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A Noise-Reduced Risk Aversion Index

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Abstract

We propose a noise reduced risk aversion index for measuring risk aversion through a laboratory experiment to overcome disadvantages of the multiple pricing list format developed by Holt and Laury (2002). We use randomized multiple list choices with coarser classification and reward weighting, supplement the rank of risk aversion with extra individual characteristics of risk attitude, and construct an index of risk aversion by standardizing the risk aversion ranking with quantile normalization. Our method reduces multiple switching problems that noisy decision makers mistakenly commit in experimental approaches, so that it is free of the framing effect which severely occurred in the HL. Furthermore, the index doesn't utilize any specific utility function or probability weighting, which allows researcher to hold the independence axiom. Since our noise reduced index of risk aversion has many good traits, it is widely used and applied to reveal fundamental characteristics of risk-related behaviors in economics and finance regardless of experimental environment.

Keywords : Risk Aversion, Experiments, Elicitation Method, Quantile Normalization

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1. Introduction

Risk attitude is fundamental in various economic and financial models. Understanding individuals risk attitudes is closely linked to the power of predicting behavioral consequences. The literature in behavioral studies has tried to measure risk aversion through laboratory experiments. A large amount of research has been dedicated to eliciting risk aversion. Since Binswanger [1980, 1981] pioneered the multiple price list (MPL) format to elicit subjects' risk aversion, the methods using the multiple price list have been increasingly used especially in laboratory experiments. The multiple price list entails giving the subjects an ordered array of binary lottery choices to make at once. The procedure requires subject to pick one of the lottery tickets and be rewarded, depending on their choice. Many experiments measuring individual risk aversion involve the specific multiple price list methods which is developed by Holt and Laury [2002] (HL). The HL designed the multiple price list procedure which consists of 10 pairs of consecutive choices with fixed rewards and probability changes where there are two options in each choice. Option A is the less risky lottery and option B is the more risky lottery in each row, and a risk-neutral choice is set by choosing option A for the first 4 rows and option B thereafter. Risk attitudes are measured by the number of rows before moving to option B. The HL method has been the standard and the most popular procedure conducted in laboratory experiments because it is easy to explain the procedure to subjects and simple to implement and provides simple incentives for truthful revelation. Although the HL method is considered to be the representative method of the multiple price list formats and be the heavily cited study of risk attitudes, the HL method has several possible disadvantages which are very well-known. It tends to be susceptible to the framing effects, the interval response, and the certainty effect, i.e., it could be sensitive to the probability weighting function, the parametric utility function-dependent, and multiple switching points.

There is another way to measure the risk aversion model-independently. Maier and Rüger [2010] (MR) applied an elicitation procedure that has the multiple price list design using options with the same probabilities and a set of varying rewards. Their method has an additional advantage because subjects, who might struggle with descriptions of gambles involving varying probabilities and payoffs, are likely to understand structures of gambles with same probabilities more easily. However, their method generates so much noise decision-making (i.e., multiple switching points) caused from obscure risk preferences from which reliable inferences cannot be drawn. Their method still elicits interval responses. Similar to the HL method, their method tends to be susceptible to framing effects.

There are some research and procedures to detect and correct the framing effect and the interval response [Anderson et al., 2006; Anderson et al., 2008; Harrison and Ruström, 2008]. In line with Quiggin [1995] generalizing non-expected utility theory, Wakker and Deneffe [1996], Diecidue and Wakker [2001] provided non-expected utility methods without any parametric assumption.

Drichoutis and Lusk [2012] modified the HL method without confounding effect of probability weighting and Abdellaoui et al. [2011] and Bruner [2009] allowed outcome scale rather than probability scale, taking rank dependant utility into account rigorously.

There are many inconsistent noisy subjects in the HL method so that they change their choice in an irrational way. In the normal MPL setting, subjects are likely to move to a more certain reward and then back to riskier rewards more than one switching. In that case, researchers have hardship to pinpoint the risk aversion of the subject. Recent studies, Dave el al. [2010] and Bosch-Domènech and Silvestre [2013] indicated the HL method is too complex and has too many choice sets for subjects to easily make noisy behaviors, so that the coarser and simpler elicitation method may be preferred for subjects who exhibit low numeracy, as it generates less noisy choices as well as similar predictive accuracy. Hirschauer et al. [2014] suggested dropping inconsistent subjects avoids biases in a population-level analysis, but it still doesn't solve the bias in a small sample. Dohmen et al. [2011] enhanced predictive accuracy of eliciting risk attitude with the German representative survey. Charness et al. [2013] provided a good review of a series of prevailing methods for eliciting risk preferences and comprehensive outline of advantages and disadvantages of different methods beyond the MPL.

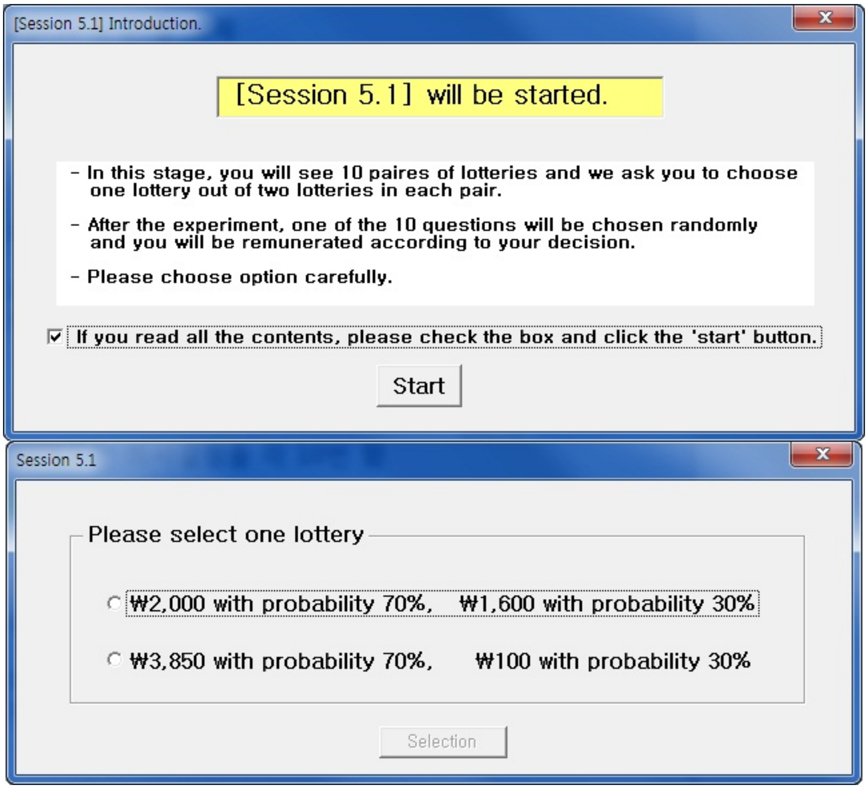
To overcome disadvantages of the multiple pricing list format, we design a new experiment, propose a eliciting method to measure noise reduced risk aversion through conducting the laboratory experiment and standardizing the risk aversion ranking by quantile normalization. What differentiates our study remarkably is that we derive a risk aversion index which doesn't make use of the expected utility theory, in the line with even adopting the context of the multiple price list format where instead of probability weighting, only rewards are changed as a weighting. Since we utilize only rank dependent preference of risk aversion and the index doesn't violate the independent axiom, it is cognitively simple for subjects to understand and meets theoretical foundations. In addition, thanks to the randomly computerized experiment, it is free of the framing effect, and using a coarser set of choices, we reduce the multiple switching problems, i.e., the index is robust toward noise decision-making. Our risk aversion index seems to serve as a general guide to rigorously elicit risk attitudes in various laboratory experiments. Another contribution of our study is that because of good traits of the index through standardizing the index with quantile normalization, researchers address crucial queries of financial phenomenon in asset markets by utilizing the new index effectively regardless of any restriction or condition of experiments.

In section 1, we review previous research regarding relevant laboratory experiments and highlight our methods. Section 2 demonstrates the experimental procedure in detail. In Section 3, we present the elicitation method of risk aversion, construct the new index using our elicitation method, and describe the data set. Section 4 presents econometric analysis on the determinants of individual risk aversion with various models. Section 5 draws a conclusion and discusses future research topics.

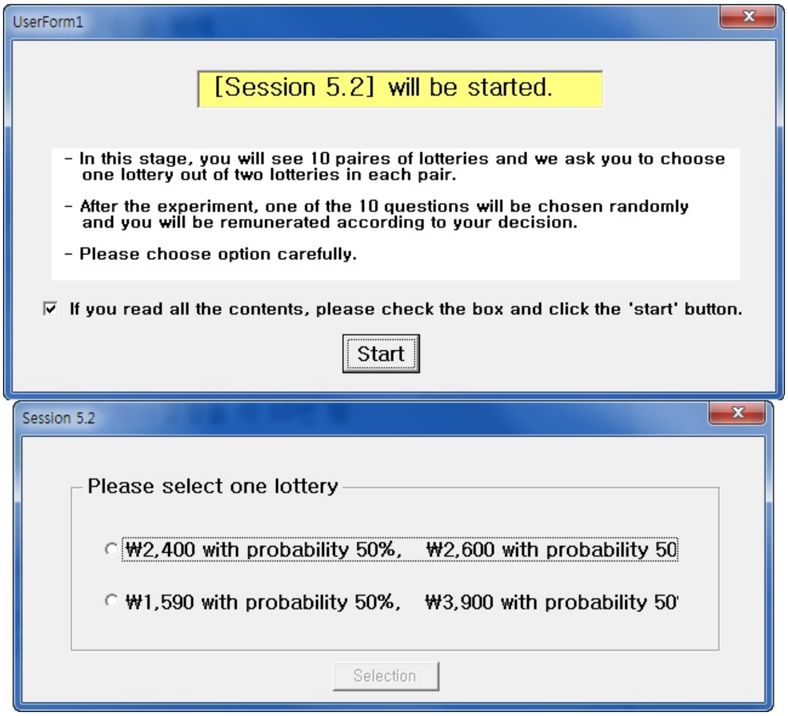
2. Experimental Procedure

In order to construct a noise reduced risk aversion index and test if effect of asymmetric informational environment on risk aversion is valid, we conducted the experiment with 161 undergraduate students at Dankook University, which is a large university in South Korea (The number of students at Jukjeon campus is 16,500). The experiment is run out on a personal computer with the questionnaire constructed in Microsoft (MS) Excel and the Visual Basic for Application (VBA) program embedded in MS Excel.

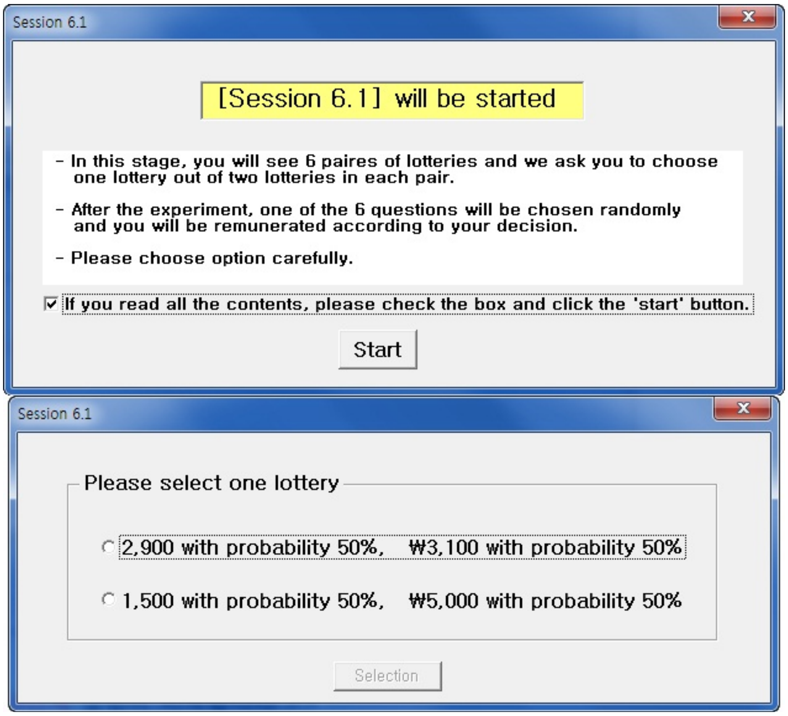
The experimental sessions consists of 4 stages : In stage 1, subjects began with instructions (see <Figure 1> and <Figure 2>) and two sample lottery choices. They were informed in advance that in this stage, they would conduct two sessions and make 10 decisions in each session. For the purpose of comparison, the first session, titled (5.1), is constructed followed by the HL method, i.e., changing probabilities and fixed rewards and the second, titled (5.2), is similar to the MR method, i.e., changing rewards and fixed probabilities. In both cases, subjects see a random pair of options appearing, because we check how severe the framing effect is in the HL and the MR. The currency unit is Korean won(₩), and approximately ₩1,020=$1.



〈Figure 1〉 Screen Shots of Instruction and Random Lottery Choices in Session (5.1)



〈Figure 2〉 Screen Shots of Instruction and Random Lottery Choices in Session (5.1)



〈Figure 3〉 Screen Shots of Instruction and Random Lottery Choices in Session (6.1)

Stage 2 started with the instruction (see <Figure 3>) that they noticed there would be 6 decisions instead of 10 decisions. In the first session, titled (6.1), subjects faced 6 distinct pair of lottery tickets in which each lottery comprised changing rewards and fixed probability, 1/2. The options were constructed corresponding <Table 2>.

In stage 3, we post experimental-surveyed basic personal information for later regression analyses. Subjects reported personal basic characteristics such as sex, age, military service, number of family members, the number of economic classes taken, religion, and average educational level of parents. Subjects were also asked six questions for measuring cognitive ability where three questions come from the cognitive reflection test (CRT) suggested in Frederick [2005] and three questions are selected from the Wonderlic Personnel Test (WPT)[1]. To distinguish cognitive ability from learning effect, six questions were prepared for measuring economic intelligence selected from Soper and Walstad [1987]. Next, we collected the past experience of risky behaviors such as lottery ticket purchases, gambling, stock investment, money lending, propensity of absolute risk aversion by asking the absolute price of lottery tickets that they are willing to buy, and the subjective risk attitudes.

In the last stage following three sessions, the subject received a real payoff in a way that we randomly chose one row, and given the option she had chosen in the row, the payoff was determined, depending on the probability she selected. It applied to three sessions, (5.1), (5.2), and (6.1). In order to reduce portfolio effect, before all of the sessions was started, we informed to subjects that each sessions are independently conducted.

The payment of reward was given in 2 steps. When subjects finished all sessions and post experimental survey, they submitted the USB where experimental results were stored. Assistants checked if answers were fully recorded sincerely. In the first step, subjects carried out “Stick selection game”, we called, in order to select questions randomly in session (5.1), (5.2) and (6.1) respectively. Because session (5.1) and (5.2) had 10 questions respectively and session (6.1) had 6 questions, 10 sticks that had numbers from 1 to 10 were used to select the questions in session (5.1) and (5.2) and 6 sticks that had numbers from 1 to 6 in session (6.1). Therefore, 3 questions were selected in total. And next, assistants checked which option subjects selected in the three pairs of lotteries corresponding the number in the sticks. In the second step, the monetary compensation was paid by, so called, “probability game.” As for the session (5.1), one reward of the option selected in the stick selection game was really given to subjects, depending on which probability they select in the probability game where one of the sticks that had numbers from 1 to 10 each. For example, it is possible to receive ₩100 with probability of 30% and ₩3,750 with probability of 70%, subjects can receive ₩100 if they pulled out the sticks numbered 1 to 3, and receive ₩3,750 if they pulled number 4 to 10. In sessions (5.2) and (6.1), since the probability was always the same

1) http://www.wonderlic.com/assessments/ability/cognitive-ability-tests.

<Table 1> Summary Statistic of Monetary Rewards

	Mean	Median	Max.	Min	St.Dev
Monetary Reward (₩(won))	7369.56	7000	15000	1000	1840.3

as 50% in all questions, compensation was determined by the coin toss game, equally probability 1/2. For example, if the head came out, subject received the reward that was written on left side and if the tail came out, subject received the reward on right side. Average reward was ₩7,369.5 and other statistics were described in <Table 1>.

3. Noise Reduced Risk Aversion Index and Data

We elicit our noise reduced index measure of risk aversion through the innovative experiment conducted with 161 undergraduate students at Dankook University, which is a large university in South Korea (The number of students at Jukjeon campus is 16,500). The experiment is run out on a personal computer with the questionnaire constructed in MS Excel and the Visual Basic program embedded in MS Excel. The procedure of our experiment is illustrated in Appendix in more detail.

3.1 New Index of Risk Aversion

To overcome the possible disadvantages of the multiple price list methods presented in the previous research, we suggest an elicitation method that is cognitively simple, provides a finer categorization, and is easily extended to a risk aversion index by quantile normalization. Designing the noise reduced index of risk aversion, we deliberately follow the method of reward changes which is similar to the MR method. Our elicitation method consists of three steps in detail.

First, we measure risk aversion by the multiple price list formats with coarser classification of six pairs of two options and through the sequence of options, the reward changes and probabilities are fixed at the level of 1/2, respectively. In the method, subjects randomly face one out of six pairs of two options and make a decision between option A and the option B. Two options have two different rewards with equal probabilities respectively and while rewards in option A are fixed, rewards of option B in each row are varying. According to the definition of increasing risk [Rothschild and Stiglitz, 1970], option B is more risky than option A because of the bigger variance in all rows except the first row, and further the risk of option B rises from the sixth row to the first row in the sense of both the mean and the variance of outcomes. As six pairs of two options show up randomly on the computer monitor, subjects choose option A or option B in each pop-up window. For the computational convenience, and the consistency and comparison with the HR and the MR method, we use the utility function, $u(x)=x^{1-r}$ and recalculate the constant relative risk aversion, r. <Table 2> presents each pair of options, rewards, range of relative risk aversion (r), difference of expected values, and difference of variances.

〈Table 2〉 An Elicitation Method Using Increasing Risk for the Risk Averse and Decreasing Expected Outcomes for the Risk Loving

Row No.	Option A		Option B		Range of RRA (r)	EV (B)-EV (A), Var (B)-Var (A)
	Prob. 1/2 Outcome 1	Prob. 1/2 Outcome 2	Prob. 1/2 Outcome 1	Prob. 1/2 Outcome 2		
1	2,900	3,100	0	4,100	(-Inf, -1.22]	-950, 4,192,500
2	2,900	3,100	0	6,000	[-1.22, 0]	0, 8,990,000
3	2,900	3,100	800	5,700	[0, 0.23]	250, 2,992,475
4	2,900	3,100	1,500	5,000	[0.23, 0.5]	250, 1,522,125
5	2,900	3,100	2,000	4,500	[0.5, 1]	250, 771,875
6	2,900	3,100	2,500	4,000	[1, 3.04]	250, 271,625

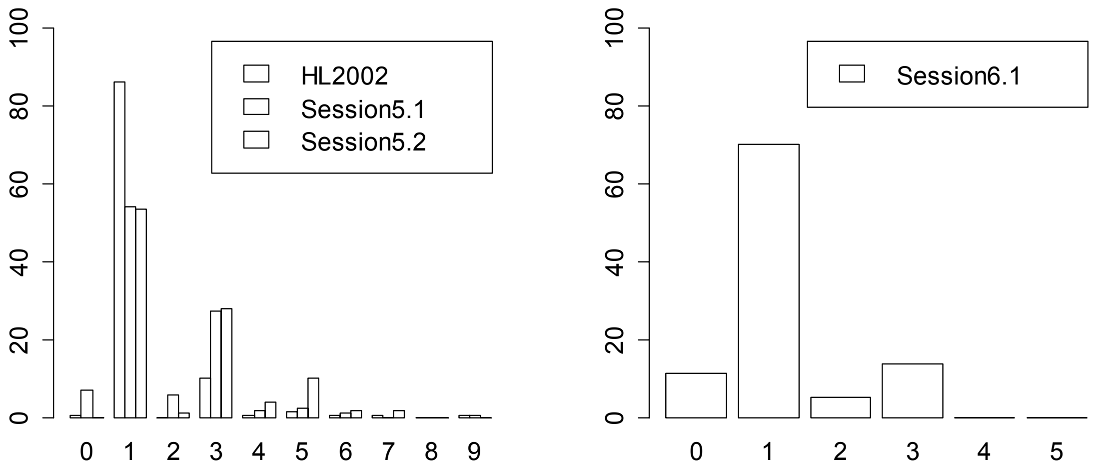
The reason we adopt the multiple price list formats using options with same probabilities to hold is that there are several advantages. In particular, holding probabilities constant (1/2), the independence axiom (the risk preference must be linear in the probabilities of the possible outcomes) cannot be violated in the method. For robustness of our method, we set up random selection in order to make subjects free of the framing effect.

Second, it is well known that the measurement of risk aversion depends on an order of price list. Thus, for robustness towards order dependency, we take random order of price list and show them to subjects. Each subject observes a pair of two price list lottery randomly and then they choose one option which is better than the other one. The procedure makes us to confirm that subjects are free of framing effect because they cannot be automatically induced in the middle choice through following the list from up to bottom. Hence we only take the rank of the level of subject's risk to get higher measurement accuracy for risk aversion.

For the purpose of comparison, we replicate the HL, titled (5.1), MR, titled (5.2) with random lottery choices, and our main experiment, titled (6.1) with the random coarser classification. <Table 3> shows the respective framing effect in each experiment. Each column describes the distribution of the numbers subject switch between option A and option B in each experiment session. As for the HL, we calculate the number of switching points with the appendix in the HL. The first column seems to show that the HL has much less severe multiple switching problem than the second column with random choices, i.e., while the number of subjects who switch just once is 86.3%, 54% of subject in session (5.1) changes. That is the evidence of existence of the framing effect in the original

〈Table 3〉 Distributions of Multiple Switching Points

	HL [2002]	session 5.1	session 5.2	session 6.1
0	1(0.47)	11(6.83)	0(0.00)	
1	183(86.3)	87(54.0)	86(53.4)	
2	0(0.00)	9(5.59)	2(1.24)	18(11.2)
3	21(9.91)	44(27.3)	45(28.0)	113(70.2)
4	1(0.47)	3(1.86)	6(3.73)	8(4.97)
5	3(1.42)	4(2.48)	16(9.94)	22(13.7)
6	1(0.47)	2(1.24)	3(1.86)	0(0.00)
7	1(0.47)	0(0.00)	3(1.86)	0(0.00)
8	0(0.00)	0(0.00)	0(0.00)	
9	1(0.47)	1(0.62)	0(0.00)	
Total obs.(Prob.)	212 (100%)	161 (100%)	161 (100%)	161 (100%)



〈Figure 4〉 Distributions of Multiple Switching Points as an Evidence of Framing Effect

〈Table 4〉 Wilcoxon Rank-Sum Test Results

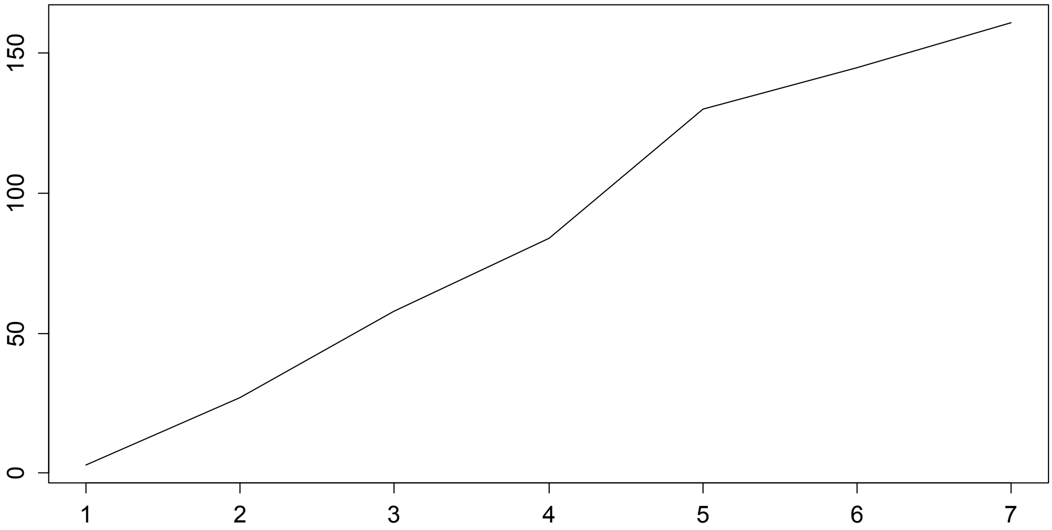
Comparison distribution (A)	Benchmark distribution (B)	H_0	Test Statistic	P-value
Session 5.1	HL[2002]	$\mu_A \le \mu_B$	20,618	0.000006924
Session 5.1	Session 6.1	$\mu_A \le \mu_B$	9,734	0.000004799

HL experiment. Since the HL didn't construct the lottery choices randomly, subjects usually chose to change rows just once during scanning the options in order from top to bottom without randomness. The third column shows the MR has the similar problem.

However, since we construct random and coarser options, our main session (6.1) shows that the problem of multiple switching is rapidly decreased, i.e., 81.4% of subjects switch less than once between option A and option B. Even with the random lottery choices, we minimize the framing effect and noisy decision makers at the same time. <Figure 4> shows the distributions of multiple switching points in HL [2002], Session 5.1 (randomly replicated HL), Session 5.2 (randomly replicated MR) and Session 6.1 (our elicitation method).

We conduct Wilcoxon rank-sum test[2)] to compare between two distributions of multiple switching points for capturing framing effect in HL [2002]. <Table 4> shows the results of Wilcoxon rank-sum test. If HL [2002]'s method doesn't free from framing effect, average multiple switching points of comparison case(Session 5.1) will be greater than benchmark case [HL, 2002]. Furthermore, if our elicitation method reduces the multiple switching problems, average multiple switching points of the comparison case (Session 5.1) will be greater than benchmark case (Session 6.1). By the results of <Table 4>, our methodology improves the framing effect problem and reduces the multiple choices.

2) The Wilcoxon rank-sum test is a nonparametric test of the hypothesis that the distributions of two matched observations are the same.



〈Figure 5〉 Cumulative Distribution of Ordered Risk Aversion in Session 6.1

<Figure 5> shows the cumulative distribution of ordered risk aversion which are measured in Session 6.1. This plot is produced with R.[3)]

Third, to standardize the elicitation of risk attitudes (1. remove unwanted variation induced from different experimental conditions, e.g. different levels of incentives, different laboratories, different environments belonging to the subjects etc., 2. reduce the effect of the aberrations in the data which distort the estimates in the regression of risk aversion) we transform risk aversion ranking to the index by quantile normalization introduced by Bolstad et al. [2003]. The quantile normalization method has several advantages. (1) Since quantile normalization follows monotone transformation, it guarantees the continuity axiom on risk preferences. (2) Using risk aversion index by quantile normalization, we can use not only the interval regression but also various estimator such as OLS, Quantile Regression Estimator. Although interval regression is widely used in many other elicitation methods, it is a cause for ambiguous elicitation of risk aversion because risk aversion cannot be uniquely determined. (3) Quantile normalization makes discrete ordered risk aversion which is measured by experimental test to continuous variable as a risk aversion index.

Since quantile normalization used in micro-array data analysis frequently is not familiar to economists or financial scholars, we would like to explain it briefly. It is a method for making two (or more) distributions same in the statistical properties. The method is based on the idea that a quantile-quantile plot shows that if the distributions are the same, the quantiles line up on a diagonal line. This proposes that the same distribution could be obtained from two disparate datasets by transforming the quantiles of each to have the same value. This is implemented by projecting onto the unit diagonal

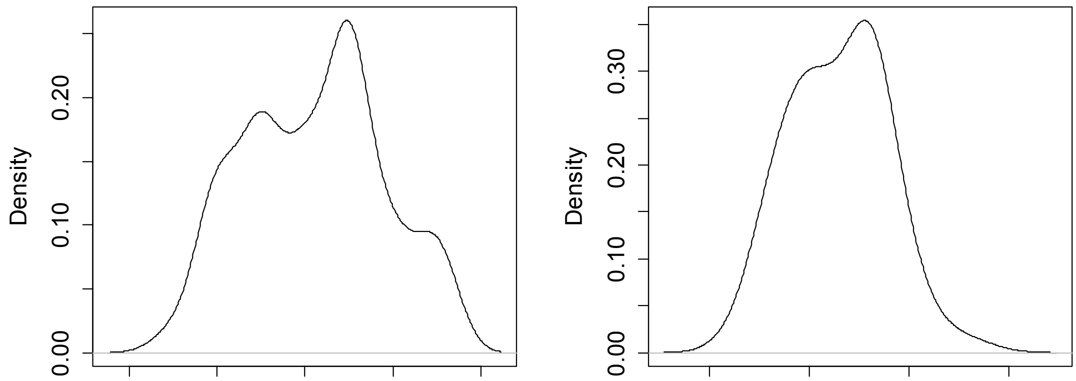
3) R is free statistical software environment using R programming language. It is widely used for statistical computing and graphics (URL : www. r-project. org).

$(1/\sqrt{2},\ 1/\sqrt{2})$. This idea is extended to M dimensions so that if a common distribution is obtained from M data vectors by the following algorithm [Bolstad et al., 2003] : Given M datasets of length p, form X of dimension $(p \times M)$ where each dataset is a column. Set $d = (1/\sqrt{M}, \cdots, 1/\sqrt{M})$. Sort each column of X to get X_{sort}. Transform from the quantiles so that they all lie along the diagonal. That is, project each row of X_{sort} onto X to obtain $X_{sort}^{'}$. Let $q_i = (q_{i1}, \cdots, q_{iM})$ be a row in X_{sort} and the projection of q_i onto d is given by $proj_d q_i = \left(\frac{1}{M}\Sigma_{j=1}^{m} q_{ij}, \cdots, \frac{1}{M}\Sigma_{j=1}^{M} q_{ij}\right)$. Note that the projection is equivalent to taking the mean quantile in a particular row. Get $X_{qnormal}$ by rearranging each column of $X_{sort}^{'}$ to have the same ordering as original X.

The left one in <Figure 6> illustrates the original density of the ordered risk aversion ranks resulted from the session (6.1) in the experiment, the benchmark case. The plot in right side of <Figure 6> is the transformed density of the ordered risk aversion ranks with quantile normalization. Since our index utilizes randomized experiments, reduces noisy-decision makers with coarser classification, and complements with additional characteristics of the subjects, it depends on only ordered ranks of risk aversion and is more robust against the framing effect and the multiple switching problems as well as probability weighting and the form of utility functions than other measures of eliciting risk aversion. With the standardization of quantile normalization, the index is generally compatible regardless of experimental circumstances.

3.2 Data

Our study collects data from 161 undergraduate students participating in the laboratory experiment and elicits risk aversion index as explained in section 2 and 3. The definitions of variables we are interested in are described in <Table 5>. We use the data set to explore the hypotheses on relation between lack of information and risk aversion and the determinants of individual risk aversion in the following two sections. The definition of variables and post experimental survey questions are described in Appendix in more detail.



⟨Figure 6⟩ Transformation with Quantile Normalization

〈Table 5〉 Description of Data

Variables	Definition	Min～Max
Index	Risk aversion index at session 6.1, quantile normalized	
time	Time spent in session 6.1 (unit : sec)	10～164
intelligence	IQ test score (6 questions, per 1 point)	0～6
Knowledge	Economic knowledge test score (6 questions, per 1 point)	2～6
Sex	gender (male 1, female 0)	
Age	Age (unit : years old)	19～30
Major	Is your major Economics? (yes 1, no 0)	
Score	Average grade, previous semester (basis : 4.5 point)	1.15～4.5
Military	Military service (yes 1, no 0)	
Num.class	How many Economic classes have you taken?	0～26
Num.family	Number of family members	2～7
Religion	Have you got religion? (yes 1, no 0)	
Father	Academic ability of father (college graduate 1, lower 0)	
Mother	Academic ability of mother (college graduate 1, lower 0)	
Edu.FM	Academic ability of parents (college graduate 1, lower 0)	

Note : the number of observations is 161.

Some important statistics of variables are summarized in <Table 6>. Total number of subjects is 161 undergraduate students, and male and female are almost evenly distributed. Average age and GPA is 22.9 and 3.6 respectively. Some of male students experienced military service which is compulsory in South Korea. Average number of family members is 4, and 28% have a religion. More than 50% of fathers receive college degree and 38% of mothers do. We are sure that the sample is fairly representative of graduate students in South Korea only but their major is relatively concentrated in Economics and Business, i.e., 54% of subjects has those disciplines, which is comparably higher than average college sample. However, when it controls the discipline effect, most of our results aren't affected.

〈Table 6〉 Summary Statistics

Variables	Mean	Probability (%)		St. Dev.
		Value = 1	Value = 0	
Index	0.5824			0.9519
time	39.4200			22.7573
Intelligence	4.1740			1.4559
Knowledge	4.9690			1.0273
Sex		49.07	50.93	
Age	22.9400			2.2368
Major		54.04	45.96	
Score	3.6100			0.5482
Military		34.78	65.22	
Num.class	8.6340			5.7464
Num.family	4.0870			0.4532
religion	0.2857	28.57	71.43	
Father	0.5714	57.14	42.86	
Mother	0.3789	37.89	62.11	
Edu.FM	0.3416	34.16	65.84	

Note : the number of observations is 161.

4. Risk Aversion and Personal Characteristics

We discuss why and how some socio-economic variables and personal characteristics might be correlated with some of the variation in risk aversion. A good trait of the index is that we avoid the interval regression, widely used in many other elicitation methods, which is a cause

〈Table 7〉 Regression Results

	OLS (DV : Index)	OLS (DV : Mid-P)	Interval Reg.	Ord. Logit (DV : order)	Ord. Probit (DV : order)
Intercept	1.4292	2.6216	2.3904		
Time	−0.0119***	−0.0129***	−0.0117**	−0.0242***	−0.0139***
Intelligence	−0.0512	−0.0462	−0.0425	−0.0748	−0.0555
Knowledge	−0.0206	−0.1202	−0.1049	−0.1267	−0.0718
Sex	−0.0224	−0.0608	−0.0522	−0.1167	−0.0665
Age	−0.0251	−0.0397	−0.0380	−0.0706	−0.0339
Major	0.4730**	0.5618**	0.5070**	1.1349***	0.5808**
Score	0.2933*	0.3124	0.2850	0.8239**	0.4378**
Military	0.0456	0.2961	0.2619	0.1194	0.1083
Num.class	−0.0278	−0.0390	−0.0353	−0.0689*	−0.0351
Num.family	−0.1297	−0.1927	−0.1686	−0.2044	−0.1420
Religion	0.1214	0.1460	0.1292	0.2953	0.1687
Edu.FM	−0.2086	−0.2391	−0.2214	−0.4287	−0.2376

Notes : ***, **, * indicate significance at the level 1%, 5%, and 10% respectively and DV is abbreviation of dependent variable.

for ambiguous elicitation of risk aversion, because risk aversion cannot be uniquely determined. Instead of interval regression, we analyze the relation between individual characteristics and risk aversion, using the OLS regression and quantile regression where the common dependant variable is the index of risk aversion we develop.

First, <Table 7> summarizes results of the various regression models such as simple OLS with the index and middle point of the interval[4] as the dependent variable, interval regression, ordered logistic, and ordered probit. The baseline specification uses time spent in the experiment, intelligence, sex, age, military, the number of economics or finance class, religion, the number of family, and average education level of parents as key explanatory variables. The only significantly meaningful coefficient is time spent in the experiment, and the sign of it is negative, implying that the more time a subject spend finishing the experiment, the more risky action she takes. The fact that subjects spend more time choosing the better option in the multiple price list format we construct demonstrates that they deliberately try their best to obtain the better rewards without directly reducing the choice set, and quickly choosing the safer option. Although intelligence is not significant, the negative sign of it is consistent with many previous researches demonstrating that the more intelligent, the more risk loving. They may believe their intellectual ability to hedge risk, so that they are willing to take more risk.

Next, we investigate which personal characteristics are good determinants of risk aversion using quantile regression models <Table 8>. We identify how risk aversion is correlated with individual and socio-economic characteristics such as time used in experiment, intelligence, sex, age, military experience, the number of classes, reli-

4) To calculate middle point (arithmetic average) of interval in each row, we use '−3' and '5' as a value of '−inf' and 'inf' respectively.

〈Table 8〉 Quantile Regression Results (dependent variable : Risk Aversion Index)

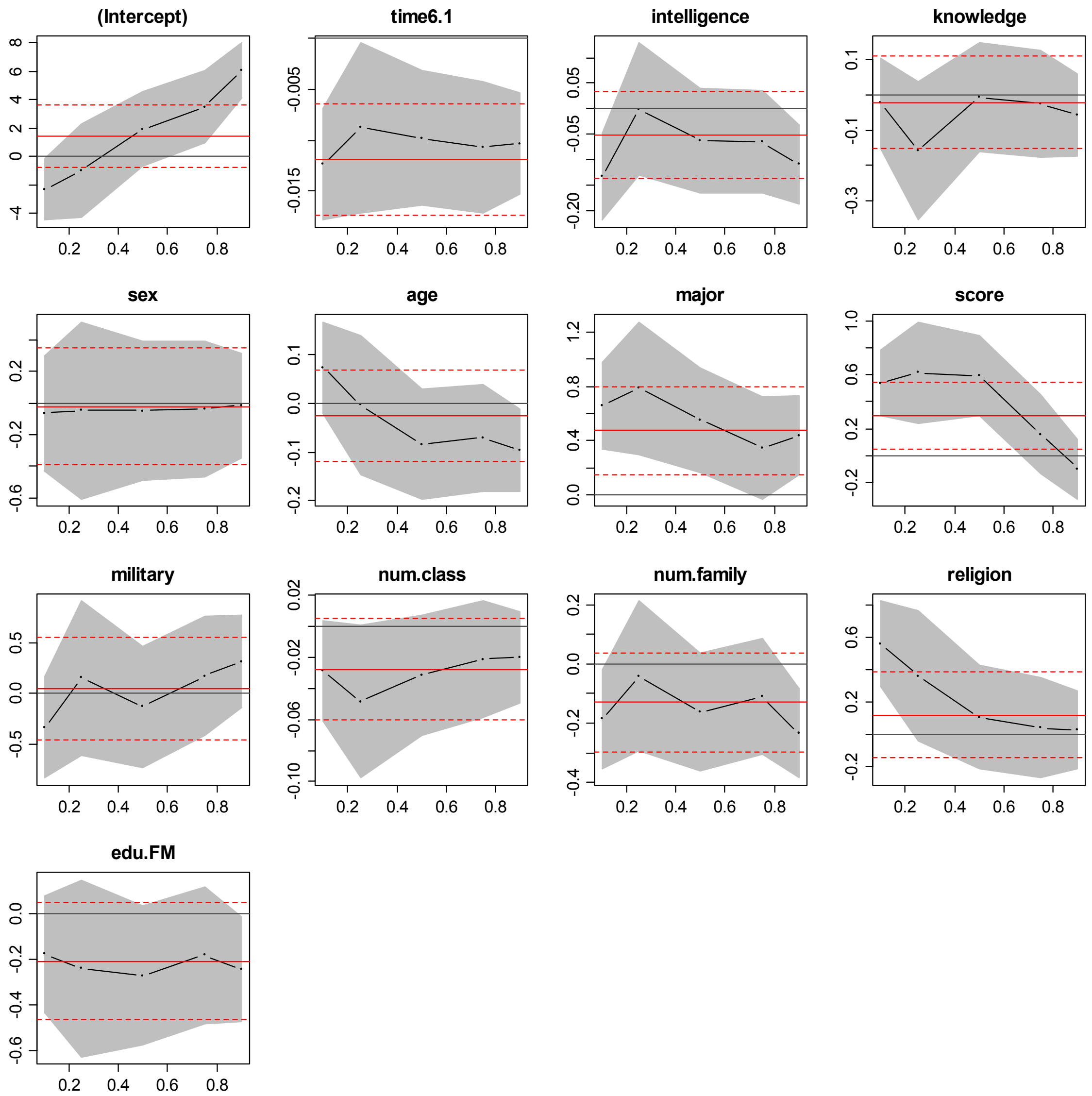
	Tau = 0.1	Tau = 0.25	Tau = 0.5	Tau = 0.75	Tau = 0.9
Intercept	-2.3158^{*}	-1.0086	1.9144	3.4980^{**}	6.0412^{***}
Time	-0.0124^{***}	-0.0088^{*}	-0.0098^{**}	-0.0107^{***}	-0.0103^{***}
Intelligence	-0.1327^{**}	-0.0007	-0.0623	-0.0651	-0.1087^{**}
Knowledge	-0.0234	-0.1583	-0.0072	-0.0256	-0.0567
Sex	-0.0646	-0.0464	-0.0484	-0.0367	-0.0158
Age	0.0744	-0.0024	-0.0837	-0.0699	-0.0953^{*}
Major	0.6552^{***}	0.7859^{***}	0.5527^{**}	0.3444	0.4366^{**}
Score	0.5399^{***}	0.6166^{***}	0.5935^{***}	0.1587	-0.1006
Military	-0.3360	0.1531	-0.1317	0.1726	0.3173
Num.class	-0.0287	-0.0487	-0.0314	-0.0214	-0.0200
Num.family	-0.1867^{*}	-0.0404	-0.1624	-0.1107	-0.2349^{**}
Religion	0.5594^{***}	0.3612	0.1076	0.0422	0.0278
Edu.FM	-0.1773	-0.2401	-0.2709	-0.1826	-0.2444^{*}

Note : ***, **, * indicate significance at the level 1%, 5%, and 10% respectively.

gion, the number of family, and average education level of parents just like in the previous regression models.

What is quite striking in the quantile regression is that the number of highly significant variables increases, compared to the previous regression analyses. But as τ approaches to 1, the results are changed slightly. As the degree of risk aversion increase, the significance level of some coefficient decreases. Especially, time spent in session 6.1 is very significant in every quantile and has negative effect on risk aversion. The more time, the more risk loving. It is quite consistent with other regression analysis. Two variables, major and the number of classes are not significant in the 90^{th} percentile. However, intelligence is significantly meaningful in the 90^{th} percentile. More intellectual subjects take more risk-loving behavior. The result is very consistent with other behavioral research which explains that people who are smarter are likely to be more confident, so that they are willing to take more risk. On the other hand, score and major have a positive effect on risk aversion, which means students who have better academic achievement are more risk averse, and they are not necessarily more intellectual. What is very obscure in the quantile regression is that age has a quite mixed effect on the index of risk aversion between 10^{th} percentile and 90^{th} percentile. At the low level of risk aversion, age has a positive effect on the risk aversion, but at the high level, it has a negative effect on the risk aversion. As the degree of risk aversion gets higher, "wisdom of the old" doesn't work and the old take more risk. Lastly, religious people may usually seem to take more risk, even though the significance level is very low.

Now we vividly illustrate overall continuous significance level of the quantile regression in <Figure 7> plotted with R. Note that the shaded gray area in <Figure 7> depicts a 90% pointwise confidence band for the quantile regression estimates and the two dotted lines represent conventional 90% confidence intervals for the least squares estimate.



〈Figure 7〉 Quantile Regression Estimates for Risk Aversion Index Model (τ ranges from 0.1 to 0.9)

In the quantile regression, we construct the confidence interval with the standard deviation derived by the option 'nid' in 'quantreg' package for R statistical software that presumes the errors are i.i.d. and computes an estimate of the asymptotic covariance matrix as in Koenker and Basset [1978]. In particular, the effect of the intellectual ability in the experiment is remarkable because the 90% point-wise confidence band gets larger as quantiles increase. It reads that model specifications become more accurate and significances of intelligence rise higher as quantiles of the index approach 1. In particular, with the second panel in <Figure 4> where no matter what risk aversion subjects take, significant levels of time spent making a decision are very sturdy, it is verified that decision making time is negatively correlated with risk aversion by taking shorter time to make a choice as a consequence of revealed preference to increase utility. Other variables such as major, score, the number of classes, the number of family, and religion are significant, depending on quantiles.

5. Concluding Remarks

There have been many studies where various experiments try to measure risk aversion which is very crucial in modeling realities in economics and finance. On the other hand, each approach in laboratory experiments has pros and cons. Following the way in HL [2002] and MR [2010], we propose the noise reduced index of measuring risk aversion which utilize only ordering of risk attitude and quantile standardization so that it has good traits. It overcomes the framing effect and the multiple switching problems and doesn't stick to any specific utility function or probability weighting. As far as we know, our index is enhanced measure to overcome several drawbacks which the HL and the MR potentially have at once.

By the various regressions and quantile regression analyses, we show that risk aversion is related to people's characteristics. Our new method of measuring risk aversion demonstrates that it would be better and more robust in experimental approaches than previous research. Since this index has good characteristics, researchers use and apply the index to some important queries in the asset investment. Our results show that people reduce time in decision making as well as risk loving attitude and the more intelligent, the more risk loving. Furthermore score and intelligent have opposite effect on risk aversion and religion also affects risk attitude. Incorporating the index of risk aversion and other financial phenomenon, we can answer many important questions in various asset markets.

The findings suggest risk attitude should be more rigorously studied and widely used to investigate people's investment strategies. While we elicit risk aversion and create the noise reduced index in an innovative way, we still need more back-up theories and more reasonable explanations in interpreting the rank preserving in our method, and should elaborate behavioral theories and design new experiments to fully shed light on the effect of time reduction on risk aversion. Moreover, next experiments would be better if we include more relevant variables and more creative structures in order to extract more economic implications.

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