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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 by conducting laboratory experiments with a pool of subjects with unusually large variation in cognitive ability; native-born South Koreans and North Korean refugees. We find that cognitive ability is related to two distinct features of probability weighting—likelihood insensitivity and optimism. Particularly, the negative association between likelihood insensitivity and cognitive ability is robust to potential confounders and stronger among lower cognitive-ability subjects. Our findings shed light on the sources of anomalous choices against expected utility theory.

Keywords: probability weighting, cognitive ability, likelihood insensitivity, North Korean refugees

JEL: C91, D01, D81, D91

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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. It has been well established that cognitive skills are an important determinant of economic and social outcomes (e.g., Herrnstein and Murray, 1994; Murnane et al., 1995; Heckman et al., 2006; Hanushek and Woessmann, 2008). A growing literature has also documented that cognitive ability is associated with qualities of decision making and economic preferences. Agarwal and Mazumder (2013) provide evidence that suboptimal behavior in real-life 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 and risk attitudes and time impatience.[1] Despite the growing interest in the literature, to our knowledge, there is no existing research studying the relationship between cognitive ability and the distortion in perception and weighting of probabilities in decisions.

This paper investigates the relationship between probability weighting and cognitive ability by recruiting 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 with some probability of winning a higher amount of money. Varying sure outcomes and winning probabilities enables us to measure each individual's risk premium across probabilities. After finishing the lottery-choice experiment, subjects completed a Raven's Progressive Matrices test comprising 24 questions and a survey on their sociodemographic information and other individual characteristics including personality.

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

We find that both groups exhibit risk seeking for low winning probabilities and risk aversion for high winning probabilities, which cannot be accommodated by EUT. The extent to which the average behavior departs from EUT is larger for NK subjects than for native-born SK subjects, while there is also a significant level of individual heterogeneity within group. On the other hand, cognitive ability measured by the Raven test is also hugely different between the two groups. On average, NK subjects achieved less than 50% of the Raven score of SK subjects.

Using the two-parameter specification of probability weighting proposed by Goldstein and Einhorn (1987), we structurally estimate the links between cognitive ability and the two features of probability weighting—likelihood insensitivity and the degree of optimism—with controlling for potential confounders. We find robust evidence that people with lower cognitive ability exhibit more severe degree of likelihood insensitivity. There is also a negative association between cognitive ability and optimism which becomes insignificant after controlling for individual characteristics. The results suggest that limitations of cognitive ability can contribute to probability distortions in such a manner of making people ignore probability changes in an intermediate range and respond excessively to changes from impossibility to small possibility and from being almost sure to certainty. By recovering the shape of probability weighting function, we further find that the inverse S-shaped structure of probability weighting function is more pronounced for people with lower cognitive ability.

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 other hand, 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 may not be a component of stable preferences. Lastly, 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 associated with the shape of nonlinear probability weighting.

The remainder of the paper is organized as follows. Section 2 describes the experiment and the survey, the sampling of subjects, 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 Appendices including the experimental instructions.

2. Experiment and Descriptive Results

2.1. Data collection

This study consists of a lottery choice experiment, a cognitive ability test, and a survey.[2] In the experiment subjects were asked to make a series of decisions regarding 40 pairs of lotteries. In each pair, subjects were asked to choose between one of two lotteries: a risky lottery (8,000 KRW with some positive probability, otherwise 0) and a safe lottery (a guaranteed amount with probability 1).[3] The chance of earning the positive amount of money in a risky lottery was visualized with a pie graph (see Online Appendix A). Subjects were given a total of 5 blocks of lottery choices, each consisting of 8 pairs of lotteries. Throughout the 5 blocks, we used the same set of safe lotteries so as not to confuse subjects unnecessarily. 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 fixed the winning amount at 8,000 KRW for each risky lottery.[4] Instead, the probability of winning 8,000 KRW varied across the five blocks with the values of 0.05, 0.25, 0.5, 0.75, and 0.95. That is, subjects faced the same risk lottery in a block, while the sure amount of safe lotteries varied across pairs. In order to avoid the issue of multiple switching points, we made subjects choose a unique switching point from a risky lottery to a sure outcome in a block.[5] We thus measured an individual subject's certainty equivalent of a risky lottery from a switching point in a block.[6] To check any order effect, we randomized the sequence of the blocks of lotteries at the individual subject level. After all choices were made, only one pair out of 40 choices was randomly selected for actual payment and subjects' relevant choices were implemented. In Online Appendix A, we present the experimental instructions given to our subjects.

After the lottery choice experiment ended, subjects were asked to perform a test which measures their cognitive ability. Cattell (1963, 1987) classifies one's intelligence as fluid intelligence

[2] 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. (2018). Subjects' participation fee for all the experiments was 45,000 KRW.

[3] At the time of the experiment (Aug 2016), $1USD is approximately 1,100 KRW.

[4] We only consider lotteries in the gain domain. 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.

[5] For other lottery choice experiments which did not allow for multiple switching, see Andersen et al. (2006), Tanaka et al. (2010), and Charness et al. (2013).

[6] Andersson et al. (2016) point out that when multiple switching is allowed in the multiple price list method, a negative relationship between cognitive ability and risk aversion can be overestimated as subjects with lower cognitive ability are more likely to err in decision making than subjects with higher cognitive ability. In our experiment, we try to minimize such effects by allowing subjects to make a unique switching point in each block. Relatedly, for better understanding of our non-student subjects about the concept of probabilities, we used real black and white balls drawn from a box to determine the realization of the lottery chosen for the actual payment.

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, independent of acquired knowledge. Most of North Korean refugees grew up with nonstandard formal education in North Korea relative to that in South Korea. Therefore, we can expect some regime-dependent differences in Crystalized intelligence. Instead, we focus on the measurement of fluid intelligence using 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). In our study, each subject was asked to solve 24 Raven test problems in 10 minutes after completing the aforementioned experiment. 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.

2.2. Subjects sampling

We collaborated with Nielsen Korea between June and July of 2016 to recruit 302 North Korean refugees and 298 native-born South Koreans. When recruiting North Korean refugees, we used 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.[7] Once entering South Korea, North Korean refugees are all naturalized and become 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. In sum, our data of the experiment and the cognitive test consist of responses from 600 subjects.[8]

Table 1 reports the mean and standard deviation (in parenthesis) of key sociodemographic variables across the NK and SK groups.[9] 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

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

[8] While the main analysis of the paper will be conducted with these two samples, we also recruited 72 undergraduate students at Seoul National University to facilitate the comparison of our experimental results with findings in the literature with convenient samples of college students. The estimation results with the sample of undergraduate students are reported in Online Appendix B.

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

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 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.[10]

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

2.3. Overview of risk taking and cognitive ability

We begin by looking at subjects' behavior of risk taking and cognitive ability scores. Risk taking behavior can be conveniently captured by risk premia, $RP = EV - CE$, where EV and CE denote the expected value and a certainty equivalent of a lottery, respectively. If RP > (<) 0, a person is said to be risk averse (seeking). Expected utility theory predicts that the sign of risk premium should remain

[10] 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.

unchanged throughout all the probabilities used in the experiment.

Figure 1. Risk premia over probabilities: Comparison between NK and SK

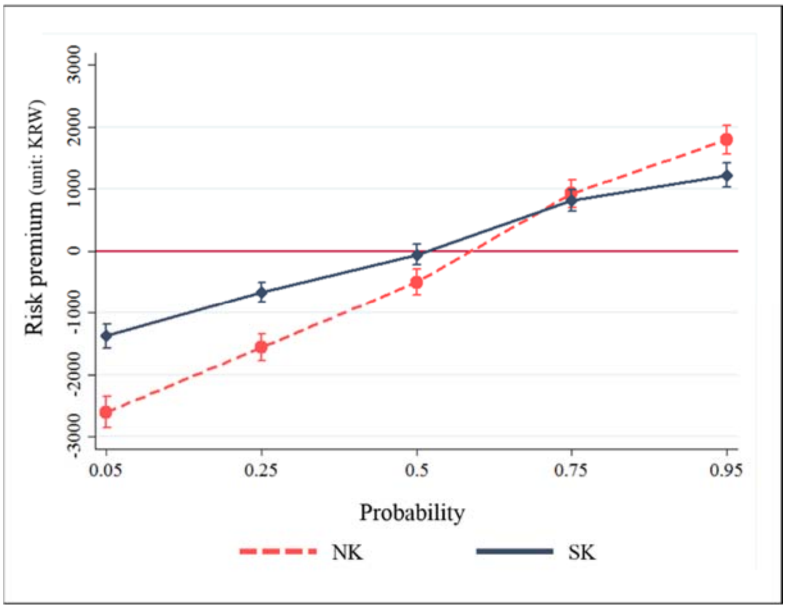
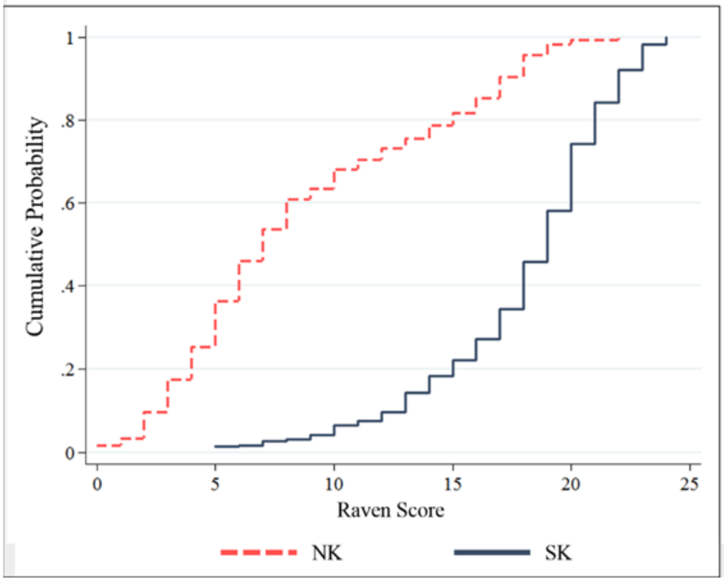


Figure 1 presents the average risk premium of each lottery for NK and SK subjects.[11] Inconsistent with the EUT, Figure 1 shows that the sign of RP is not constant across probabilities, changing from negative to positive when the winning probability varies from 0.5 to 0.75 in both NK and SK subjects. To be more specific, subjects exhibited the following patterns of risk attitudes: 1) risk seeking for relatively low probability of winning 8,000 KRW and 2) risk averse for relatively high probability of winning. When the probability of winning is lower than 0.5, NK subjects are more risk seeking than SK subjects (i.e. the average absolute value of RP for NK subjects is greater than that of SK). On the other hand, when the probability of winning is higher than 0.5, the pattern above is reversed that NK subjects are more risk averse than SK subjects.

Cognitive ability, as measured by the Raven test, is also significantly different across NK and SK subjects. While the average number of correct answers is 17.75 (74%) in SK sample, it is only 8.65 (36%) in NK sample. It means that NK subjects in our study only achieved less than 50% of the Raven score of SK subjects. Figure 2 depicts cumulative probability plots for the Raven scores which further show that the distribution of NK subjects' Raven scores is first-order stochastically dominated by that of SK subjects' Raven scores. This difference is statistically significant (Kolmogorov-Smirnov test, *p*-value < 0.01).

[11] Online Appendix B compares average risk premia of NK and SK subjects with those of undergraduate students. The average behavior of the undergraduate students exhibits a similar departure from EUT, albeit to a lesser extent.

Figure 2. Cumulative distribution of Raven score



In sum, from the descriptive features of our data, we have the following findings: (1) both NK and SK subjects systematically deviate from EUT by exhibiting risk seeking for low probability of winning and risk aversion for high probability of winning, (2) the extent of this behavioral departure appears larger for NK subjects than for SK subjects, and (3) NK subjects perform substantially worse in Raven test than SK subjects. In the subsequent part of this paper, we will mainly focus on the relationship of these observations.

3. Econometric Specification

This section presents the econometric specification for estimating the association of cognitive ability on 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:

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

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) 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).[12] 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 γ, 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 $(\delta/(1+\delta), \delta/(1+\delta))$. 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 Harrison and Rutström (2008) and Harrison (2008). A simple stochastic specification is employed to describe likelihoods conditional on differences in prospect theory values of two lotteries. We construct the Fechner index by computing $\nabla EV = EV(R) - EV(S)$, where $EV(R)$ represents the prospect theory value of the risky lottery R while $EV(S)$ represents the prospect theory value of the safe lottery S. Using the index ∇EV, we define the probability of the risky lottery being chosen with the logistic function:

$$F(\nabla EV) = \frac{\exp(\nabla EV)}{1 + \exp(\nabla EV)}$$

Therefore, the likelihood function to estimate α, γ, and δ with the set of observed choices $y = \{y_{it}\}$ is defined as:

[12] 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.

$$\ln \mathrm{L}\,(\alpha, \gamma, \delta | y) = \sum_{i,t} y_{it} \ln F(\nabla EV) + (1 - y_{it}) \ln(1 - F(\nabla EV))$$

where y_{it} is 1 if an individual i selects a risk lottery in the tth decision problem and 0 otherwise. The log likelihood function can be maximized by simultaneously estimating 3 parameters ($\alpha,\ \delta,\ \gamma$). Standard errors are clustered at the individual level.[13] As we described in the previous section, we collected individual characteristics including sociodemographic information and personality along with their Raven test scores. 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:

$$\alpha = \alpha_0 + \alpha_1 Raven + X'\alpha_2$$
$$\delta = \delta_0 + \delta_1 Raven + X'\delta_2$$
$$\gamma = \gamma_0 + \gamma_1 Raven + X'\gamma_2$$

where $Raven$ is the subject's Raven test score and X is the vector of individual characteristics including sociodemographic information and personality traits.[14] Thus, α_1, δ_1, and γ_1 respectively measure the association of Raven score with each of the preference parameters of prospect theory.

4. Estimation Results

To have a glance at the relationship between cognitive ability and probability weighting, we first estimate and compare γ and δ across subgroups with different levels of cognitive ability. We pool all NK and SK subjects and divide subjects into 5 quintile groups of standardized Raven scores. γ and δ are estimated for each quintile group without including any control variable.[15]

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

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

[15] In Appendix B, we present the corresponding estimation result of 5 quintile groups by cognitive ability for each of NK and SK samples.

Figure 3. Estimates of γ and δ across Raven score quintiles

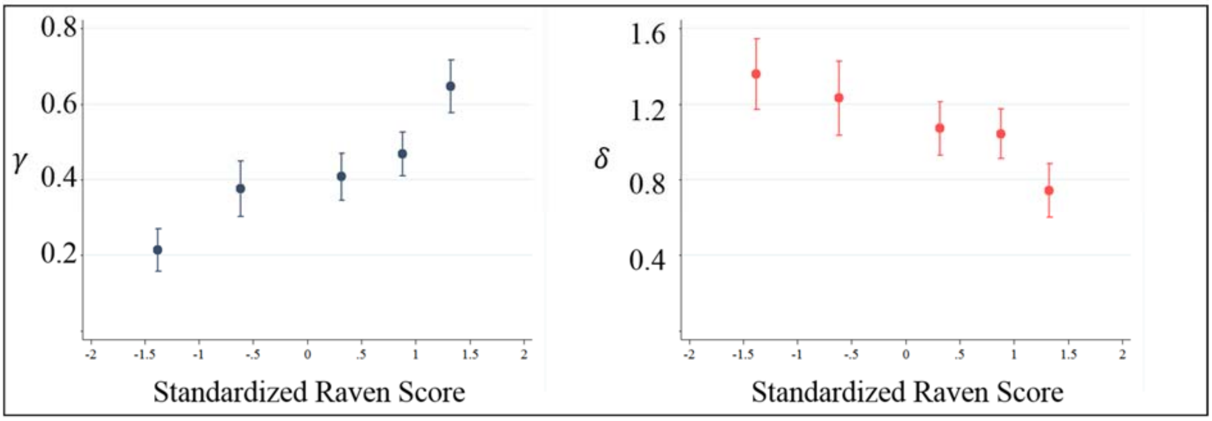


Figure 3 depicts the estimated values of γ and δ with their 95% confidence intervals across the five quintile groups. The left panel shows the positive relationship between Raven score and the estimated parameter of likelihood insensitivity γ. The estimated γ for the lowest cognitive ability group (1st quintile) is 0.21 and increases with Raven score so that the highest cognitive ability group has γ of 0.65. Because all estimated values of γ are below 1, the smaller value of γ in this region makes the degree of likelihood insensitivity stronger, and this translates into the negative relationship between cognitive ability and likelihood insensitivity. That is, subjects who have lower cognitive ability respond less sensitively to changes in probability and thus induce more distortions in weighting them into decisions. We also observe that the association between the degree of optimism and cognitive ability is negative, i.e., the estimated δ decreases as the Raven score increases. Hence this simple investigation suggests that cognitive ability is associated with both insensitivity to likelihood and the degree of optimism, which jointly shapes the weighting function.[16]

We next look at the relationship between cognitive ability and probability weighting across NK and SK subjects in a bit more detail. In Table 2, we first compare estimated parameters between NK and SK subjects. Given that the cognitive ability of SK subjects is on average higher than that of NK subjects and that both likelihood insensitivity and optimism are negatively related to cognitive ability, we can anticipate that the estimated value of γ would be higher for SK subjects, while the estimated value of δ would be higher for NK subjects. This is confirmed by columns (1) and (4) of Table 2.

[16] One interesting observation is that the estimates for γ are across the quintile groups below 1 while the corresponding estimates for δ are around 1, meaning that monotonic deviations from EUT in cognitive ability only applies to likelihood insensitivity. As will be shown later, this pattern is robust to the inclusion of individual characteristics.

Table 2. Estimation results

	NK			SK		
	All	Low	High	All	Low	High
Mean Raven score	8.7	4.4	13.6	17.8	15.3	21.2
	(1)	(2)	(3)	(4)	(5)	(6)
γ						
	0.283***	0.226***	0.352***	0.518***	0.464***	0.603***
	(0.020)	(0.028)	(0.028)	(0.021)	(0.028)	(0.030)
δ						
	1.323***	1.392***	1.224***	0.924***	0.992***	0.817***
	(0.062)	(0.093)	(0.079)	(0.042)	(0.058)	(0.060)
α						
	0.907***	0.881***	0.948***	1.031***	1.002***	1.087***
	(0.014)	(0.020)	(0.021)	(0.019)	(0.022)	(0.035)
ln L	-5317.103	-2993.441	-2282.871	-3924.828	-2433.343	-1452.572
Individuals	302	162	140	292	170	122
Observation	12,080	6480	5600	11920	6800	4,880

Notes: Robust standard errors are clustered at the individual subject and presented in parentheses. ***, **, and * indicate significance level at 1%, 5%, and10%, respectively.

We then split further each group by Raven score to have the NK and SK low-ability (resp. high-ability) group defined as NK and SK subjects whose Raven scores are below (resp. above) the median Raven score of each group, respectively. On average, the NK low-ability group has 4.4 Raven score and the NK high-ability group gets 13.6 Raven score. The SK low-ability and SK high-ability groups have their average Raven scores, 15.3 and 21.2, respectively. Estimated (γ, δ) for each of the subgroups are (0.23, 1.39) for the NK low-ability group (column (2)), (0.35, 1.22) for the NK high-ability group (column (3)), (0.46, 1.00) for the SK low-ability group (column (5)), and (0.61, 0.81) for the NK high-ability group (column (6)).[17] This subgroup analysis again confirms that both likelihood insensitivity and optimism negatively relates to cognitive ability.

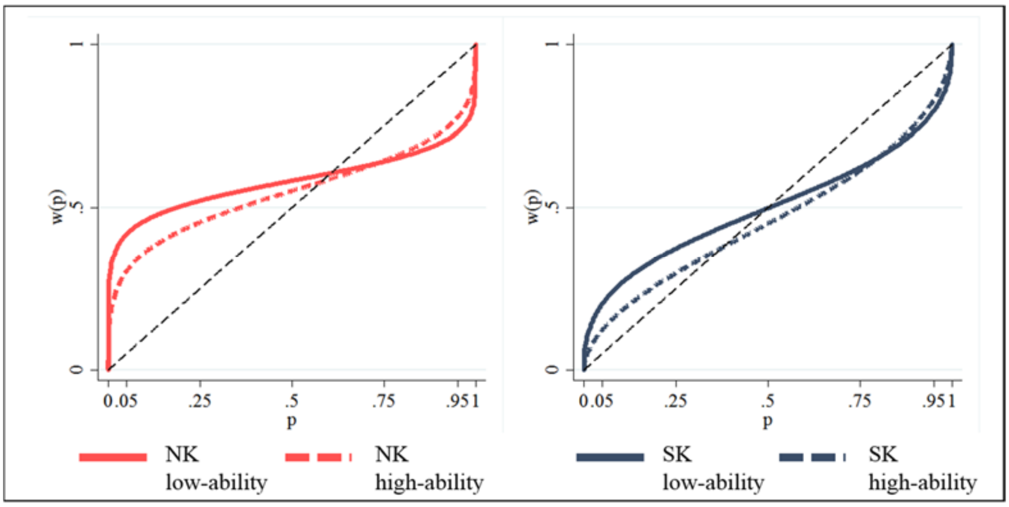
In addition, these estimated parameters can tell us about how each subgroup perceives changes in probabilities and weigh them into decisions. For instance, when the winning probability increases by 0.5 (from 0.25 to 0.75), the NK low-ability group perceives this increase as 0.12, while the NK high-ability group recognizes the same change as 0.20. The SK low-ability and high-ability groups perceive this change as 0.25 and 0.32, respectively.

In order to see how the estimated two parameters determine the shape of probability weighting

[17] We review the ranges of the estimated values of weighing parameters, using the functional form of Goldstein and Einhorn (1987), in the literature and summarize the comparison of our results with those found in the literature in Online Appendix B. All the existing studies, except for Booij et al. (2010) who used a general adult population in the Netherlands, employed undergraduate students as their subjects group. The estimation results with the SK group lie in the range of those reported in the literature, whereas the results with the NK group are a bit out of the range of parameter estimates in the literature. We note that the level of cognitive ability of the NK group is likely lowest among the pools of subjects used in the literature.

and the role of cognitive ability in its feature, we present the graphical illustration of estimated weighting functions for each of the NK and SK groups in Figure 4, based on the subgroup analysis in Table 2.

Figure 4. Estimated probability weighting functions across subject groups



In each panel, the 45 degree line depicts a linear probability which is consistent EUT. Across 4 groups along with cognitive ability, the lower the level of cognitive ability is, the higher is the extent to which a probability weighting function deviates from the 45 degree line and become more inverse S-shaped, implying that subjects less sensitively respond to changes in intermediate probabilities. In contrast, as the level of cognitive ability decreases, the point at which a probability weighting function intersects with the 45 degree line is shifted upward. Thus subjects become more optimistic. In sum, we conclude that cognitive ability is strongly associated with the extent to which probabilities are distortedly reflected into choice.

We next move to delve more systematically into the relationship between probability weighting and cognitive ability by conducting the maximum likelihood estimation with controlling for sociodemographic variables and other individual characteristics common to both NK and SK groups as well as variables confined only to NK group. Sociodemographic variables include gender, age, education, marital status, income, and the number of household numbers. Big 5 control includes openness, conscientiousness, extraversion, agreeableness, and neuroticism. Financial literacy measures individual's knowledge about basic financial resource, like interest rate. Controls specific to North Korean refugees include 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, information 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 subjective assessment on quality of life after escape from North Korea. Table 3 reports the estimation results.[18]

Table 3. Robust analysis

	Pooling NK & SK		NK only			SK only	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
γ							
Standardized Raven	0.087***	0.069***	0.070**	0.066**	0.076**	0.003	0.011
	(0.020)	(0.020)	(0.029)	(0.031)	(0.032)	(0.040)	(0.039)
Constant	0.249*	0.257*	0.322	0.367	0.033	0.487	0.269
	(0.138)	(0.153)	(0.207)	(0.227)	(0.284)	(0.358)	(0.368)
δ							
Standardized Raven	-0.116**	-0.090	-0.151	-0.146	-0.052	0.020	0.059
	(0.055)	(0.060)	(0.096)	(0.091)	(0.099)	(0.080)	(0.095)
Constant	1.815***	1.982***	1.477***	1.922***	3.649***	2.231***	2.105***
	(0.324)	(0.362)	(0.498)	(0.563)	(1.166)	(0.677)	(0.550)
α							
Standardized Raven	0.037**	0.028*	0.033	0.023	-0.003	-0.007	-0.015
	(0.015)	(0.016)	(0.021)	(0.020)	(0.030)	(0.031)	(0.040)
Constant	0.939***	0.864***	1.158***	1.087***	0.811**	0.731***	0.635**
	(0.105)	(0.119)	(0.146)	(0.161)	(0.324)	(0.242)	(0.299)
Sociodemographic controls	Y	Y	Y	Y	Y	Y	Y
Big 5 and financial literacy	N	Y	N	Y	Y	N	Y
NK-specific controls	-	-	N	N	Y	-	
ln L	-9113.177	-9020.853	-5199.015	-5153.375	-5024.757	-3835.738	-3710.616
Individuals	594	594	302	302	302	292	292
Observation	23,760	23760	12,080	12080	12080	11,680	11,680

Notes: Robust standard errors, clustered by individual subject, are presented in parentheses. ***, **, and * indicate significance level at 1%, 5%, and 10%, respectively. Sociodemographic controls include female, age, education, marital status, log household income, and the number of household members. Big 5 includes openness, conscientiousness, extraversion, agreeableness, and neuroticism. NK-specific controls include the indicator of whether any family member is left in North Korea, lower economic class in North Korea, the number of years lived in North Korea, informal market experience, 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 subjective assessment on quality of life after escape from North Korea.

By pooling the sample of NK and SK subjects, we report the estimated relationship between probability weighting parameters and standardized Raven score with sociodemographic controls in column (1). As expected from the previous analysis, there is a strong negative correlation between each of the probability weighting parameters and cognitive ability. One standard deviation increase in Raven

[18] We relegate the full description of the estimation results in Table 3 to Online Appendix B.

scores is associated with 0.087 decrease in the parameter of likelihood insensitivity and 0.116 reduction in the parameter of optimism. In column (2), we include the additional controls of Big 5 personality traits and financial literacy score. The negative association between likelihood insensitivity and cognitive ability remains statistically significant, whereas the degree of optimism is no longer significantly correlated with Raven score.

Because the relationship between probability weighting and cognitive ability may not be the same between NK group and SK group and the analysis in columns (1) and (2) pooled between-group and within-group variations, we repeat the same estimation exercise in each of the NK and SK groups. We report the estimation results for the NK group in column (3) with controlling for sociodemographic variables and in column (4) with the further controls of personality traits and financial literacy score. Columns (6) and (7) present the corresponding results for the SK group. For the NK group, we add in the estimation specification the further controls of variables specific to that group. The results are presented in column (5). We overall find that there is a robust negative association between likelihood insensitivity and cognitive ability for the NK group, whereas we do not observe such a significant relationship for the SK group. Because the NK group performed substantially worse in the Raven test, this finding suggests that the negative and significant relationship between cognitive ability and likelihood insensitivity is prominent for people who have the low level of cognitive ability. On the other hand, the optimism parameter is not significantly correlated with Raven score for both of the NK and SK groups.

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 skills that are essential for the computation of expected benefits and costs of available options and the evaluation of optimal choices.

This paper has taken a first step on the examination of the relation between cognitive ability and probability weighting. We found that people with lower cognitive ability are more prone to probability distortions and exhibit the stronger tendency of co-existence of risk seeking and aversion over different 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.

References

Agarwal, S. and B. Mazumder (2013). 'Cognitive abilities and household financial decision making', *American Economic Journal: Applied Economics*, vol. **5**(**1**), pp. 193-207.

Andersen, S., G. W. Harrison, M. I. Lau and E. E. Rutström (2006). 'Elicitation using multiple price list formats', *Experimental Economics*, vol. **9**(**4**), pp. 383-405.

Andersson, O., H. J. Holm, J.-R. Tyran and E. Wengström (2016). 'Risk aversion relates to cognitive ability: Preferences or noise?', *Journal of the European Economic Association*, vol. **14**(**5**), pp. 1129-1154.

Benjamin, D. J., S. A. Brown and J. M. Shapiro (2013). 'Who is 'behavioral'? cognitive ability and anomalous preferences', *Journal of the European Economic Association*, vol. **11**(**6**), pp. 1231-1255.

Booij, A. S., B. M. S. van Praag and G. van de Kuilen (2010). 'A parametric analysis of prospect theory's functionals for the general population', *Theory and Decision*, vol. **68**(**1-2**), pp. 115-148.

Bruhin, A., H. Fehr-Duda and T. Epper (2010). 'Risk and rationality: Uncovering heterogeneity in probability distortion', *Econometrica*, vol. **78**(**4**), pp. 1375-1412.

Burks, S. V., J. P. Carpenter, L. Goette and A. Rustichini (2009). 'Cognitive skills affect economic preferences, strategic behavior, and job attachment', *Proceedings of the National Academy of Sciences*, vol. **106**(**19**), pp. 7745-7750.

Carpenter, P. A., M. A. Just and P. Shell (1990). 'What one intelligence test measures: a theoretical account of the processing in the Raven Progressive Matrices Test', *Psychological Review*, vol. **97**(**3**), pp. 404.

Cattell, R. B. (1963). 'Theory of fluid and crystallized intelligence: A critical experiment', *Journal of Educational Psychology*, vol. **54**(**1**), pp. 1.

Cattell, R. B. (1987). *Intelligence: Its structure, growth and action*: Elsevier.

Charness, G., U. Gneezy and A. Imas (2013). 'Experimental methods: Eliciting risk preferences', *Journal of Economic Behavior & Organization*, vol. **87**, pp. 43-51.

Charness, G., A. Rustichini and J. Van de Ven (2018). 'Self-confidence and strategic behavior', *Experimental Economics*, vol. **21**(**1**), pp. 72-98.

Choi, S., K. S. Hahn, B.-Y. Kim, E. Lee and J. Lee (2018). 'The economic cost of ideological indoctrination: Communism's shadow', *Working Paper*.

Dohmen, T., A. Falk, D. Huffman and U. Sunde (2010). 'Are risk aversion and impatience related to cognitive ability?', *American Economic Review*, vol. **100**(**3**), pp. 1238-1260.

Dohmen, T., A. Falk, D. Huffman and U. Sunde (2018). 'On the relationship between cognitive ability and risk preference', *Journal of Economic Perspectives*, vol. **32(2)**, pp. 115-134.

Falk, A., A. Becker, T. J. Dohmen, B. Enke and D. Huffman (2015). 'The nature and predictive power of preferences: Global evidence', *Working Paper*.

Fehr-Duda, H. and T. Epper (2012). 'Probability and risk: Foundations and economic implications of probability-dependent risk preferences', *Annual Review of Economics*, vol. **4**(**1**), pp. 567-593.

Frederick, S. (2005). 'Cognitive reflection and decision making', *Journal of Economic Perspectives*, vol. **19**(**4**), pp. 25-42.

Gill, D. and V. Prowse (2016). 'Cognitive ability, character skills, and learning to play equilibrium: A level-k analysis', *Journal of Political Economy*, vol. **124**(**6**), pp. 1619-1676.

Goldstein, W. M. and H. J. Einhorn (1987). 'Expression theory and the preference reversal phenomena', *Psychological Review*, vol. **94**(**2**), pp. 236.

Hanushek, E. A. and L. Woessmann (2008). 'The role of cognitive skills in economic development', *Journal of Economic Literature*, vol. **46**(**3**), pp. 607-668.

Harrison, G. W. (2008). 'Maximum likelihood estimation of utility functions using Stata', *University of Central Florida, Working Paper*, pp. 06-12.

Harrison, G. W. and E. Elisabet Rutström (2008). 'Risk aversion in the laboratory', *Risk Aversion in Experiments,* pp. 41-196: Emerald Group Publishing Limited.

Harrison, G. W. and E. E. Rutström (2009). 'Expected utility theory and prospect theory: One wedding and a decent funeral', *Experimental Economics*, vol. **12**(**2**), pp. 133-158.

Heckman, J. J., J. Stixrud and S. Urzua (2006). 'The effects of cognitive and noncognitive abilities on labor market outcomes and social behavior', *Journal of Labor Economics*, vol. **24**(**3**), pp. 411-482.

Herold, F. and N. Netzer (2015). 'Second-best probability weighting', *Working Paper*.

Herrnstein, R. J. and C. Murray (1994). *Bell curve: Intelligence and class structure in American life*: Simon and Schuster.

Jaeggi, S. M., M. Buschkuehl, J. Jonides and W. J. Perrig (2008). 'Improving fluid intelligence with training on working memory', *Proceedings of the National Academy of Sciences*, vol. **105**(**19**), pp. 6829-6833.

Kahneman, D. and A. Tversky (1979). 'Prospect theory: An analysis of decision under risk', *Econometrica*, vol. **47**(**2**), pp. 263-292.

Lattimore, P. K., J. R. Baker and A. D. Witte (1992). 'The influence of probability on risky choice: A parametric examination', *Journal of Economic Behavior & Organization*, vol. **17**(**3**), pp. 377-400.

Mani, A., S. Mullainathan, E. Shafir and J. Zhao (2013). 'Poverty impedes cognitive function', *Science*, vol. **341**(**6149**), pp. 976-980.

Murnane, R. J., J. B. Willett and F. Levy (1995). 'The growing importance of cognitive skills in wage determination', *Review of Economics and Statistics*, vol. **77**(**2**), pp. 251-266.

Oechssler, J., A. Roider and P. W. Schmitz (2009). 'Cognitive abilities and behavioral biases', *Journal of Economic Behavior & Organization*, vol. **72**(**1**), pp. 147-152.

Raven, J. C. (1938). 'Progressive matrices: A perceptual test of intelligence', *London: HK Lewis*.

Steiner, J. and C. Stewart (2016). 'Perceiving prospects properly', *American Economic Review*, vol. **106**(**7**), pp. 1601-1631.

Tanaka, T., C. F. Camerer and Q. Nguyen (2010). 'Risk and time preferences: Linking experimental and household survey data from Vietnam', *American Economic Review*, vol. **100**(**1**), pp. 557-571.

Tversky, A. and C. R. Fox (1995). 'Weighing risk and uncertainty', *Psychological Review*, vol. **102**(**2**), pp. 269.

Tversky, A. and D. Kahneman (1992). 'Advances in prospect theory: Cumulative representation of uncertainty', *Journal of Risk and Uncertainty*, vol. **5**(**4**), pp. 297-323.

Tversky, A. and P. Wakker (1995). 'Risk attitudes and decision weights', *Econometrica*, vol. **63**(**6**), pp. 1255-1280.

Van de Kuilen, G. (2009). 'Subjective probability weighting and the discovered preference hypothesis', *Theory and Decision*, vol. **67**(**1**), pp. 1-22.

Wakker, P. P. (2008). 'Explaining the characteristics of the power (CRRA) utility family', *Health Economics*, vol. **17**(**12**), pp. 1329-1344.

Wakker, P. P. (2010). *Prospect theory: For risk and ambiguity*: Cambridge university press.

Wu, G., J. Zhang and R. Gonzalez (2004). *Decision under risk*: Blackwell Handbook of Judgment and Decision Making.