Probability Weighting and Cognitive Ability

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Abstract

Probability weighting is a major concept for accommodating systemic departures from expected utility theory. We examine the relation between probability weighting and cognitive ability with two experiments: one recruiting subjects with a large variation in cognitive ability and the other using the within-subject manipulation of time constraints in lottery choices and cognitive tests. We find a significant association that subjects with a lower cognitive score or more interrupted cognition due to time pressure respond less discriminately to intermediate probabilities and more over-sensitively to extreme probabilities. Our findings shed light on the sources of anomalous choices against expected utility theory.

Keywords: probability weighting, cognitive ability, likelihood insensitivity, time pressure

JEL: C91, D01, D81, D9

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1. Introduction

Probability weighting is a major innovation for accommodating systemic departures from expected utility theory (EUT) which is the canonical model of decision making under risk (e.g., Kahneman and Tversky, 1979). The literature has documented two distinct features of probability weighting—likelihood insensitivity and the degree of optimism—which jointly describe people's inability to discriminate sufficiently between intermediate probabilities and their over-sensitivity to extreme probabilities (Tversky and Fox, 1995; Tversky and Wakker, 1995; Wakker, 2010). Understanding the sources of such distortion in perception and weighting of probabilities in decisions is important because it helps researchers and policy makers treat probability weighting as merely a behavioral bias to be corrected or a stable component of rational preferences.

Cognitive ability is necessary for processing information on probabilities and making financial calculations. Both psychology and economics literatures suggest that limitations of cognition can play an important role in shaping probability weighting. For instance, Kahneman and Fredrick (2005) explain the bias of probability assessment as a product of the interaction of two different cognitive processes—one with automatic and intuitive reasoning and the other with conscious and deliberative reasoning. Steiner and Stewart (2016) theoretically show that probability weighting could be an optimal perception under constraints in information processing. However, to the best of our knowledge, there is no rigorous empirical evidence on the relationship between probability weighting and cognitive ability.

This paper investigates the relationship between probability weighting and cognitive ability with two distinct experiments. In Study 1, we recruit the sample of subjects with an unusually large variation in cognitive ability and relate it to probability distortion elicited from an incentivized lottery choice experiment. The naturally occurring variation of cognitive ability is a merit but there are factors that can confound the assessment of the relationship between cognitive ability and probability distortion. Motivated by this concern, in Study 2, we use the within-subject manipulation of time constraints with which subjects make decisions in lottery choices and answer cognitive test questions. Time pressure is a natural way of interrupting cognitive process and has been widely used as a tool of manipulating the implementation of cognition in economics and psychology (e.g., Luce, 1986; Jensen, 2006; Baillon et al., 2018). A tight control of time constraints induces exogenous variations of subjects' cognition and choices under risk. Hence, Study 2 offers a cleaner test for the relationship between probability weighting and cognition.

In Study 1, we recruit native-born South Korean citizens (henceforth, SK subjects) and North Korean refugees (henceforth, NK subjects) who differ substantially in cognitive ability. In a financially incentivized experiment, each subject made decisions over sets of lotteries that allow us to detect the presence and extent of probability weighting. The decision problem in the experiment involves a safe lottery with a sure outcome and a risk lottery which has some probability of winning a higher amount of money. Varying sure outcomes and winning probabilities enables us to measure everyone's risk premium across probabilities. After finishing the lottery-choice experiment, subjects completed standard Raven's Progressive Matrices test and a survey on their sociodemographic information and other individual characteristics. In Study 2, each subject in the homogeneous group of university students participates in the two sets of similar but richer lottery choice problems and the two sets of advanced Raven's Progressive Matrices test with and without time pressure. The Raven test is often considered the best available measure of fluid intelligence concerning the ability to solve novel problems that depend relatively little on acquired knowledge (Nisbett et al., 2012).

Every group of subjects in our studies exhibits commonly the pattern of risk seeking behavior for lotteries with low probability of winning and risk aversion for lotteries with high winning probability. It is well explained by an inverse S-shaped weighting function. By splitting each of NK and SK groups with their Raven score in Study 1, we observe that subjects with a lower cognitive test score exhibit the stronger pattern of risk seeking for low winning probability and risk aversion for high winning probability. Turning to Study 2, we observe similarly that time constraints interrupt subjects' cognitive process and lowers their Raven score, and that time pressure makes stronger the pattern of co-existence of risk seeking and risk averse behavior across different winning probabilities.

Using the two-parameter specification of probability weighting proposed by Goldstein and Einhorn (1987), we structurally estimate the relationship between cognitive ability and the two features of probability weighting—likelihood insensitivity and the degree of optimism—with controlling for potential confounders in Study 1 and exploiting the exogenous manipulation of time pressure in Study 2. In Study 1, we find significant evidence that subjects with lower cognitive ability exhibit more severe degree of likelihood insensitivity but there is no significant relationship between cognitive ability and the degree of optimism. These findings are robust to the inclusion of controls of sociodemographic information, personality, financial literacy, and a rich set of variables concerning NK subjects' experiences in their home country and South Korea. Analogously, in Study 2, we find that a larger reduction of the Raven score due to time constraints is significantly associated with a stronger degree of likelihood insensitivity in decisions under time pressure. Therefore, the coherent findings from both studies lend support to the hypothesis that limitations of cognitive ability can contribute to probability distortions in such a manner that people respond less discriminately to intermediate probabilities and more over-sensitively to extreme probabilities.

One may concern whether the estimation results of this paper are driven by decision errors which are in turn related to cognitive ability or to response time (e.g., Andersson et al., 2016; Recalde et al., 2018). Our econometric specifications allow randomness of choices to depend on Raven score and many other individual characteristics, and the findings of the paper remain robust to the inclusion of response time variable. Hence, the relationship between cognitive ability and probability weighting that we establish in the paper is not driven by decision errors correlated with Raven score and response time.

Our findings shed light on the potential sources of nonlinear probability weighting. Recent theoretical studies rationalize inverse S-shaped probability weighting as an optimal response when the decision maker cannot avoid some noise in information processing (Steiner and Stewart, 2016) or as an evolutionary solution to pre-existing biases in human evaluation of payoffs (Herold and Netzer, 2015). On the empirical side, Van de Kuilen (2009) presents experimental evidence that probability distortions can be reduced when subjects repeat choices with payoff feedback, which appears to suggest that probability weighting is easily malleable. On the other hand, a few studies have investigated the relation between probability weighting and sociodemographic variables (Harrison and Rutström, 2009; Booij et al., 2010; Bruhin et al., 2010; Fehr-Duda and Epper, 2012). This paper adds to the important discussion about the potential sources of probability weighting and argues that cognitive ability is closely related to the shape of nonlinear probability weighting.

We also contribute to the literature that cognitive ability is not only a determinant of economic and social outcomes (e.g., Murnane et al., 1995; Heckman et al., 2006; Hanushek and Woessmann, 2008) but also is associated with qualities of decision making and economic preferences. Christellis et al. (2010), Agarwal and Mazumder (2013), and Binswanger and Salm (2017) provide evidence that suboptimal behavior in financial decision making is associated with cognitive ability. Frederick (2005), Burks et al. (2009), Oechssler et al. (2009), Dohmen et al. (2010), Benjamin et al. (2013), and Falk et al. (2015) all report the correlations between cognitive ability, risk attitudes and time impatience.[1] To our knowledge, our paper is the first paper examining empirically the relationship between cognitive ability and the distortion in perception and weighting of probabilities in decisions.

Finally, it is worthwhile to connect our paper to the experimental literature of using time constraints in domains of individual decision making, for instance, choice under risk aversion (Kocher et al. 2013; Madan et al. 2015; Kirchler et al. 2017; Kocher et al. 2019).[2] Young et al. (2012) report that time pressure leads to increases in optimism and likelihood insensitivity, but do not look at how cognitive process is associated with probability weighting. Baillon et al. (2018) uses time pressure to manipulate subjects' cognitive process under ambiguity. Their finding that ambiguity insensitive behavior is affected by time pressure is consistent with the main result of our paper. Although these studies look at how time pressure affects behavior, our paper is distinct from them by investigating the relationship between cognitive ability and probability weighting induced by time constraints.

The remainder of the paper is organized as follows. Section 2 describes the experimental design for both experiments and the overview of risk attitudes and cognitive ability. Section 3 illustrates the econometric technique of estimating the two-parameter specification of probability weighting. Section 4 presents the estimated results on the relationship between probability weighting and cognitive ability under various specifications. We conclude in Section 5. Further information is available in Online Appendix including the experimental instructions.

2. Experimental Design

2.1. Study 1

[1] For a recent survey on the relationship between cognitive ability and risk preferences, see Dohmen et al. (2018).

[2] See Spiliopoulos and Ortmann (2018) for a recent review on experimental studies with time constraints and analyzing response time data particularly in strategic decision making.

2.1.1 Design and sampling

We recruit North Korean refugees and native-born South Koreans who display large observational variations in cognitive ability. Study 1 consists of a lottery choice experiment, a cognitive ability test, and a survey.[3] In the lottery choice part, we elicited certainty equivalents for 5 different two-outcome lotteries. Subjects were asked to make a series of decisions from 5 blocks using these lotteries. In each decision block, on the left side of the screen, there is a fixed risky lottery (8000 KRW with some positive probability, otherwise 0). On the right side of the screen, there are increasing 8 rows of safe lotteries (guaranteed amount with probability 1). The chance of earning the positive amount of money in a risky lottery was visualized with a pie graph. The safe lottery at the top of each block guarantees a minimum amount of 500 KRW with subsequent amounts increasing by 1,000 KRW increments, reaching 7,500 KRW for the safe lottery at the bottom of each block. To make our experimental design as simple as possible, we fix the winning amount at 8,000 KRW for each risky lottery.[4] The probability of winning 8,000 KRW varies across the five values of 0.05, 0.25, 0.5, 0.75, and 0.95 with randomized sequence in each subject level. We ask subjects to choose a unique switching point from a risky lottery to a sure outcome in each of 5 different probability blocks. After all choices are made, one row from one decision block was randomly selected for each subject, and the subject's choice in that row determines her payment. Experimental instructions are reported in Online Appendix A.

After the lottery choice experiment ends, subjects are asked to perform a test which measures their cognitive ability. Cattell (1963, 1987) classifies human intelligence with fluid intelligence and crystalized intelligence. Crystalized intelligence is mainly dependent on one’s lifetime acquired skills and knowledge such as verbal skills and numeracy, while fluid intelligence captures abilities to think logically and solve problems in novel situations, relatively independent of acquired knowledge. Most of North Korean refugees grew up with a communist style of education in North Korea which is different from that in South Korea. Therefore, we can expect some regime-dependent differences in crystalized intelligence.

[3] The experiment reported here is a part of a larger project using the same subjects. The other experiment involves continuous double auctions and is reported in Choi et al. (2019). Subjects’ participation fee for all the experiments was 45,000 KRW. At the time of the experiment (Aug 2016), 1 USD is approximately 1,050 KRW.

[4] We only consider lotteries in the gain domain in fixed amount. Since we recruit a non-student sample and anticipate that some of them have low cognitive ability, we try to prevent our results from hinging on subjects’ misunderstanding of complex lotteries with gains and losses.

Instead, we focus on the measurement of fluid intelligence using standard Raven's progressive matrices test (Raven, 1938). The test is a nonverbal test to measure the level of cognitive ability and has been widely used in social science including economics (e.g., Carpenter et al., 1990; Jaeegi et al., 2008; Burks et al., 2009; Mani et al., 2013; Gill and Prowse, 2016; Charness et al., 2018; Proto et al., 2019). In Study 1, each subject was asked to solve 24 standard Raven test problems after completing the lottery choice experiment. This task was not incentivized. Once all tasks were done, subjects were informed about the realization of their selected lottery and got paid in cash. On average, they received 5,700 KRW in the lottery choice experiment. After the experiment was completed, we conducted a survey and collected subjects' sociodemographic information and other individual characteristics including Big 5 personality traits and financial literacy.

We collaborated with Nielsen Korea between June and July of 2016 to recruit 302 North Korean refugees and 292 native-born South Koreans. When recruiting North Korean refugees, we used a stratified sampling method with respect to age, gender, and year of entry into South Korea to make our NK sample as representative as the population of North Korean refugees residing in South Korea.[5] Once entering South Korea, North Korean refugees are all naturalized and become official South Korean citizens. We recruit native-born South Koreans as comparable in the characteristics of age and gender as our sample of North Korean refugees. Throughout the paper, we simply refer to North Korean refugees as NK subjects and native-born South Koreans as SK subjects.

Table 1 reports the mean and standard deviation (in parenthesis) of key sociodemographic variables across the NK and SK groups.[6] First, the composition of gender and age is not significantly different between NK and SK sample implying that our sample is balanced regarding gender and age (*p*-values for two-sided t test: 0.50 and 0.58, respectively). Low education indicates if the highest level of education completed by subjects is less than the graduation of high school. The composition of low education is significantly different between NK (19%) and SK (9%). Household income represents each household's monthly income. A NK household earns on average about 1,779,200 KRW, while a SK household earns about 5,476,400 KRW per month. Regarding marital status, about 33% of NK subjects and 53% of

[5] Official statistics for the population of North Korean refugees is available from the Ministry of Unification in South Korea.

[6] Online Appendix B.1. contains the summary statistics for other variables of North Korean refugees, which will be used in the estimation exercise of the paper.

SK subjects are currently married, and this difference is significant at the 5% level of significance. This is in line with the difference in household size excluding the respondent. NK subjects have on average 1.37 household members, while SK subjects have 2.2 members. About 38% of NK live alone, while only 14% of SK do so. NK subjects were also asked to answer how many years they lived in North Korea. On average, our NK subjects lived 27.48 years in North Korea and have lived 7.29 years in South Korea.[7]

Table 1. Summary Statistics of Subject Characteristics

	NK	SK
Age	39.01	38.56
	(9.24)	(10.19)
Female	0.71	0.69
	(0.45)	(0.47)
Low education	0.19	0.09
	(0.39)	(0.29)
Household income	177.92	547.64
	(235.50)	(249.73)
Married	0.33	0.53
	(0.47)	(0.50)
Number of household members	1.37	2.20
	(1.64)	(1.26)
Years in NK	27.48	
	(9.55)	
Years in SK	7.29	
	(3.48)	
Subjects	302	292

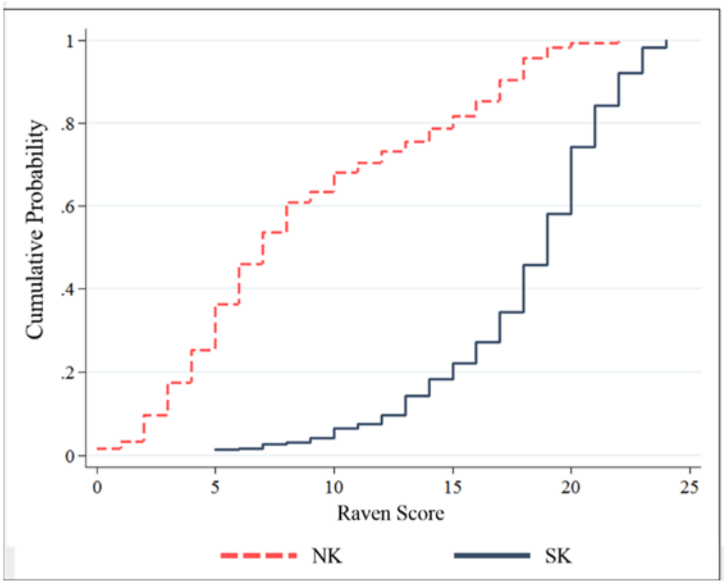
2.1.2. Cognitive ability

Figure 1 shows cumulative distributions of cognitive ability, as measured by the 24 standard Raven test across NK and SK samples. We observe two kinds of large variations in cognitive ability. The first variation is between NK and SK samples. While the average number of correct answers is 17.75 (74%) in the SK sample, it is only 8.65 (36%) in the NK sample. It implies that NK subjects in Study 1 only achieved less than 50% of the Raven score of SK subjects, and the difference is statistically significant (t-test, p-value < 0.01). The second

[7] Average age of NK sample is different with the sum of Years in NK and SK because some of them stayed in another country like China, Vietnam, and Thailand prior to their relocation to South Korea.

variation is within each of the NK and SK samples: we observe a large level of heterogeneity of Raven test score within each sample. We also observe that the standard deviation of the NK sample is significantly bigger than that of the SK sample, which implies greater within-subject variations in the NK sample (F-test, *p*-value<0.01). These large observational variations in the measure of cognitive ability offer us an unusual opportunity to examine the relationship between probability weighting and cognitive ability.

Figure 1. Cumulative distribution of Raven score



2.2. Study 2

2.2.1 Design and sampling

In order to investigate the relationship between probability weighting and cognitive ability more clearly, we introduce the controlled experimental manipulation of time pressure in lottery choice and cognitive ability tasks in Study 2. Time pressure is a natural way of interrupting cognitive process and has been commonly used as a tool of manipulating the implementation of cognition in psychology and economics (Jensen, 1986; Luce, 2004; Baillon et al., 2018). Because individuals can respond differently to a time constraint, we use a within-subject experimental design of time pressure and exploit such individual heterogeneity as an exogenous variation of examining the relationship between probability weighting and cognitive ability.

Specifically, the experimental design of Study 2 consists of four parts: a) lottery choices without time pressure, b) lottery choices with time pressure, c) a cognitive ability test without time pressure, and d) a cognitive ability test with time pressure. Table 2 shows the summary of the design and treatments. We have four treatments to control for the order effect. Within each treatment, by comparing the set 1 of lottery choices without time pressure (henceforth, Risk no TP) with the set 2 with time pressure (henceforth Risk TP), we assess the effect of time pressure on probability weighting at the individual level. Each set of lottery choices consists of 15 lotteries with varying probabilities as in Study 1. On the left side of the screen, there is a fixed risky lottery and on the right side of the screen, there are 31 equally spaced certain outcomes ranging from the lottery's minimum payoff to the maximum payoff. Subjects are asked to choose a unique switching point from a risky lottery to certain outcomes. Each lottery's certainty equivalence is then calculated as a midpoint between certain amounts around the switching point. In the two sets of lottery choices, we have a comparable level of the expected value for lotteries with different winning probabilities. In Online Appendix A.3, we report the list of lotteries in the two lottery choice sets. In the Risk TP task, we ask subjects to make each decision in 13 seconds. If subjects do not choose within the time limit, we make the first row of certain amounts as a default switching point. This information is commonly known to subjects. In both tasks with and without time limit, the sequence of lotteries in each task is randomized at the individual subject level.

Table 2. Treatment design of Study 2

Treatments	Task 1	Task 2	Task 3	Task 4
T1 (#31)	Raven set 1 no TP	Risk set 1 no TP	Risk set 2 TP	Raven set 2 TP
T2 (#33)	Raven set 1 no TP	Risk set 1 TP	Risk set 2 no TP	Raven set 2 TP
T3 (#34)	Raven set 1 TP	Risk set 2 no TP	Risk set 1 TP	Raven set 2 no TP
T4 (#37)	Raven set 1 TP	Risk set 2 TP	Risk set 1 no TP	Raven set 2 no TP

Notes: In parenthesis, the number indicates the number of participants in each treatment.

To measure cognitive ability, we use the Raven's advanced progressive matrices set II (Raven APM set 2). The Raven APM set 2 is composed of 36 questions and known as a more difficult version of the Raven test compared to the Raven's standard progressive matrices test that are used in Study 1. We divide 36 questions into two sets and locate equally the problems according to the answer rate reported by Bors and Stokes (1998).[8] In the Raven test without time pressure (henceforth Raven no TP), subjects, on average, solve 18 problems with their own pace. In the Raven test with time pressure (henceforth Raven TP), we impose 30 seconds of time limit on each question. Given that Arthur and Day (1994) suggest 36 questions for 40 minutes as a guideline of the Raven APM set 2, we expect that 30 seconds would be an effective time constraint for our subjects. The reason why we impose the time constraint on each question rather than on the whole set is because we want to control for subjects' skill to allocate time across problems. When subjects do not answer a question within the time limit, it is treated as wrong and this rule is announced at the beginning of the task. We also randomize the sequence of questions of each Raven set at the individual level. Both the Raven tests with and without time pressure are incentivized: the larger number of correct answers, the higher is a probability that subjects get monetary rewards (5000 KRW). Subjects are informed of their reward results at the end of the experiment, but not of exact test scores. This incentive scheme allows us to exclude a case in which subjects' aversion to know their exact ability may affect their performance in tests (Kocher et al. 2019).

The experiment was programmed using o-Tree (Chen et al, 2016). We conducted 9 sessions at Seoul National University in July 2019. In total 135 subjects participated in the experiments. Subjects were recruited through the university's official website. On average, they were paid 28,400 KRW including the 5000 KRW participation fee. About 65% of students were male and all participants were undergraduate students from diverse majors at Seoul National University.

2.2.2 Time pressure and cognitive ability

Before we proceed for the main analysis of the data, we examine the effectiveness of the experimental manipulation of time pressure. We investigate this by comparing response times

[8] Bors and Stokes (1998) report the answer rate higher than 85% from freshman undergraduates in US for the first 12 items. Therefore, we put question 1-6 in the set 1 and 7-12 in the set 2. They also report the middle part (13-24) of the Raven APM set 2 has the largest variation in answer rate between samples, so we put 13-18 in set 1 and 19-24 in set 2. Lastly, we divide 25-30 in set 1 and 31-36 in set 2. We also have a balance test result between two Raven sets in the Online Appendix B.2.

of the tasks with and without time pressure, and showing the extent to which the Raven test score is dropped when time pressure is introduced.

We first consider how response times for the lottery choice task and the Raven test change when time pressure is imposed. Table 3 reports the results of linear fixed effects regression of response time on the dummy of time pressure in both the lottery choice experiment and the Raven test. Robust standard errors clustered by individual subject are reported in parentheses. Column (1) shows the effect of the time constraint on subjects' response time in the lottery choice experiment. The average response time per decision without time pressure is about 15.1 seconds. When the restriction of 13 seconds per decision is imposed, the corresponding response time drops by 7.6 seconds. The difference between them is significant at the 1% level. Regarding the Raven test, we find analogously the strong effect of time pressure on subjects' response time. Column (2) shows that it took 53.8 seconds per question in the Raven test without time restriction. When the restriction of 30 seconds per question is introduced, the response time is reduced by 36.1 seconds. The difference again is significant at the 1% level. Note that the rate of missing data due to violating a time restriction is low in both tasks, probably because of our incentive scheme: less than 1% in both tasks. Taken together, these results show that our time pressure manipulation effectively decreases the amount of time spent on each task.

Table 3. Effects of time pressure on response time (unit: seconds)

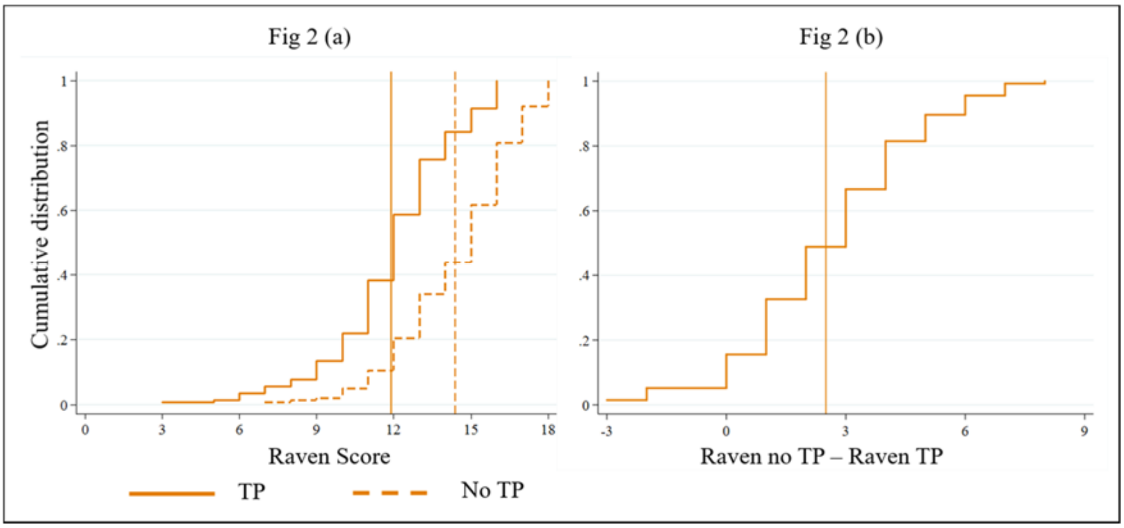
	(1)	(2)
Samples	Lottery choices	Raven test
Time pressure	-7.564	-36.103
	(0.500)	(2.209)
Constant	15.123	53.780
	(0.250)	(1.096)
R^2	0.165	0.204
N	4,043	4,821
Individual fixed effect	Y	Y
# of missing obs. (%)	7 (0.16%)	39 (0.8%)

Notes: Robust standard errors are clustered by individual subject and presented in parentheses.

We now turn to examine the effect of time pressure on subjects' performance in the

Raven test. Figure 2 (a) shows the cumulative distributions of Raven scores with and without time pressure with average scores represented by vertical lines. In the Raven no TP task, subjects solve on average 14.5 questions correctly, while 11.9 questions are answered correctly in the Raven TP task. This difference is significant at the 1% level (t-test; p-value < 0.01). Figure 2 (b) presents the distribution of the individual difference of Raven scores with and without time pressure. On average, subjects answer 2.6 questions more correctly in the Raven no TP task, which is represented by vertical line in Figure 2 (b). More than 84% of subjects perform strictly better when there is no time pressure, and for those subjects, the average difference of correct answers is 3.2. This result lends strong support to the notion that time pressure interferes cognitive process for most of our subjects.

Figure 2. Distributions of Raven scores in Study 2



Notes: Horizontal lines represent mean value of Raven test.

3. Econometric Specification

This section presents the econometric specification for estimating the association of cognitive ability with risk preferences. We denote a lottery by $L = (x_1, p; x_2)$ with two non-negative outcomes such that $x_1 > x_2 \geq 0$, p for the probability of winning x_1, and $(1-p)$ for getting x_2. Following the model of prospect theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992), we assume that an individual evaluates a lottery L in the following manner:

$$u(L) = \omega(p)u(x_1) + (1 - \omega(p))u(x_2)$$

Then the certainty equivalence of lottery L, $\widehat{CE(L)}$, is represented by following

$$\widehat{CE(L)} = u^{-1}(\omega(p)u(x_1) + \big(1 - \omega(p)\big)u(x_2))$$

For the exercise of estimation, we specify functions of utility over money and probability weighting parametrically. First, we assume that utility over monetary outcomes is defined as follows:

$$u(x) = x^{\alpha}, \; \alpha > 0$$

where α is the parameter of the utility curvature. Previous studies including Wakker (2008), Harrison and Rutstrom (2009), and Booij et al. (2010) show that the power function fits well into experimental and observational data. For the probability weighting function, we use the functional form suggested by Goldstein and Einhorn (1987).[9] The advantage of this functional form is its clarity regarding the interpretation of parameters. The probability weighting function is defined as

$$\omega(p) = \frac{\delta p^{\gamma}}{\delta p^{\gamma} + (1-p)^{\gamma}}, \quad \delta \geq 0, \qquad \gamma \geq 0$$

where γ captures likelihood insensitivity and δ reflects the degree of optimism. The parameter γ determines the slope of probability weighting. The smaller $\gamma < 1$, the more curved the probability weighting function, i.e., flatter in the range of intermediate probabilities and steeper near the ends. The individual becomes less responsive to changes in intermediate probability as the value of γ gets smaller. On the other hand, the parameter δ determines the crossing point between the probability weighting function and the 45-degree line and can be interpreted as the relative degree of optimism. The crossing point is $(\delta/(1+\delta), \delta/(1+\delta))$.

[9] See Lattimore et al. (1992), Wu et al. (2004), and Bruhin et al. (2010) for previous empirical studies which used the same functional form in estimating risk attitudes.

With the inverse S-shaped weighting function, if δ increases, the optimistic region with respect to the relatively small probability expands. When $\gamma = \delta = 1$, the probability weighting function becomes linear in p, equivalent to the one used in EUT.

We follow the estimation procedure used in Bruhin et al. (2010) and l'Haridon and Vieider (2019). The observed certainty equivalent *CE(L)* will be equal to the certainty equivalent calculated from our model plus some independently distributed error term $\varepsilon(L)$.

$$\widehat{CE(L)} = CE(L) + \varepsilon(L)$$

Here, $\varepsilon(L)$ follows normal distribution $N(0,\mu(L)^2)$, where $\mu(L)^2$ is called as Fechner error (Hey and Orme, 1994; Loomes and Sugden,1995; Loomes, 2005). We allow this Fechner error term to depend on the difference between the high and low outcome of lottery L, specifically $\mu(L)^2 = \mu^2 * |x_1 - x_2|$ for $\mu > 0$.

Let $\theta = (\alpha, \gamma, \delta, \mu)$ denote the set of parameters to be estimated. The likelihood function of individual *i* at lottery L is given by

$$\psi(\theta, L) = \phi(\frac{\widehat{CE(\theta)} - CE_i(L)}{\mu_i(L)})$$

where ϕ denotes the density function of the standard normal distribution. Then the log likelihood function for the data has a form of

$$\ln \mathcal{L}(\theta) = \sum_{i,L} \ln \psi(\theta, L)$$

The log likelihood function can be maximized by simultaneously estimating parameters (α, δ, γ, μ). Standard errors are clustered at the individual level.[10]

In the estimation of Study 1, we assume $\alpha = 1$ for the following reasons.[11] First, we did not vary the monetary outcome of risky option (8000 KRW and 0 KRW) because we needed

[10] The use of clustering to allow for panel effects from unobserved individual effects is common in the literature. See Harrison and Rutström (2008).

[11] Abdellaoudi et al. (2011) and l'Haridon and Vieider (2019) assumed this linear utility in monetary outcome.

to implement a short and simple experimental design for non-student subjects. This lack of variations in monetary outcome leads to make the maximum likelihood estimation hardly converge when there are many control variables. Second, our monetary outcomes are relatively small—less than 8 dollars—which suggests that the assumption of linear utility is innocuous particularly for the non-student sample in Study 1.

In order to establish the association between cognitive ability and preference parameters while controlling for individual characteristics, we specify each parameter in the following linear form:

$$\gamma = \gamma_0 + \gamma_1 Raven + X'\gamma_2$$
$$\delta = \delta_0 + \delta_1 Raven + X'\delta_2$$
$$\mu = \mu_0 + \mu_1 Raven + X'\mu_2$$

where $Raven$ is the subject's standard Raven test score and X is the vector of individual characteristics including sociodemographic information and personality traits.[12] Thus, δ_1, $\gamma_{1,}$ and μ_1 respectively measure the association of Raven score with each of the preference parameters of prospect theory and the parameter of choice error. To check the robustness of our results from fixing α as 1, we allow α to models with a small number of control variables which can be estimated. Moreover, we change α from 0.5 to 1.5 and shows that our results are robust across different level of α. These robustness exercises are in Online Appendix B.3.

In the estimation of Study 2, we have enough variations in monetary outcome in order to estimate all the preference parameters including α. We interpret the individual score of Raven no TP as a baseline level of cognitive ability that the individual can use in choosing under risk without time pressure, and the score difference between Raven no TP and Raven TP as an individual-level interruption of cognitive ability due to time pressure that the individual faces similarly in choosing under risk with time pressure. We set the following econometric specification in which TP is a dummy variable for the Risk TP task:

$$\gamma = \gamma_0 + \gamma_1 TP * (Raven\ no\ TP - Raven\ TP) + \gamma_2\ TP + \gamma_3 Raven\ no\ TP$$
$$\delta = \delta_0 + \delta_1 TP * (Raven\ no\ TP - Raven\ TP) + \delta_2\ TP + \ \delta_3 Raven\ no\ TP$$

[12] Harrison and Rutström (2009) also uses the linear specification which allows for capturing the heterogeneity of individual attitudes toward risk.

$$\mu = \mu_0 + \mu_1 TP * (Raven\ no\ TP - Raven\ TP) + \mu_2\ TP + \ \mu_3 Raven\ no\ TP$$
$$\alpha = \alpha_0 + \alpha_1 TP * (Raven\ no\ TP - Raven\ TP) + \alpha_2\ TP + \ \alpha_3 Raven\ no\ TP$$

The primary interest of Study 2 is in the estimates of γ_1 and δ_1 which represent the induced association between probability weighting—likelihood insensitivity and optimism, respectively—and cognitive ability when both choice under risk and cognitive activities are exogenously interrupted by time pressure. In addition, we can understand the effect of time pressure on both preferences and noises of decisions under risk through the estimates of $(\gamma_2, \delta_2, \mu_2, \alpha_2)$. Finally, by looking at estimates of $(\gamma_3, \delta_3, \mu_3, \alpha_3)$, we can examine how the parameters governing choices in the Risk no TP task are associated with the baseline level of cognitive ability measured under no time pressure, Raven no TP.

4. Results

We begin by providing an intuitive summary of the data that describes the patterns of risk attitudes over different lotteries across subgroups divided according to the cognitive test score in Study 1 and experimental manipulation of time pressure in Study 2. We then present the results of the maximum likelihood estimation specified in the previous section in order to establish the association between probability weighting and cognitive ability.

4.1. Risk attitudes and cognitive ability

We consider the risk premium as a simple measure of risk attitude in a lottery choice problem. It is defined by the difference between the expected value and the certainty equivalent of a lottery L, $RP(L) = EV(L) - CE(L)$. If $RP(L)$ > (<) 0, a person is said to exhibit risk averse (risk seeking) behavior. Expected utility theory predicts that the sign of $RP(L)$ should remain unchanged across lotteries with different winning probability in the experiment.

In Study 1, we split each NK and SK group by the Raven score to have the NK and SK low (resp. high) group defined as NK and SK subjects whose Raven scores are below (resp. above) the median of the Raven score for each group. The mean raven score of NK low (NK high) is 4.4 (13.6) and that of SK low (SK high) is 15.5 (21.2).

Figure 3.A presents the average risk premium of each lottery for NK and SK subgroups. Five different risk premia are linked to show a change in behavior as the probability changes, showing in slope. First, we note that the relation of risk premium to probabilities for every subgroup is inconsistent with the prediction of EUT because subjects exhibit risk seeking behavior for lotteries with low probability of winning and risk aversion for those with high probability of winning. Second, within each NK and SK group, the low cognitive ability group is 1) more risk seeking for lotteries with low probability of winning 8,000 KRW and 2) more risk averse for those with high probability of winning than the high cognitive ability group.[13] Third, when comparing between NK and SK groups, we observe that NK subjects who achieve much lower Raven score exhibit the stronger pattern of risk seeking for low winning probability and risk aversion for high winning probability than SK subjects.

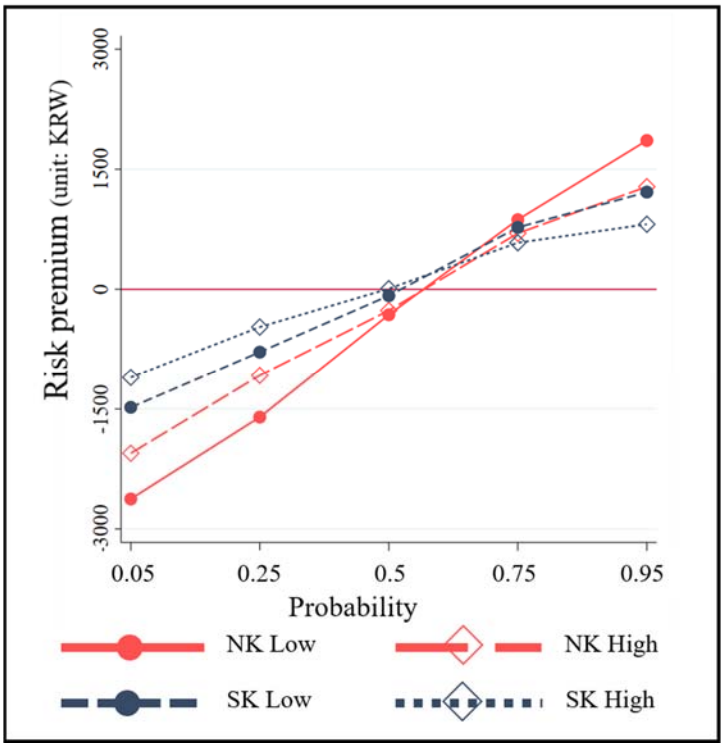
In order to understand how the patterns of risk premium translate into probability weighting, we estimate the probability weighting function for each subgroup in Study 1, without control of any individual characteristics.[14] Figure 3.B draws the estimated probability weighting functions for the four subgroups. The 45-degree line depicts the linear probability weighting which EUT assumes. The pattern of risk seeking behavior for lotteries with low winning probability and risk aversion for those with high winning probability is explained by an inverse S-shaped function of probability weighting that is empirically well established in the literature (e.g., Fehr-Duda and Epper, 2012). It implies that subjects respond less sensitively to a change in intermediate probabilities. Such insensitivity to intermediate probabilities appears to become more prominent in a subgroup with lower cognitive ability.

[13] We note that within NK group, the average risk premium between high and low cognitive group is significantly different at 10% significance level when the probability is 0.05, 0.25, and 0.95 (t-statistics: 1.8, 1.9, and 2.4 respectively). Within SK group, the average risk premium is also significantly different at 10% significance level when the probability is 0.05, 0.25, and 0.95 (t-statistics: 2.2, 1.9, and 2.6 respectively).

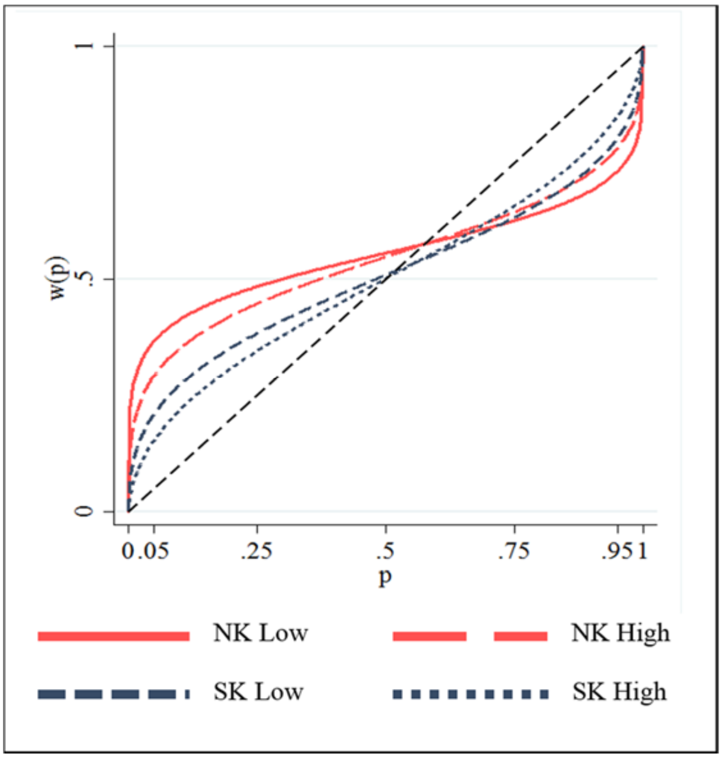
[14] In Online Appendix B.4, we report the detail of the estimation results for Figure 3.B.

Figure 3. Risk Premium and Probability Weighting: Study 1

A. Risk premium



B. Probability weighting

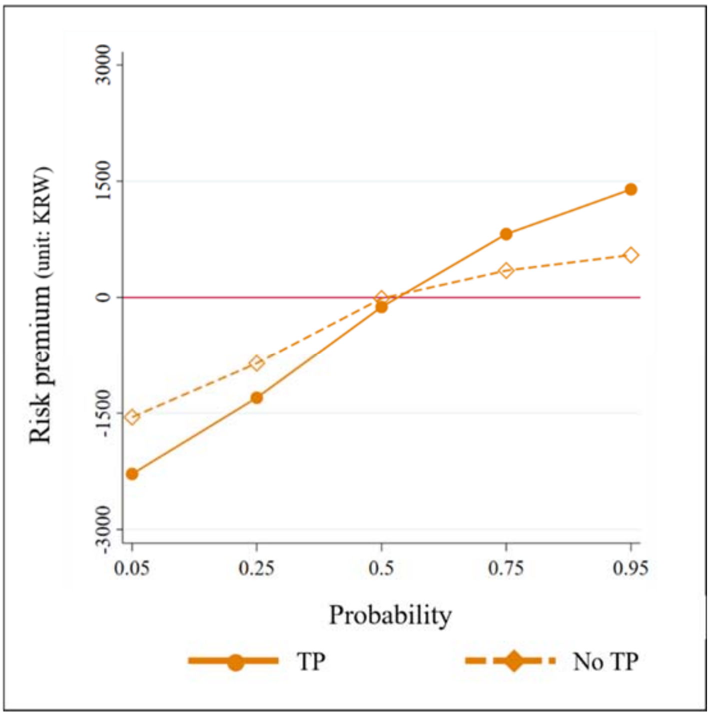


We next turn to Study 2 and examine the impact of time pressure on risk attitudes.

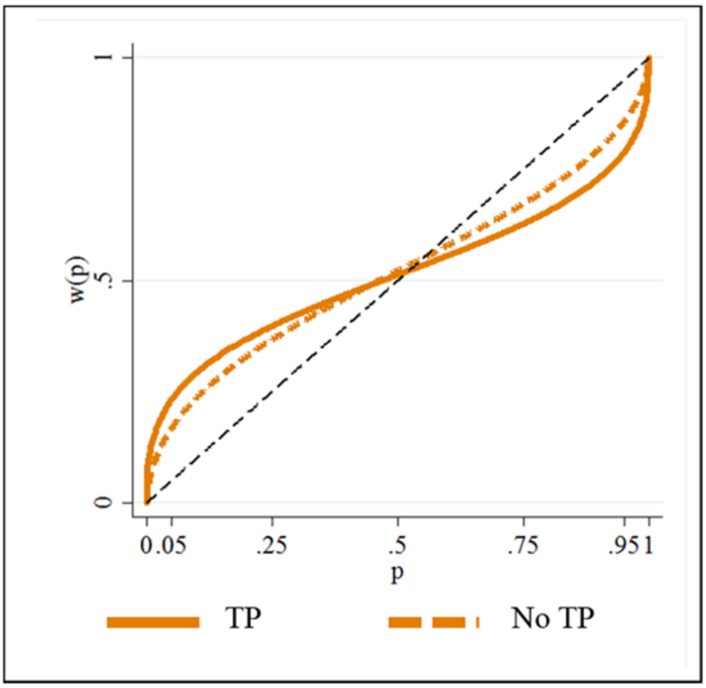
Figure 4.A presents the average risk premia across different winning probabilities with and without time pressure. Figure 4.B displays the estimated probability weighting functions with and without time pressure. The experimental manipulation of time pressure makes stronger the pattern of risk seeking for low winning probability and risk aversion for high winning probability, and thus the extent to which the weighting function becomes inverse S-shaped. Given the finding in Figure 2 that time pressure interrupts cognitive process and lowers Raven score, the findings in Figure 4 are in line with those in Figure 3. That is, a time constraint affects both the exercise of cognition and decision making under risk in the direction that confirms the association between risk attitudes and cognitive ability, found in Figure 3.

Figure 4. Risk Premium and Probability Weighting: Study 2

A. Risk premium



B. Probability weighting



4.2. Probability weighting and cognitive ability

In this subsection we present the maximum likelihood estimation results to examine more systematically the relationship between cognitive ability and the two features of probability weighting—likelihood insensitivity and optimism.

Starting with Study 1, we conduct the maximum likelihood estimation for each of the NK and SK groups as well as the data of pooling both groups. The results are presented in Table 4 with robust standard errors clustered by individual subject.[15] A baseline specification in each sample—columns (1), (4), and (6)—controls for sociodemographic variables including gender, age, education, marital status, income, and the number of household members. We also control further for Big 5 personality and financial literacy in columns (2), (5), and (7). For the NK group data, we make addition controls specific to North Korean refugees in column (3), including the indicator of whether any family member is left in North Korea, economic class in North Korea, the number of years lived in North Korea, informal market experience in North Korea, military service experience, communist party membership, whether birthplace is in a border region with China or the two big cities of North Korea (Pyoungyang or Gaesung), and

[15] We relegate the full description of the estimation results in Table 4 to Online Appendix B.5.

subjective assessment on quality of life after escape from North Korea. Lastly, we note that we attach the estimation result allowing utility curvature parameter α except for column (3) in the Online Appendix B.3 which is consistent with the Table 4.

Table 4. Maximum likelihood estimation: Study 1

	NK only			SK only		Pooled	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
γ							
Raven	0.008	0.007	0.009	0.010	0.011	0.009	0.009
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
Constant	0.282	0.352	0.144	0.177	-0.061	0.352	0.292
	(0.163)	(0.168)	(0.240)	(0.268)	(0.304)	(0.146)	(0.157)
δ							
Raven	-0.016	-0.016	-0.013	-0.007	-0.002	-0.012	-0.009
	(0.011)	(0.011)	(0.011)	(0.010)	(0.009)	(0.007)	(0.008)
Constant	1.533	1.713	3.069	1.914	2.124	1.661	1.753
	(0.513)	(0.544)	(0.902)	(0.637)	(0.687)	(0.409)	(0.435)
μ							
Raven	-0.001	-0.001	-0.001	-0.000	0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
Constant	0.158	0.130	0.262	0.321	0.278	0.232	0.224
	(0.054)	(0.070)	(0.111)	(0.074)	(0.089)	(0.050)	(0.061)
Sociodemographic controls	Y	Y	Y	Y	Y	Y	Y
Big 5 and financial literacy	N	Y	Y	N	Y	N	Y
NK-specific controls	N	N	Y	-	-	-	-
ln $\mathcal{L}$	-3055.5	-3046.5	-3010.2	-2496.1	-2449.6	-5568.8	-5538.0
Individuals	302	302	302	292	292	594	594
Observation	1510	1510	1510	1460	1460	2970	2970

Notes: Robust standard errors, clustered by individual subject. We control NK dummy variable in each parameter in column (6) and (7).

Within each sample of the NK and SK groups, we find a significant negative correlation between likelihood insensitivity and the cognitive test score. This association is robust to the inclusion of additional controls in each sample of the NK and SK groups. A one standard deviation increase in the Raven score for the NK group (resp. the SK group) is significantly associated with 0.049 (resp. 0.043) increase in the value of the parameter γ

which implies a lesser degree of likelihood insensitivity.[16] On the other hand, we find that the Raven score is neither related to the degree of optimism nor to the parameter of choice error. The estimation results with the pooled sample of the NK and SK groups corroborates the findings on the within-group association of the Raven score with probability weighting and choice error. We put robustness check results using Prelec-II (Prelec, 1998) and Abdellaoudi et al. (2011) weighting function in Online Appendix B.6 and B.7 and we find a robust result.

In summary, the behavior of subjects in Study 1 departs from EUT by exhibiting risk seeking for lotteries with a low winning probability and risk aversion for those with a high winning probability. This behavioral pattern is well captured by likelihood insensitivity of probability weighting. Cognitive ability is an important factor that explains such a deviation from EUT.

We next turn to the econometric exercise with the data of Study 2. Table 5 presents the maximum likelihood estimation results based on the econometric specification discussed in Section 3. Column (1) presents the average effect of time pressure on each parameter, captured by the coefficient of the dummy variable of TP. Column (2) reports the results of the main specification. Our primary interest is in the coefficient of TP x (Raven no TP- Raven TP) in Column (2) that shows the experimentally induced relationship between the time pressure effect on cognitive ability and the underlying preferences recovered from decisions under time pressure. Robust standard errors, clustered by individual subject, are reported in parenthesis.

[16] The standard deviation of the Raven score for the NK group and the SK group is 5.49 and 3.95, respectively.

Table 5. Maximum likelihood estimation: Study 2

	(1)	(2)		(1)	(2)
γ			μ		
Constant	0.615	0.349		0.210	0.184
	(0.052)	(0.142)		(0.024)	(0.052)
TP	-0.137	-0.076		0.010	0.010
	(0.028)	(0.038)		(0.009)	(0.014)
TP x (Raven no TP- Raven TP)		-0.023			0.000
		(0.011)			(0.004)
Raven no TP		0.019			0.002
		(0.009)			(0.003)
δ			α		
Constant	1.030	1.114		1.103	1.703
	(0.125)	(0.629)		(0.145)	(0.762)
TP	-0.054	0.051		0.150	0.043
	(0.073)	(0.209)		(0.077)	(0.250)
TP x (Raven no TP- Raven TP)		-0.037			0.038
		(0.072)			(0.094)
Raven no TP		-0.007			-0.041
		(0.043)			(0.048)
Treatment sequence dummy	Y	Y			
ln $\mathcal{L}$	-35962.8	-35929.9			
Individuals	135	135			
Observation	4043	4043			

Notes: Robust standard errors, clustered by individual subject, are presented in parentheses.

First, we find in column (1) that the experimental manipulation of time pressure strengthens on average the degree of likelihood insensitivity and risk tolerance but has no effect on optimism and decision error. Secondly, regarding the relationship between cognitive ability and probability weighting that is induced by time pressure, we find in column (2) that the reduction of the cognitive test score due to time pressure is significantly related to the stronger degree of likelihood insensitivity shown in decisions under time pressure: a one standard deviation in the reduction of the Raven score due to time pressure is associated with 0.059 decrease in the value of the parameter γ estimated from decisions under time pressure.[17] It implies that subjects who experience a larger reduction of the Raven score due to time pressure exhibit the stronger degree of likelihood insensitivity in lottery choices under time pressure. It thus lends strong support to the main argument of this paper that probability weighting, in

[17] The standard deviation of the difference of Raven scores with and without time pressure is 2.58.

particular likelihood insensitivity, is related to cognitive ability.

It is worth noting that a higher score of the Raven test with no time pressure is negatively correlated with likelihood insensitivity. This pattern is consistent with the findings of Study 1. On the other hand, we find no significant and stable relation between the interruption of cognitive ability due to time pressure and other parameters of the specification, including the parameter of decision error.

Given that time pressure has a clear effect on cognitive ability and probability weighting at the aggregate-level analysis, we also look at individual heterogeneity in response to time pressure. Column (1) of Table 5 is re-estimated for each individual and we present the distribution of TP coefficients for each parameter in Figure B.9.1 in Online Appendix B.9. A substantially large proportion of subjects experience the negative effect of time pressure on likelihood insensitivity than on other parameters: 76% for likelihood insensitivity, and 56%, 47%, and 41% for δ, α, and μ, respectively. We then regress this responsiveness coefficient of TP for each parameter on the difference in the Raven test score due to time pressure. The results are reported in Table B.9.2 in Online Appendix B.9. We find that the interrupted cognitive ability for each individual is negatively correlated with the magnitude of TP coefficients in γ at the 5% level, which is consistent with the finding from the aggregate-level estimation.

We summarize the findings of Study 2 as follows. First, the experimental manipulation of time pressure on average reduces the Raven test score and strengthens the degree of likelihood insensitivity. Second, a larger reduction of the Raven score due to time pressure at the individual level is associated with a stronger degree of likelihood insensitivity in decisions under time pressure. By taking together the findings of Study 1 and Study 2, we conclude that likelihood insensitivity is closely related to cognitive ability.

4.3. Discussion

There is a growing concern in the literature that certain behavioral patterns observed in the laboratory may be driven by randomness of decision making which is related to cognitive ability or to response time. For instance, Andersson et al. (2016) report evidence suggesting that cognitive ability is related to random decision making and cast doubt on the previously established relation between cognitive ability and risk preferences. Recalde et al. (2018) suggest that the shorter response time is associated with erroneous decision making in public-good games. One may be concerned about whether our findings is also driven by error-prone behavior particularly when subjects' cognitive ability is low or when time pressure forces subjects to make faster decisions.

In order to address this concern, we first note that our econometric specifications allow choice errors to depend on Raven score and many other individual characteristics. As can be shown in Online Appendix B.5, choice errors for subjects in Study 1 are not correlated with their Raven scores. Similarly, as shown in Table 5, randomness of subjects' choices in Study 2 is unrelated to time pressure. It is probably because the lottery choice problems in our study are straightforward and do not require cognitive sophistication.

Next, we check whether faster decision making is associated with cognitive ability, erroneous decision making and the findings of the paper. For this purpose, we include subjects' response time in the analyses reported in Tables 4 and 5. The results are reported in Online Appendix B.8 and remain robust with the inclusion of the response time variable. In addition, we find no significant correlation between subjects' response time and Raven score in each study.[18]

By considering these, we conclude that our findings regarding probability weighting and cognitive ability is not driven by choice errors correlated with Raven score or time pressure.

5. Conclusion

The idea of representing risk attitudes with nonlinear probability transformation underlies all nonexpected utility theories including prospect theory. Because the prevailing form of probability transformation found in the literature distorts human perception and decisions away from objective information on probabilities, it is important to understand what factors shape such biases in decision making under risk. One natural factor to be considered is cognitive ability that is essential for the computation of expected benefits and costs of available options and the evaluation of optimal choices.

This paper experimentally examined the relationship between cognitive ability and probability weighting with two different studies. The first study exploits an unusually large variation in the cognitive test score in the subject pool and the second one manipulates time

[18] In Study 1, the correlation between response time and Raven score is -0.0481 (significance level: 0.294). In Study 2, the correlation between response time in Risk no TP and Raven no TP is -0.0136 (significance level: 0.5402).

constraints with which subjects make choices under risk and perform the cognitive tests. Both studies established consistently that cognitive ability is closely related to likelihood insensitivity in such a manner that subjects with lower cognitive ability respond less discriminately to intermediate probabilities and more over-sensitively to extreme probabilities. One avenue for future work is to understand mechanisms which generate this association between cognitive ability and probability weighting. As the theory of Steiner and Stewart (2016) suggests, one potential channel may concern noise in information processing that could result from limitations of cognitive ability.

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