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AGING, PROBABILITY WEIGHTING, AND REFERENCE POINT ADOPTION: AN EXPERIMENTAL STUDY

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Aging, probability weighting, and reference point adoption: an experimental study*

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Abstract

We examine generational differences in risk-taking behavior by means of a laboratory experiment with monetary incentives. We estimate the parameterized models in the framework of cumulative prospect theory and examine the risk aversion, probability weightings and reference point adoption of elderly and young groups. The results of our experiment indicate that the elderly group is less sensitive to changes in probability and tends to underestimate large probabilities and overestimate small probabilities more strongly than does the young group. Furthermore, we find that the elderly update their reference point after gains and tend to derive their utility from gains and losses not from levels of wealth. In sum, we find that the elderly group's behavior departs more from the traditional expected utility theory than does the young group's behavior.

Keywords: age; cumulative prospect theory; risk aversion; probability weights; reference point.

JEL codes: C91; D81.

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1. Introduction

Since the seminal work of Kahneman and Tversky (1979), prospect theory has challenged the dominant expected utility paradigm to the extent that it has been argued that expected utility theory (EUT) should be replaced with prospect theory as the foundation of decision making under risk (e.g., Camerer, 1998). There has been a large body of experimental work that supports prospect theory, and economic parameters regarding risk aversion, loss aversion, and probability weighting have been estimated using such experiments (e.g., Prelec, 1998; Gonzalez and Wu, 1999). Some studies, for example, Fehr-Duda et al. (2006), have examined gender difference, whereas others, such as Humphrey and Verschoor (2004), have examined cross-cultural differences in decision making under risk within the framework of prospect theory. Furthermore, a few studies have tested and supported prospect theory using real-life datasets (see, for example, Jullien and Salanie (2000), which used data from the UK betting market for horse races).

Surprisingly, however, little work has been done on generational differences in decision making under risk, presumably because experimental laboratories normally use students as subjects.[1] How well older people make economic and risk-taking decisions is an important issue for social policy (see Kovalchik et al. (2004), p. 2) because wealth tends to accumulate over people's lifetimes, and therefore, a large portion of wealth is in the hands of older people. The role of this study is to shed light on the differences in risk-taking behavior between elderly and young individuals.

[1] An exception is Kovalchik et al. (2004). They examined the risk-taking behavior of two populations—old and young—along with other types of decisions with a potential for age effects. In their studies of risk-taking behavior, subjects were asked to select cards from one of two decks to earn cash. The cards were preorganized so that one deck (B) had the more advantageous composition. They found that both populations gradually concentrated their choices on deck B. Overall, they concluded that the older adults' decision behavior was similar to that of the young adults. Our current study differs from their study in that we explicitly estimate the parameters of risk-taking behavior and compare the estimated parameter values between the two populations.

We obtain elderly and young individuals' certainty equivalences for risky lotteries using an experiment based on the procedure of Becker, DeGroot, and Marschak (1964), and we estimate the parameterized value functions and probability weighting functions for the two groups of subjects: old and young.[2] In addition to risk aversion and probability weighting, we examine how subjects update their reference points during repeated rounds in the experiment. Although the reference point plays a prominent role in prospect theory, the manner in which it is updated through time as a function of the outcomes of past decisions is unknown. The issue of reference point adoption is also important in real-world situations, such as financial markets: it has been argued that the well-observed disposition effect—the tendency to sell stocks that have gained value too soon and to keep stocks that have lost value too long—can be explained by investors' reference point adoption (see, for example, Kliger and Kudryavtsev (2008)). For each group, we estimate and compare the two alternative models based on two different assumptions about the reference point adoption.

The results of our experiment indicate that the old group is risk loving, whereas the young one is risk averse, although this difference disappears after controlling for gender. A more robust difference was found in probability weighting. We find that the old tend to underestimate large probabilities and overestimate small probabilities more than do the young. Furthermore, the model selection test indicates that the old tend to update their reference point after gains, whereas the young do not have this tendency. In sum, the elderly group's behavior departs more significantly from the traditional EUT than does the young group's behavior.

2. The experiment

The participants were 31 elderly subjects from *Silver Jinzai Center* (an employment agency for elderly people) in Osaka and 32 young employed subjects who were recruited through e-mails and fliers. In contrast to the subjects of most existing experimental studies, all our young subjects are

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[2] We assume that individuals report their true willingness to accept at the BDM although it has been an issue and resulted in a large body of work (see Karni and Safra (1989)).

currently employed. We believe that this composition—retired elderly people and young employed people—more realistically represents the population whose financial transactions affect society than would be the case if students were used as subjects. The subjects were promised a 5000-yen base payment for participation. In addition, they were told that their gains from winning and selling lotteries would be added to the 5000-yen participation fee to yield their final payments. Table 1 shows the characteristics of the two subgroups. It can be seen that the old group consists of a greater proportion of males, less-educated individuals, and lower-income earners.

We used an experiment based on the Becker, DeGroot, and Marschak (1964) procedure. The Becker–DeGroot–Marschak mechanism is widely used to elicit decision makers' selling prices for lotteries. The same procedure was used with our participants in the two groups. Each subject takes part in 20 rounds, following five practice rounds. At the beginning of each round, a subject is given a ticket for lottery L, which yields 1000 points with probability p and zero points with probability $1-p$. In each round, the probability p is randomly assigned at the beginning of each round. After observing the probability p, subjects are asked to announce the minimal price for which they are willing to sell the lottery. After the announcement of the selling price, a random offer price is selected out of a [1, 1000] segment. If it exceeds the subject's declared selling price for the lottery, he or she has to accept the offer price and receive the monetary payoff of the offer price. If the offer price is below his or her selling price, the subject plays the lottery. If the lottery is won, the subject receives 1000 points, whereas if the lottery is lost, the subject receives nothing. After 20 rounds are played, earned points are exchanged for yen at the rate of 1000 points for 250 yen.

3. The econometric models

We invoke the concepts of cumulative prospect theory (CPT) (Tversky and Kahneman, 1992) and estimate the models based on this theory. The model nests the traditional EUT so that we can test the two alternative theories of risk-taking behavior.

In our experiment, a two-outcome lottery yields 1000 points with probability p and zero points with probability $1-p$. Let a_i denote the initial wealth of an individual at round i with $a_1 = 0$. The variable a_i is the accumulation of the past gains by selling or winning lotteries. Then, for our two-outcome lottery, the outcome when the lottery wins is $a_i + 1000$, whereas when the lottery loses, the outcome is $a_i + 0$. One aspect of CPT is that individuals derive utility from gains and losses relative to a reference point, not from total wealth or consumption. Now let r_i denote the reference point and let wta_i be the declared selling price at round i. Then, the certainty equivalence CE_i is defined by the following equation:

$$v(CE_i) = \pi_1 v(a_i + 1000 - r_i) + \pi_2 v(a_i + 0 - r_i)\,, \tag{1}$$

where $CE_i = a_i + wta_i - r_i$. Decision weights are denoted by $\pi_j\,(j = 1,2)$, and v is the value function defined on the points. The decision weights depend on the subject's domain-specific probability weighting function $w(p)$. In our two-outcome case, the decision weights can be represented as follows:

$$\pi_1 = w(p)$$
$$\pi_2 = 1 - w(p).$$

We have to choose functional forms for v and w to make the model estimable. One of the functional forms most frequently used for the probability weighting function w is a one-parameter version introduced by Quiggin (1982) as well as Tversky and Kahneman (1992). Here, we consider the latter version of the probability weighting function:[3]

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[3] Other studies such as Lattimore et al. (1992), Prelec (1998), and Gonzalez and Wu (1999) proposed two-parameter functional forms that are more flexible and probably more appropriate to use. However, we use a one-parameter form because the number of observations is very small when we

$$w(p) = \frac{p^{\gamma}}{(p^{\gamma} - (1-p)^{\gamma})^{1/\gamma}}; \gamma > 0.$$

For the value function, we assume that the valuation of outcomes is represented by the following power functional (Tversky and Kahneman, 1992):

$$v(x) = \begin{matrix} x^{\alpha} & x \geq 0 \\ -\lambda(-x)^{\beta} & x < 0 \end{matrix}.$$

As noted in the following, we assume that an individual's reference point is either zero for each round $(r_i = 0 \forall i)$ or a_i $(r_i = a_i)$ for round i. Therefore, we will not have negative outcomes in our lottery experiment, and the parameters λ and β are not identified. The parameter α is assumed to be greater than zero, and the value function is either concave ($\alpha < 1$), convex ($\alpha > 1$), or linear ($\alpha = 1$).

Now, we turn to the reference points. The extension of CPT models to dynamics remains a controversial issue. In particular, the manner in which reference points are updated through time as a function of the outcomes of past decisions is unknown.[4] A natural hypothesis is that the reference point adapts in response to past outcomes, shifting upward following a gain and downward following a loss. To reflect this hypothesis, we first assume that the reference point r_i is updated following gain in each round so that $r_i = a_i$. Then, equation (1) is rewritten as follows:

$$\begin{aligned} v(CE_i) &= \pi_1 v(1000) + \pi_2(0) \\ &= w(p_i)v(1000) \end{aligned},$$

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estimate the likelihood function for each individual below and, in such a case, it is preferable that the number of parameters to be estimated be small.

[4] However, recent research such as Arkes et al. (2006) has examined this issue and found the asymmetric adaptation of gains and losses.

where $CE_i = a_i + wta_i - a_i = wta_i$. Note that, under this assumption, the individual derives his utility from gain from the lottery not from the outcome level. We refer to this model as Model 1. Next, we consider the case in which a reference point is not adopted at all: $r_i = a_1 = 0$ for all i . In this case, equation (1) is rewritten as follows:

$$\begin{aligned} v(CE_i) &= \pi_1 v(a_i + 1000) + \pi_2 (a_i + 0) \\ &= w(p_i)v(a_i + 1000) + (1 - w(p_i))v(a_i) \end{aligned},$$

where $CE_i = a_i + wta_i - 0 = a_i + wta_i$. We refer to this model as Model 2. Note that under these functional forms of the value function and the probability weighting function, Model 2 nests the EUT. Under this model, the individual is assumed to value the final asset level, and when $\gamma = 1$, there is no probability weighting, as in EUT. Therefore, EUT is addressed as a special case of Model 2.

We estimate Model 1 and Model 2 and compare which model performs better for the of old and young. The two models are polar cases, in the sense that one assumes complete reference point adoption whereas the other assumes no such adoption occurs. In reality, of course, individuals may perform somewhere between these two polar cases. Therefore, in order to compare the two models, we conduct the likelihood ratio test of Vuong (1989), which does *not* require us to assume that one of the two models is correctly specified. The Vuong test assumes that both of the competing nonnested models are incorrect and compares their distance from the correct specification. Therefore, we can obtain the information that reveals which model is closer to the true model.

Finally, our empirical models for Model 1 and Model 2 are specified as follows:

Model 1: $wta_i = v^{-1}[w(p_i)v(1000)] + \varepsilon_i$,

Model 2: $wta_i + a_i = v^{-1}[w(p_i)v(a_i + 1000) + (1 - w(p_i))v(a_i)] + \varepsilon_i$,

where we assume that $\varepsilon_i \sim N(0, \sigma)$. We estimate parameters α, γ, σ by maximum likelihood estimation.

4. The results

First, we estimate Model 1 and Model 2 using the entire sample, and the two groups: old and young. Table 2 shows the results. It can be seen that the estimated values are very similar between the two models (for the same sample). The results of estimated α suggest that, on average, elderly individuals are risk loving whereas young individuals are risk averse. The value of γ for the old group is estimated to be significantly lower than that for the young group, implying that elderly individuals are less sensitive to the change in probability. Figure 1 presents the probability weighting functions for the old and young groups using the estimated values of γ. They imply that the old tend to overestimate small probabilities and underestimate large probabilities more strongly than do the young.

Table 3 shows the results from the Vuong tests. The results show that Model 1 is preferred for the estimations using the entire sample and the old sample, at the 10% and 5% levels, respectively. It seems that old individuals tend to update their reference points in each period. For the young sample, neither of the alternative models is preferred. However, the likelihood ratio is higher for Model 2, and hence, other model selection tests such as Akaike information criteria would choose Model 2 for the young sample. Our selection tests indicate that the old and the young are different in their methods of reference point adoption. Elderly individuals tend to update their reference points every time after gains and, therefore, tend not to take their initial wealth a into account in their risk-taking behavior. Their utility is derived from gains from the lotteries not from the outcome levels. Realizing that Model 2 is identical to EUT when γ is one, our results, which indicate a lower γ and a better fit of Model 1 for the old, imply that the behavior of the elderly departs more significantly from traditional EUT than does that of the young.

Because the characteristics of our two groups differ significantly, as shown in Table 1, the above results indicating behavioral differences between the two groups may merely be a reflection of the differences in the each group's characteristics. In order to control for these characteristics, we conduct the same estimation for *each individual* and obtain the same parameter values for each individual. Then, we regress these parameters on their characteristics, including age, and determine whether age has significant effects on the parameter values. We conduct a Vuong test for each individual and use the parameter values from the selected model for the regression. When the Vuong test does not prefer either model, we use the one that has a higher likelihood.

Table 4 presents the results from estimations for 23 elderly individuals and 32 young individuals.[5] We show the average and median values for each parameter. The results continue to indicate that elderly individuals have a higher α and a lower γ. Table 5 presents the results from the regressions on α and γ. Here, we use age, education, income, a male dummy, and a constant for control variables.[6] The results show that once the other characteristics are controlled for, age does not have a significant effect on α. However, age still has a significant effect on γ, and older individuals have a lower γ, implying that older individuals tend to have more distorted probability weighting functions. In addition, the results show that more highly educated individuals are more risk averse, whereas male individuals are less risk averse at a significant level. Furthermore, we found that more highly educated individuals have less-distorted probability weighting functions, which is intuitive. In addition, individuals with higher incomes have less-distorted probability weighing functions.

5. Conclusion

Our experimental study demonstrates that generational differences in risk-taking behavior crucially depend on probability weights and reference point adoption. We found that elderly individuals are less sensitive to the probability change. In addition, we found that elderly individuals

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[5] There are some elderly individuals who obviously do not behave nonstrategically, and whose parameter values are extremely unrealistic. For example, some individuals always hit the same number for 20 rounds. We excluded these elderly samples from our further estimation.

[6] The education variable in Table 1 is converted to the actual number of years of education. For the income and age variables in Table 1, the median value in each category is used.

tend to update their reference points after gains and do not derive utility from total level of wealth. That is, elderly individuals seem to depart more significantly from traditional EUT. As most developed countries face aging populations and the main wealth holders are elderly individuals, such behavioral differences should be taken into account where social policy is concerned.

We have estimated only one specification of CPT. The next step should be to consider more flexible functional forms, including weighting functions with two parameters and semiparametric forms. Furthermore, the current study cannot identify the degree of loss aversion. Although we do not find any difference in risk aversion between the two generations, elderly individuals may exhibit higher loss aversion, and such behavioral differences will have important policy implications. Therefore, our next direction is to consider an experimental design that would enable us to determine the degree of loss aversion.

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Table 1 Characteristics of the entire sample, old and young subsamples (percentages)

		All	Old	Young
Sex	Male	63.49	74.19	53.13
	Female	36.51	25.81	46.88
Age				
	20s	7.94	0.00	15.63
	30s	7.94	0.00	15.63
	40s	22.22	0.00	43.75
	50s	11.11	0.00	21.88
	60s	34.92	67.74	3.13
	70s	11.11	22.58	0.00
	Unknown	4.76	9.68	0.00
Education				
	Elementary school – Junior high	3.17	6.45	0.00
	– High school	30.16	58.06	3.13
	– Polytechnic	1.59	0.00	3.13
	– Junior college	9.52	6.45	12.5
	– University (non science)	42.86	19.35	65.63
	– University (science)	9.52	9.68	9.38
	– Graduate school	3.17	0.00	6.25
Income				
	No income	12.7	19.35	6.25
	Less than 1 million yen	3.17	3.23	3.13
	1–2 million yen	11.11	9.68	12.5
	2–4 million yen	19.05	25.81	12.5
	4–6 million yen	11.11	16.13	6.25
	6–8 million yen	1.59	0.00	3.13
	8–10 million yen	12.7	0.00	25
	10–12 million yen	4.76	0.00	9.38
	12–14 million yen	3.17	0.00	6.25
	More than 14 million yen	1.59	0.00	3.13
	Unknown	19.05	25.81	12.5

Table 2 Estimation results for Models 1 and 2

	Model 1 (full adoption of reference point)			Model 2 (no reference point adoption)		
	All	Old	Young	All	Old	Young
α	1.0842***	1.3643***	0.9520*	1.0843***	1.3642***	0.9517*
	(0.1257)	(0.0333)	(0.5483)	(0.1257)	(0.0333)	(0.5491)
γ	0.5267***	0.3922	0.6766***	0.5268***	0.3925***	0.6765***
	(0.0569)	(0.0681)	(0.1077)	(0.0569)	(0.0681)	(0.1077)
σ	239.4308***	232.3844***	229.4452***	239.4317***	232.3892***	229.4450***
	(45.8356)	(52.7820)	(52.7524)	(45.8382)	(52.7849)	(52.7530)

Note: The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3 Vuong test of Model 1 against Model 2

	Vuong statistics Model 1 vs. Model 2
All	1.81*
Old	2.50**
Young	–0.60

Note: The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4 Individual estimation results

	All		Old		Young	
	Mean	Median	Mean	Median	Mean	Median
α	1.3573	1.0099	1.8646	1.1142	1.0085	0.9777
γ	0.6614	0.6828	0.5418	0.5167	0.7437	0.7576
σ	135.7924	112.6086	108.9852	89.5142	154.2223	126.9430

Table 5 Regression results for α and γ

	α	γ
Age	0.0002	–0.0031***
	(0.0026)	(0.0007)
Education	–0.0893***	0.0422***
	(0.0177)	(0.0050)
Income	0.0001*	0.0001***
	(0.0001)	(0.0000)
Male	0.3737***	–0.0348*
	(0.0703)	(0.0201)
Constant	2.1605***	0.1985***
	(0.3387)	(0.0968)

Note: The symbols ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

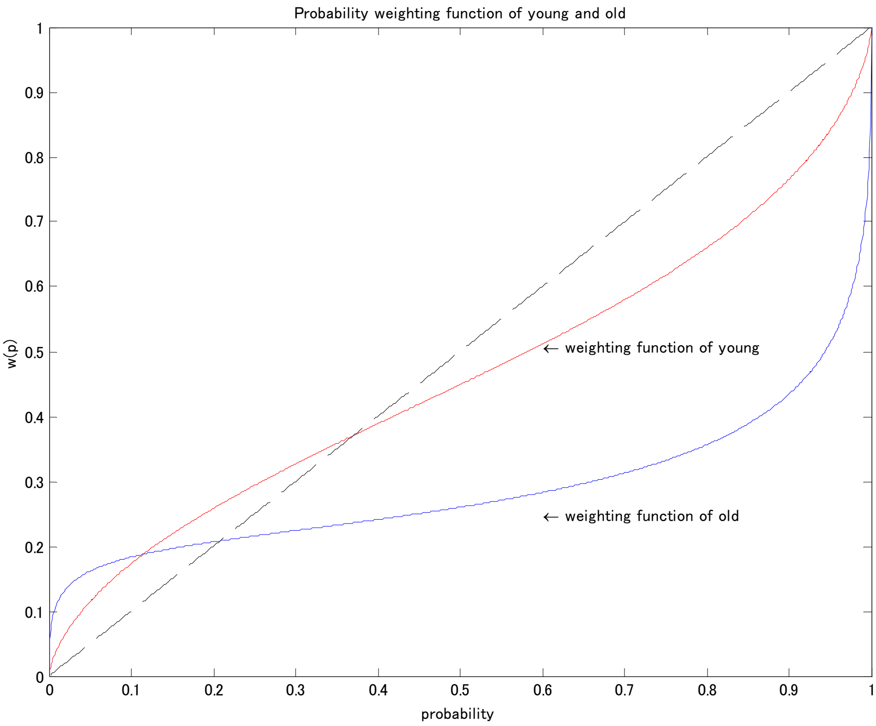

Figure 1: Estimated probability weighting functions of the old and the young.