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The effect of risk attitudes on search behavior: A laboratory search experiment

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Abstract

This paper tests the effect of risk preferences on search activities by using a laboratory experiment. We used an infinite-horizon sequential search model with no recall in which an individual gains over search. We elicit the risk preferences from observed search activities of participants and from the multiple price list (MPL) method. We found the statistically significant effect of risk preferences elicited from the MPL method on the duration of search. The search duration is on average shorter for a risk averse individual than for risk loving one, which is consistent with the theoretical prediction. The significant effect of risk preferences on search activities has not been observed in the previous literature that used search model with recall in which an individual pays from the initial endowment over search (Schunk 2009, Schunk and Winter 2009). Therefore, the correlation between risk preferences and search activities depends on the type of search models.

JEL Classification: D81, D83

Keywords: Risk preference, Sequential search, MPL

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1 Introduction

In this paper, we study the effect of risk preferences on search behavior by using a laboratory experiment that embodying labor search. Search behavior is risky. Consider a fundamental sequential labor search model in Lippman and McCall (1976). An individual draws a wage offer from a given wage offer distribution. If the drawn wage offer is equal to or higher than her or his reservation wage, the individual accepts the offer, but otherwise, the individual rejects the offer and draw a new wage offer from the same wage offer distribution. However, rejecting a wage offer have a risk: There is no guarantee to get a new offer. Even if she or he draws a new offer, additionally, there is no guarantee that the new offered wage is higher than the one that the individual rejected before. Individual search behavior, therefore, differs by the extent of risk aversion: A risk averse individual has a lower reservation wage than a risk loving individual, and therefore, the search duration is on average shorter for the former than the latter.

Schunk (2009), Schunk and Winter (2009) studied the relationship between search behavior and risk preferences by using laboratory experiments. They cannot observe any significant correlation between search behavior and risk preferences that elicited from the multiple price list (MPL) method (Holt and Laury 2002), the certainty-equivalent method (Wakker and Deneffe 1996), and the trade-off method (Abdellaoui 2000). Instead, they observe a significant correlation between search behavior and the extent of loss aversions.

The potential reason why they found a significant correlation between the extent of loss aversion and search activities but not between the extent of risk preferences and search activities is that they design a sequential search model with recall in which individual pays from the initial endowment. This embodies "consumer search". In the consumer search model, a good is sold at many locations, but the price of good is different at each location. An individual does not know the price of good at a location *ex ante*. Therefore, he or she searches sequentially for a lower price among locations. However, he or she has to pay the fixed cost as she or he visits a new location for an additional search activity. Schunk

(2009) and Schunk and Winter (2009) designed the consumer search model: Participants are exogenously given an initial endowment as the value of good. They have to pay the fixed cost when they draw a new point. In addition, a recall option is incorporated into their experimental design, which means that the participants are allowed to recall previous draws. Therefore, if the participants decide to finish search activity, they can choose the good at the lowest point among the previous draws. In this design, participants tend to consider search activity into which the loss frame is embodied: The participants set the initial endowment as a reference point, and they are inclined to avoid to lose own endowment by paying the fixed cost of additional search. Moreover, risk preferences may not affect search behavior because the recall option is allowed. Even if a new draw is higher than the one that they rejected before, they can purchase a good at the one that they rejected before.

We instead consider the sequential search model developed by (Lippman and McCall 1976) with no recall and no initial endowment. We focus attention on search activity into which the gain frame is embodied. This is "labor search" in contrast to consumer search. Therefore, it seems that risk preferences are more important than loss aversion in labor search model. In this paper, we study the effect of risk preferences on search behavior by using a laboratory experiment that embodying labor search. As our best knowledge, this is the first paper that focuses on differences between the two search models in terms of the effect of risk preferences. A growing literature uses a laboratory search experiment to test the theoretical prediction obtained from a sequential search model (Asano et al. 2015, Boone et al. 2009, Cox and Oaxaca 1989, 1992). Our study is also in line with the past literature.

Our findings are summarized below. First, we found the statistically significant effect of risk preferences elicited from the MPL method (Holt and Laury 2002) on search behavior. Secondly, the search duration is on average shorter for a risk averse individual than for a risk loving one, which is consistent with the theoretical prediction in (Lippman and McCall 1976). Thirdly, there is no upward or downward bias between risk preferences elicited from search activities and that from the MPL method. Finally, our search model is susceptible to probability weighting but not gambler's fallacy or the decreasing reservation point by search duration.

The rest of our paper is organized below. The next section develops an infinite-horizon sequential search model used in our experiments. Section 3 explains the experimental design, and Section 4 shows the result. We discuss the result in Section 5. The conclusion is provided in Section 6.

2 Model

In this section, we explain an infinite-horizon sequential search model developed by Lippman and McCall (1976). We then derive the reservation point and the expected duration of search. Moreover, we explain how to elicit risk attitudes from observed search activities.

A representative individual i engages in search activity. Individual i draws a point from a uniform distribution, where the lower bound is $m-a$ and the upper bound is $m+a$. Because a point follows the uniform distribution, the expected draw is m. The individual decides whether to accept or reject the point. If the individual accepts the point, then the search behavior is ended, and the point becomes the individual's payoff. If the individual rejects the point, then the individual decides to continue the search behavior and moves to the next round to draw 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 search activity with the probability λ, in a case of which the payoff of the individual is zero. Therefore, the individual continues to search to obtain a higher point, facing a risk of forced termination of search behavior. In addition, we assume in our laboratory experiment that the discount rate is zero for simplicity because the search behavior is conducted only at a laboratory. The individual can search as long as possible unless she/he stops searching or is forced to end search activity. Therefore, this model describes the essence of infinite-horizon sequential search activity.

The value function of individual i is given:

$$V_i = \mathrm{E}\max[u_i(Cx), (1-\lambda)V_i], \tag{1}$$

where V_i is the present value for individual i, $u_i(Cx)$ is the utility function, and x is the accepted point. C represents the conversion rate between the accepted point and JPY. Equation (1) can be rewritten below:

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

where R_i represents individual i reservation point.

Assuming that individual i is risk neutral, then her or his utility function can be rewritten as $u_i(Cx) = p_i Cx$, where p_i is the individualistic parameter that decides the utility from an accepted point. According to the reservation point property, the reservation point R_i is the value that satisfies $u_i(CR_i) = p_i CR_i$. Substituting the utility function into equation (2) yields:

$$\frac{(1-\lambda)p_i CR_i}{\lambda} = p_i C \int_{R_i}^{m+a} [x - R_i] \left(\frac{1}{2a}\right) dx. \tag{3}$$

Note that individualistic parameters p_i and the conversion rate C are at the both sides. Because p_i can be canceled out, then the equation determining the reservation point is:

$$(1-\lambda)R = \lambda \int_{R}^{m+a} [x - R] \left(\frac{1}{2a}\right) dx. \tag{4}$$

Risk neutral individuals share the same reservation point, regardless of the level of the individualistic parameter. Therefore, the lower subscript i can be eliminated. The right hand side of equation (4) represents the expected marginal gain of an additional search behavior, and the left hand side indicates the marginal cost of an additional search behavior. Note that the reservation point does not vary with the search duration in the infinite-horizon sequential search model.

Because the duration of search of individual i follows the Geometric distribution, the expected duration of search, S, can be calculated as:

$$S = \frac{2a}{(m+a)-R}. \tag{5}$$

We set the expected value of point distribution, m as 500, and the scale of range of point distribution, a as 500. We prepare two types of probability of termination of search behavior, λ as 5% and 2%. Under each probability, the reservation point for a risk neutral agent can be calculated by using equation (4), and the expected search duration can be calculated by using equation (5) and the reservation point.

Table 1: The reservation point and the expected search duration for risk neutral agent

	$m = 500, a = 500$	
	$Large(\lambda = 5\%)$	$Small(\lambda = 2\%)$
Reservation point	724	817
Expected search duration	3.62	5.46

In the direct response method, an individual's reservation point cannot be observed directly, but her/his search duration can be observed. According to te reservation point property, the reservation point is lower for risk averse individual than for risk neutral individuals, and the expected search duration is shorter for the former than for the latter, which is reported at the second row of Table 1. Therefore, in the direct response method, we use an individual's average search duration as a proxy of her or his expected search duration, then we measure the extent of risk attitude, varying by the probabilities of termination of search activity.

3 Experimental Design and Measuring Risk Attitudes

Our experiment consisted of two parts, Part 1 and 2. The order of Part 1 and Part 2 was randomly determined in each session.

In Part 1, participants conducted a search experiment. We prepared two conditions (*Large* and *Small*). The probability of termination of search activity was different between two types of games. We set λ as 5% in *Large* condition and as 2% in *Small* condition. Participants played search activities in *Large* and *Small* conditions ten times for each. Note that the order of two conditions was random to control for the order bias.

We have so far assumed that a representative individual i is risk neutral. We explain the way of eliciting the degree of risk attitudes, using data from laboratory search experiments. We assume that an individual's utility exhibits CRRA, $u(x) = \frac{x^{1-\theta}}{1-\theta}$ if $\theta \neq 1$ and $u(x) = \ln(x)$ if $\theta = 1$. θ represents the parameter of risk aversion: $\theta = 0$ means that the individual is risk neutral, $\theta > 0$ means that individual is risk averse, and $\theta < 0$ means that the individual is risk loving.

By substituting the CRRA utility function into equation (2), the reservation point can be obtained as the function of θ, $R(\theta)$. The expected search period can be written as the function of θ, that is,

$$S(\theta) = \frac{2a}{(m+a) - R(\theta)}. \tag{6}$$

As we mentioned above, we cannot observe the reservation point directly. Hence, by using an average search duration, we estimate the parameter of risk aversion for individual i, θ_i, by minimizing the following objective function of the sum of squared sum:

$$SSE(\theta_i; S_i) = \left(S^L(\theta_i) - \bar{S}_i^L\right)^2 + \left(S^S(\theta_i) - \bar{S}_i^S\right)^2, \tag{7}$$

where $S_i^L(\theta_i)$, $S_i^S(\theta_i)$ are the calculated expected search duration for θ_i in *Large* and *Small* conditions, respectively. $\bar{S}_i^L$, $\bar{S}_i^S$ are the average search duration for individual i in *Large* and *Small* conditions, respectively.

In Part 2, participants answered a monetary incentivized questionnaire concerning risk preference. We used the multiple price list (MPL) method developed by Holt and Laury (2002). Table 2 displays an example of contents of the questionnaire. Participants chose a preferred one between lottery A and lottery B for each row. If the participants choose lottery A, they receive x_A with probability p or y_A with probability $1-p$. On the other hand, if the participants choose lottery B, they receive x_B with probability p or y_B with probability $1-p$. Noting that $x_A > y_A$, $x_B > y_B$, $x_A < x_B$, and $y_A > y_B$. We prepared four patterns of outcomes: (x_A, y_A) versus (x_B, y_B) as (1500,1300) versus (2000,0), (1050,900) versus (2000,0), (1200,950) versus (1400,700), and (1050,900) versus (1400,700). The order of outcomes was randomly determined in each session. As the row does down, p increases by 10 percentage points and the increasing rate of the expected value is larger in the column of lottery B than in the column of lottery A. According to their risk preferences, some participants switch their choices from lottery A to lottery B. Similarly to the way of measuring risk attitudes from observed search activities, we assume that the utility exhibits CRRA. From the lottery choices, we can infer the interval of the degree of risk aversion. For example, if the number of lottery B chosen by individual i for k type of outocme, r_{ik} is 5, then we can infer the interval of degree of risk attitudes for individual i for k type of outcomes, $\theta_{5k} < \theta_{ik} \leq \theta_{6k}$. Nothing that we dropped samples who chose lottery B at all rows (i.e. $r_{ik} = 10$). The log likelihood for individual i for k type of outcome is as follows:

$$\begin{aligned} l_{ik}(\mu,\sigma) &= 1[r_{ik}=0]\log\left[\Phi\left(\frac{\theta_{1k}-\mu}{\sigma}\right)\right] + 1[r_{ik}=1]\log\left[\Phi\left(\frac{\theta_{2k}-\mu}{\sigma}\right) - \left(\Phi\frac{\theta_{1k}-\mu}{\sigma}\right)\right] \\ &\quad + \cdots + 1[r_{ik}=9]\log\left[1-\Phi\left(\frac{\theta_{10k}-\mu}{\sigma}\right)\right], (\theta_{1k} < ... < \theta_{10k}) \end{aligned} \tag{8}$$

We run the interval regression to find the expected degree of risk aversion for individual i for each type of outcomes. In this paper, we define the degree of risk aversion elicited from the

MPL method for individual i is the mean of the expected degree of risk averse elicited from the MPL method by using the interval regression.

Table 2: An example of contents of questionnaire concerning risk preference

Choice Number	Lottery A	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 finishing Part 1 and Part 2, we randomly choose one decision that determines the reward of experiments, based on the payoffs among 60 times decision making (10×2 trials in Part 1 and 10×4 choices in Part 2). If a decision in Part 1 is chosen, we conveted 1 point to JPY 2. And if a decision in Part 2 is chosen, then we drew a lottery to determine the outcome according to the choice. In addition, we paid all participants JPY 1000 as a show-up fee.

4 Result

4.1 Summary Statistics

The participants of our experiment consist of students at Osaka University, Japan. The experiments were conducted in December 2016. We recruited the participants by using ORSEE(Greiner et al. 2004) and run the experiments by using z-Tree (Fischbacher 2007). The number of participants was 59, 26 of which was male. We dropped 3 participants because they made a inconsistent choice in the MPL method: Choosing lottery A although lottery B at a lower expected value is chosen or choosing lottery A at probability $p = 1$ although they can get the higher outcome certainly by choosing lottery B.

Table 3 shows the summary statistics. Because participants played ten trials of search activities for each condition, we show the average search durations in the result. The average search duration in *Small* condition is longer than that in *Large* condition. Therefore, the smaller termination of probability is, the longer average search duration is. This is consistent with the theoretical prediction in Pissarides (2000). We show risk attitudes elicited from the MPL method, which is the average number of individual who choose lottery B at each type of outcomes. As the number of lottery B chosen by an individual is larger, she or he is more risk loving. The proportions of risk aversion by using the MPL method has not so far been in the previous literature (Crosetto and Filippin 2016, Holt and Laury 2002, 2005). The proportions of risk aversion from average search duration are larger than that from the MPL method.

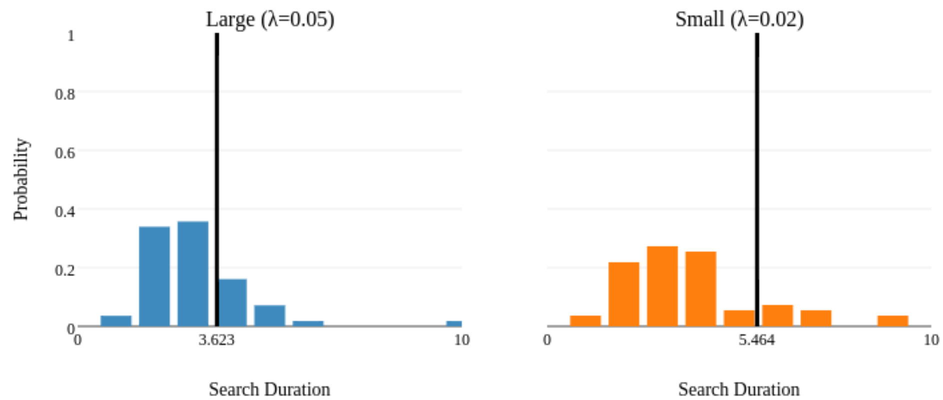
Figure 1 displays the histogram of the average search duration in *Large* and *Small* conditions. In total, the average search duration is shorter than the expected duration of search for a risk neutral individual predicted by the theoretical search model. This implies that the participants were overall risk averse in our experiment.

Table 3: Summary statistics

	Mean	S.D.	% Risk averse
Large ($\lambda = 5\%$)	2.90	2.48	76.79
Small ($\lambda = 2\%$)	3.82	4.01	83.93
Risk Attitudes (MPL)	3.33	1.23	73.21
Male	0.46	0.5	
N	56.00		

Note: *Large* and *Small* show the average search duration among ten trials at each condition, respectively.
Risk attitudes (MPL) shows the average number of individuals that choose lottery B at each type of outcomes. Noting that as the number of lottery B chosen by an individual is larger, she or he is more risk loving.

Figure 1: The histogram of average search duration



Note: The vertical lines in figure represent the expected search durations for risk neutral agent

4.2 Regression Analysis

We run regressions to estimate the effect of the degree of risk aversion elicited from the MPL method on the average search duration and the correlation between the two estimated degrees of risk aversion from the sequential search model and the MPL method. Table 4 shows the result. The degree of risk aversion, θ elicited from the MPL method significantly affected the average search duration and the degree of risk averse, θ elicited from observed search activities using Equation 7. These results are in contrast to the result from laboratory search experiment in Schunk (2009), Schunk and Winter (2009). They cannot observe the significant correlation between observed search behavior and risk attitudes elicited from the MPL method. Although the constant term is statistically significant in column (4), the constant term is not statistically significant when the degree of risk aversion elicited from the MPL method is controlled for (Columns 5 and 6). This implies that there is no upward or downward bias between two risk preference parameters. The average search duration is longer and the degree of risk aversion is smaller for male. This is consistent with the result that male is more risk loving than female (Crosetto and Filippin 2013). However, these gender differences are statistically insignificant.

Table 4: OLS result

Dependent variable	Average search duration			θ(Search)		
	(1)	(2)	(3)	(4)	(5)	(6)
Small	0.847***	0.847***	0.847***			
	(0.204)	(0.204)	(0.205)			
Male	0.587		0.513	−0.349		−0.313
	(0.438)		(0.389)	(0.237)		(0.211)
θ*(MPL)*	−0.657***	−0.642***		0.326**	0.317**	
		(0.226)	(0.221)		(0.140)	(0.135)
Constant	2.711***	3.717***	3.462***	0.579***	0.0523	0.208
	(0.185)	(0.384)	(0.309)	(0.0733)	(0.251)	(0.179)
Observations	112	112	112	56	56	56
R-squared	0.091	0.155	0.176	0.053	0.114	0.152

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

5 Discussion

In this section, we test the robustness of our search model and discuss the result.

First, we test the gambler's fallacy. People become obsessed with an idea that sequential events are conditionally dependent even thought those are conditionally independent. Hence, they underestimate the probability that an outcome that occurred before occurs again. The gambler's fallacy is observed in many situations (Chen et al. 2016). In search activities, two potential gambler's fallacies exist: Participants do not consider that the termination risk is conditionally independent among (1) trials or (2) rounds. (1) If the participants do not consider the termination risks among trials are not conditionally independent, they then underestimate the termination risk after a termination. In this case, the participants who were terminated before are more likely to search longer afterward. Therefore, the degree of risk aversion will be underestimated. (2) If participants do not consider the termination risks among rounds are not conditionally independent, then participants who move to the next round consider that the termination risk is higher than that at the last round. Then, they overestimate the termination risks by rounds. In this case, the participants decrease reservation point by rounds, then the payoffs decrease by the accepted rounds.

To test these hypotheses, we run the regression using the fixed effect model to observe a change of the average search duration between before and after termination within a participant, and a change of the average payoff among accepted rounds within a participant. Table 5 shows the result. The dependent variables in columns (1) and (2) are the search duration, and *After termination* shows the difference of average search duration between before and after termination. We cannot observe any significant effect of termination on the average search duration when the samples are restricted to those were terminated more than or equal to one (column 1) or once (column 2). Moreover, the dependent variable in column (3) is the payoff, and *Large*×*Accepted round*, *Small*×*Accepted round* show the difference of average payoff among the accepted rounds in *Large* and *Small* conditions, respectively. Those are statistically insignificant in Table 5 in column (3). Therefore, the gambler's fallacy does not play a critical role in our search model.

Table 5: Gambler's Fallacy

Dependent variable	Search duration		Payoff
	(1)	(2)	(3)
Small	0.84***	0.66***	85.15***
	(0.20)	(0.34)	(20.15)
After termination	0.02	−0.30	
	(0.27)	(0.40)	
Large × *Accepted round*			8.34
			(5.23)
Small × *Accepted round*			4.81
			(3.23)
Constant	2.89***	3.00***	694.14***
	(0.19)	(0.30)	(17.76)
Number of termination	≥ 1	$= 1$	
Fixed effect	Yes	Yes	Yes
Observations	998	323	1120
R-squared	0.091	0.155	0.176

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

Other concern is about the reservation point property. In infinite-horizon sequential search model, the reservation point is constant among search duration. However, Brown et al. (2011) showed reservation point decrease by search duration. If participants decrease their reservation point by search duration, then the degree of risk aversion is overestimated. We can test the possibility by comparing the payoffs among accepted point, and we cannot observe such a possibility (Table 5 in column 3). [1]

Second, we test the probability weighting. The previous literature found that probability weighting function is an inverse S-shaped; people tend to overestimate small probability and underestimate large probability. In our experimental design, the termination risk is small (5% in *Large* and 2% in *Small* conditions). If participants overestimate the termination risk, then the degree of risk averse is overestimated. To check the possibility, we compare with the degree of risk averse between elicited from *Large* condition and that from *Small* condition. Because the probability weighting function is inverse S-shaped according to previous literature, the overestimation of termination risk in *Small* condition is larger than that in *Large* condition. Therefore, the degree of risk averse in *Small* condition is larger than that in *Large* condition. We estimate the degree of risk averse by rearranging Equation 7 to aggregate level. Consistent with our hypothesis, in total, the degree of risk averse in *Small* condition is larger than that in *Large* condition. When we separated our samples by gender, the bias is not observed fro male subsample but observed for female subsample. Therefore, our search model is susceptible from probability weighting. It should be noted when we interpret the result of our search model.

[1] Brown et al. (2011) found that the key determinants of decreasing reservation point are elapsed time and accumulated cost of search. In the experimental design in Brown et al. (2011), they set an arrival rate of point, which is the probability that a new point is offered in a second. Therefore, participants have to wait until a new point is offered if they decide to continue to search activity. In addition, participants have to pay a fixed search cost during waiting for a new offer. However, in our experimental design, if participants continue to search activity, then a new point will be proposed immediately if they are not terminated. Moreover, the cost of additional search is zero. Therefore, we consider the problem of decreasing reservation point by search duration is not severe in our experimental design as that in Brown et al. (2011).

Table 6: Probability weighting

	Total	Male	Female
Small (λ=2%)	0.20***	0.17	0.22***
	(0.07)	(0.11)	(0.08)
Constant	0.35***	0.23	0.43***
	(0.09)	(0.17)	(0.08)
N	112	52	60

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

6 Conclusion

In this paper, we tested the effect of risk preferences on search behavior by using a laboratory experiment that embodying labor search.

We found the statistically significant effect of risk preferences elicited from the MPL method (Holt and Laury 2002) on search behavior. Consistent with the theoretical prediction in (Lippman and McCall 1976), the search duration for risk averse individual is on average shorter than that of a risk loving individual. The significant effect of risk preferences on search activities is not observed in Schunk (2009), Schunk and Winter (2009), which used search model embodying consumer search. Therefore, the extent of the effect of risk preferences on search activities depends on search model. Moreover, there is no upward or downward bias between risk preferences elicited from search activities and that from the MPL method. Our search model is susceptible to probability weighting but not gambler's fallacy or the decreasing reservation point by search duration.

Our research has several limitations. First, we do not see the correlation between the risk preference that is elicited from a laboratory search experiment and the behavior in the real world such as wage and unemployment spells. Second, we do not see the correlation between search behavior and personal preferences except for risk preference. Future research is needed to tackle these limitations.

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