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An Experimental Test of a Search Model under Knightian Uncertainty*

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Abstract

This paper's objective is to design a laboratory experiment to explore the effect of Knightian uncertainty on a subject's search behavior in a finite sequential search model. Our finding is that the average search duration is shorter when there is Knightian uncertainty in the sense that the true point distribution is unknown to subjects, compared to when the point distribution is known. We also find direct evidence that subjects reduce their own reservation point when there is ambiguity about the point distribution. These results support the implication of Nishimura and Ozaki (2004). Moreover, ambiguity notably affects the search behavior of risk averse subjects, but not of either risk neutral or risk prone subjects.

JEL classification: C91, D81

Keywords: experiment, search model, ambiguity, risk attitude, optimal stopping rule

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1 Introduction

Let us consider the situation in which the prospect of labor market conditions in the future is "uncertain." In this situation, does an increase in "uncertainty" lengthen or shorten the search duration of an unemployed worker? In the literature on job search, it is well known that an increase in risk in the sense of Rothschild and Stiglitz (1971) such as a mean-preserving spread lengthens an individual's search duration.[1] However, from a different point of view, it can be also considered that an increase in "uncertainty" about the prospect of labor market conditions in the future makes the individual more cautious about the prospect and shortens her or his search duration because she or he is concerned that more appealing job offers will not be forthcoming. Considering the notion of *Knightian uncertainty* or *ambiguity* that is differentiated from that of risk, Nishimura and Ozaki (2004) show theoretically that an increase in Knightian uncertainty shortens an individual's search duration. It is noted in this paper that Knightian uncertainty and ambiguity are used interchangeably. The purposes of this paper are first to design a laboratory experiment of a finite sequential search model with ambiguity in the sense that a point distribution from which a subject draws is unknown and second, to ascertain whether the result of Nishimura and Ozaki (2004) is supported experimentally. Similarly to Nishimura and Ozaki (2004), Knightian uncertainty is to be understood in the sense that the true point distribution is unknown to subjects throughout this paper. This paper finds that the presence of Knightian uncertainty shortens subjects' search duration. Our result is consistent with the prediction of Nishimura and Ozaki (2004).

Knight (1921) points out the importance of the distinction between risk and uncertainty. Knight (1921) claims that risk is measured by randomness that can be characterized by a unique probability measure while uncertainty cannot be captured by a unique probability measure. Based on Knight (1921), Ellsberg (1961) provides some evidence that decision makers prefer to act on known rather than unknown or vague probabilities.

Ambiguity can be analyzed in the framework of multiple-prior expected utility (MEU) theory. Gilboa and Schmeidler (1989) axiomatize the MEU theory, showing that a decision maker's be-

[1] For a survey of job search models, see Lippman and McCall (1976).

liefs are captured by a set of probability measures and that her preferences are represented by the minimum of expected utilities over the set of probability measures. MEU has deepened our understanding of a decision maker's behavior under ambiguity.[2] Chen, Katuščák, and Ozdenoren (2007) investigate experimentally the effect of Knightian uncertainty on bidding behavior and revenue on the first and second price-sealed bid auctions. They find that in the first price auction, bids are lower in the presence of Knightian uncertainty and that the first price auction generates significantly higher revenue than the second price auction, regardless of the presence of Knightian uncertainty.

This paper focuses on the effect of Knightian uncertainty on individual search activity. The experimental task of testing sequential search models is tractable, so many experimental studies have been conducted over the past years (Cox and Oaxaca, 1989; Harrison and Morgan, 1990). The purpose of these past studies was to test the reservation price property in the sequential search model. Some experimental tasks then deal with the policy effects on search behavior: Boone, Sadrieh, and van Ours (2009) design a laboratory experiment to test the effect of unemployment benefit sanctions on an individual's search behavior. There is another direction that addresses the relationship between search behavior and heterogeneous preferences. Schunk (2009) finds that the search model with loss aversion, rather than with risk aversion, is more suitable for the search behavior of a subject in the laboratory. One of the recent topics in this field is to explore why subjects stop searching earlier than the theoretically optimal level (Schunk and Winter, 2009). Our experimental task focuses on the effect of information available for the search activity on a subject's search behavior. Our experiment can contribute to understanding the role of information on the wage distribution from which an individual worker draws randomly during her search activity.

It is notable that our experiment designs two search methods where recall is not allowed. In the first method, a subject decides either to accept or to reject every time a point is drawn by a

[2] For example, see Epstein and Wang (1994). In a closely related paper, Schmeidler (1989) axiomatizes Choquet expected utility (CEU) theory and shows that decision maker's beliefs are captured by a *nonadditive measure* and her preferences are represented by the *Choquet integral*. For applications of CEU, see Dow and Werlang (1992), Nishimura and Ozaki (2004), or Asano (2006).

computer, while in the second method, the subject *ex ante* commits to her reservation points for all rounds subjectively prior to starting a game and then begins to search, based on a list of these reservation points. The main benefit of the second method is that we can explicitly observe a long trend in the reservation point over all the rounds that is usually unobservable in empirical studies. Because recall in search activity is not allowed in this experiment, in order to adhere closely to the framework of Nishimura and Ozaki (2004), it is expected from Schunk and Winter (2009) that subjects are discouraged from searching. If a subject is required to declare her reservation point for each round before drawing a point and then decides either to accept the point or to reject it and move on to the next round, we would not obtain enough data to observe a trend in the reservation point.[3] In addition, this second method is designed to induce subjects to behave according to the optimal stopping rule, so that the subjects would calculate their reservation point for each round backward from the last round. If there is no difference in search behavior between the two methods, we can say that the subjects engage in search activity according to the optimal stopping rule. We find that this claim is overall supported, although at the individual level, there are some subjects who did not behave in accordance with the optimal stopping rule.

Our experiment yields two findings. The first is that the search duration is on average shorter when there is Knightian uncertainty, compared to when the point distribution is known. It implies that subjects are more likely to accept the offered point when the point distribution is unknown than when the point distribution is known in advance. These results support the implication of Nishimura and Ozaki (2004). Secondly, we find that using the subjective data on a series of reservation points obtained from the second method, subjects reduce their own reservation point over all rounds under Knightian uncertainty, although marginally. This is subjective but direct evidence supporting the implication of Nishimura and Ozaki (2004). These two findings reinforce one another; that is, these findings suggest that ambiguity about the distribution lowers

[3] We previously conducted a sequential search model experiment in which a subject was required to declare her or his reservation point for each round before drawing a point. However, because subjects did not search long in the environment where recall was not allowed, we could not obtain enough data to estimate a trend in the reservation point.

the reservation point. This implies that subjects are encouraged to accept an offered point in an earlier round, thereby leading to shorter search duration.

We also test whether or not the effect of ambiguity on search behavior differs by the extent of attitude toward risk. Our finding is that risk averse subjects respond by lowering their reservation point, thus shortening their search duration when there is ambiguity about the point distribution, compared to when the point distribution is well recognized, but that search behaviors of those who are either risk neutral or risk prone are not significantly affected by ambiguity about the point distribution. This result differed from our theoretical prediction claiming that ambiguity shifts down a trend in the reservation point, regardless of the extent of attitude toward risk.[4]

The organization of this paper is as follows. Section 2 provides a brief summary of job search under risk and ambiguity. Section 3 provides an experimental design and hypotheses. Section 4 provides the results of our experimental data in this paper. The final section provides our concluding remarks

2 Search Models under Ambiguity

We consider a simple discrete-time sequential job search model based on Lippman and McCall (1976) and Nishimura and Ozaki (2004). Throughout this section, let $(S, \mathcal{B}_S)$ be a measurable space, where S is a Borel subset of $\mathbb{R}_+$ and $\mathcal{B}_S$ is the Borel σ-algebra on S. A generic element $s \in S$ is regarded as a wage offer in each period. In each period, an unemployed worker decides whether she accepts a wage offer and stops searching for a job or obtains unemployment compensation $c > 0$ and continues searching. She is assumed to know the true wage distribution F_0 with the lower bound a and the upper bound b. Let T be the time at which she accepts the offer and stops

[4] In the literature, there are studies on the correlation between attitudes toward risk and ambiguity but not in the context of a search model. Ellsberg's experiment shows that a risk averse subject is also ambiguity averse (Halevy and Feltkamp 2005, Halevy 2007). However, Borghans et al. (2009) and Cohen et al. (2010) show that there is essentially no correlation between them.

searching for a job. Her objective is to maximize her expected life-time income:

$$E_0\left[\sum_{t=0}^{\infty}\beta^t y_t\right],$$

where

$$y_t = \begin{cases} c & \text{for} \quad t < T \\ s_T & \text{for} \quad t \geq T, \end{cases}$$

and $\beta \in (0,1)$ represents the discount factor. The unemployed worker's search behavior is determined according to the *reservation property* such that she accepts a wage offer s if $s \geq R$, but rejects it, receives compensation c, and continues searching if $s < R$, where R represents the reservation wage. The reservation wage is determined uniquely by the following:

$$R = c + \frac{\beta}{1-\beta}\int_R^b [1 - F_0(x)]dx.$$

It can be noted that an increase in risk in the sense of a *mean-preserving spread* increases the reservation wage because stretching the right tail of the wage distribution encourages her to increase her reservation wage on the one hand, but on the other hand, stretching the left tail does not affect her reservation wage. If she is assumed to be risk averse, that is, her utility function is characterized by some concave function, the effect of an increase in mean-preserving spreads on the reservation wage then is not determined. The effect depends on the curvature of her utility function, that is, the degree of her risk aversion.[5]

We next consider a job search model within the framework of ambiguity based on Nishimura and Ozaki (2004). We assume that an individual does not know the true wage distribution F_0 from which a wage offer is drawn, and that her beliefs are characterized by a set of probability measures $\mathcal{P}_0$, which is defined below.

In order to provide as simple as possible a job-search model under ambiguity, let P_0 be the probability measure on S and F_0 be the corresponding probability distribution on $\mathbb{R}_+$. In this subsection, let $S = [a,b]$ and P_0 be the uniform distribution on $[a,b]$, where $a < b$. Let M be the set of all probability measures on $(S, \mathcal{B}_S)$. In this subsection, we also assume that M is the set of

[5] For further arguments, see Kohn and Shavell (1974) and Nishimura and Ozaki (2004).

all wage distributions on $[a, b]$ corresponding to probability measures on $\mathcal{B}_S$. The ε-*contamination* of P_0 is the set of the probability measures on S defined by the following:

$$\mathcal{P}_0 \equiv \{(1-\varepsilon) + \varepsilon Q \,|\, Q \in M\},$$

where $\varepsilon \geq 0$. If $\varepsilon = 0$, then the set of probability measures $\mathcal{P}_0$ is a singleton set, that is, $\mathcal{P}_0 = \{P_0\}$. On the other hand, if $\varepsilon > 0$, then $\mathcal{P}_0$ is a set of probability measures. The larger ε is, the larger the set of probability measures is, which implies that if an unemployed worker's beliefs are characterized by $\mathcal{P}_0$, then she becomes less certain about the true probability measure P_0. Therefore, the positive real number ε represents the degree of ambiguity.[6]

Within the framework of ambiguity, an unemployed worker's beliefs are assumed to be captured by $\mathcal{P}_0$, and her preferences are represented by the minimum of her expected life-time income over the set of probability measures $\mathcal{P}_0$. Therefore, her objective is to maximize her expected life-time income:

$$\min\left\{\int_S I(s)P(ds) \,|\, P \in \mathcal{P}_0\right\},$$

where $I(s)$ is her life-time income. Note that $I(s)$ is some bounded measurable function of a wage offer s.[7] Under the above setting, it can be shown that the unemployed worker's search behavior is determined according to the reservation wage property. Moreover, there exists the reservation wage R by the following:

$$\begin{aligned} R &= c + \frac{\beta}{1-\beta}\int_R^b (1-\varepsilon)P_0(\{s|s \geq x\})dx \\ &= c + \frac{\beta}{1-\beta}(1-\varepsilon)\int_R^\infty [1 - F_0(x)]dx. \end{aligned}$$

[6] For an axiomatization of ε-contaminations, see Nishimura and Ozaki (2006). For applications of ε-contaminations to economics, see Nishimura and Ozaki (2004) or Asano (2010).

[7] For any adapted income process ${}_0\boldsymbol{y} = (y_0, y_1, y_2, \ldots)$ and an initial wage offer $s_0 \in S$, the expected life-time income is defined by:

$$I_{s_0}({}_0\boldsymbol{y}) = \lim_{t\to\infty} y_0 + \beta\int_S \left(y_1 + \beta\int_S \left(y_2 + \cdots \beta\int_S y_t\mu(ds_t)\cdots\right)\mu(ds_2)\right)\mu_{s_0}(ds_1)$$

where $\beta \in (0, 1)$ is the discount factor and all the integrations are the Choquet integral with respect to a nonadditive measure μ. See Nishimura and Ozaki (2004) for details.

Within a more general setting, Nishimura and Ozaki (2004) show that an increase in ambiguity *decreases* the reservation wage. They also argue that the same implication is obtained even if the utility function is assumed to be risk averse. The next section designs a laboratory experiment to test the implications

3 Experimental Design

3.1 Search Model in Experiment

An individual subject faces games of 20 rounds by way of a finite sequential search model in which recall is not allowed. A point is drawn randomly from a given point distribution by a computer faced by a subject in the first round, and then the subject decides either to accept the point or to reject it. If the subject accepts the point, her or his search activity is concluded, and the accepted point is converted to her or his payment. If the subject rejects the point, she or he moves on to the second round where a point is drawn again from the given point distribution. We here use "point" to put a search model to the test to prevent subjects from associating "wage" with job search. The subject can continue to search until the 20th round, and if the subject rejects a point drawn in the last round, her or his search activity is automatically terminated, and no point is obtained.

We begin to develop the value function of search theoretically. The value of search in each round is solved backward. The value of search in the 20th round is:

$$U_{20} = \int_{\underline{x}}^{\overline{x}} x dF(x),$$

where $F(x)$ represents the point distribution with a lower bound of $\underline{x}$ and an upper bound of $\overline{x}$. An individual does not receive any point if she or he rejects a point drawn in the last round, so her or his reservation point must be $\underline{x}$ in the final round ($R_{20} = \underline{x}$). We assume here that utility is linear in the accepted point, implying that the individual is risk neutral. Backward to the 19th round, the value of search is given by:

$$U_{19} = \beta \int_{\underline{x}}^{R_{19}} U_{20} dF(x) + \int_{R_{19}}^{\overline{x}} x dF(x) = \beta F(R_{19}) U_{20} + \int_{R_{19}}^{\overline{x}} x dF(x),$$

where β represents a discount factor. When a drawn point is lower than R_{19}, the individual rejects this offer and moves to the 20th round, while in the reserve case, she or he accepts and receives the point as a one-shot payment in the 19th round.[8] The reservation point of the 19th round is calculated by $R_{19} = U_{20} = \int_{\underline{x}}^{\overline{x}} x dF(x)$. In a similar manner, the value of search in the Nth round is:

$$U_N = \beta F(R_N) U_{N+1} + \int_{R_N}^{\overline{x}} x dF(x), \tag{1}$$

and the reservation point for the Nth round is obtained by $R_N = U_{N+1}$.

As in the previous section, we consider the finite sequential search model into which ambiguity is incorporated, based on Nishimura and Ozaki (2004). Let P_0 be the uniform distribution on $[\underline{x}, \overline{x}]$, and then the ε-*contamination* of P_0 is the set of the probability measures defined by $\mathcal{P}_0 = \{(1-\varepsilon) + \varepsilon Q \,|\, Q \in M\}$, where the positive real number ε can represent the degree of ambiguity. In this setting with ambiguity, the value of search in the Nth round and the corresponding reservation point are given by:

$$\begin{aligned} U_N &= (1-\varepsilon)\left[\beta F(R_N) U_{N+1} + \int_{R_N}^{\overline{x}} x dF(x)\right], \qquad (2) \\ R_N &= U_{N+1}. \end{aligned}$$

These equations imply that an increase in ambiguity decreases the value of search in the Nth round and therefore its reservation point. A trend in the reservation point is shifted down when there is ambiguity in the sense that the point distribution is unknown, compared to when the point distribution is known with certainty.

The model is solved numerically to observe a trend in the reservation point and the effect of ambiguity on the reservation point. We assume that the point distribution is uniform between a

[8] In the standard model, an individual who accepts x in the 19th round can receive x in the 20th round as well as in the 19th round. That is, the individual's value of payment is $x + \beta x$. In this experiment, however, we design for simplicity that the accepted point is given once as a payment so that subjects can easily understand how to pay throughout the experiment.

lower bound of 1 and an upper bound of 3000 and that to be consistent with our experimental design, there is no discount over the rounds; $\beta = 1$. Because subjects are discouraged from searching longer in an environment where recall is not allowed, $\beta = 1$ mitigates the disincentive to search.[9] The utility function for risk neutrality is defined as linear in the accept point, whereas the utility function for risk aversion is assumed to show constant relative risk aversion (CRRA) with the measure of risk aversion being 0.5. Table 1 displays several trends in the reservation point, varying with the degree of risk attitude and ambiguity about the point distribution.

The trends for a risk neutral individual are shown graphically in Figure 1. As we would expect, the declining trend in the reservation point can be observed in the finite sequential search model, regardless of the extent of ambiguity. The reservation point decreases as the end of the search is closer. Moreover, an increase in the degree of ambiguity shifts down the trend in the reservation point monotonically, which implies that an individual is encouraged to accept an offer in an earlier round when the point distribution is ambiguous, compared to when there is no ambiguity about the point distribution. A comparison of eq(1) and eq(2) implies that the declining rate of the reservation point is ε at any round according to Table 2.

The values of search in the Nth round for a risk averse subject without and with ambiguity about the point distribution are correspondingly given by:

$$U_N = \beta F(R_N)U_{N+1} + \int_{R_N}^{\overline{x}} u(x)dF(x), \tag{3}$$

and

$$U_N = (1 - \varepsilon) \left[\beta F(R_N)U_{N+1} + \int_{R_N}^{\overline{x}} u(x)dF(x)\right], \tag{4}$$

where $u'(\cdot) > 0$ and $u''(\cdot) < 0$. In a similar manner, the reservation point of the Nth round is obtained by $R_N = U_{N+1}$. We see that eq(3) and eq(4) share the same reservation point property

[9] Because there are many papers showing that subjects do not search long in laboratory experiments (Schunk and Winter: 2009), we dispense with any discount factor to encourage subjects to search longer. We previously conducted our experiment with a discount factor taking below a value of one. The results obtained in that experiment were that subjects terminated their search activity in a very early round.

as obtained in eq(1) and eq(2). First, an increase in the extent of ambiguity shifts down the trend in the reservation point according to Table 1. Figure 2 provides a graphical view. More ambiguity shifts the trend in the reservation point down even more largely, thus leading to a decrease in the average search duration. Secondly, Table 2 shows that a negative effect of ambiguity on the reservation point does not differ in magnitude between a risk neutral individual and a risk averse individual. The risk averse individual reacts as negatively to ambiguity as the risk neutral individual does. This result is obtained because attitude toward risk and ambiguity are incorporated independently in the model.

3.2 Treatments and Hypotheses

There are four treatments in our experiment. In the first treatment (T1), subjects are provided with common information on a point distribution. We employ a uniform distribution with a lower bound of 1 and an upper bound of 3000. In the second treatment (T2), the subjects are informed that a distribution is unknown except for the lower bound of 1 and the upper bound of 3000 and that a different distribution may be selected in every *round* by the computer. This prevents the subjects from updating their information about the true distribution of a point in a Bayesian manner and rules out the learning effect on search behavior.[10] We do not provide them with the true distribution of a point. However, to facilitate a comparison of (T1) and (T2), the distribution is actually set the same as the uniform distribution with a lower bound of 1 and an upper bound of 3000. The comparison of these two treatments allows us to identify the difference in search behavior caused uniquely by ambiguity by controlling the distribution shape. If the distribution actually changes every round, we cannot identify whether the difference in the search durations between the two treatments is attributable to ambiguity or to the variants in distributions.

The third treatment (T3) is a search activity in which a subject *ex ante* commits to a series of her or his reservation points over all the 20 rounds under the uniform distribution with a lower

[10] There are some papers that would rather focus on uncertainty and learning of the shape of the wage distribution through Bayesian updating in a search model (Morgan, 1985; Burdett and Vishwanath, 1988; Dubra, 2004).

bound of 1 and an upper bound of 3000. Subjects are requested to fill in their own reservation points in all the 20 rounds before starting a game. First, they fill in the reservation point in the first round and then fill in the reservation point in the second round as if they had moved on to the second round. The same procedure is undertaken until the 20th round. After listing 20 numbers of the reservation point on the sheet, each subject clicks the button to start to search. The computer randomly picks a first-round point and compares it with the first-round reservation point. If the point drawn is lower than the first-round reservation point, her or his search activity continues with the computer drawing a second-round point. Otherwise, the computer stops searching and gives the subject the drawn point. We suppose that subjects automatically calculate a series of reservation points backward from the last round and then actually fill in forward from the first round. Therefore, (T3) is designed in such a way that subjects are induced to behave in accordance with the optimal stopping rule. The main benefit of this treatment is that we can directly observe a 20 round-long trend in the reservation point. This is usually difficult to observe in an experiment of sequential search without recall because subjects finish searching long before the final round. This allows us to directly measure the effect of ambiguity on the trend in the reservation point. A comparison of (T1) and (T3) also allows us to verify whether subjects engage in search activity following the optimal stopping rule. If there is no difference in search attitude between the two treatments, it is concluded that subjects actually follow the optimal stopping rule when engaging in search activity. The fourth treatment (T4) is similar to (T3) except for the realization of the point distribution; that is, a subject *ex ante* commits to a series of her or his reservation points over all 20 rounds under various unknown distributions with a lower bound of 1 and an upper bound of 3000.

Our experiment consists of two sessions. Each experimental session consists of 11 games. The difference between the two experimental sessions is the order of the 11 games. The game orders are as follows in the sessions.

- Session 1: (T1-practice), (T2), (T2), (T2), (T2), (T4), (T1), (T1), (T1), (T1), (T1), (T3).
- Session 2: (T1-practice), (T1), (T2), (T1), (T2), (T3), (T1), (T2), (T1), (T2), (T1), (T4).

In Session 1, subjects engage in search activity in which there is Knightian uncertainty for the point distribution in the earlier games ((T2) and (T4)), and then they play search games in which the point distribution is recognized in advance ((T1) and (T3)). This order rules out the possibility that subjects infer that the unknown distribution is uniform in (T2) and (T4) games. In Session 2, subjects alternately engage in search activity under the given and then the unknown point distributions.

We next display experimental hypotheses to test the theoretical implications of Nishimura and Ozaki (2004). We test three hypotheses regarding Knightian uncertainty, the optimal stopping rule in search activity, and risk attitude.

- H1: The reservation point is lower when the point distribution is unknown, compared to when the point distribution is well known ((T1) versus (T2), and (T3) versus (T4)). Therefore, the search duration is shorter under an unknown point distribution than under a given distribution

A subject's reservation point is lower, and therefore, she or he accepts a drawn point in an earlier round when the point distribution is unknown to her or him, compared to when the point distribution is well known. This results in the shorter search duration in the presence of Knightian uncertainty.

- H2: Subjects engage in search activity following the optimal stopping rule. ((T1) versus (T3), and (T2) versus (T4)).

If there is no difference in the average search duration between (T1) and (T3) (or (T2) and (T4)), it can be said that subjects engage in search activity following the optimal stopping rule; that is, they calculate in advance their own reservation points for all 20 rounds, backward from the last round and stop search if a drawn point exceeds the corresponding reservation point but otherwise continue to search.

In addition, our experiment explores a difference in search activity by risk attitude. To identify each subject's attitude toward risk, we conducted a questionnaire to all participants after the experiment and asked them about their attitude toward risk. We asked them what price they would be willing to pay for a lottery with a 25% chance of winning JPY200, but with a 75% chance of winning nothing. We then calculated the index measuring the extent of absolute risk aversion using Cramer et al. (2002).[11] Let this index denote risk aversion (A). If this index is positive, a subject is considered to be risk averse, but on the other hand, if negative, the subject is treated as risk prone. If the index is exactly zero, the subject is risk neutral. Similarly, we calculated a similar index using the willingness-to-pay price for a lottery of winning much more than for our first lottery, in fact, JPY2000 with a 25% chance, but 75% chance of winning nothing. This index denotes risk aversion (B).[12] Comparing the declining rates of the reservation point with and without ambiguity in the point distribution (eq(1)-eq(4)), leads us to hypothesize that:

- H3: The negative effect of point distribution ambiguity on the search duration does not differ with the extent of risk attitude. There is no correlation between attitude to risk and ambiguity.

We investigate a change in the negative effect of ambiguity on the search decision, depending on the extent of risk aversion.

3.3 Administration and Payoffs

This two-session experiment was conducted on December 17th, 2009 in the experimental laboratory of the Institute of Social and Economic Research at Osaka University. Subjects consisted of 44 undergraduate and graduate students of Osaka University excluding junior and above economics

[11] According to Cramer et al. (2002), the extent of absolute risk aversion is calculated as,

$$\frac{0.25 \times 200 - price}{0.5(0.25 \times 200^2 - 2 \times 0.25 \times 200 + price^2)},$$

where the price is the one that a subject would be willing to pay for a lottery in which she or he has a 25% chance of winning JPY200, but a 75% chance of winning nothing.

[12] The questionnaire also included questions allowing us to produce indices measuring the extent of relative risk aversion using Kimball, Sahm, and Shapiro (2008). However, we did not obtain robust results and therefore we discarded these indices.

majors, with 21 participating in the first session and 23 in the second. Each participant was in an individual booth, from which she or he could not observe other subjects. The experiments were run entirely on computers using Z-tree (Fischbacher, 2007) laboratory experiment software. Table 3 presents the summary statistics.

Instructors handed an instruction sheet to each subject and presented each with full information about the search task. The instructors emphasized that (i) subjects' payoff was truncated at JPY0 (i.e., they could not incur losses from the search task); and (ii) they would earn an attendance fee of JPY1000.[13] Performance pay was determined by one of the results from the 11 games randomly chosen by each subject, with one point equal to JPY1. The participants were paid on completion of the experiment. The expected total payoff was JPY2500–3000, and because the time taken for the experiment was approximately one and a half hours, the effective hourly payoff to participants was about JPY1600–2000, which is approximately twice as large as the average hourly wage for college students. Payments were made to each subject, one by one, while they were completing the questionnaire.

4 Results

4.1 Search Duration

Table 4 displays average search durations by various treatments and their differences between treatments. In the first column, the average search duration is 6.81 for the treatment in which the point distribution is well known to subjects as a uniform distribution with a lower bound of 1 and an upper bound of 3000 (T1) and 5.63 in the treatment with ambiguity in the sense that the point distribution is unknown except for a lower bound of 1 and an upper bound of 3000 (T2). The former is longer than the latter, and the null hypothesis (H1) that the difference of (T1)–(T2) is equal to or shorter than zero is rejected at the 1% level of significance. This implies that subjects reduce their reservation point when facing ambiguity about the point distribution, thereby leading

[13] One US dollar was equivalent to JPY82.92 as of January 15, 2011.

to shorter search duration. This result is consistent with the prediction of Nishimura and Ozaki (2004). The second column shows the effect of ambiguity about the point distribution on average search duration, given that a subject *ex ante* commits to reservation points prior to her or his game and then decides either to reject or to stop searching in light of precommitted reservation points. The average search duration is shorter with ambiguity about the point distribution, but the null hypothesis is not significantly rejected. We now compare average search durations in the first row, capturing the effect of a difference in search activity method on search duration under the uniform distribution with a lower bound of 1 and an upper bound of 3000 ((T1) versus (T3)). Hypothesis (H2), that there is no difference in average search duration, regardless of search activity methods, is not significantly rejected. It implies that subjects engage in search activity following the optimal stopping rule because (T3) is designed such that subjects are induced to follow the optimal stopping rule. The same result is obtained if there is ambiguity about the point distribution ((T2) versus (T4)).

Tables 5 and 6 show average search durations, by the extent of absolute risk aversion. The sampled data are analyzed by risk aversion index (A) in Tables 5-1, 5-2 and 5-3 and risk aversion index (B) in Tables 6-1, 6-2 and 6-3. According to the first columns of Tables 5-1 and 6-1 confined to risk averse subjects, the search duration is shorter when the point distribution is unknown (T2), relative to when it is well known to subjects as a uniform distribution with a lower bound of 1 and an upper bound of 3000 (T1). Therefore, the null hypothesis (H1) is significantly supported. The differences are larger in magnitude in Tables 5-1 and 6-1 than in Table 4, which implies that the search duration is further shortened for risk averse subjects when there is Knightian uncertainty. On the other hand, the first columns of Tables 5-2, 5-3, 6-2, and 6-3 show that for risk neutral and risk prone subjects, the differences in search duration between (T1) and (T2) are statistically minimal. These results suggest that ambiguity about the point distribution does not affect search behavior of risk neutral and risk prone subjects. These results differ from our theoretical prediction and thus do not support (H3); that is, our experimental outcomes imply that when the point distribution is ambiguous in terms of Knightian uncertainty, the trend for the reservation point is shifted down only for risk averse subjects. There is essentially a correlation between attitude toward risk and ambiguity.

Table 7 estimates linear models for determinants of search duration. The first two columns use data from (T1) and (T2) while the last three columns include data from all treatments ((T1)–(T4)). The dependent variable is the search duration of each game that each subject experienced. In columns (1) and (2), *Knight* is a dummy variable representing 1 if subjects draw a point from unknown distributions with a lower bound of 1 and an upper bound of 3000 (T2) and 0 if subjects draw a point from a uniform distribution with a lower bound of 1 and an upper bound of 3000 (T1). Its coefficient is negative at the 1% level of significance in column (1). The result remains the same after controlling for individual subject and session effects (see column (2)) capturing not only an individual subject's risk attitude (risk averse or risk prone), but loss attitude (loss averse or loss prone) and other unobservables. Because the subject dummies indicating individual characteristics and the session dummy are not correlated with the *Knight* term at all, its coefficient remains the same even after these dummies are included. Our finding is that the search duration is shorter when the point distribution is unknown because of Knightian uncertainty, relative to when the point distribution is known. This result implies that subjects reduce their own reservation point if there is ambiguity about the point distribution. We therefore support (H1), and this result is consistent with the main prediction of Nishimura and Ozaki (2004). The coefficient on *Knight* remains significant using all observations, inclusive of precommitted data ((T3) and (T4)) (column (3)).

Columns (4) and (5) add two dummy variables, one each for ambiguity and search method and their cross term. Similarly to the estimates of columns (1)–(3), *Knight* is a dummy indicating 1 if subjects draw a point from unknown distributions with a lower bound of 1 and an upper bound of 3000 (either (T2) or (T4)) and 0 if subjects draw a point from a uniform distribution with a lower bound of 1 and an upper bound of 3000 (either (T1) or (T3)). *Precommitted* is another dummy representing 1 if subjects *ex ante* commit to their reservation points over all the 20 rounds in advance and then decide either to reject or to stop searching, based on precommitted reservation points ((T3) or (T4)) and 0 if subjects decide whether to reject or accept every time a point is drawn in each round ((T1) or (T2)). *Knight*Precommitted* is the cross term of the two dummy variables.

Knight is negative at the 1–5% level of significance in columns (4) and (5), so we confirm the same result as columns (1)–(3); that is, the search duration is shorter when there is Knightian uncertainty, compared to when the point distribution is well known. Ambiguity about the point distribution decreases a subject's reservation point, thus encouraging her or him to accept in an earlier round.

Precommitted is statistically insignificant, implying that there is no difference in search behavior between the decision rule in which a subject *ex ante* commits to reservation points for all 20 rounds prior to a game and that in which a subject decides every time a point is drawn in each round. (T3) and (T4) are designed so that subjects would follow the optimal stopping rule in the sense that they *ex ante* are subject to calculate their reservation point in each round backward from the last round. Subjects therefore engage in search activity following the optimal stopping rule, which supports (H2).

Tables 8 and 9 estimate determinants of search duration by the extent of absolute risk aversion, index (A) in Table 8, and index (B) in Table 9. Columns (1)–(3) of both tables use the subsample from nonprecommitted games ((T1) and (T2)), while columns (4)–(6) use all observations including data from precommitted games ((T1), (T2), (T3), and (T4)). We begin with columns (1)-(3) of both tables. Confined to risk averse subjects, the coefficient on *Knight* remains negative at the 1–5% level of significance in column (3), and its coefficient is larger in absolute magnitude than that displayed in Table 7. On the other hand, columns (1) and (2) show that the significance of *Knight* is lower when using the subsamples of risk neutral and risk prone subjects. We confirm that the search duration is furthermore shorter for risk averse subjects when there is Knightian uncertainty, relative to when the point distribution is well known among subjects, but that ambiguity about the point distribution does not affect the search behavior of risk neutral and risk prone subjects. These results are consistent with those from Tables 5 and 6 showing a correlation between attitude toward risk and ambiguity.

4.2 Determinants of the Reservation Point

This subsection reports the direct effect of ambiguity about the point distribution on the reservation point. Table 10 shows the estimates of determinants of the reservation point using the round-based data from (T3) and (T4) in which subjects commit in advance to their own reservation points for all 20 rounds and then start to search. The benefit of this method is to allow us to detect a change in the reservation point from direct but subjective viewpoints.

In column (1), *Knight* is statistically insignificant, contrary to our expectation. One reason for this result is that subjects who do not follow the optimal stopping rule are included in the estimation. We then extract the data from those who precisely did follow the optimal stopping rule (referred to as *OSR-consistent)* and then re-estimate the determinants of the reservation point. A subject is among the *OSR-consistent* subsample if the following conditions are satisfied;

- for any given round, a subject accepts a point drawn in (T1) if the point is no less than the corresponding reservation point in (T3);
- for any given round, a subject accepts a point drawn in (T2) if the point is no less than the corresponding reservation point in (T4);
- for any given round, a subject rejects a point drawn in (T1) if the point is lower than the corresponding reservation point in (T3);
- for any given round, a subject rejects a point drawn in (T2) if the point is lower than the corresponding reservation point in (T4),

and zero otherwise. At the individual level, not all subjects follow the optimal stopping rule. We here impose the strict assumption to distinguish between subjects who precisely follow the optimal stopping rule and those who do not. According to Table 11, 96% of round-based decisions are consistent with the optimal stopping rule, but when grouped by game, only 21% of games are consistent with the optimal stopping rule. In addition, only 20% of subjects follow the optimal stopping rule while searching. It is also interesting to note that, on average, *OSR-consistent* subjects earn more than *OSR-inconsistent* subjects. Among those who follow the optimal stopping rule, the average payment is larger when the point distribution is well known as a uniform distribution, relative to when the point distribution is unknown. This is consistent with our prediction. However, among our other subjects the opposite is the case.

As seen in column (2) of Table 10 using the *OSR-consistent* subsample, *Knight* turns out to be negative at the 10% level of significance. It implies that subjects marginally reduce their own reservation point when the point distribution is unknown because of Knightian uncertainty, compared to when the point distribution is known to subjects. We confirm the same results from Table 7, and therefore (H1) is again supported. It should be emphasized that although we reach this conclusion indirectly from the estimates of individual search duration from Table 7, Table 10 provides direct evidence to support the implication of Nishimura and Ozaki (2004); that is, the reservation point is lower in the presence of Knightian uncertainty about the point distribution.

Next we explore how the effect of ambiguity on the reservation point differs by the degree of attitude toward risk. Tables 12 and 13 estimate the determinants of the reservation point, separating the sample by the extent of absolute risk aversion. Table 12 uses risk aversion index (A) while Table 13 uses risk aversion index (B). It is noted that estimates shown in both tables are obtained, using the *OSR-consistent* subsample. According to column (3) of Table 12, the coefficient on *Knight* is negative and larger in absolute magnitude than that displayed in column (2) of Table 10, but its significance is reduced. Similarly, *Knight* is statistically insignificant for risk averse subjects in column (3) of Table 13. When limited to those who are either risk neutral or risk prone, columns (1) and (2) of Tables 12 and 13 show that *Knight* remains insignificant.[14] However, from differences in magnitude of the coefficients, we can say that risk averse subjects lower their reservation point slightly and thus complete searching in an earlier round when the

[14] It is noted that there is no estimate for risk prone subjects in Table 13 because there are no observations of risk prone subjects who correctly follow the optimal stopping rule when the sample is analyzed by risk aversion index (B).

point distribution is unknown.

5 Concluding Remarks

This paper designed a laboratory experiment to explore the effect of Knightian uncertainty on a subject's search behavior in a finite sequential search model and tested the implications of Nishimura and Ozaki (2004). We utilized various approaches to test the effect of ambiguity about the point distribution on sequential search behavior.

It is particularly worth noting that we designed two search methods. In the first a subject decides either to accept or to reject every time a point is drawn, while in the second a subject commits to their reservation points for all 20 rounds prior to a game and only then begins to search. The second method is designed to embody the optimal stopping rule in which a subject must calculate their reservation points for all 20 rounds backward from the last round. If there is no difference in search behavior between the two methods, we can say that subjects always follow the optimal stopping rule. This was supported by our estimates although there are some subjects who do not follow the optimal stopping rule.

One finding is that the average search duration is shorter with ambiguity rather than certainty about the point distribution, implying that subjects are more likely to accept the offered point when the point distribution is unknown, compared to when the point distribution is well known in advance. This result supports the prediction of Nishimura and Ozaki (2004). We also show that subjects explicitly reduce their own reservation point when there is Knightian uncertainty, using the data from (T3) and (T4) in which subjects commit in advance to their own reservation point for all 20 rounds and then start to search. Although the data are obtained subjectively, this is direct evidence supporting the implication of Nishimura and Ozaki (2004). The estimated results from these different approaches reinforce each other, supporting the view that introducing ambiguity about the point distribution lowers the reservation points, thus encouraging subjects to accept an offered point in an earlier round and therefore leading to shorter search duration. Ambiguity about the point distribution has a significantly negative impact on search duration for risk averse subjects, but not for those who are either risk neutral or risk prone.

This experiment used a simple and specific environment of individual sequential search, controlling information about the point distribution and search methods. However, the essence of the results can be applied to the labor market. The presence of Knightian uncertainty about the wage distribution induces individuals to be more cautious about search activity, which lowers the reservation wage and thereby the accepted wage. It implies that the presence of Knightian uncertainty reduces the welfare level of individuals. These experimental outcomes are useful to understand the role of information in determining the level of individual welfare.

6 Appendix: Instruction

Note: Session 1 Instructions. Session 2 differs in the order of games.

Welcome to our experiment! In this experiment, you will be asked to play 11 games. In each game, within a limited number of 20 rounds, you will be asked to choose either to receive a point that is randomly selected from a selected distribution or to refuse this point and move on to the next round to wait for a higher point. If you are willing to accept an offered point, you click "Y" displayed on your PC screen, but if not, you click "N". If you do not accept a point offered in the final round, your score will be zero automatically. Your score will be decided on the basis of the points that you accept.

We have prepared 11 games and would like you to play them. Before starting the experiment, we would like you to try the following practice. Please let us know if you have any questions.

- Practice: In each round, the computer randomly selects a point from a uniform distribution with a lower bound of 1 and an upper bound of 3000. You decide whether or not to accept the point drawn from this distribution. If you accept the point, you then finish your search and the point is your score. If you do not accept the point, you move on to the next round and observe a point newly drawn by the computer. You can continue to search up to 20 rounds.

Before starting each game, we explain how to play it in more detail.

- Game 1: In each round, the computer randomly selects a point from an unknown distribution except that it has a lower bound of 1 and an upper bound of 3000, and a different distribution *may* be randomly selected every *round* by the computer. You decide whether or not to accept the point drawn from the unknown distribution. If you accept the point, you then finish your search and the point is your score. If you do not accept the point, you move on to the next round and observe a point newly drawn by the computer. You can continue to search up to 20 rounds.
- Game 2: the same as Game 1.
- Game 3: the same as Game 1.
- Game 4: the same as Game 1
- Game 5: In each round, the computer randomly selects a point from an unknown distribution except that it has a lower bound of 1 and an upper bound of 3000, and a different distribution *may* be randomly selected every *round* by the computer. Please type in the minimum point that you are willing to accept (hereafter the reservation point) for all 20 rounds before starting this game. First, please type in your reservation point in the blank for the first round on the PC screen, and then type in your reservation point in the blank for the second round, as if you had moved on to the second round. Please repeat this until the 20th round. After finishing your list of 20 reservation point numbers on your PC Display, click "OK". The computer then starts to draw a point from an unknown distribution and compares it with your reservation point for the first round. If the drawn point is equal to or higher than your reservation point for the first round, you then finish your search and the point is your score. If the drawn point is lower than your reservation point for the first round, the computer moves on to the second round and draws a point. Your search activity is left to the computer.
- Game 6: In each round, the computer randomly selects a point from a uniform distribution with a lower bound of 1 and an upper bound of 3000. You decide whether or not to accept

the point drawn from this distribution. If you accept the point, you then finish your search and the point is your score. If you do not accept the point, you move on to the next round and observe a point newly drawn by the computer. You can continue to search up to 20 rounds.

- Game 7: the same as Game 6.
- Game 8: the same as Game 6.
- Game 9: the same as Game 6.
- Game 10: In each round, the computer randomly selects a point from a uniform distribution with a lower bound of 1 and an upper bound of 3000. You decide on whether or not to accept the point drawn from this distribution. Please type in the minimum point that you are willing to accept (hereafter your reservation point) for all 20 rounds before starting this game. First, please type in your reservation point for the first round on the PC screen and then type in your reservation point for the second round, as if you had moved on to the second round. Please repeat this until the 20th round. After finishing listing 20 reservation point numbers on your PC Display, click "OK". The computer then starts to draw a point from the uniform distribution and compares it with the reservation point of the first round. If the drawn point is equal to or higher than your reservation point for the first round, you then finish your search and the point is your score. If the drawn point is lower than your reservation point for the first round, the computer moves on to the second round and draws a point. Your search activity is left to the computer.

After the experiment, please respond to our questionnaire. You will be paid an attendance fee of JPY1000. Your performance pay is determined by one of the points from the 11 games randomly chosen by you. This payment treats one scoring point as JPY1. You will be paid both fees as soon as the experiment is completed. Please be quiet and do not communicate with other participants during the experiment. Thank you for your participation.

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Table 1
Trends in the Reservation Points

	No Ambiguity		Ambiguity (Epsilon=0.1)		Ambiguity (Epsilon=0.25)		Ambiguity (Epsilon=0.5)	
	Risk Neutral	Risk Averse	Risk Neutral	Risk Averse	Risk Neutral	Risk Averse	Risk Neutral	Risk Averse
Round	R1	r1	R2	r2	R3	r3	R4	r4
1	2749.3	2738.4	2474.3	2464.6	2061.9	2053.8	1374.6	1369.2
2	2737.8	2726.1	2464.0	2453.5	2053.3	2044.6	1368.9	1363.1
3	2725.2	2712.5	2452.7	2441.3	2043.9	2034.4	1362.6	1356.3
4	2711.3	2697.5	2440.2	2427.8	2033.5	2023.2	1355.7	1348.8
5	2695.9	2680.9	2426.3	2412.8	2021.9	2010.6	1347.9	1340.4
6	2678.7	2662.2	2410.8	2396.0	2009.0	1996.6	1339.3	1331.1
7	2659.3	2641.1	2393.4	2377.0	1994.5	1980.9	1329.7	1320.6
8	2637.4	2617.2	2373.7	2355.5	1978.1	1962.9	1318.7	1308.6
9	2612.4	2589.8	2351.1	2330.8	1959.3	1942.3	1306.2	1294.9
10	2583.4	2558.0	2325.1	2302.2	1937.6	1918.5	1291.7	1279.0
11	2549.6	2520.7	2294.7	2268.6	1912.2	1890.5	1274.8	1260.3
12	2509.5	2476.3	2258.6	2228.6	1882.1	1857.2	1254.8	1238.1
13	2461.1	2422.4	2215.0	2180.1	1845.8	1816.8	1230.5	1211.2
14	2401.3	2355.5	2161.2	2120.0	1801.0	1766.7	1200.7	1177.8
15	2325.5	2270.2	2092.9	2043.2	1744.1	1702.7	1162.7	1135.1
16	2225.4	2157.1	2002.9	1941.4	1669.1	1617.8	1112.7	1078.5
17	2086.2	1998.8	1877.6	1798.9	1564.7	1499.1	1043.1	999.4
18	1875.4	1758.3	1687.8	1582.4	1406.5	1318.7	937.7	879.1
19	1500.5	1334.2	1350.5	1200.8	1125.4	1000.7	750.3	667.1
20	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Note: The utility function for risk neutrality is defined as linear in the accepted point (x) while the utility function for risk aversion is CRRA with the measure of risk aversion, 0.5.

Table 2
Decrease Rates of the Reservation Point by Risk Attitude and Ambiguity

Risk Neutral	Risk Averse	Risk N[eutral	Risk Averse	Risk Neutral	Risk Averse
(R2-R1)/R1	(r2-r1)/r1	(R3-R1)/R1	(r3-r1)/r1	(R4-R1)/R1	(r4-r1)/r1
-0.10	-0.10	-0.25	-0.25	-0.50	-0.50

Note: The decrease rate is the same for all rounds. The decrease rate is the same as the epsilon value indicating the extent of ambiguity.

Table 3
Summary Statistics

	Session 1	Session 2	Total
# of subjects	21	23	44
# of females	11	7	18
Average age	20.6	19.4	20
Average absolute risk aversion (A)	0.0012	0.0014	0.0013
# of subjects (risk aversion (A)>0)	11	11	22
# of subjects (risk aversion (A)=0)	3	5	8
# of subjects (risk aversion (A)<0)	6	6	12
Risk aversion (A) unavailable	1	1	2
Average absolute risk aversion (B)	0.00038	0.00032	0.00035
# of subjects (risk aversion (B)>0)	16	15	31
# of subjects (risk aversion (B)=0)	2	5	7
# of subjects (risk aversion (B)<0)	2	2	4
Risk aversion (B) unavailable	1	1	2
# of subject-games	252	276	528
Average outcome (JPY)	2703.5	2661.2	2681.3
Average search duration	7.4	5.4	6.4
# of subject-game-rounds	4620	5060	9680
Average reservation point			
Round 1	2623.0	2440.8	2527.7
Round 2	2609.6	2414.6	2507.7
Round 3	2594.9	2381.5	2483.4
Round 4	2592.0	2366.2	2474.0
Round 5	2587.9	2362.8	2470.3
Round 6	2589.8	2334.5	2456.3
Round 7	2577.9	2300.7	2433.0
Round 8	2572.9	2283.2	2421.4
Round 9	2571.4	2255.9	2406.5
Round 10	2556.4	2241.6	2391.9
Round 11	2492.3	2163.3	2320.3
Round 12	2450.9	2139.2	2288.0
Round 13	2404.0	2095.7	2242.8
Round 14	2352.8	2053.2	2196.2
Round 15	2320.4	1974.8	2139.7
Round 16	2229.4	1891.0	2052.5
Round 17	2157.8	1775.7	1958.0
Round 18	2022.2	1601.7	1802.4
Round 19	1778.6	1288.5	1522.4
Round 20	569.5	437.5	500.5

Table 4
Average Search Durations (Total)

	Nonprecommitted games	Precommitted games	Difference	
Uniform	6.81 [T1]	7.20 [T3]	-0.40	(0.90)
Knight	5.63 [T2]	6.16 [T4]	-0.53	(0.77)
Difference	1.18	1.05		
	(0.50)	(1.23)		

Note: Standard errors in parentheses. Averages are calculated on the treatment base.

Table 5-1
Average Search Durations by the Extent of Risk Attitude (A) (Risk Averse Subjects Only)

	Nonprecommitted games	Precommitted games	Difference	
Uniform	6.66 [T1]	6.27 [T3]	0.39	(1.22)
Knight	5.05 [T2]	6.22 [T4]	-1.17	(1.05)
Difference	1.61	0.05		
	(0.67)	(1.68)		

Note: Standard errors in parentheses. Averages are calculated on the treatment base. The extent of risk attitude is calculated from a subject's response to the post-experimental questionnaire: how much is a subject willing to pay for a lottery of a 25% chance of winning JPY200, but a 75% chance of winning nothing according to Cramer, Hartog, Jonker, and van Praag (2002).

Table 5-2
Average Search Durations by the Extent of Risk Attitude (A) (Risk Neutral Subjects Only)

	Nonprecommitted games	Precommitted games	Difference	
Uniform	7.85 [T1]	7.00 [T3]	0.85	(2.19)
Knight	6.91 [T2]	4.88 [T4]	2.03	(2.04)
Difference	0.94	2.13		
	(1.30)	(2.52)		

Note: Standard errors in parentheses. Averages are calculated on the treatment base. The extent of risk attitude is calculated from a subject's response to the post-experimental questionnaire: how much is a subject willing to pay for a lottery of a 25% chance of winning JPY200, but a 75% chance of winning nothing according to Cramer, Hartog, Jonker, and van Praag (2002).

Table 5-3
Average Search Durations by the Extent of Risk Attitude (A) (Risk Prone Subjects Only)

	Nonprecommitted games	Precommitted gaames	Difference	
Uniform	6.55 [T1]	8.83 [T3]	-2.28	(1.78)
Knight	6.04 [T2]	7.08 [T4]	-1.04	(1.45)
Difference	0.51	1.75		
	(0.92)	(2.75)		

Note: Standard errors in parentheses. Averages are calculated on the treatment base. The extent of risk attitude is calculated from a subject's response to the post-experimental questionnaire: how much is a subject willing to pay for a lottery of a 25% chance of winning JPY200, but a 75% chance of winning nothing according to Cramer, Hartog, Jonker, and van Praag (2002).

Table 6-1
Average Search Durations by the Extent of Risk Attitude (B) (Risk Averse Subjects Only)

	Nonprecommitted games	Precommitted games	Difference	
Uniform	6.63 [T1]	6.90 [T3]	-0.27	(1.06)
Knight	5.21 [T2]	6.13 [T4]	-0.92	(0.36)
Difference	1.42	0.77		
	(0.57)	(1.52)		

Note: Standard errors in parentheses. Averages are calculated on the treatment base. The extent of risk attitude is calculated from a subject's response to the post-experimental questionnaire: how much is a subject willing to pay for a lottery of a 25% chance of winning JPY2000, but a 75% chance of winning nothing according to Cramer, Hartog, Jonker, and van Praag (2002).

Table 6-2
Average Search Durations by the Extent of Risk Attitude (B) (Risk Neutral Subjects Only)

	Nonprecommitted games	Precommitted games	Difference	
Uniform	6.83 [T1]	7.14 [T3]	-0.31	(2.00)
Knight	6.93 [T2]	5.00 [T4]	1.93	(2.04)
Difference	-0.10	2.14		
	(1.24)	(2.38)		

Note: Standard errors in parentheses. Averages are calculated on the treatment base. The extent of risk attitude is calculated from a subject's response to the post-experimental questionnaire: how much is a subject willing to pay for a lottery of a 25% chance of winning JPY2000, but a 75% chance of winning nothing according to Cramer, Hartog, Jonker, and van Praag (2002).

Table 6-3
Average Search Durations by the Extent of Risk Attitude (B) (Risk Prone Subjects Only)

	Nonprecommitted games	Precommitted games	Difference	
Uniform	8.65 [T1]	9.00 [T3]	-0.35	(3.58)
Knight	7.25 [T2]	9.00 [T4]	-1.75	(2.82)
Difference	1.40	0.00		
	(1.91)	(4.93)		

Note: Standard errors in parentheses. Averages are calculated on the treatment base. The extent of risk attitude is calculated from a subject's response to the post-experimental questionnaire: how much is a subject willing to pay for a lottery of a 25% chance of winning JPY2000, but a 75% chance of winning nothing according to Cramer, Hartog, Jonker, and van Praag (2002).

Table 7
Search Duration under Knightian Uncertainty

	Nonprecommitted games				All observations					
	(1)		(2)		(3)		(4)		(5)	
Knight (=1)	-1.178		-1.178		-1.139		-1.178		-1.178	
	(0.488)	***	(0.451)	**	(0.456)	**	(0.488)	**	(0.455)	***
Precommitted (=1)							0.395		0.395	
							(1.010)		(0.872)	
Knight*Precommitted							0.133		0.133	
							(1.314)		(1.175)	
Subject dummies			Yes.						Yes.	
Session dummy			Yes.						Yes.	
R-squared	0.014		0.266		0.012		0.014		0.253	
N	396		396		484		484		484	

Note: Robust standard errors in parentheses. *** 1%, ** 5%, * 10% significance.

Table 8

Search Duration under Knightian Uncertainty by the Extent of Risk Attitude (A)

	(1) Risk prone	(2) Risk neutral	(3) Risk averse	(4) Risk prone	(5) Risk neutral	(6) Risk averse
Knight (=1)	-0.508	1.215	-1.607	-0.508	-0.944	-1.607
	(0.862)	-(0.780)	(0.631) **	(0.877)	(1.222)	(0.657) **
Precommitted (=1)				2.283	-0.850	-0.391
				(1.759)	(1.818)	(1.073)
Knight*Precommitted				-1.242	-1.181	1.561
				(2.349)	(2.747)	(1.534)
Subject dummies	Yes.	Yes.	Yes.	Yes.	Yes.	Yes.
Session dummy	Yes.	Yes.	Yes.	Yes.	Yes.	Yes.
R-squared	0.190	0.243	0.298	0.244	0.223	0.274
N	108	72	198	132	88	242

Note: Robust standard errors in parentheses. *** 1%, ** 5%, * 10% significance. The extent of risk attitude is calculated from a subject's response to the post-experimental questionnaire: how much is a subject willing to pay for a lottery of a 25% chance of winning JPY200, but a 75% chance of winning nothing according to Cramer, Hartog, Jonker, and van Praag (2002).

Table 9

Search Duration under Knightian Uncertainty by the Extent of Risk Attitude (B)

	(1) Risk prone	(2) Risk neutral	(3) Risk averse	(4) Risk prone	(5) Risk neutral	(6) Risk averse
Knight (=1)	-1.400	0.100	-1.423	-1.400	0.100	-1.423
	(1.808)	(1.209)	(0.533) ***	(1.866)	(1.223)	(0.564) **
Precommitted (=1)				0.350	0.314	0.271
				(2.241)	(2.255)	(0.921)
Knight*Precommitted				1.400	-2.243	0.648
				(3.611)	(2.520)	(1.316)
Subject dummies	Yes.	Yes.	Yes.	Yes.	Yes.	Yes.
Session dummy	Yes.	Yes.	Yes.	Yes.	Yes.	Yes.
R-squared	0.153	0.177	0.290	0.226	0.168	0.921
N	36	63	279	44	77	341

Note: Robust standard errors in parentheses. *** 1%, ** 5%, * 10% significance. The extent of risk attitude is calculated from a subject's response to the post-experimental questionnaire: how much is a subject willing to pay for a lottery of a 25% chance of winning JPY2000, but a 75% chance of winning nothing according to Cramer, Hartog, Jonker, and van Praag (2002).

Table 10

Knightian Uncertainty on Reservation Point

	Reservation point in precommitted games	
	(1)	(2)
Knight (=1)	0.965	-52.788
	(13.127)	(28.365) *
Subject dummies	Yes.	Yes.
Round dummies	Yes.	Yes.
Session dummy	Yes.	Yes.
R-squared	0.831	0.859
N	1760	360
	All observation	OSR-consistent subjects only

Note: Robust standard errors in parentheses. *** 1%, ** 5%, * 10% significance. A subject is among the OSR-consistent subsample if the following conditions are satisfied; (1) for any given round, a subject accepts a point drawn in (T1) if the point is no less than the corresponding reservation point in (T3); (2) for any given round, a subject accepts a point drawn in (T2) if the point is no less than the corresponding reservation point in (T4); (3) for any given round, a subject rejects a point drawn in (T1) if the point is lower than the corresponding reservation point in (T3); (4) for any given round, a subject rejects a point drawn in (T2) if the point is lower than the corresponding reservation point in (T4), and zero otherwise.

Table 11
Detecting Inconsistency with the Optimal Stopping Rule

	Consistent with OSR	Inconsistent with OSR	Difference
Number of observations			
round-base	2395 [96%]	94 [4%]	
game-base	312 [21%]	84 [79%]	
subject-base	9 [20%]	35 [80%]	
Average final payoff			
uniform	2732.04	2495.40	236.64 (47.03)
knight	2711.73	2536.58	175.15 (60.08)

Note: Standard deviations in parentheses.

Table 12

Knightian Uncertainty on Reservation Point by the Extent of Risk Attitude (A)

	Reservation point in precommitted games		
	(1)	(2)	(3)
	risk prone	risk neutral	risk averse
Knight (=1)	-10.000	-29.417	-55.000
	(6.882)	(48.261)	(41.616)
Subject dummies	Yes.	Yes.	Yes.
Round dummies	Yes.	Yes.	Yes.
Session dummy	Yes.	Yes.	Yes.
R-squared	0.9994	0.7572	0.7511
N	40	160	80
	OSR-consistent subjects	OSR-consistent subjects	OSR-consistent subjects

Note: Robust standard errors in parentheses. *** 1%, ** 5%, * 10% significance. The extent of risk attitude is calculated from a subject's response to the post-experimental questionnaire: how much is a subject willing to pay for a lottery of a 25% chance of winning JPY200, but a 75% chance of winning nothing according to Cramer, Hartog, Jonker, and van Praag (2002).

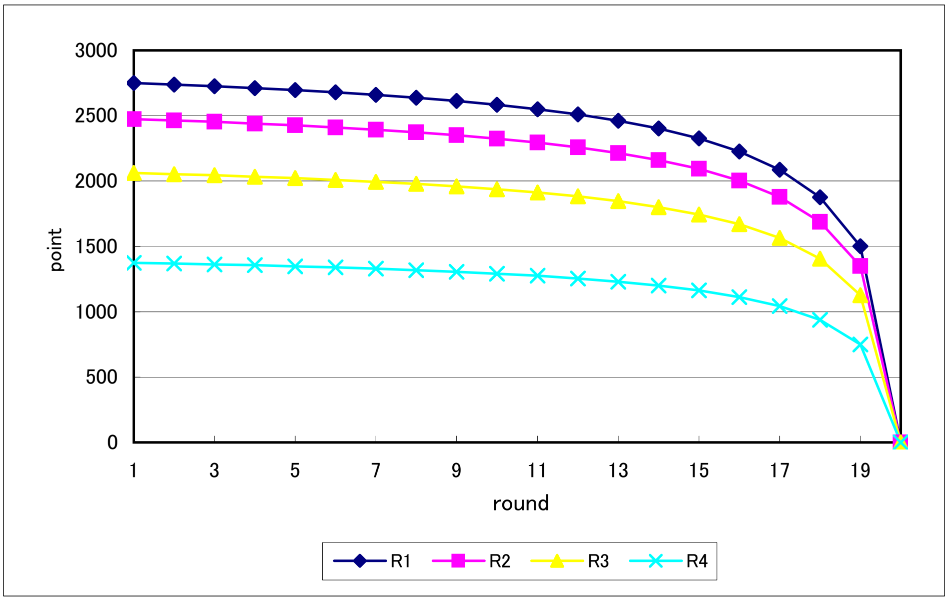
Table 13

Knightian Uncertainty on Reservation Point by the Extent of Risk Attitude (B)

	Reservation point in precommitted games		
	(1)	(2)	(3)
	risk prone	risk neutral	risk averse
Knight (=1)		-43.333	-19.250
		(38.944)	(44.507)
Subject dummies		Yes.	Yes.
Round dummies		Yes.	Yes.
Session dummy		Yes.	Yes.
R-squared		0.905	0.654
N	No observations	120	160
	OSR-consistent subjects	OSR-consistent subjects	OSR-consistent subjects

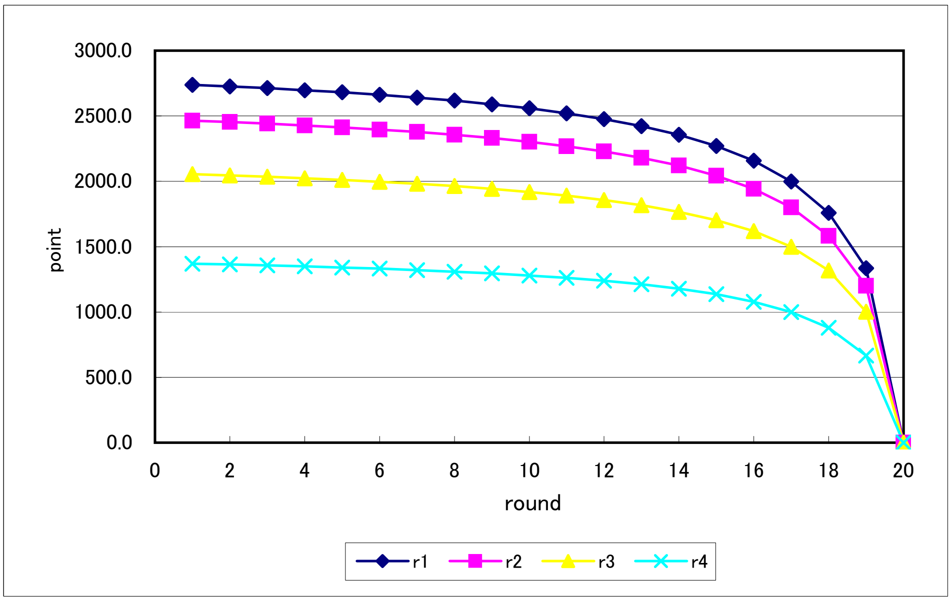
Note: Robust standard errors in parentheses. *** 1%, ** 5%, * 10% significance. The extent of risk attitude is calculated from a subject's response to the post-experimental questionnaire: how much is a subject willing to pay for a lottery of a 25% chance of winning JPY2000, but a 75% chance of winning nothing according to Cramer, Hartog, Jonker, and van Praag (2002).

Figure 1:Trends in the Reservation Point by the Extent of Ambiguity (Risk Neutral Agent)



R1: No ambigutiy
R2: Ambiguity (Epsilon = 0.1)
R3: Ambigutiy (Epsilon = 0.25)
R4: Ambigutiy (Epsilon = 0.5)

Figure 2:Trends in the Reservation Point by the Extent of Ambiguity (Risk Averse Agent)



r1: No ambigutiy
r2: Ambiguity (Epsilon = 0.1)
r3: Ambigutiy (Epsilon = 0.25)
r4: Ambigutiy (Epsilon = 0.5)