew a point every round over a search activity, using a laboratory experiment for searching. We set two treatments: in the first treatment, an additional draw

[8]However, there is a recent paper examining the difference of strategy choices between the random termination and discount factor methods in a model with repeated games (Fréchette and Yuksel, 2017).

will result in the search being coercively terminated with some probability, but the draw is not discounted for payoff over the search activity (the *Termination* treatment). In the second treatment, a point drawn in the next round of the search activity will be discounted by a fixed rate, but there is no coercive termination of the search (the *Discount* treatment).

Our prediction was that individuals would feel loss from coercive termination of the sequential search for any positive reference point if they behaved on the basis of the reference-dependent model, but that they would not feel such a loss if they behaved on the basis of the expected utility model. Therefore, we hypothesized that the effects of the discount factor and the termination risk on search behavior would be different in the reference-dependent model. We then compared the within-subject difference in search behavior between the two treatments to test the validity of the reference-dependent model in search activities.

There are merits and demerits in our approach. The merit is that reference points are allowed to vary between and within individuals. Therefore, individual heterogeneity in the degree of loss aversion is not required to test the reference-dependent model. However, the drawback is that the linearity of utility function is required.

We checked the validity of our approach and obtained supportive results; that is, we found that the model fitting was better under linear utility than under CRRA-type nonlinear utility.

The main result did not support the hypothesis that the reference-dependent model explained participants' behaviors well in sequential search activities. Search behaviors were not significantly different between the two treatments. The result was robust if we compared the individual heterogeneity of search behavior with individual preferences with respect to risk and feelings of gain or loss, which were elicited from the questionnaire. The effect of the degree of loss aversion on the number of search rounds was not significant.

In contrast with our result, Schunk (2009) and Schunk and Winter (2009) found a significant correlation between the individual heterogeneity of search behavior and the degree of loss aversion. We conjectured that this difference was due to the difference of experimental design; however, it is unclear what the limitation of our analysis is, and further research is required to investigate this in future.

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7 Appendix: Instruction

Introduction

- You are requested to participate in our laboratory experiment regarding individual decision-making.
- This experiment consists of three parts involving decision-making.
- The number of trials for decision-making is 65 in total (30 in Part 1, 30 in Part 2 and 5 in Part 3).
- Each part will be explained in detail by the experimenter before that part of the experiment begins.
- After the experiment, we will conduct a questionnaire with you.

Reward for the Experiment

- In this experiment, we pay JPY 500 as a show-up fee and a reward based on your points from the trials.
- At the end of the experiment, we randomly draw one choice you made among 60 choices in Parts 1 and 2.

Part 1

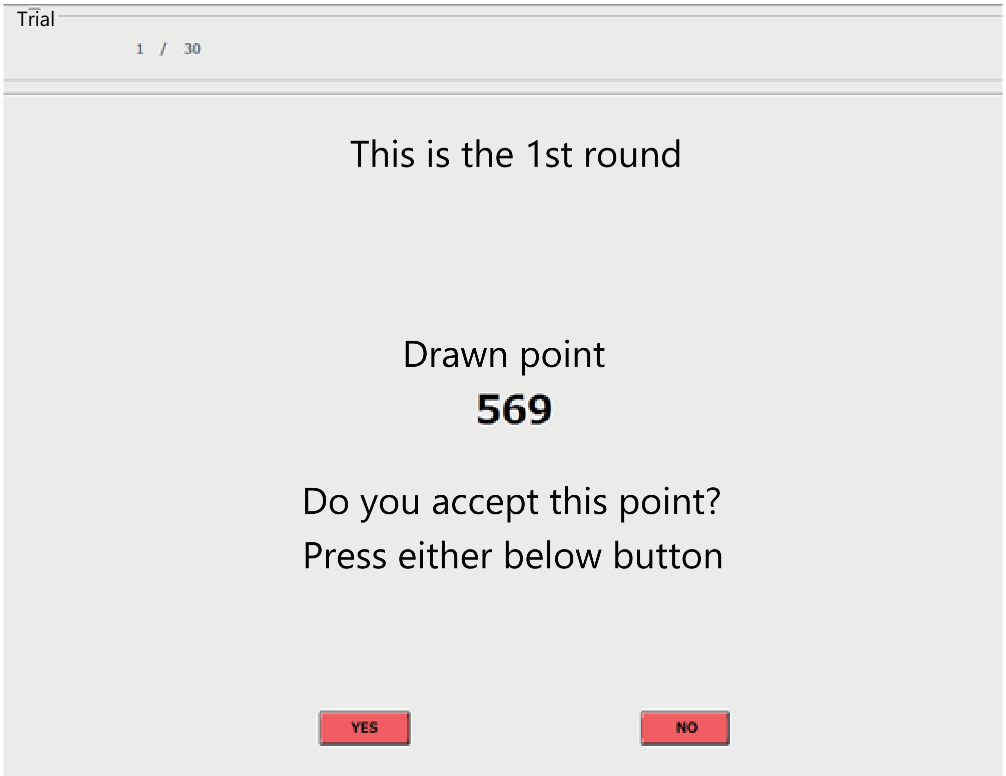
- In Part 1, you decide whether to accept a point drawn randomly and then receive a payoff based on the point, or you reject the point and wait for another point drawn randomly in the next round.
- This experiment consists of two types of game (Game A and Game B).
- Each type of game is composed of 15 trials. Therefore, there are a total of 30 trials.

- In each trial, you make a decision in each round.
- In each round, a point is drawn randomly.
- The higher your accepted point is, the higher your pay is.
- You decide whether you accept a random draw and finish searching or reject the draw and then move on to the next round, with the chance of receiving a higher draw.
- However, in Game A, there is a probability that you cannot move on to the next round. If you cannot move on to the next round, your point is 0 in the trial.
- In Game B, although you can move on to the next round for certain, your points in the next rounds are discounted consistently.
- The order of Game A and Game B is randomly determined.
- The conversion rate between points and JPY is: 1 point = JPY1.
- More details regarding the rules of the games will be provided later.

What to do in Game A

- We will explain the rules of Game A.
- When Game A begins, the PC monitor displays the screen below.

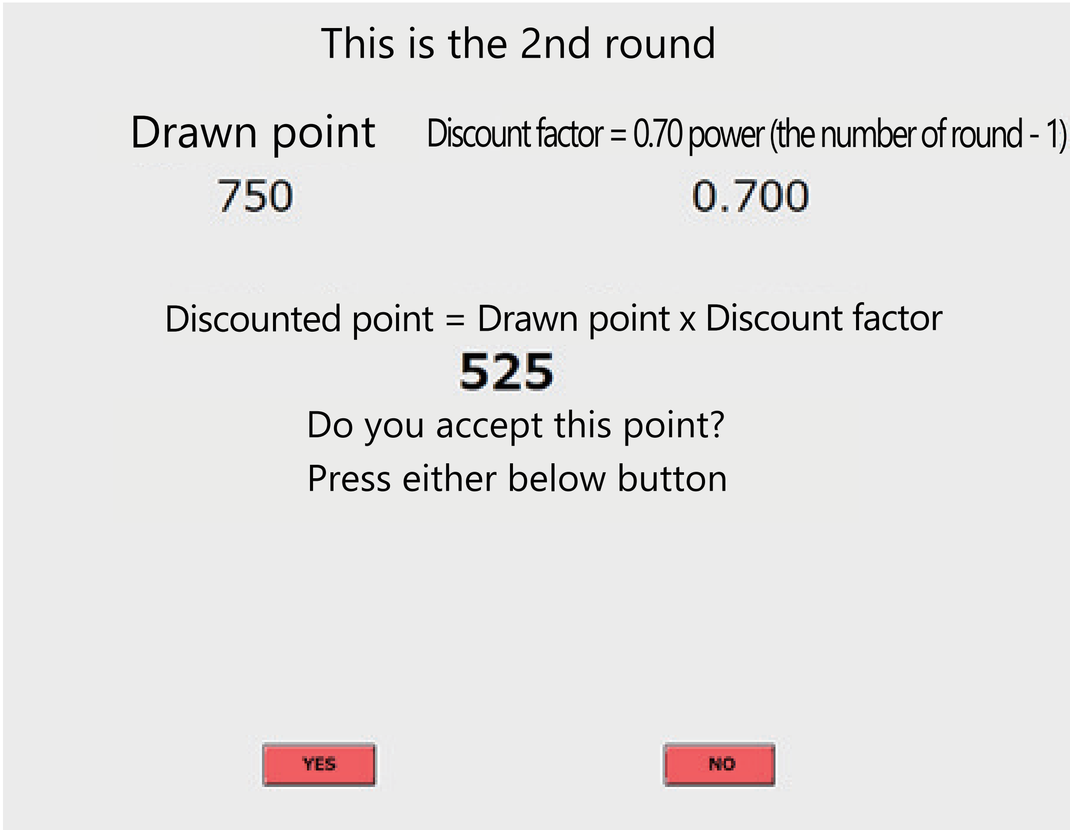
- The upper left of the screen indicates the number of this trial (the 1st trial in this case).
- The upper center of the screen indicates the number of this round (the 1st round in this case).
- The drawn point is displayed in the center of the screen (569). The point is drawn randomly from between 0 and 3,000. Note that the probabilities of drawing each point are equal.



- You decide whether to accept or reject the drawn point.
- If you press the lower left [YES] button, the trial ends, and the point in your hand becomes the final point you obtain (569).
- If you press the lower right [NO] button, you can move on to the next round with a 70% probability, and a newly drawn point is displayed on the center of the screen. In other words, with a 30% probability (on average, in 3 out of 10 trials), the trial ends coercively, in which case your point in the trial is zero.

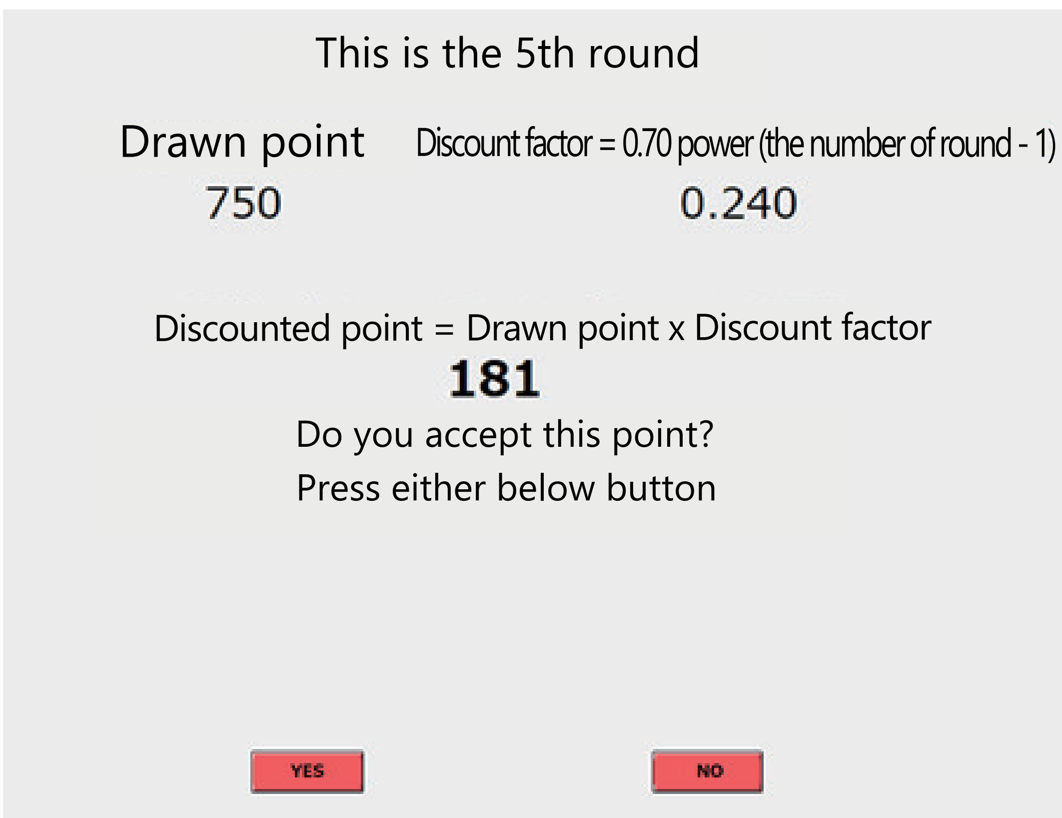
What to do in Game B

- We will explain the rules of Game B.
- When Game B begins, the PC monitor displays the screen below.



- The upper left of the screen displays a drawn point (750). The point is drawn randomly from between 0 and 3,000. Note that the probabilities of drawing each point are equal.
- In contrast with Game A, you can definitely move on to the next round in Game B.
- However, your drawn point will be discounted by a fixed discount factor when you move on to the next round.
- Your point is discounted by 0.70 power (the number of round - 1). Because the point in the first round is not discounted, it is the same as the drawn point.
- The above screen displays an example in the second round. The discount factor in this round is displayed on the upper right of the screen (In this case, the discount factor is defined as 0.700). Thus, the discounted point is calculated by the drawn point multiplied by 0.700 (the discounted point is rounded up).
- The center of the screen displays the discounted point (525).

- You decide whether to accept or reject the drawn point.
- If you press the lower left [YES] button, the trial then ends, and the point in your hand becomes the discounted point (525).
- If you press the lower right [No] button, you can definitely move on to the next round, and a newly drawn point is displayed on the upper left of the screen.
- As the number of rounds you move on to increases, your drawn point is discounted more.
- The PC monitor displays an example in the fifth round.



- The upper left of the screen displays the drawn point (750).
- The discount factor in the fifth round is calculated as 0.240 (0.70 powered by 4).

- Thus, the discounted point is given by 181, the drawn point, 750, multiplied by 0.240.

Flow of Part 1

- Before the real trials, you will have a practice session. Note that the results of the practice session do not affect your reward.
- Before the next trial starts, you will be informed about it its rules. If you have any questions at this time, please raise your hand and ask the staff.

Part 2

- In this part, you make a decision about lottery choices.
- In this part, you see a table displayed on the PC monitor below.

- The left and right columns show the contents of lottery A and lottery B, respectively.
- For example, in the "Choice 1" row, if you choose lottery A, you can receive JPY 1,500 with a 10% probability or JPY 1,300 with a 90% probability. If you choose lottery B instead, you can receive JPY 2,000 with a 10% probability or JPY 0 with a 90% probability.
- You choose either of the two lotteries in each row.
- After you finish choosing, press the [OK] button on the lower right of screen.
- In Part 2, there are three types of combinations of lotteries.

Flow of Game B

The screen displays a discounted drawn point (X)

Discount factor is 0.70 power (the number of round - 1)

↓

Click either [YES] or [OK]

Click [YES] → Trial is end

Click [NO] → Back to X

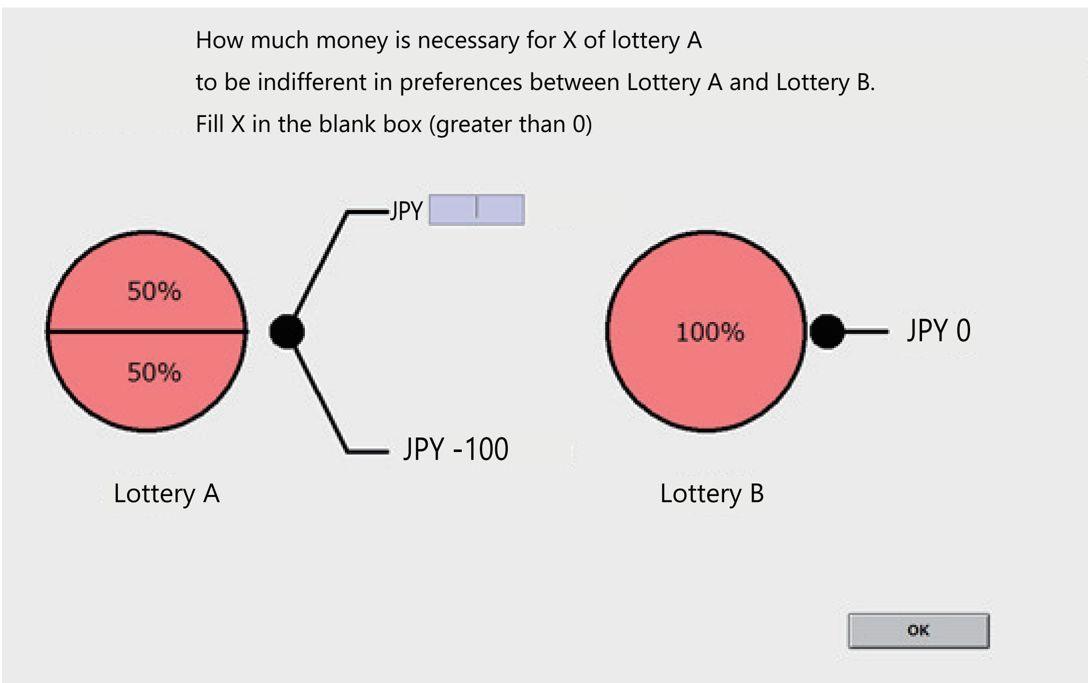
	Lottery A	Lottery B
Choice 1	JPY 2,000 (10%) JPY 0 (90%)	JPY 1,500 (10%) JPY 1,300 (90%)
Choice 2	JPY 2,000 (20%) JPY 0 (80%)	JPY 1,500 (20%) JPY 1,300 (80%)
Choice 3	JPY 2,000 (30%) JPY 0 (70%)	JPY 1,500 (30%) JPY 1,300 (70%)
Choice 4	JPY 2,000 (40%) JPY 0 (60%)	JPY 1,500 (40%) JPY 1,300 (60%)
Choice 5	JPY 2,000 (50%) JPY 0 (50%)	JPY 1,500 (50%) JPY 1,300 (50%)
Choice 6	JPY 2,000 (60%) JPY 0 (40%)	JPY 1,500 (60%) JPY 1,300 (40%)
Choice 7	JPY 2,000 (70%) JPY 0 (30%)	JPY 1,500 (70%) JPY 1,300 (30%)
Choice 8	JPY 2,000 (80%) JPY 0 (20%)	JPY 1,500 (80%) JPY 1,300 (20%)
Choice 9	JPY 2,000 (90%) JPY 0 (10%)	JPY 1,500 (90%) JPY 1,300 (10%)
Choice 10	JPY 2,000 (100%) JPY 0 (0%)	JPY 1,500 (100%) JPY 1,300 (0%)

OK

- Thus, you have to choose either lottery A or B 30 times.
- If the reward is paid based on the choices in Part 2, one choice is chosen randomly among 30 choices. If you choose lottery A (B) in the selected choice, your reward is actually determined on the basis of the probability distribution of outcomes in lottery A (B).
- For example, "Choice 1" is randomly chosen as displayed on the image on the screen. If you choose lottery A, you can receive the larger outcome (1,500) with a 10% probability or the smaller outcome (1,300) with a 90% probability. If you instead choose lottery B, you can receive the larger outcome (2,000) with a 10% probability or the smaller outcome (0) with a 90% probability.

Part 3

- In this part, you make a decision about lottery choices.
- In this part, you see a screen displayed on the PC monitor below.
- Lotteries A and B are shown on the screen.
- For example, if you choose lottery A, you can receive JPY X or lose JPY 100, with equal probabilities. If you choose lottery B, you can receive JPY 0 for certain.
- You decide how much money is necessary for X of lottery A to be indifferent in preferences between the two lotteries.
- In Part 3, there are five types of choices between lotteries A and B.


How much money is necessary for X of lottery A
to be indifferent in preferences between Lottery A and Lottery B.
Fill X in the blank box (greater than 0)
JPY
50%
50%
JPY -100
Lottery A
100%
JPY 0
Lottery B
OK