Rationality Extension, Preference Aggregation, and Pareto Efficiency of Group Decision under Risk*

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Abstract

In this paper, we study three fundamental questions on group decisions: (1) does group rationality originate from individuals' rationality? (2) are members' risk preferences reflected in group decisions? (3) Do groups make Pareto efficient choices? In our experiment, the subjects made choices over a consumption bundle on a linear budget set, 18 times in isolation, and 18 times in pairs. We adopt a parametric revealed preference approach to measure rationality and develop a new measure of Pareto efficiency. Several results emerge from our analysis. First, we find that rationality risk preference of group choices are remarkably heterogeneous depending on members' rationality and preferences. Nevertheless, we see strong evidence for rationality extension and preference aggregation. Second, we detect significant heterogeneity in efficiency across groups, even when members are highly rational. Third, we present the relationship among group rationality, group risk preference, and Pareto efficiency as well as effects of socio-demographic characteristics, friendship network, and cognitive ability on group choices.

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1 Introduction

1.1 Overview

Prevalence of group decision making such as committees, firms, couples, etc. Understanding group decision making is a long-standing issue in social science with traditional focus on the (im-)possibility of aggregating individually rational agents' preferences into a collectively rational preference (Arrow (1950)).

There are three fundamental issues of group decision making: (i) extension from individual rationality to collective rationality; (ii) preference aggregation; and (iii) welfare. Investigating three issues is not an easy task due to identification and measurement problems.

We report a large-scale experiment that enables us to explore the aforementioned questions at the individual and group level. Subjects face a set of decision problems under risk in isolation and then in pair. The decision problem is a standard portfolio choice one with two-state uncertainty. The experiment adopts a well-established design in the literature (Choi et al. (2007), Choi et al. (2014)).

In this paper, we focus on the decision in pair, the smallest unit of a group. Another important feature of our experiment is that pairs could freely deliberate (face-to-face deliberation, discussion allowed before and during making choices). Not only does free-deliberation represent many of group decision situation in the real world (Ambrus et al. (2015)), but also it is hard to impose a constructed deliberation process such as voting when only two people in a group (other than unanimity). How people make a group decision with externally given decision process is also an important question dealt with in Jackson and Yariv (2011).

Also, we designed the decision environment and the payoff structure so that subjects bargain over two different public goods sharing the same amount of endowment. This is the simplest decision environment which helps us to simply focus on our main questions; how the quality of individual decisions affects the quality of joint decisions. Therefore, our analysis does not cover either bargaining depending on endowment nor altruism/trust towards the other.

The rest of paper is organized as follows. In Section 2, we introduce... Section 3... In Section 4, we study how individuals' rationality extends to... In Section 5, we study how group choice compromises individuals' risk preferences. In Section 6, we provide a series of welfare analysis. Finally, we conclude thoughts in Section 8. Appendices A–C gather additional tables and figures, robustness checks, and mathematical proofs.

To Euncheol: 이후에 ID를 익명화해서 데이터를 바꾸고, 본문에 반영해야 함.

2 Experimental Design and Procedure

2.1 Experimental Design

Our experimental design is essentially identical to the one proposed by Choi et al. (2007). Subjects were asked to make choices under risk. Each choice is interpreted as an optimal portfolio of Arrow securities in a linear budget set. Specifically, there are two equally probable states of nature denoted by $s \in \{r, b\}$, and there are two associated Arrow securities.[1] Each subject allocates his wealth between the two Arrow securities. His choice is represented by (x_r, x_b) in a normalized linear budget set $p_r x_r + p_b x_b = 1$, where $x_s \geq 0$ denotes the demand for the security that pays off in state s, and $p_s > 0$ is the unit price of it.

Figure 1 illustrates the decision environment that our subjects face. The horizontal axis represents values of x_r, and the vertical axis denotes values of x_b. A, B, and C present possible portfolio choices on a common linear budget set for a given price pair (p_r, p_b) with $p_r < p_b$. As portfolio A lies on the 45° line (the dashed line in the figure), it promises a fixed return regardless of what the true state is. Portfolio B corresponds to the choice in which all the wealth is invested to the cheaper one associated with state r. Portfolio C represents an intermediate choice between A and B.

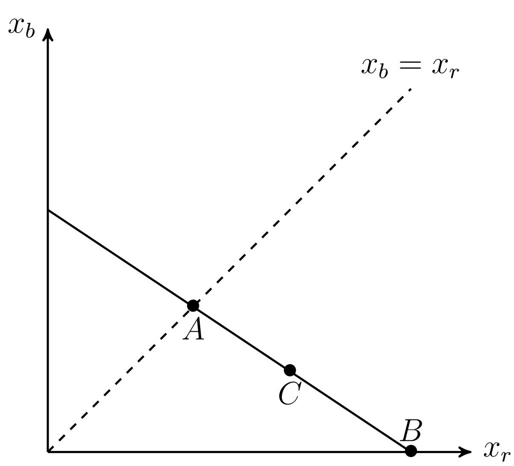


Figure 1: An illustration of the experimental design

[1] Unlike Choi et al. (2007), we do not make any variation of the likelihood of the two states.

2.2 Sample and Procedures

We collected a dataset from 12 middle schools in Daegu city, the fourth largest city in South Korea, in coordination with the Daegu Metropolitan Office of Education.[2] We randomly selected (1) 4 classrooms of the first grade from each school,[3] and (2) 4 classrooms of the second grade from 4 schools.[4] The number of participants was 1610 from 64 classrooms. We experimented for 8 days in the third and fourth weeks in August, 2016. To rule out possible spill-over effects, four experimenters conducted experiments simultaneously in four classrooms from the same grade in a school.[5] In each experiment day, we conducted morning and afternoon sessions in order to cover eight classes.

Each experimental procedure lasted 100 minutes, including a short break. The procedure consisted of four sequential economic experiments, and the latter two experiments are relevant to the current paper.[6] To be specific, students first participated in individual decision problem described in the previous subsection. This session consisted of 18 independent decision rounds. Each round started with the computer choosing a linear budget set, intersecting with each axis between 300 KRW and 3000 KRW, but at least one of the intercepts is greater than or equal to 1500 KRW.[7] Then, a subject moved a mouse pointer in the computer screen along the selected linear budget line. At this moment, a small box next to the pointer displayed the exact monetary value of the portfolio in KRW. By clicking the left mouse button, the subject made a decision, and the following decision round continued with a new budget line randomly and independently chosen. More detailed information and full experimental instructions, including sample screenshots of the experiment, are available in the online appendix.

[2] All the experiment procedures, including the surveys, were computerized through oTree, an online platform for economic experiments (Chen et al. 2015). For each student, we provided a laptop that was connected to the internet via a wifi router in each classroom. In addition, one technician was sitting in the classroom to fix any technical problems during our experiments. As a result, students were able to solely concentrate on our experiments, which is essential for producing a reliable experimental dataset.

[3] For all-men or all-women schools, we selected 2 classrooms from each school.

[4] More detailed information about these 12 schools is available at Choi et al. (2019).

[5] The experimenters were graduate students of economics at Seoul National University, and they were all trained for one day to conduct our experiments.

[6] The two former experiments were dictator and public goods game experiments combined with a friendship survey. In the current paper, only the friendship responses are used for a series of econometric analysis.

[7] The average exchange rate in 2016 for the US dollar to KRW was 1161.

After the 18 rounds of individual choices, subjects played collective decision problems with a classmate partner.[8] For this, subjects were randomly matched into a pair within a classroom, and one was asked to move and sit with her partner. Each paired subjects were allowed 90 seconds to discuss how to make choices in the next rounds of collective decisions. The free conversation was approved, and no particular guidance was given to the subjects on the way of making consensus. After their discussion, subjects made 18 rounds of collective decisions in the same decision environment.

One notable feature is that the subjects made decisions of common allocation. That is, if the chosen portfolio became a realized payoff, then both subjects were paid exactly the same amount of money, and they were informed this payoff rule in the beginning of the collective decision experiment. Some students were not able to find a partner when their classroom consisted of an odd number of students. For this reason, we analyze 1572 students who were matched with a classmate.

The 10-minute break was given to subjects after the rounds of collective choices; then students participated friendship survey where they listed up to 10 closest friend from the same grade, which was followed by a short math test as a cognitive ability survey and a non-cognitive survey.[9] We include survey responses as covariates in later econometric analysis.

During a series of experiments, subjects were not provided with any feedback on their experimental outcomes. At the end of the experiment, the computer selected one decision round for each subject's individual decisions, where each round was equally probable to be chosen. In addition, the computer chose one decision round for each pair's collective decisions with equal probabilities. Each subject was paid the amount that he had earned in the selected individual and collective decision rounds.[10]

[8] In this regard, our experiment design employs a within-subject design.

[9] The non-cognitive survey includes questionnaires measuring (1) the Rosenberg self-esteem scale, (2) life satisfaction, and (3) perception about studying. See Appendix A for details of the related questions and statistics.

[10] We only informed the total payoffs to the subject after experiments. Therefore, subjects could not distinguish the source of the monetary payoffs. As our subjects were adolescents, the payoffs were paid in electric money, which can be spent at about 10 thousands of chain convenience stores in the country. This payment rule was requested by the teachers in the field for educational purpose.

Remarks on the experimental design. All the subjects participated in joint decisions after finishing their individual choices. Indeed, we find some differences between single and collective decisions, which might result from the learning by introspection; however, they are not main concerns of the current paper. Instead of the differences between individual and collective decisions, we focus on how the properties of individual decisions influence those in group decisions.[11] In addition, the current experimental design is natural and easy to implement. For example, it would be an awkward situation to make a collective choice before getting used to the decision environment. Note also that the learning from feedback is not likely to exist as subjects were notified of their payoffs at the end of the experiments.

The constructed pairs within a classroom provide two particular benefits. First, we can study the causal effect of individual characteristics on group decisions, excluding the effect of hidden factors could be related to the self-matching process. Those factors exist in previous experimental evidence on couples' decisions in the literature (e.g., Abdellaoui et al. 2013; Bateman and Munro 2005; Palma et al. 2011; Yang and Carlsson 2016). Couples could have considered the quality of their joint decision in real life in the matching stage.[12] Moreover, couples often tend to develop their own ways of opinion consensus. These factors obviously matter for collective decisions, but they are not directly observable to a researcher.

Second, we might construct a more realistic collective decision environment compared to the joint decision with strangers. Although we may manage this concern by recruiting subjects who are strangers to each other, it might be far different from joint decision environment in reality.[13] As we usually coordinate with someone whom we already know, we believe that it is better to pair up subjects who feel natural to make joint decision with conversations.

[11] There are several papers analyzing differences between individual and group decisions, and they employed either a between-subject design (e.g., Cooper and Kagel 2005; Charness et al. 2007; Shupp and Williams 2007) or an within-subject design in which the order effect is considered explicitly (e.g., Masclet et al. 2009; Deck et al. 2012). On the contrary, for the papers examining aggregation of individual decisions into group decisions (e.g., Ambrus et al. 2015; Palma et al. 2011), subjects are required to participate in individual decisions and group decisions sequentially as in the current paper.

[12] For more discussion on the matching in the marriage market, see Browning et al. (2014).

[13] Ambrus et al. (2015), Baillon et al. (2016), Bone et al. (1999), Charness et al. (2007), Cooper and Kagel (2005), and Deck et al. (2012) are examples of such subject recruitment methods.

3 Data and Parametric Preference Recovery

3.1 Data Description

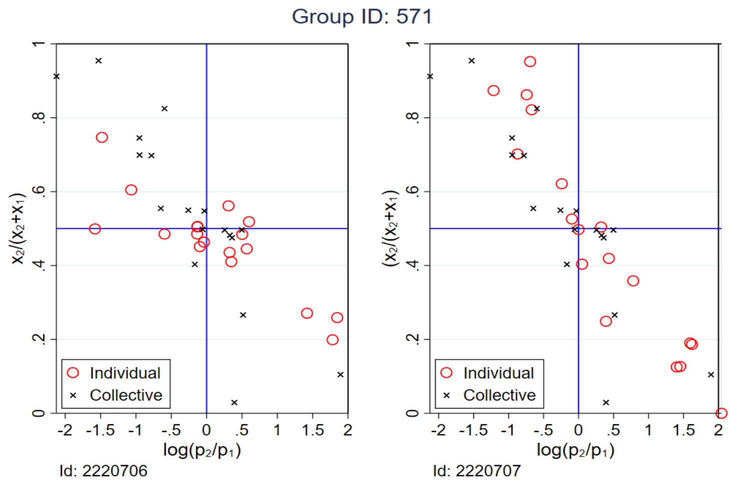
Figure 2 presents an overview of some features of the experimental dataset from individual and collective decisions. There are four sub-figures labeled (a)–(d). Each sub-figure consists of two figures depicting the relationship between the log-price ratio $\log\left(\frac{p_b}{p_r}\right)$ and the investment ratio $\frac{x_b}{x_r+x_b}$ in the members' individual and collective decisions for each pair.

To introduce features of individual and collective decisions, let us start with Figure 2-(a).[14] The figure presents the choices of the subjects in group ID 571, which consists of two members with IDs 2220706 and 2220707. The left figure shows the choices by the member with ID 2220706 and his joint decisions with the partner simultaneously; the red circles correspond to his individual choices, and the black crosses mean the collective decisions. Similarly, the right figure depicts the choices by the member with ID 2220707 and her collective decisions; thus, the left and right figures have common black crosses. Both subjects smoothly responded to prices in their portfolio allocation, although the slope of ID 2220707 is steeper than the other subject. Furthermore, we also find that they made smooth changes of allocations to prices, and the slope is intermediate.

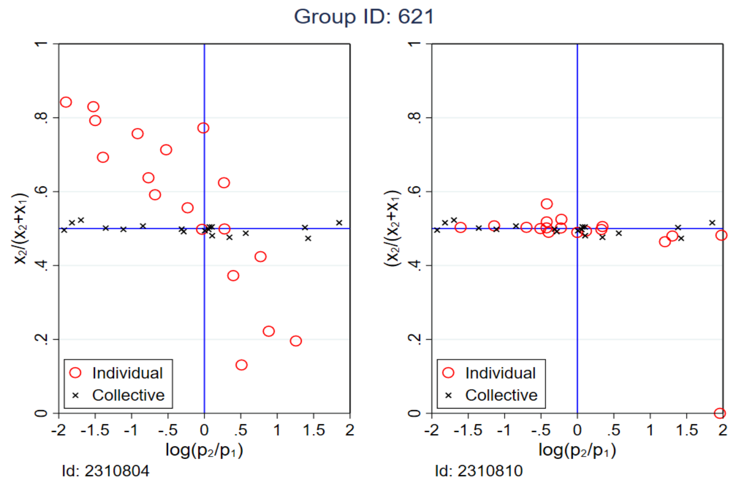
Figure 2-(b) depicts interesting collective choice patterns. On the one hand, the subject with ID 2310804 made smooth choices as the subjects in Figure 2-(a). On the other hand, the subject with ID 2310810 chose nearly safe portfolios of $x_r = x_b$ regardless of the price ratio. When they made collective decisions, they also implemented almost safe portfolios. This feature tells us that the preference of subject with ID 2310810 was substantially reflected in their collective choices.

Figure 2-(c) presents another important pattern of individual and collective decisions. The subject with ID 1410803 allocated all of his wealth to the cheaper one. We can infer that his behavior is consistent with risk neutrality. On the contrary, his partner with ID 1410813 chose

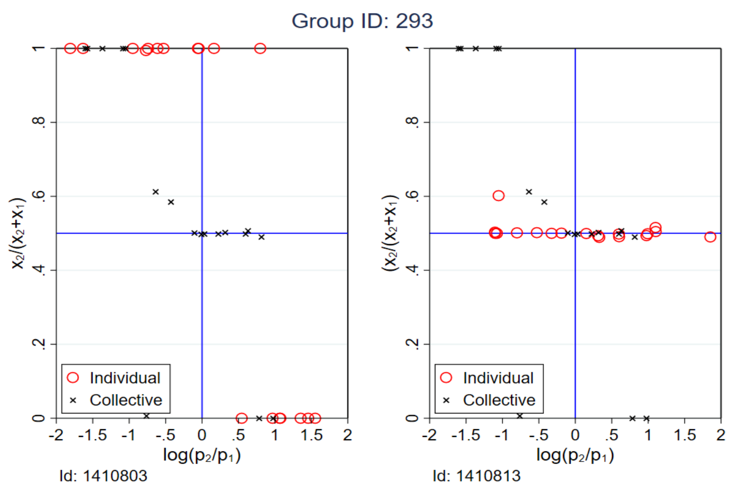
[14] One can find figures for the entire subjects in the online appendix. Click here for a link.



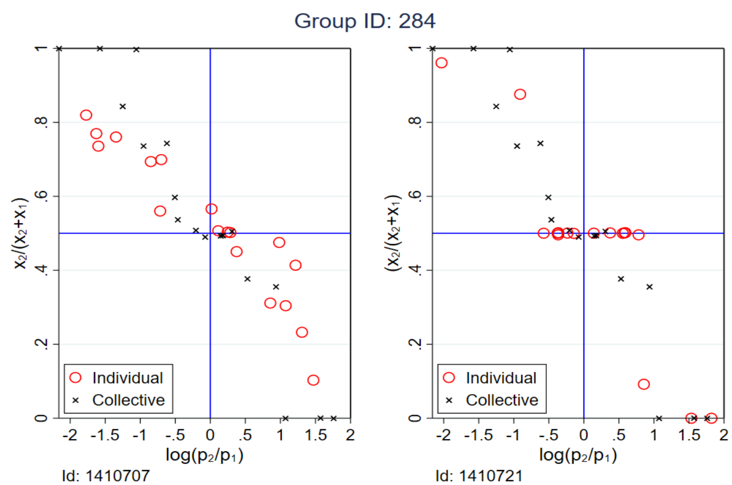
(a) Group ID 571



(b) Group ID 621



(c) Group ID 293



(d) Group ID 284

Figure 2: Examples of the relationships between the log-price ratio and the investment share

almost sure portfolios independent of the price ratios. This behavior would be consistent with infinite risk aversion. Their joint decisions exhibit interesting patterns. On the one hand, if the price ratio was around zero, they chose nearly safe portfolios as the subject with ID 1410813. On the other hand, if the price ratio was substantially different from zero, then they invest all the wealth to the cheaper one as the subject with ID 1410803. Despite the consistency of the members' choice behavior, their collective choices are inconsistent with a standard EU theory.

Figure 2-(d) is the case in which one subject exhibited choice patterns consistent with the EU theory (ID 1410707, the left figure), but the other subject (ID 1410721, the right figure) presents choice behavior that is not. They implemented somewhat smooth responsiveness of portfolio allocations compromising both group members' optimal choices.

The above four figures are illustrating examples, and for most subjects, the dataset exhibits much less regular patterns. Overall, a review of the full dataset reports significant heterogeneity not only across subjects' individual decisions but also across collective decisions by paired subjects with certain regularities. No single theory can exist and explain how characteristics in their own choices extend to those in group decisions. As such, in the following subsection, we explain how we analyze the experimental dataset with a recent technique developed in the revealed preference theory literature.

3.2 Recovery Method

We employ the parametric recovery method of preference suggested by Halevy et al. (2018). For a given triple of a dataset (D), a consistency measurement (f), and a (parametrized) class of utility functions ($\mathcal{U}$), their method returns the *money metric index* (MMI) of $\mathcal{U}$ that represents the incompatibility between the dataset D and the class of utility functions $\mathcal{U}$.[15] The MMI is denoted by $I_M \in [0,1]$, and it can be decomposed by two values. One value is denoted by $I_C \geq 0$ which depends on the consistency measurement f but independent of the utility funciton class $\mathcal{U}$. Thus, $I_M - I_C \geq 0$ measures the cost of restricting the utility functions to have a specific parametric form that a researcher chooses. As such, this method allows us to recover preferences

[15] In the current paper, we require $\mathcal{U} \subseteq \mathcal{U}^c$, where $\mathcal{U}^c$ represents the set of all locally-nonsatiated, acceptable, and continuous utility functions on $\mathbb{R}^2_+$ as in Halevy et al. (2018).

for both consistent and inconsistent subjects.

As for the consistency measurement f, we consider Afriat's *critical coefficient efficiency index* (CCEI).[16] The underlying principle of the CCEI is that if the expenditure at an observation decreases by some number, then any violation associated with the observation disappears. The CCEI is defined as the maximum of the expenditure contractions to eliminate all violations of the GARP.[17] By definition, the original CCEI is identical to $1 - I_C$. In this paper, we use $I_C \in [0, 1]$ as the measure of consistency of a choice dataset, and the closer I_C is to *zero*, the more consistent by construction.

As for the parametric class of utility functions $\mathcal{U}$, we consider the *disappointment aversion utility* (DAU) functions proposed by Gul (1991):

$$U(x; \rho, \alpha) = \alpha u(\max\{x_r, x_b\}) + (1 - \alpha)u(\min\{x_r, x_b\}), \tag{3.1}$$

where $\alpha \in (0, 1)$, and $u : \mathbb{R} \to \mathbb{R}$ is the *constant absolute risk aversion* (CARA)[18] utility function of the form $u(x) = -e^{-\rho x}$ with $\rho > 0$.[19] If $\alpha > \frac{1}{2}$, a subject is said to be elation seeking; but, if $\alpha < \frac{1}{2}$, she is called disappointment averse. Otherwise, if $\alpha = \frac{1}{2}$, then the DAU function is the same as the standard EU function. In this regard, the EU function is a special case of the DAU function.

To classify each subject's utility type as one of the EU or the DAU models, we employ the identification strategy proposed by Halevy et al. (2018). As the EU function takes a particular value of the probability weight α, we evaluate the relative change of the MMI to the cost from misspecification with the EU functions. Specifically, we reject the EU specification if the restriction of $\alpha = \frac{1}{2}$ incurs at least 10 percent increase of the cost. Formally, for a given choice

[16]Of course, the CCEI is not the only way of measuring inconsistency. In Appendix B, we consider Varian's efficiency measure as an alternative inconsistency measurement, and present that the main findings in the current paper are still observed. Chambers and Echenique (2016) provide a comprehensive review of measurements and related theories.

[17]Formally, define a modified revealed preference relation R_e by $x^k R_e y$ if and only if $ep^k \cdot x^k \geq p^k \cdot y$. Define the strict revealed preference relation P_e as $x^k P_e y$ if and only if $ep^k \cdot x^k > p^k \cdot y$. Then, the original CCEI is defined as the supremum over all the numbers e such that the revealed preference pair $\langle R_e, P_e \rangle$ is acyclic. The CCEI is well-defined as the revealed preference pair at $e = 0$ is acyclic obviously.

[18]In Appendix B, we present that all the main findings remain the same when we consider the *constant relative risk aversion* (CRRA) utility function over the wealth space as an alternative utility function class.

[19]Note that a DAU model is equivalent to a rank-dependent utility model (Quiggin 1982) because our decision problem is associated with two states.

datset D, we reject the EU specification if

$$\frac{I_M(D, f, EU) - I_M(D, f, DAU)}{I_M(D, f, DAU) - I_C(D, f)} \geq 0.1,$$

where f is the consistency measure associated with the CCEI, EU is the set of EU functions, and DA denotes the set of DAU functions. [To Euncheol: bootstrapping방식으로도 같은 결과를 준다는 것을 report.]

We close this section by introducing two particular choice patterns that generate identification problems. The first pattern is the case in which all the choices were made at a corner intersecting with either x_r or x_b axis. This behavior can be perfectly rationalized by either the risk-neutral DAU function ($\rho = 0$) or the extremely elation-seeking DAU function ($\alpha = 0$) independent of the risk preference parameter ρ. The other pattern is the case in which all choices were made at the intersection of the budget set and the 45° line. This choice behavior is consistent with either the extremely risk-averse DAU function ($\rho = \infty$) or the extremely disappoint averse DAU function ($\alpha = 1$) independent of the value of ρ. In favor of the standard EU theory, we simply set $\alpha = \frac{1}{2}$ and find a value of ρ that minimizes the MMI for both cases generating an identication problems.[20]

4 Rationality Extension

Table 1 presents summary statistics of the consistency measure I_C from the experimental dataset: the number of observations, the sample mean, standard deviation, and the p-value of the mean comparison test between samples from individual decisions and collective decisions. The averages are 0.897 and 0.910, respectively.[21] The difference is small but statistically significant at

[20]In our dataset, there are XX number of students exhibiting the first pattern. Among them, RESULTS? There are YY students showing the second pattern. Among them, [To Minseon: 여기 숫자 부탁해요].

[21]The average CCEI score in individual decision is slightly greater than 0.881 in Choi et al. (2007), but lower than 0.954 in Choi et al. (2014). However, one should not directly compare these numbers for several reasons. First, subjects are different across the papers. Our subjects are adolescents in South Korea, but the subjects in Choi et al. (2007) were recruited adults from CentERpanel, a Dutch population-representative longitudinal dataset. The subjects in Choi et al. (2014) are undergraduate students from the University of California at Berkeley. Second, in terms of the number of decision rounds, our subjects faced 18 rounds, and it is the smallest as there were 50 and 25 rounds for Choi et al. (2007) and Choi et al. (2014), respectively. Hence, the GARP test is less stringent for our subjects' decisions. The full distributions of CCEI scores from individual and joint decisions are gathered in Appendix A.

the 0.05 level. This finding of more consistent group decisions is in line with previous findings with various games such as the beauty contest (Kocher and Sutter 2004), signaling games (Cooper and Kagel 2005), and predicting the date for ice break-ups in Alaska (Adams and Ferreira 2010).[22]

	Observations	Mean	Standard deviation	p-value
individual decision	1,572	0.897	0.136	0.032
collective decision	786	0.910	0.141	

Table 1: Summary statistics of the CCEI scores

To examine how consistency in individual decisions extends to that in group choices, we first compare the cumulative distribution functions (CDFs) of collective CCEIs by group members' CCEIs. In Figure 3, the solid red line depicts the CCEIs when both members' CCEIs are higher than 0.8; the dotted blue line corresponds to the CCEIs when one subject's CCEI is above 0.8, but the other member's CCEI is below 0.8; and the solid black line exhibits the case when both members' CCEIs are lower than 0.8. One can easily find that the distribution represented by the solid red line first-order stochastically dominates the distribution represented by the blue dotted line, which first-order stochastically dominates the distribution denoted by the black solid line.[23] The finding shows that individual rationality extends to collective rationality.

In order to establish that rationality in group choices is determined by members' individual-level rationality, we consider the following linear fixed effects model:

$$y_g = \alpha + \beta_1 \, \text{CCEI\_Max}_g + \beta_2 \, \text{CCEI\_Distance}_g + \gamma_1 \, X_{(i,j)\in g} + \gamma_2 \, Z_g + \varepsilon_g, \tag{4.1}$$

where y_g the CCEI from group g's decisions, CCEI_Max is the maximum of the members' CCEIs, CCEI_Distance$_g$ is the difference between the members' CCEI values, $X_{(i,j)\in g}$ is the individual characteristics of the members, and Z_g includes other covariates such as school charac-

[22]To test whether any learning effect exists, we split the rounds from individual decisions into the first half and the rest to compare the means and distributions of the CCEI scores for each part. We find no statistically significant difference in the averages. For more details about this study, see Appendix A. However, there still exists a possibility that this higher average of the CCEI in group decisions might originate from learning by introspection as previously discussed.

[23]A series of Kolmogorov-Smirnov tests confirm these conclusions. The Kolmogorov-Smirnov distance between CDF lines of (Low, Low) and (Low, High) groups is 0.18 with corrected p-value 0.03. Corresponding values for (Low, High) and (High, High) group comparison are 0.20, 0.00, respectively.

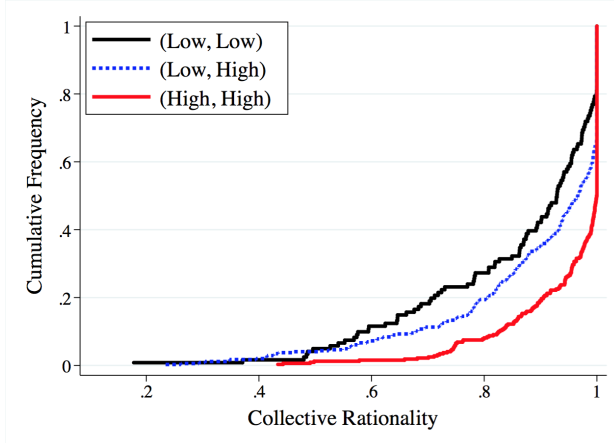


Figure 3: Illustration of rationality extension by first-order stochastic dominance

teristics. To control for any possible bias generated by experimenters, we consider the class-fixed effect, which is not explicitly denoted in the equation.[24] Table 2 summarizes results.[25]

Overall, we find that collective decisions exhibit a higher level of consistency as its members' decisions are more consistent in their individual choices. In particular, the column of Model 1 shows that not only the member with relatively higher CCEI, but also the other member with lower CCEI matters; the coefficient for CCEI_Distance$_g$ is negative and statistically significant. This finding and the degree of individual CCEI levels remain substantial after controlling for other covariates such as math score and friendship, as presented in the last column of Model 2. We also observe that there is a consistency shift in the joint decision (constant positive and significant). Joint decision is more consistent also with larger individual cognitive score, even after controlling individual CCEI scores.[26]

[24] $X_{(i,j)\in g}$ includes group members' cognitive skills measured by their math scores in our survey, their friendship, and their non-cognitive skills.

[25] The corresponding full table is in Appendix A.

[26] To minseon: The relationship between collective CCEI score and math score could be just correlation. Check if math score is still significant after controlling higher order terms of individual CCEIs. If still that's the case, regression result suggest there is something in the cognitive score that boosts up the quality of joint decision, after controlling individual CCEIs. Regression results with higher order terms of individual CCEI are presented in Appendix A. For a related experimental evidence on how education increases individual CCEI, see Kim et al. (2018).

Collective consistency	**Coefficient**	
	Model 1	Model 2
CCEI_Max_g	0.368***	0.302***
	(0.083)	(0.089)
CCEI_Distance_g	−0.277***	−0.233***
	(0.056)	(0.058)
Math_Score_Max_g		0.012**
		(0.005)
$\text{Math\_Score\_Distance}_g$		−0.010**
		(0.005)
Constant	0.582***	0.664***
	(0.077)	(0.084)
Class Fixed Effect	Yes	Yes
Individual Characteristics	No	Yes
School Characteristics	No	Yes
Friendship	No	Yes
Observations	786	786
R-squared	0.200	0.235

Significance: *** (1%), ** (5%), * (10%).

Table 2: Econometric analysis on rationality extension

5 Preference Aggregation

In this section, we report results on relationships between individual and collective decisions. Risk preference is not only determined by the utility parameter ρ, but also the subjective probability weight on the asset returning higher outcome, α. For this reason, in the following subsection, we first present the aggregation of utility types by using the estimated values of α's. Then, by using a single measure of risk preference, we show that individual risk preference does extend to that in group decisions.

5.1 Aggregation of Utility Types

Table 3 summarizes the statistics of utility types parameterized by α, the probability weight for a higher return. Panel A shows the number of observations, the sample mean, standard deviation, and the p-value of the mean comparison test between samples from individual decisions and collective decisions. Panel B–C present the same statistics for restricted samples with I_M,

I_C, and $I_M - I_C$ lower than or equals to 0.1, respectively. The results indicate that collective decisions are closer to the standard EU theory than individual choices.To Minseon: 아래 표 숫자들 업데이트 부탁해요.

	Observations	Mean	Standard deviation	p-value
		Panel A: Complete sample		
individual decision	1,572	0.408	0.491	0.000
joint decision	786	0.539	0.499	
		Panel B: $I_M \leq 0.1$		
individual decision	985	0.359	0.480	0.000
joint decision	553	0.524	0.499	
		Panel C: $I_C \leq 0.1$		
individual decision	985	0.359	0.480	0.000
joint decision	553	0.524	0.499	
		Panel D: $I_M - I_C \leq 0.1$		
individual decision	985	0.359	0.480	0.000
joint decision	553	0.524	0.499	

Table 3: Summary statistics of probability weightings

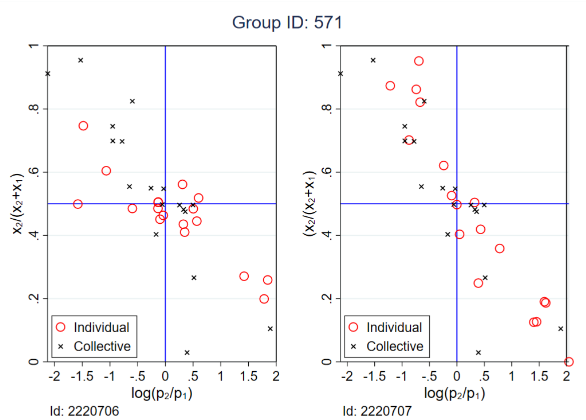
To minseon: 이메일에서 이야기 나눈대로 아래에 simple regression을 한번 넣어봅시다. 이후에 현재와/regression중에 하나 고르지요 Table 4 summarizes the results, and we find that individuals' utility types are reflected to the utility type of the groups. Specifically, when both individuals follow the EU specification, only 25% of their groups follow the DA specification; on the contrary, 60% of the group decisions are well-explained by the DAU if both individuals follow the DAU.

		Collective Risk Type	
		EU	DAU
Individual Risk Type	EU & EU	127	42
	EU & DAU	121	96
	DAU & DAU	27	52

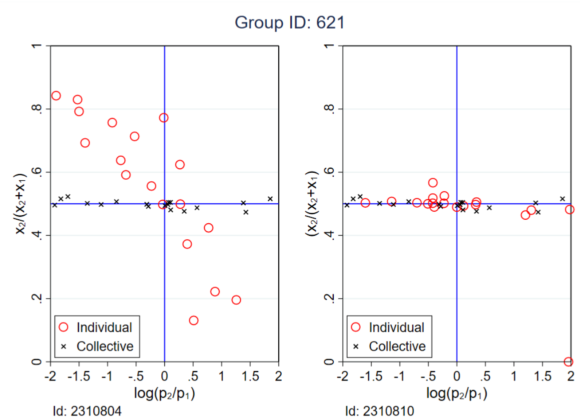
Table 4: Aggregation of utility types

We close this subsection by explaining how choice patterns exhibit utility type aggregation with scatter plots in Figure 4, which are identical to those in Figure 2. Recall that, in each plot, the red circles represent individual choices, and the black crosses denote collective choices.

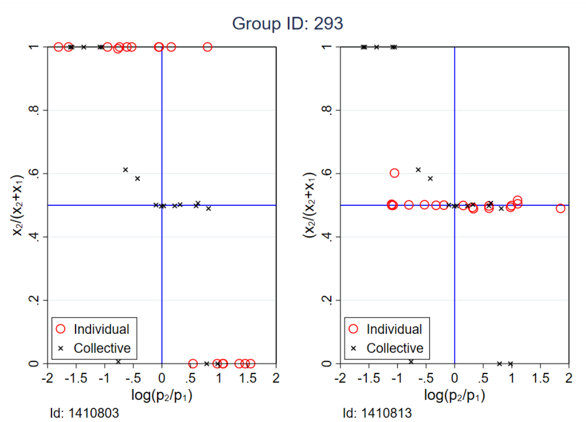
For the subjects in Figure 4-(a) and Figure 4-(b), our recovery method classifies their utility types as the EU model in both individual and their collective choices. However, their individual and collective choices are remarkably different. The subjects in Figure 4-(a) exhibit smooth choice behavior; in their individual and collective choices, the proportion of x_r nicely decreases as p_r increases. The choices in the left of Figure 4-(b) show a similar smooth pattern, but the other choices in the right figure in Figure 4-(b) are accumulated at equal share of x_r and x_b. Interestingly, their collective choices are also tightly accumulated at the equal shares.



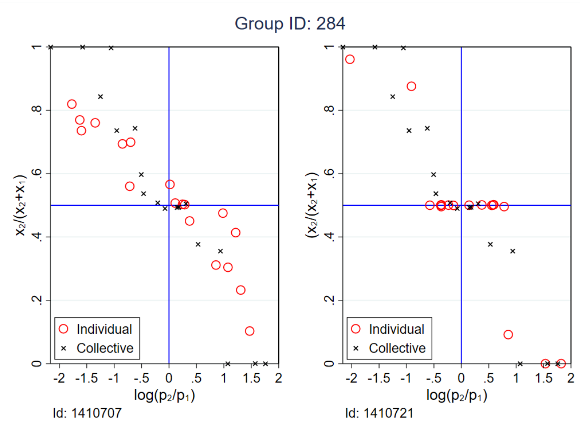
(a) Individually both EU & Collectively EU



(b) Individually both EU & Collectively EU



(c) Individually both EU & Collectively DAU



(d) Individually EU and DAU & Collectively EU

Figure 4: Examples of Risk Preference Type Aggregation

Each subject's utility function in Figure 4-(c) is classified as the EU function based on their individual choice behavior, but their collective decision is classified as a DAU function. The left subject is extremely risk neutral as he chose the intercepts only, but the right individual is extremely risk averse as his choices are accumulated at the equal ratio. The collective choices are similar to the right individual's when the price ratio is close to one. However, when the prices are substantially different, their collective choice behavior is more similar to the left individual's one. This collective choice behavior is well explained by a DAU model with a kink indifference curve. Therefore, the utility function aggregating members' preference is not necessarily in the same class of the members' utility functions.

Figure 4-(d) is the case where one individual's decisions are consistent with the EU theory (the left plot) but the other member's choices are with the DAU theory (the right plot). One can easily find that to some extent, the group made compromised choices reflecting both members' choice patterns. As a result, even though the group decision is consistent with the DAU theory, it is less distinctively than what we see in the right individual's decisions.

5.2 Aggregation of Risk Preferences

We represent risk preference of a decision maker by a single index, which depends on α as well as ρ.[27] This index is based on a risk premium calculation as in Choi et al. (2007). For given values of α and ρ, the risk premium is calculated as $(2\alpha - 1) + 2\rho\alpha(1-\alpha)$.[28] We take this index as a simple measure of subjects' risk preference.

Table 5 presents summary statistics of the individual and collective risk preferences. The average of the risk premium from individual decisions is 0.324, which is strictly greater than the average from joint decisions with statistical significance.[29] This observation indicates that individual decisions tend to be more risk averse. This observation is consistent with several findings in the literature such as Abdellaoui et al. (2013) and Palma et al. (2011).[30]

[27]In the appendix, we show that risk aversion in group decisions reflect those of individual choices using a non-parametric risk aversion measure.

[28]See Appendix C for a proof.

[29]As for the observation in Section 4, this finding can be a result of learning by introspection.

[30]Comparisons of risk preferences in individual and collective decisions depend on experimental design. For examples, groups consisting of more than three members tend to be more risk averse than individuals (e.g., Ambrus et al. 2015; Masclet et al. 2009). Ambrus et al. (2015) argue that it may result from the fact that the distribution of individual risk aversion is so right-skewed. Thus, the median individual who plays a pivotal role in collective decision has a preference of more risk-averse than the mean individual. When it comes to groups of two people, there is less consensus. For instance, Abdellaoui et al. (2013) and Palma et al. (2011) state that individuals are more risk averse as in our observation; but Bateman and Munro (2005) report the opposite.

	Observations	Mean	Standard deviation	p-value
	Panel A: Complete sample			
individual decision	1,572	0.408	0.491	0.000
joint decision	786	0.539	0.499	
	Panel B: $I_M \leq 0.1$			
individual decision	985	0.359	0.480	0.000
joint decision	553	0.524	0.499	
	Panel C: $I_C \leq 0.1$			
individual decision	985	0.359	0.480	0.000
joint decision	553	0.524	0.499	
	Panel D: $I_M - I_C \leq 0.1$			
individual decision	985	0.359	0.480	0.000
joint decision	553	0.524	0.499	

Table 5: Summary statistics of probability weightings

[은철: 위의 테이블 risk premium 버전으로 update? 여러개의 panel을 구성? appendix로 보내야 할 것들과 구분...]

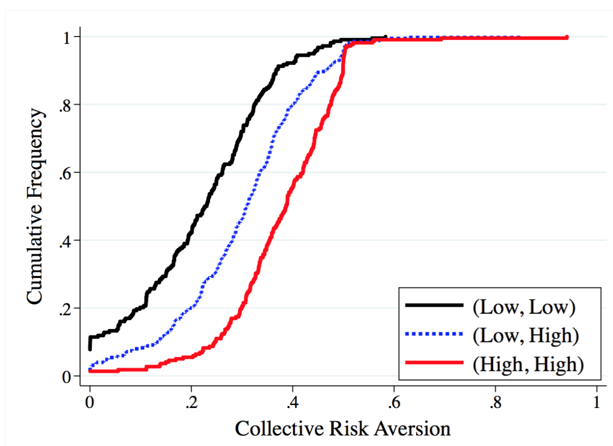


Figure 5: Risk Aggregation by Individual Risk Attitudes

Figure 5 illustrates how collective risk preferences are related with the composition of individuals'. The red line represents the CDFs of the risk-aversion measure when the group consists of both members' measures are above the median. The blue line corresponds to the cumulative distribution for the groups consisting of one member above the median and one member below the median. The black line is for the groups when both members are below the median. One can observe that there exist natural first-order stochastic dominance relationships between the CDFs.

To present robustness of the preference aggregation, we consider the following linear fixed effects model:

$$y_g = \alpha + \beta_1 \,\text{Risk\_Aversion\_Max}_g + \beta_2 \,\text{Risk\_Aversion\_Distance}_g + \gamma_1 X_{(i,j)\in g} + \gamma_2 Z_g + \varepsilon_g, \tag{5.1}$$

where y_g the risk aversion measure of group g, Risk_Aversion_Max$_g$ is the maximum of the members' CCEIs, Risk_Aversion_Distance$_g$ is the difference of the members' CCEI values, $X_{(i,j)\in g}$ is the individual characteristics of the members such as their math scores (cognitive skill) in our survey, their friendship, and their non-cognitive skills, and Z_g includes other covariates such as school characteristics. Table 6 presents the result.[31]

Collective risk premium	**Coefficient**	
	Model 1	Model 2
Risk_Premium_Max	0.792***	0.759***
	(0.066)	(0.073)
Risk_Premium_Distance	−0.421***	−0.434***
	(0.053)	(0.062)
Math_Score_Max		0.000
		(0.005)
Math_Distance		0.005
		(0.004)
Constant	0.004	−0.175**
	(0.027)	(0.077)
Class Fixed Effect	Yes	Yes
Individual Characteristics	No	Yes
School Characteristics	No	Yes
Friendship	No	Yes
Observations	786	786
R-squared	0.372	0.382

Significance: *** (1%), ** (5%), * (10%).

Table 6: Preference Aggregation

We find that as a group contains a member of higher risk aversion, if other things are equal, the group tends to make a more risk-averse choices. In particular, we observe that the member

[31] The corresponding full table is in Appendix A.

with lower risk aversion also matters in prefernce aggregation as well as the member who is highly risk averse. These findings hold after controlling for other covariates, and they coincides with the findings in the literature (e.g., Abdellaoui et al. 2013; Bateman and Munro 2005; Palma et al. 2011; Deck et al. 2012).[32]

6 Welfare Assessment

In this section, we analyze how the quality of the group decision is determined by members' consistency and risk preferences. To this end, we first introduce a measurement of welfare in the following subsection. Then, we provide the determinants of the welfare.

6.1 Measurement

The bottom line of our welfare evaluation is that there is a possibility of increasing the utility of two subjects simultaneously if a collective choice is *not* Pareto efficient. To normalize utility loss for each subject, we measure the equality of a group decision as the average ratio of the wasted utility to the possible maximum waste. We explain the details as follows.

We identify the set of Pareto-efficient choices in our experimental setting. A collective choice problem of two subjects is illustrated by Figure 6. The black solid line represents a budget line with $p_b > p_r$. Let x^i denote the optimal portfolio choice of agent i. Thus, the black solid curve represents the indifference curve of subject 1, which is tangential to the budget line at x^1.[33] Similarly, the blue dotted curve denotes the indifference curve of subject 2, which is tangential to the budget line at x^2. It turns out that any choice on the linear budget line located between the ideal choices is Pareto-efficient.[34]

We measure inefficiency of the subjects' collective choices only when they are not Pareto-

[32]Several papers find that with an one-dimensional measure of risk aversion, the group risk aversion is summarized by a convex combination of the individuals' aversion measures (e.g., Abdellaoui et al. 2013; Ambrus et al. 2015; Baillon et al. 2016; Bateman and Munro 2005; Palma et al. 2011; Deck et al. 2012). For instance, in Deck et al. (2012), for about 92.8% of the subject pairs, their joint risk aversion measure falls in between the members'. However, with a non-parametric measure of risk aversion in Appendix B, only 38.5% of the subject pairs exhibit a collective risk aversion in the middle of individuals' aversion measures. Moreover, for another 38.5% of pairs, their collective was smaller than the the minimum of the group members' risk aversion. [To minseon: Is this correct? Please check it again. We may delete some of this this footnote.]

[33]This shape of the indifference curve means that subject 1's utility type is elation-seeking.

[34]See Appendix C for a formal proof.

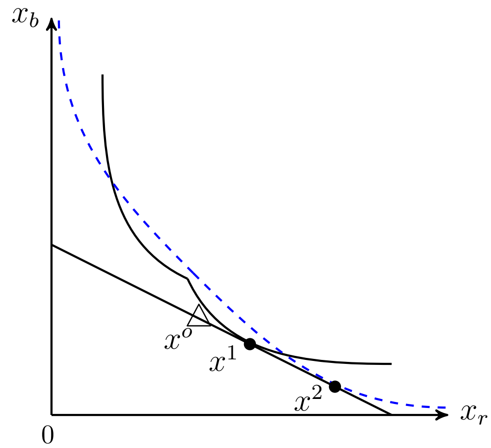


Figure 6: Illustration of Inefficiency Measurement

efficient. x^o on the budget line in Figure 6 is such an example, and there is a way to increase both subjects' utility. As a reference choice, we set the *closest* Pareto-efficient choice, and measure the differences of the utilities between the observed and the reference choices. For instance, the closest switch from the observation to a Pareto-efficient choice is x^1. To normalize utility loss for each agent, we measure divide the difference by the utility difference between her worst choice and the reference choice. The ratio takes a value between zero and one. Of course, if the subjects make a Pareto-efficient choice, then it is the closest reference choice. Thus, the welfare loss is measured as zero.

For each pair, we calculate the welfare loss as the average of the utility loss ratios:

$$\text{Average welfare loss} = \frac{1}{18}\sum_{k=1}^{18}\frac{1}{2}\sum_{i=1}^{2}\frac{U^i(x_{kr}) - U^i(x_{kc})}{U^i(x_{kr}) - U^i(x_{kw})},$$

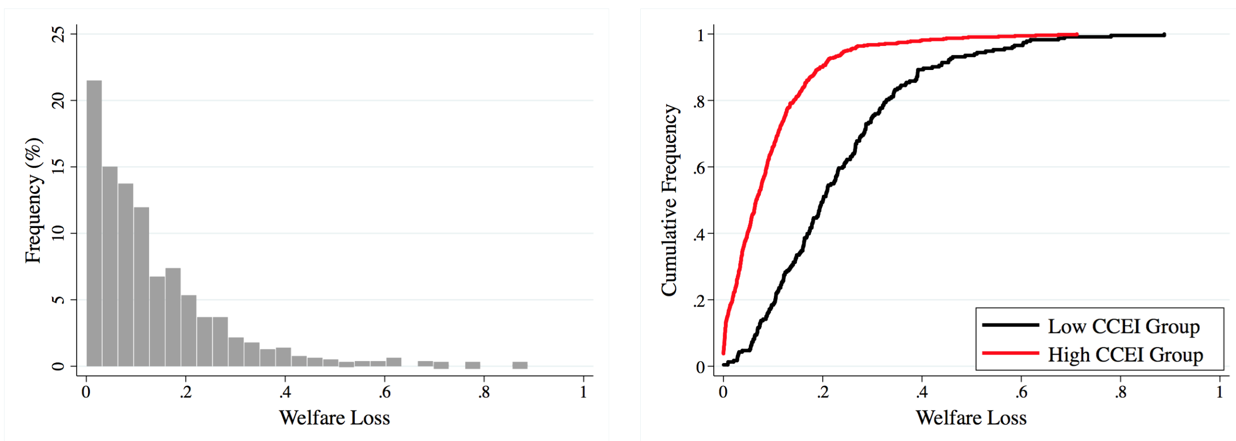
where U^i is the estimated utility of subject i, x_{kc} is group's choice in the k-th round in the experiment, x_{kr} is the corresponding reference choice, and x_{kw} means the worst choice of subject i in k-th round in the experiment.

We finally remark that our measure of welfare loss may misrepresent quality of the subjects whose risk preferences are closely aligned. For example, consider one extreme case where $x^1 = x^2$. To make a Pareto-efficient choice, they need to choose the exact optimal choice. On the other extreme is that x^1 is located at the 45° line, but x^2 is located at the intersection with x_r-axis. For this pair, it is highly likely that the subjects will make a Pareto-efficient choice.

This is a common problem with linear budget constraint experiments, and we will discuss how this problem affects our analysis in the next subsection.[35]

6.2 Data and Results

Figure 7-(a) presents the distribution of welfare losses from our dataset. One can see that more than 20% of decisions are Pareto-efficient, but there also exists substantial proportion of the group decisions involving high welfare loss.



(a) distribution of welfare loss

(b) heterogeneous welfare loss by group CCEI levels

Figure 7: Distributions of Welfare Loss

To find determinants of group decision qualities, we first find that subjects pairs making consistent decisions with utility maximization theory generates lower welfare loss. Specifically, Figure 7-(b) presents that the CDF of the pairs with lower I_C values is first-order stochastically dominated by the CDF of higher I_C values. Now, to argue that this finding is robust, we conduct an econometric analysis, which results in Table 7. Overall, the table confirms that the group-level consistency is a crucial determinant for the quality of group decisions after controlling for other possible factors such as individual-level consistency and risk preference.

Model 1 – Model 3 shows how welfare loss is related to the individual CCEI levels; as each group member tends to behave like a utility maximizer, the corresponding group choice also more likely to be explained by a utility maximization model. In terms of risk preference, the

[35] See Halevy et al. (2018) for more discussions.

quality of group decision increases as subjects have more similar risk preference. However, it can be due to the limitation of the experimental design and the welfare measurement. That is, as the subjects' ideal portfolio choices get far away from each other, it becomes easier for the group to make a Pareto-efficient choice.

Group Inefficiency	**Coefficient**			
	Model 1	Model 2	Model 3	Model 4
CCEI_Group	-0.571^{***}	-0.503^{***}	-0.527^{***}	-0.414^{***}
	(0.042)	(0.039)	(0.043)	(0.078)
CCEI_Max		-0.296^{***}	-0.242^{***}	-0.692
		(0.045)	(0.051)	(0.671)
CCEI_Distance		0.165^{***}	0.178^{***}	0.289
		(0.042)	(0.052)	(0.257)
Risk_Aversion_Max		-0.009	0.023	-0.024
		(0.056)	(0.063)	(0.089)
Risk_Aversion_Distance		-0.057^{*}	-0.073^{*}	-0.123^{*}
		(0.031)	(0.040)	(0.066)
Math_Score_Max			0.002	0.008
			(0.005)	(0.007)
Math_Distance			-0.004	-0.010
			(0.003)	(0.006)
Constant	0.651^{***}	0.866^{***}	0.807^{***}	1.154^{*}
	(0.038)	(0.048)	(0.061)	(0.653)
Class Fixed Effect	Yes	Yes	Yes	Yes
Individual Characteristics	No	No	Yes	Yes
School Characteristics	No	No	Yes	Yes
Friendship	No	No	Yes	Yes
Observations	786	786	786	274
R-squared	0.442	0.487	0.497	0.436

Significance: *** (1%), ** (5%), * (10%).

Table 7: Welfare Determinants

Model 4 is the report of the same regression restricted for the groups consisting of high CCEI subjects. In particular, we require both group members to have CCEI higher than 0.9. It turns out that the relationship between the individual CCEI's are still related to the group CCEI's, but not statistically significant. The notable observation is that the group CCEI is still positively related to the group CCEI's substantially.

[Euncheol: bargaining?]

7 Related Literature

This paper relates to three strands of literature.

Standard revealed preference theory and experiments.

The household problems.

Rationality Extension

[Minseon: More discussion about Arrow (1950) and subsequent theoretical papers?]

Whether individual rationality extends to that of group is also a theoretical question, where the conclusion could vary depending on the theoretical framework. If the group preferences can be represented as a convex combination of individual utility functions as in cooperative model from family economics ((Browning, Chiappori, and Weiss (2014)), individual utility functions' satisfying GARP is a sufficient condition for group utility functions' being consistent. In contrast, following bargaining approach (Nash ())[36] or a non-cooperative model from family economics (Browning, Chiappori, and Weiss (2014)), individual rationality does not necessarily result in that of group.

Notably, all of these theories assume that each group member is rational. Therefore when at least one of individual choices are not consistent to utility maximization, there is not much guidance from the theory. If any, learning from joint decision could happen. From revealed preference approach, GARP also measures the waste from the inconsistency of the decision. By making decisions in a pair, subjects can learn how to minimize this cost, increasing CCEI measure. This view is in line with that from papers that show groups' decisions are more consistent with predictions from economics theory (Kerr, MacCoun, and Kramer (1996), Cooper and Kagel (2005), Charness, Karni, and Levin (2007), Adams and Ferreira (2010), Charness and Sutter (2012), Carbone, Georgalos, and Infante (2019))

Meanwhile, unitary model (Browning, Chiappori, and Weiss (2014)) or representative agent model (Lucas (1976)) just impose a well-behaving group utility function that does not have to be necessarily a function of individuals' utility functions. Following this approach, group

[36] really?

rationality is imposed and whether individual rationality is a necessary condition for group rationality is vague.

We did not impose any decision process, so any one of these theories can happen. Especially, quantifying the relationship between individual nationalities and group rationality could be an empirical question even if we adopt just one theoretical point of view.

Risk Preference Aggregation

We cover two main questions in relation to risk preference aggregation. The first question, whether individual risk aversions are reflected in that of group has been dealt with by previous studies with different subject pool and decision environment.

One of main differences across papers is the number of subjects in a group.

decision in pair: Bateman and Monroe (2005), De Palma, Picard, and Ziegelmeyer (2011), Deck, Lee, Reyes, and Rosen (2012), Bone, Hey, and Suckling (1999), Abdellaoui, l'Haridon, and Paraschiv (2013)

decision in group with more than three people: Shupp and Williams (2007), Masclet et al. (2009), Jackson and Yariv (2011), Ambrus, Greiner, and Pathak (2015, JPubE)

In contrast to the first main question, there has been little evidence on how individual probability weighing types are aggregated into that of group. Bone et al. (1999) first ask a question if group decision violates common ratio property less often than individuals do. But even with within-subject design, they present little evidence on how the weighting types are aggregated into group decision. More recent paper, Bateman and Monroe (2005), follows the similar structure.

Abdellaoui et al. (2013) investigates more on the probability weighting type aggregation. Using choices between a fixed lottery and a varying certainty equivalent, they estimate the utility function using Non-linear Least Squares (NLLS) and conclude that couple's decision departs from EUT as much as individuals decisions do (on average), and the probability weighting from joint decision is a convex combination of those of members, with the weight of 0.4 on that of women.

However, they did not partial out the effect of inconsistency from EU violation. We measure both consistency and probability weighting type, which makes this distinction possible. Also, they wrote as if the convex combination of utility functions is equal to the convex combination of risk aversion/ probability weighting parameters. We dig into the issue of Pareto efficiency on the utility domain in the next section.

Welfare analysis.

In his canonical paper, Harsanyi (1955) shows that given both individual and group preferences satisfying Von Neumann-Morgenstern axioms, an weak assumption on the link between individual and group preferences[37] suffices to derive that the group preferences can be represented as a weighted sum of individual utility functions.

Pareto efficiency has been assumed in the literature of family economics. Logic: repeated game in a stable environment (Chiappori (1998)) Chiappori and De Rock et al. present parametric/ non-parametric testing for this Pareto efficiency assumption respectively, when researchers only can observe joint decision. Thanks to the experimental design, we can observe both individual and joint decision. We present a simple and intuitive way to test Pareto efficiency given this rick data. It might not be applicable to other studies that do not have individual decisions. But our data and measure give clear picture about the Pareto efficiency which at least can help other studies judge how strong the efficiency assumption is.

It could be violated. ludber and Pollak (2003) show that the household decision could be inefficient when the decision environment is non-stationary (one-shot decision).

Testable implications from the literature? Testing so far has been binary: reject or do not reject the testable implication. Has there been ANY paper that measures the degree of inefficiency? isn't it only possible when you can estimate both individuals utility functions separately?

same Pareto weight over 18 choices? or time-varying weight should be allowed too? knowledge about the repetition

[37] *Postulate c. - If two prospects P and Q are indifferent from the standpoint of every individual, they are also indifferent from a social standpoint*

- did not know that they will be matched to the same partner at the end of the semester
- did know that they make 18 times of joint decision
- did not know the budget set coming up next

utility representation of group decisions.

We here note that Note that we use the same functional form for individual and group decision. Jackson and Yariv (2019) show this is impossible if the group decision is known to be Pareto efficient, which we do not impose. [Minseon: more discussion about the specification error from MMI?]

8 Conclusion

A Appendix: Tables and Figures

A.1 Additional Tables and Figures for Section 2

[Non-cognitive survey questionaires, (1) Rosenberg self-esteem scale (reference?), (2) life satisfaction (reference?), and (3) perception about studying (reference?)]

[Some basic statistics of the non-cognitive survey results]

A.2 Additional Tables and Figures for Section 3

A.3 Additional Tables and Figures for Section 4

[Full distributions of CCEIs]

[Comparisons of the first half and the rest.]

[Full table here]

A.4 Additional Tables and Figures for Section 5

[Full distributions of utility types]

[Full distributions of risk premiums]

[To 은철: check whether there was any subject greater than $\frac{1}{2}$; maybe add some statistics here? 횟수 / 사람 명수 / CCEI와의 연관성; because low/high is classified by the median. MS: See Dropbox/RP/Data/FOSD.log]

[Full table here]

A.5 Additional Tables and Figures for Section 6

B Appendix: Robustness Checks

B.1 Alternative Consistency Index

[Tables with Varian measure]

B.2 Alternative Utility Parameterization

[Tables with CRRA utility function]

B.3 Non-Parametric Approach to Preference Aggregation

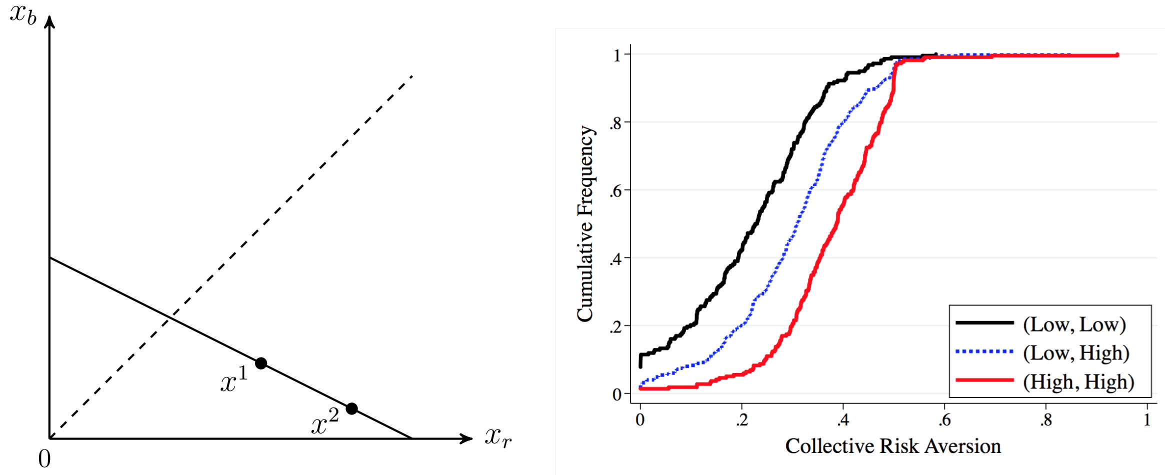
For each choice in a given budget set, we measure the degree of risk aversion as the relative demand share of the expensive asset at the choice. The budget set in Figure 8-(a) describes a situation in which x_b is more expensive than x_r (i.e., $p_b > p_r$). When a choice j is represented by $x^j = (x_r^j, x_b^j)$, we calculate the risk aversion of the choice by $\frac{x_b^j}{x_b^j + x_r^j} \in [0, 1]$, which measures the ratio of the more expensive choice.[38]. Since the probability of choosing each state is exactly $\frac{1}{2}$, a extremely risk-neutral agent chooses the corner solution that maximizes the expected value. In this case, our risk measurement returns zero. On the contrary, extremely risk averse agent should choose a point on the 45° degree line which returns the risk aversion measure of $\frac{1}{2}$. Therefore, the bigger the measure is, the more risk aversion.[39] In figure Figure 5-(a), choice 1 captures larger risk aversion than choice 2. We use the average of risk aversion of 18 choices to summarize individual or pair risk aversion.

Table 8 presents summary statistics of the individual and pair risk aversion. The average of risk aversion from individual decisions is 0.324, which is strictly greater than the average from joint decisions with statistical significance[40]. This observation indicates that individual

[38]Conversely, if $p_b < p_r$, then the risk preference is measured by $\frac{x_r^j}{x_b^j + x_r^j}$

[39]Note that a choice with the ratio strictly greater than $\frac{1}{2}$ is first-order stochastically dominated by any other choices with a ratio strictly lower than $\frac{1}{2}$. In our data, 22.89% of individual decisions (6,477 out of 28,294) and 21.12% of group decisions (2,988 out of 14,148) were first-order stochastically dominated. These numbers significantly drop if we use the cutoff of 0.6 rather than 0.5, allowing a trembling around the the intersection of the 45° line and the budget line. Specifically, 2,276 and 812 choices among individual and pair decision have the risk aversion grater than 0.6. More detailed discussions are in the Appendix.

[40]Same as in section section 4, could be because of learning by introspection.



(a) Illustration on (x_r, x_b)-space

(b) distribution of risk preferences

Figure 8: Risk Aggregation by Individual Risk Attitudes

decisions tend to more risk averse, which has been also shown in Abdellaoui et al. (2013) and De Palma et al. (2011).[41]

	Observations	Mean	Standard deviation	p-value
individual decision	1,572	0.324	0.132	0.000
joint decision	786	0.298	0.139	

Table 8: Summary Statistics of Risk Preferences

Figure 8-(b) shows how group-level risk preferences are related with the composition of individual-level preferences. The red line represents the cumulative distribution of the risk-aversion measure when the group consists of both members' measures are above the median. The blue line corresponds to the cumulative distribution for the groups consisting of one member above the median and one member below the median. The black line is for the groups when both members are below the median. One can observe that there are natural first-order stochastic dominance relationships between the groups.

[41] Previous studies show various results depending on the experimental designs. Studies with groups consisting of more than three members find that groups are more risk averse than individuals (Ambrus et al., 2015; Masclet et al., 2009). Ambrus et al. (2015) argues that it results from that the distribution of individual risk aversion is so skewed that the median individual is more risk-averse than the mean individual, and they are pivotal in group decisions. On the contrary, there is less consensus from experiments with groups of two people. While De Palma et al. (2011) and Abdellaoui et al. (2013) show that individuals are more risk averse, Bateman and Monroe (2005) reports that group decision are more risk averse. Also, in Deck et al. (2012), it depends on the winning probability.

To present robustness of the preference aggregation, we consider the following linear fixed effects model:

$$y_g = \alpha + \beta_1 \, \text{Risk\_Aversion\_Max}_g + \beta_2 \, \text{Risk\_Aversion\_Distance}_g + \gamma_1 \, X_{(i,j)\in g} + \gamma_2 \, Z_g + \varepsilon_g, \tag{B.1}$$

where y_g the risk aversion measure of group g, $\text{Risk\_Aversion\_Max}_g$ is the maximum of the members' CCEIs, $\text{Risk\_Aversion\_Distance}_g$ is the difference of the members' CCEI values, $X_{(i,j)\in g}$ is the individual characteristics of the members such as their math scores (cognitive skill) in our survey, their friendship, and their non-cognitive skills, and Z_g includes other covariates such as school characteristics. Table 6 presents the result.[42] As a group contains a member of higher risk aversion, if other things are equal, the group tends to make a more risk-averse choices. This finding still holds after controlling for other covariates.

Collective Risk Aversion	**Coefficient**	
	Model 1	Model 2
Risk_Aversion_Max	0.792***	0.759***
	(0.066)	(0.073)
Risk_Aversion_Distance	−0.421***	−0.434***
	(0.053)	(0.062)
Math_Score_Max		0.000
		(0.005)
Math_Distance		0.005
		(0.004)
Constant	0.004	−0.175**
	(0.027)	(0.077)
Class Fixed Effect	Yes	Yes
Individual Characteristics	No	Yes
School Characteristics	No	Yes
Friendship	No	Yes
Observations	786	786
R-squared	0.372	0.382

Significance: *** (1%), ** (5%), * (10%).

Table 9: Preference Aggregation

To sum up, 1) both individuals' risk aversion affect that of pair and 2) there is a risk-aversion shift in the pair decision. Even with different choice environment and risk aversion measure, the

[42]The corresponding full table is in Appendix A.

first result coincides with findings from the previous studies (Abdellaoui et al. 2013; Ambrus et al. 2015; Baillon et al. 2016; Bateman and Munro, 2005; De Palma et al., 2011; Deck at al., 2012). Especially, studies on the pair decision (Abdellaoui et al. (2013), Bateman and Munro (2005), De Palma et al. (2011), Deck et al. (2012)). On the contrary, previous studies have shown that the one-dimensional measure of group risk aversion can be represented as a convex combination of those of group members (Abdellaoui et al. 2013; Ambrus et al. 2015; Baillon et al. 2016; Bateman and Munro, 2005; De Palma et al., 2011; Deck at al., 2012). For example, in Deck at el. (2012), for 92.8 % of the pairings, the pair choice falls weakly inside the range defined by the individual choices. On the contrary, in our experiment and non-parametric measure, 303 pairs out of 786 pairs have group risk aversion in the middle of those of two individuals. Meanwhile, 303 pairs have a collective risk aversion that is smaller than the minimum of individual risk aversion within the pair.[43]

[43]Why? Hard to give a concrete evidence, only conjectures. The usual setting, Multiple Price List (MPL) in the previous studies is simpler than our choice environment. Or, could be coming from order effect. Unlike consistency, there seems to be an order effect in the risk aversion parameter.

C Appendix: Proofs

C.1 Derivation of the Risk Premium Index

We here briefly explain the index of the risk preference. One can find details of the index in Choi et al. (2007). The risk aversion index is based on the notion of *risk premium*. Consider an agent with initial wealth of M_0 and a hypothetical lottery that returns $(1-h)M_0$ or $(1+h)M_0$ with equal probabilities. The risk premium of this lottery r satisfies the following equation:

$$u((1-r)M_0) = \alpha u((1-h)M_0) + (1-\alpha)u((1+h)M_0),$$

where u is a Bernoulli utility function over the wealth space.

If u is the CARA function of the form $u(x;\rho) = \frac{-e^{-\rho x}}{\rho}$, then the above equation becomes

$$\frac{-e^{-\rho(1-r)M_0}}{\rho} = \alpha\frac{-e^{-\rho(1-h)M_0}}{\rho} + (1-\alpha)\frac{-e^{-\rho(1+h)M_0}}{\rho}.$$

By rearranging terms, we obtain the following expression and the approximation of the risk premium as a function of h:

$$r(h) = 1 + \frac{1}{\rho M_0}\log\left(\alpha e^{-\rho(1-h)M_0} + (1-\alpha)e^{-\rho(1+h)M_0}\right) \approx (2\alpha-1)h + \left(2\rho M_0\alpha(1-\alpha)\right)h^2.$$

When the initial wealth is normalized by $M_0 = 1$ as in our experiment, we finally obtain the risk premium index as $r(1) = (2\alpha - 1) + 2\rho\alpha(1-\alpha)$. By repeating the above procedure with a CRRA utility function of the form $u(x;\rho) = \frac{x^{1-\rho}}{1-\rho}$, one can verify that the above index is a risk premium index for the CRRA utility funciton as well.

C.2 Proofs in Section 6

We here provide a proof of claim in Section 6.

Claim 1 *Let $U^i = \alpha u^i(x_{\max}) + (1-\alpha)u^i(x_{\min})$ be a utility function of agent $i \in \{1,2\}$, where $\alpha \in (0,1)$, and $u^i : \mathbb{R}_+ \to \mathbb{R}_+$ is an strictly increasing and strictly concave utility function. For a given budget line $B(p_1,p_2,I) = \{(x_r,x_b,I)\,|\,p_1x_r + p_2x_b = I, x_r \geq 0, x_b \geq 0\}$, let x^i be the optimal portfolio choice for agent i with $x^1 \neq x^2$. Then, $x = (x_r,x_b) \in B(p_1,p_2,I)$ is Pareto efficient if and only if it is a convex combination of x^1 and x^2.*

Proof. We first find that an indifference curve of U^i is not necessarily convex if $\alpha < \frac{1}{2}$ (i.e., an elation seeking type); however, each of its restricted indifference curves defined as the intersection of the indifference curve and the region under the 45° line is strictly convex. Throughout the proof, without loss of generality, we assume that $p_2 > p_1$ and $U^1 \neq U^2$.

Fix $x \in B(p_1, p_2, I)$, which is not a convex combination of x^1 and x^2. Then, without loss of generality, we can assume that there exist some $t, s > 0$ such that

$$x = \frac{tx^1 - sx^2}{t - s} \quad \text{and} \quad t > s.$$

Since the restricted indifference curves below the 45° line for agent 1 and agent 2 are convex, it follows that $U^i(x_r, x_b) \leq U^i(x_r^2, x_b^2)$ for all $i \in \{1, 2\}$, and the inequality is strict for at least one agent. Thus, x is not Pareto efficient.

We now prove the converse. Let x be a convex combination of x^1 and x^2. Suppose, by a way of contradiction, that there exists $y = (y_1, y_2) \in B(p_1, p_2, I)$ that Pareto dominates x. Without loss of generality, we assume that

$$U^1(y_1, y_2) > U^1(x_r, x_b) \quad \text{and} \quad U^2(y_1, y_2) \geq U^2(x_r, x_b).$$

Since the restricted indifference curves below the 45° line for agent 1 and agent 2 are strictly convex, if such y exists, it must be that $y_1 < y_2$. Let $z = (y_2, y_1)$, which is the reflection of y over the 45° line. Since the indifference curves of agent 1 is symmetric about the 45° line, it follows that $U^1(y_2, y_1) = U^1(y_1, y_2) > U^1(x_r, x_b)$. Thus, z is located in the strict upper-contour set of the indifference curve passing through x. Since $p_2 > p_1$, it follows that $p_1 y_2 + p_2 y_1 < I$. Since the restricted indifference curves of agent 1 are convex below the 45° line, we have

$$U^2(y_2, y_1) = U^2(y_1, y_2) < U^2(x_r, x_b),$$

which contradicts the assumption that y Pareto dominates x. Therefore, we conclude that x is not Pareto dominated by any portfolio on the budget line. ■

D Online Appendix A

To minseon: 일단 여기에 작업하고, 나중에 online appendix로 만들지요.

D.1 Instruction

D.2 Sample Screenshots

D.3 Survey Questions and Statistics

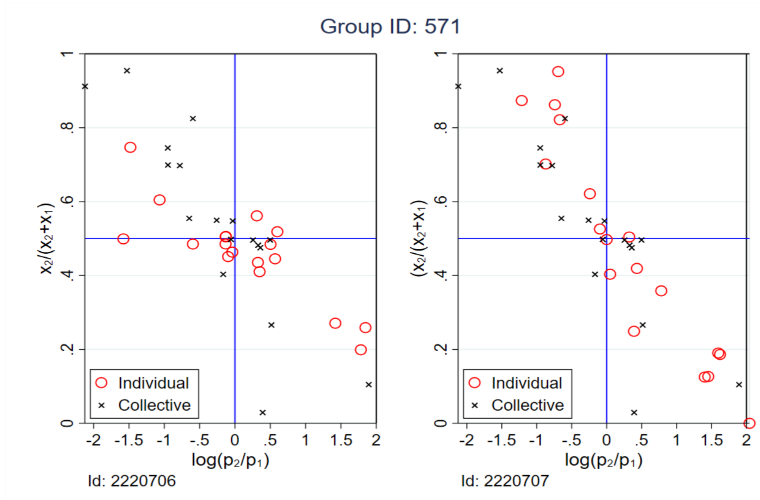
Cognitive attributes.

Non-cognitive attributes.

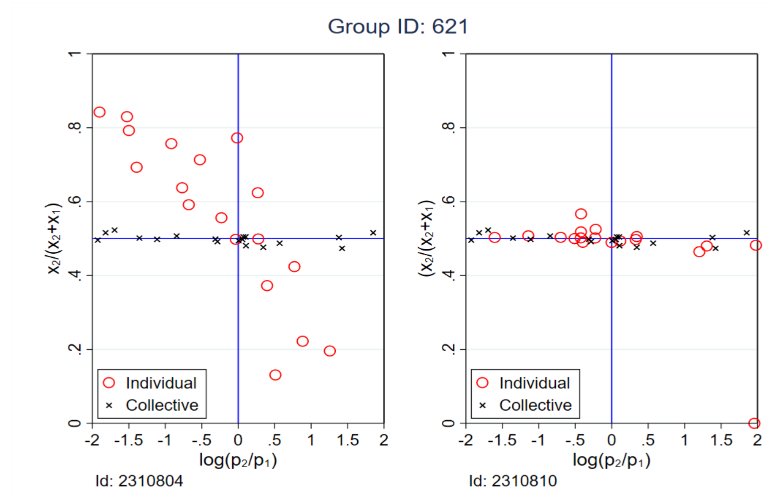
E Online Appendix B

We here collect all the figures of individual and group decisions.

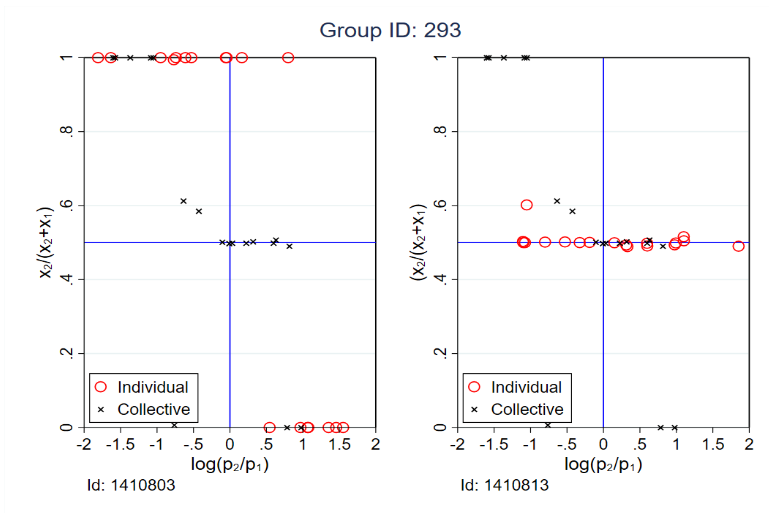
To Minseon: 이것을 위한 코드를 따로 하나 만들어야 할 것 같아요. latex로 옮기는건 제가 RA를 고용할게요.



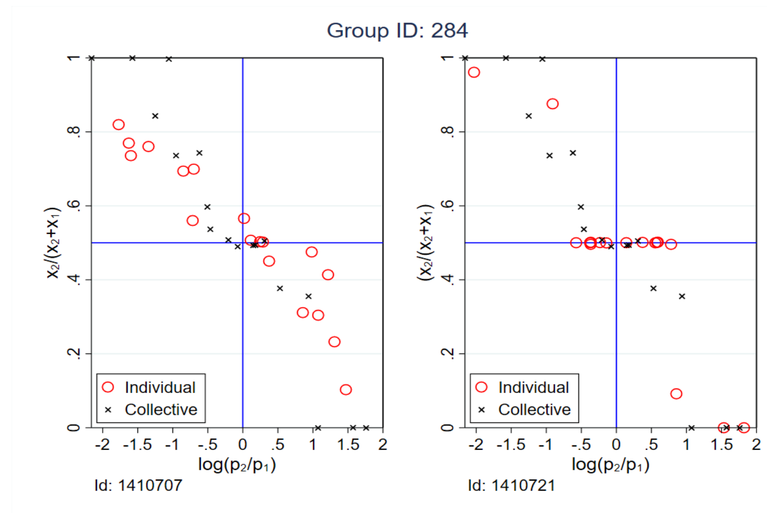
(a) Group ID 571



(b) Group ID 621



(c) Group ID 293



(d) Group ID 284

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