Behind the Veil of Ignorance: Risk Aversion or Inequality Aversion?

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Abstract

This paper successfully decomposes risk attitude and social preference behind the veil of ignorance. Using a novel experiment wherein subjects move graphically along a slider to divide a pie of money between high and low reward in both lottery and VoI treatments, we are able to collect rich data sets at individual level. We check individual preference characteristics including consistency and homotheticity in pure risk and in distributive scenarios and employ two structure models to estimate underlying motivations. The results show aversions of unequal distribution behind VoI are not the same concepts as risk aversions and they are highly heterogeneous among subjects. A significant amount of subjects demonstrate other-regarding preference in the sense of aversion for unequal distribution and of not being jealous when receiving low rewards.

KEYWORDS: Vei of ignorance, Social preference, Risk attitude

1 Introduction

The idea of the "veil of ignorance"(VoI) i.e., that individuals who make choices for society do not know the assignment of others and their own social and economic positions in advance, has a long tradition in the literature (for example, Vickrey [1945, 1960]; Friedman [1953]; Harsanyi [1953, 1976]; Rawls [1958, 1971]; Kolm [1998]). In Rawls's famous "A Theory of Justice", VoI was termed as a foundation for theories of social justice, and since then an enormous body of literature has utilized that framework to study distributive justice. When determining income distribution behind the veil of ignorance, individuals are faced with a situation that is strikingly similar to that of choosing a lottery. Harsanyi [1953] proposed that under the assumption of equiprobability of each possible position, the choice of a particular income distribution would be a clear instance of a choice involving risk. Dahlby [1987] also showed that in the Harsanyi framework, many inequality indices can be interpreted as measuring the riskiness of an income distribution as viewed from veil of ignorance.

However, large literatures have shown that subjects exhibit social preferences in laboratory experiments, especially those in which distributive justice is an important consideration. In the existence of social preference, it is often argued that the evaluation of income distribution behind VoI would consist of both a risk component and a distributive concern (Cowell and Schokkaert [2001]). Is this truly the case? If so, can risk preference and social preference be represented by well-behaved preference orderings? And how can these two preferences be identified and separated behind VoI?

In this paper, we explore those questions by eliciting individual preferences in both lottery and VoI environments. In the lottery case, a subject allocates some money between two state-contingent commodities (high reward and low reward) with equal probability to be realized. While in the VoI case, a subject decides the distribution of some money between himself and his counterpart without knowing which part he will receive. The risks are the same in these two cases. Consequently, if a subject exhibits other-regarding preference or inequality aversion, he would choose a more equal income distribution in the latter case than in the first. This also means his indifference curve should be more concave in the VoI environment. By comparing choices made by the same subject in the above two environments, we can recover individual preference and thus apply nonparametric techniques in order to check preference characteristics including rationality and homotheticity. Furthermore, structured parametric models would allow us to decompose individual preference behind VoI into a notion of risk and a notion of distributive concerns. The analyses of these two components would provide us more insight into understanding perception of risk and perception of distributive preferences, as well as the relationships between risk and social preference.

We achieve this by an innovative experiment design wherein subjects can graphically move along a slider to decide proportions of a pie of money between high and low reward. All possible proportions are induced from linear budget sets, which provide us access to consumer demand theory in analyzing individual preference. In addition, this construction applies well both in lottery and VoI environments. In the case of the lottery environment, utilities are maximized between two state contingent commodities, while in the VoI environment, utilities maximization is between two possible distributions – one of the pair would receive low reward and another one high reward. Variations of these budget sets across decision periods allow us to collect a rich individual-level data sets and thus to compare and decompose underlying motivations in different environments.

We begin our analysis with an overview of individual behavioral types, from which we can intuitively observe several types of indifference curves in two treatments. We then employ revealed preference theory to test whether individual choices are consistent with utility maximization and whether utility functions are homothetic. We find that almost all 92 subjects behave rationally and the measurements are quite efficient when compared with 4600 hypothetical subjects. A large number of subjects do not exhibit homothetic indifference curves. When the income level increases, the demand for risk and inequality can either decrease or increase. We then employed two structure models to decompose different motivations. We found aversions of unequal distribution behind VoI are not the same concept as risk aversions and that they are highly heterogeneous among subjects. A significant amount of subjects demonstrate other-regarding preference in the sense of aversion for unequal distribution and of not being jealous when receiving low rewards.

The rest of the paper is structured as follows. In section two we briefly summarize related literature. In section three, we introduce the experiment design and procedures. Section four describes both aggregate and individual data. In section five, we outline the revealed preference analysis. Section six explores the econometric analysis and section seven proposes future work. Section eight concludes the paper.

2 Literature Review

This paper first relates to experimental literatures of social preference. Abundant laboratory and field experimental evidence suggest that the classic economic model of selfish economic agent fails and that subjects exhibit social preference. For example, subjects show altruism by offering a fraction of endowments to partners in the dictator game (Forsythe et al. [1994]) and reject unfair allocations in the ultimatum game (Güth et al. [1982]); they contribute in the public goods game (Isaac and Walker [1988]) and reciprocate in the trust game (Berg et al. [1995]) by returning positive amounts of money. To incorporate these anomalies into a unified economic theory, many models have been proposed to explain preferences over the distribution of payoffs in the game. For example, the inequality aversion models by Fehr and Schmidt [1999] and Bolton and Ockenfels [2000]; the quasi-maximin model by Charness and Rabin [2002][henceforth CR]; the altruism model by Andreoni and Miller [2002] [henceforth AM], Messer et al. [2010] and Cox and Sadiraj [2006] [henceforth CS]; and the competitiveness model by Fisman et al. [2007]. A handful of recent laboratory studies have used simple distributional experiments and their variants to test these models. However, the results are quite ambiguous. In a paper which reviewed models and experimental evidences of distributive preference, Engelmann and Strobel [2007] [henceforth ES] concluded that a large variety of distributional motives including maximin preferences, efficiency concerns, inequality aversion, and competitiveness have an impact on the choices in purely distributional games.

There is rarely consensus regarding the relative importance of each motivations of distributive preference in the literature. Among them, the most intensive conflict ones are efficiency concerns and inequality aversion. Engelmann and Strobel [2004, 2006, 2007] conducted a three player dictator game wherein the dictator has a fixed, intermediate income and can choose among three different money distributions between a high-income and a low-income person. They found efficiency concerns and maximin preferences are stronger than inequality aversion and thus violate inequality aversion models. Bolton and Ockenfels [2006] and Fehr et al. [2006] argued that ES's experimental design and subject pools might make efficiency more favorable. They separately conducted new experiments and found inequality aversion is more important than efficiency concern.

The reasons for these arguments are mainly due to measurements of importance and interaction of other distributive motivations. The first reason means how trade-offs are measured in these distributive games. For example, in some dictator-type games, the importance of efficiency and inequality are quantified indirectly by how much sacrifice of their own payoffs subjects are willing to make for each motivation; while in other games where subjects choose or vote among several distributions, the trade-offs are made between efficiency and inequality directly. In most cases, these quantifications of trade-offs are dependent on specific experiment set-ups and thus will generate contradictory results. The second reason is that in many strategic distributive experiments (eg. CR and CS), concerns other than distributional motivations matter. For example, the choice of fair distribution might result from reciprocity or beliefs, rather than from inequality aversion.

In our experiment, the measurement of trade-offs belongs to the second category. Subjects were able to directly compare efficiency and inequality by simply observing size and division of the pie and thus can make decisions. Since all distributional proportions are induced from linear budget sets with slopes larger than one, the greater the proportion of the pie assigned to low reward, the smaller the total pie size would be and this will vividly show in the interface via shrinking the pie. To ensure the absence of selfishness and to elicit impartial individuals, veil of ignorance is essential to our experiment. In addition, VoI helps to isolate other strategic considerations such as reciprocity and competitiveness. In this simple distribution task, there is no second stage and, no second match or feedbacks of others, so reciprocity is not a concern here. The setting is also free from competitiveness concern because no one knows their position until the end of the game. Also, VoI guarantees the same context as in risk environment, which makes individual results comparable and also makes the decomposition possible.

This paper also contributes to the links between risk and inequality. There are several studies in which preferences over inequality and risk are identified. Generally, these studies fall into two categories. In the first category, inequality aversion measures are derived from a social welfare function and then are compared with existing risk aversion parameters. For example, in Atkinson [1970]'s seminal work on measuring inequality aversion, a social welfare function was constructed as an additive function of individuals' utilities that is in the form of a constant relative risk aversion (CRRA) function. Amiel et al. [1999] estimated inequality aversion parameters in this social welfare function through a leaky-bucket experiment, where respondents were hypothetically able to transfer money from a rich individual to a poor one, incurring a loss of money in the process. They found a rather low inequality aversion compared with most existing estimates of risk aversion. This result can be explained by Chambers [2012], who theoretically shows that if one social welfare function is less inequality averse than another, the household preference induced by optimally allocating aggregate bundles according to this social welfare function is less risk averse than the other.

There is also a large amount of literatures regarding experiments wherein subjects are presented with trade-offs between equality and efficiency and are required to choose or rank several income distributions as an impartial social planner (Scott et al. [2001]; Michelbach et al. [2003]; Traub et al. [2005, 2009]; Bernasconi [2002]). This approach automatically involves assumptions that welfare functions exist and that inequality or risk preferences can be inferred from these functions. However, these conditions might not be satisfied. Another point is that payoffs for social-planners are not related to income distributions they choose for society, which may lead to the concern of whether incentives are compatible in the experiment.

Another category rooted in Harsanyi [1953]'s point of view is that, inequality aversions are measured in terms of representative individuals' attitudes to risky situations. For this category, an estimation of inequality aversion is a simple analogue to risk aversion. Rothschild and Stiglitz [1973] discussed the formal analogy of mathematical structures between inequality and risk aversion. For experiments in this category (for example, Johannesson and Gerdtham [1995]; Beckman et al. [2002]; Johansson-Stenman et al. [2002]), subjects are also presented with the task of choosing distributions for the society, but in this case, they are one member of the society, though they may not know what their position will be. The more an individual is willing to give up in order to achieve a more egalitarian distribution, the more averse the individual is to inequality. This conclusion is based on the assumption that individuals are risk neutral when making decisions. Otherwise, behaviors can be the result of either risk aversion or inequality aversion.

There is scarce literatures explicitly separating risk aversion and inequality aversion through individual choice approach. Schildberg-Hörisch [2010] used a dictator game in risk and VoI treatments in order to test whether decisions behind the veil are driven by risk attitudes alone or also by social preferences. By controlling the individual risk preference through risk treatment, they found that on average, subjects appear to be more risk averse in VoI than in risk treatment. However, using a similar experiment design, Frignani and Ponti [2012] obtained the opposite results – that the behaviors of subjects under the veil of ignorance are dominated by risk aversion. Other works on differentiating risk and inequality aversion behind veil of ignorance are non-incentivized questionnaire studies, including Amiel and Cowell [1994, 2000], Amiel et al. [2009], Kroll and Davidovitz [2003], Bosmans and Schokkaert [2004] and Carlsson et al. [2005].

This paper takes steps down the same path as Schildberg-Hörisch [2010] and Frignani and Ponti [2012]. We adopt the context of an induced budget experiment approach where choices are inferred from linear budget lines with varying slopes across periods. This approach first provides more information than binary choices made in

Frignani and Ponti [2012]. Second, a wide range of budget sets with varying slopes provides more variations of the trade-offs between efficiency and equality than in Schildberg-Horisch [2010] where the transfer rates is fixed with a 50% efficiency loss. These variations allow for statistical estimations of individual preference rather than estimations through pooling data or assuming homogeneity across subjects. This induced budget experiment approach was proposed by Andreoni and Miller [2002] in a dictator game with varying transfer rates. Choi et al. [2007a,b], Fisman et al. [2007] fully developed this technique in studying individual choices under uncertainty, preferences for giving (trade-offs between own payoffs and the payoffs of others) and social preference (trade-offs between the payoffs of others) in front of the veil of ignorance. Becker et al. [2013a,b] provided a theoretical framework to decompose preferences into a distributive justice and a selfishness part. They also tested the theory by conducting an experiment which is a combination of a dictator game with either a social planner or a veil of ignorance experiment. Compared to these studies, this paper addresses different research questions. With the combination of risk and VoI treatments, we are able to isolate risk preference and social preference at the individual level. In addition, subjects in our experiment were presented with a graphic and thus user-friendly interface with the task of splitting a pie both in both lottery and distribution case. These choice scenarios provide more meaningful and intuitive settings for efficient elicitation of individual preference.

The primary contributions of this paper are the elicitation and decomposition of individual preference over risk and social preference behind veil of ignorance. The novel experimental technique provides real situations of splitting a pie in two environments and allows for the collection of rich individual data about preferences. The application of revealing preference techniques and structured parametric analysis allows us to probe relationships between risk attitude and social preference, which will provide additional interpretations and insights in studies on distributive justice, social preference and public policy making.

3 Experimental Design

3.1 Utilities

In our experiment, individuals made decisions both in lottery and VoI environments. In the lottery treatment, subjects decided the allocation of some money between two state contingent commodities – High Reward and Low Reward, denoted as y and x respectively. Subjects could either receive the money allocated to High Reward or to Low Reward with equal probability of 50%. The two states of nature were denoted as s_h and s_l, then preference orderings over consumption of two commodities (x, y) can be represented by a function of the following form:

$$L(x, y) = \frac{1}{2}U(x, s_l) + \frac{1}{2}U(y, s_h)$$

In the VoI treatment, subjects still decided the allocation between High Reward and Low Reward. However, this time, they chose the distribution of a pie of money between themselves and another subject who was paired with them. If they received the High Reward, their partner would receive the Low Reward and vice versa. Keeping the denotations the same as in lottery treatment, the preference orderings over consumptions of the distribution (x, y) can be represented by the following function form:

$$V(x, y) = \frac{1}{2}U(x, y, s_l) + \frac{1}{2}U(y, x, s_h)$$

Our aim in the experiment is to compare decisions made in these two environments and furthermore, to decompose the motivations behind them. Theoretically, if motivations in the VoI environment contain both risk aversion and other-regarding concerns, the marginal rate of substitution between x and y in the VoI case should be larger than in the lottery case. It also can be inferred that there are differences existing in curvatures of indifference curves of $V(x, y)$ and $L(x, y)$, as well as in corresponding demand curves. These concepts in classic demand theory would provide us tools for decomposing social preference and risk preference.

3.2 Budget Sets

In each period of lottery treatment and VoI treatment, subjects were asked to allocate a budget set between two rewards. A typical budget set can be represented by:

$$y + px = z$$

where p is the price of low reward and z is the biggest possible pie size. For each choice of consumption bundle (x, y), the pie size is $x + y$. In the experiment, we set

p larger or equal to one, indicating that there is an efficiency loss when assigning more proportions of a pie to Low Reward. According to this linear budget line, each one more dollar assigned to Low Reward will bring a constant decrease of $p - 1$ in pie size. It also means that for each 1% increase in proportions for Low Reward, the rate of efficiency loss is not constant – the larger the current proportions assigned to High Reward, the higher the efficiency loss rate.

There are 40 budget sets for each treatment. The prices for the Low Reward are ranging from 1 to 5 and the incomes are from 50 to 260 with steps of 30. Compared with other induced budget experiments, these variations are much larger and more controlled, which is essential for both within and between subjects analysis.

The full menu of budgets offered is shown in Figure 1. In the experiment, instead of directly presenting subjects with budget sets, we designed an innovative graphic interface with which subjects choose the proportions of High and Low Reward. Each proportion can be represented in a ray from origin. For example, suppose coordinates of point A in Figure 1 is (65,195), then a blue ray pass through origin and point A is the proportion line of 195/(65+195)=75%. Thus, each proportional choice made will determine a point on the budget line. We restricted the proportion for High Reward no less than 50% of total pie size and Low Reward no larger than 50% to avoid confusion. This is equivalent to restricting decision areas for proportion line from 50% to 100%, which are indicated by thick lines in the figure.

3.3 Experimental Procedures

We ran our experiment in November 2013 at the Financial and Experimental Economics Laboratory (FEEL) at Xiamen University. A total of 92 subjects were recruited via ORSEE (Greiner [2004]) and came from a broad range of majors. We conducted 9 sessions and each one lasted around 100 minutes. The payment was 55yuan on average.

Each session contained two stages and each stage consisted of 40 independent decision problems. After stage 1 was completed, a break of 10 minutes followed in order to refresh minds for subjects. Stage 2 then commenced. All budget sets, default points on the slider are same in these two stages, but they appeared in different orders.

Upon arrival, each subject drew a number card from an opaque box and was guided

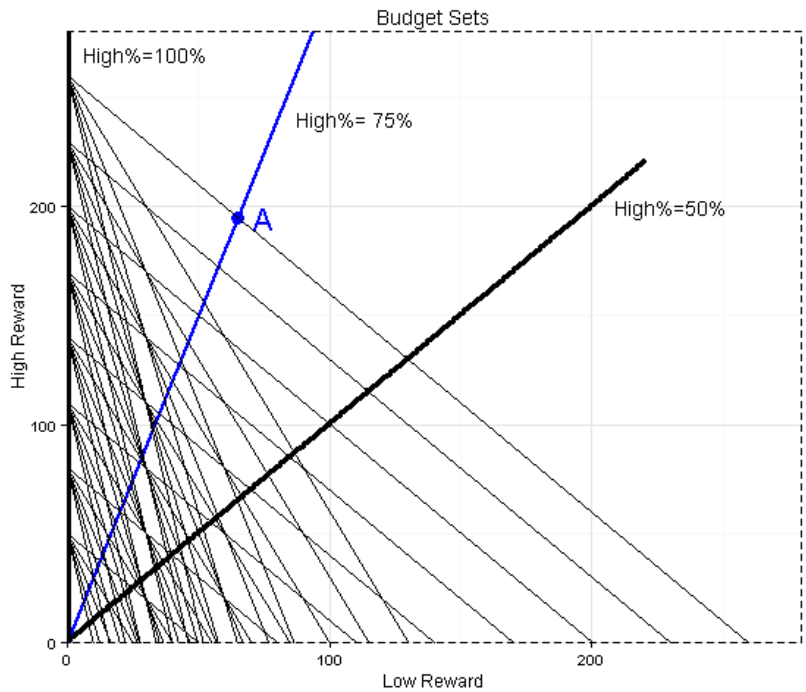

Figure 1: Budget Sets in the Experiment

to a computer desk. Then the instruction (Appendix A.1) of stage 1 was read aloud to all participants and they would receive a hard copy as well. All participants were informed that a second part of the experiment would follow after the break. At the end of the instruction, all questions were answered and a simple quiz was required to be finished to ensure that all subjects understood the experiment. In stage 2, the procedure was similar. A new instruction (see Appendix A.2) was distributed and again read aloud to all participants and then a quiz was also to be completed. After both experiments in stage 1 and stage 2 were completed, participants were to fill out a questionnaire regarding their understanding of the experiment, their socio-demographic issues and their self-reported risk attitudes.

A typical experiment interface is illustrated in the Figure 2. The pie indicates shares allocated to High (red) and Low (blue) Rewards. When a subject made division choices by moving the green triangle along the slider, shares for High and Low in the pie as well as the size of the pie would change accordingly in the graph. The table on the right hand side shows the current and the nearest divisions of the pie (Low%

and High%), the amount of Low Reward and High Reward (Low$ and High$) as well as the current size of the pie (Total$). These monetary values are calculated from the budget set in current period. By checking this table, subjects were able to find the monetary assignment between two rewards and possible efficiency loss. The calibrations of the slider are set either from 0% to 50% or from 50% to 100%, indicating proportions allocated to Low Reward or High Reward, respectively. The minimum proportion change both on the slider and in the table is 1%. In another words, in each period, there are a total of 50 proportion lines intersect with the current budget line in 50 points. Each point is represented by one point on the slider and one line in the table and the subject chose their most preferred one point on a budget line.

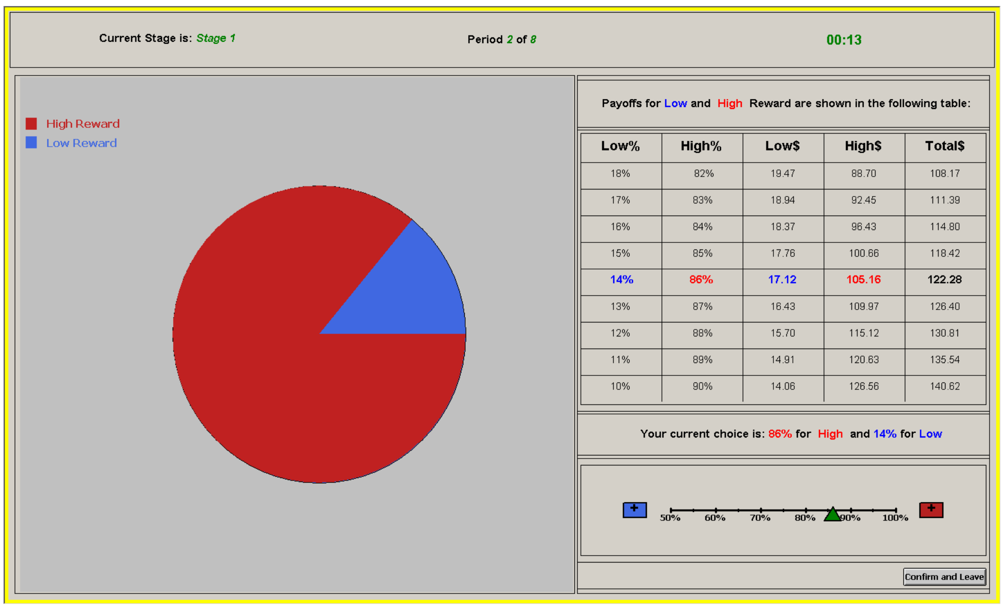

Figure 2: Decision Screen

In the experiment, we had two treatments and two interfaces. One is assigning proportion for Low Reward (0%-50%) and the other one for High Reward (50%-100%). To account for ordering effects and interface effects, we had four framings shown in Table 1. Others are same, such as orders of budget sets appeared in one session or default points on the slider in one period. Subjects in the same session had the same framing.

After 80 periods were finished, only one of 80 periods will be randomly selected as

Table 1: Experimental Framings

Framing	Treatment 1	Treatment 2	Interface
VLH	VoI	Lottery	High
LVH	Lottery	VoI	High
VLL	VoI	Lottery	Low
LVL	Lottery	VoI	Low

the payment period. Contingent on the payment period belongs to stage 1 or stage 2, the payment method was different. If the randomly selected period is in stage 1, each subject will toss their own individual coin to determine whether they receive the High or Low Reward. If the randomly selected period is in stage 2, only one of two divisions will determine payoffs for the pair and one of the pair will receive the High Reward and the other the Low Reward. We only pay one period until experiments finished because we don't want to introduce income effect.

4 Data Description

In this section, we first give a brief summary of aggregate data in Lottery and VoI treatments. Then we move to individual data by presenting several illustrative behavior types. An overview of experimental data shows that there are several heterogeneous decision patterns both in risk and distribution scenarios, however, the differences between these patterns are highly likely to be hidden behind aggregate data.

4.1 Aggregate Data

Table 2 reports means and standard errors of proportional and monetary amounts allocated to High Reward in two treatments. For all 40 budget sets, average proportions allocated to High Reward are 72.65% in Lottery treatment and 72.27% in VoI treatment. The differences are quite small with regard to means and variances. To make further comparison, we also list same statistics in different framings. Although variations between the two treatments are much larger than in the overall case, the directions of change are quite contradictory. For example, if we compare VLH and LVH framing, it seems that the first treatment incurs more unequal or risky choices. However, this principle doesn't hold for comparisons between VLL and LVL. The same contradiction also exists in comparisons between framings with the same ordering.

Table 2: Summary Statistics of Choices in Two Treatments

Framing	#sbj	L%(H)	V%(H)	L$(H)	V$(H)
VLH (A)	28	70.77(14.54)	72.45(14.40)	79.86(49.24)	83.19(49.55)
LVH (B)	22	74.33(13.52)	71.74 (14.99)	86.54(49.26)	82.12(50.45)
VLL (C)	22	74.21(14.98)	73.21(16.06)	86.35(50.77)	86.1154.92
LVL (D)	20	71.72(15.45)	71.57(16.61)	83.39(53.20)	83.39(53.47)
Total	92	72.65(14.69)	72.27(15.45)	83.78(49.68)	83.67(51.59)

We formally test framing effects in Appendix B. The ordering effects are examined between VLH&VLL and LVH&LVL, and interface effects between VLH&LVH and VLL&LVL. We employed a paired t test and a Wilcoxon rank sum test to see whether there were significant differences of means and distributions between the two treatments. p values reported in Table B1 show that there are ordering effects in proportional choices made in the VoI treatment, which means implementing VoI treatment first will encourage subjects to choose more unequal distributions in a VoI environment. However, ordering effects don't appear in the case of monetary choices. Distributions of VoI choices in four framings (See Figure B1) show great similarities between framings with the same interface but different orders. Thus, ordering effects found here can be ignored in the following analysis of pooling data.

We also report results of treatment effects at the aggregate data level (see Table B2 in Appendix B). We use a t test to check whether means of proportional choices and monetary amounts assigned to High Reward are the same for different framings and for aggregate data. We also use asymptotic Wilcoxon signed rank test to see whether the distributions of two paired vectors are the same. The results show that proportional choices made in Lottery treatment are significantly larger than those in VoI treatment. This means that in the aggregate level, subjects exhibited other-regarding preferences or inequality aversion. By checking results for four framings, we can come to a similar conclusion in framing B and C, but not in A and D.

More interestingly, choices made in framing A show that subjects allocate a higher proportion to High Reward in lottery treatment than in VoI treatment, which implies that they may display inequality-loving.

4.2 Individual Data

The results of aggregate data have shown that treatment effects may be in two opposite directions. Since pooling data together may offset effects in these two directions, in this section, we move to data at the individual level, which may help us to reveal some behavioral patterns among subjects.

To begin with, we summarize the results of individual treatment effects (see Table B3 in Appendix B). Around 40% of subjects don't show significant difference choices between two treatments and 34% chose a more risky lottery in Lottery treatment than in VoI treatment, which clearly implies that a number of people exhibited social preference. Surprisingly, 26% of individuals allocated a greater proportion to High Reward in VoI treatment than in the Lottery. The preference for inequality can be explained by the fact that efficiency concerns dominated social preferences for these subjects.

Next, we presented choices made by 10 illustrative subjects (see Figure B2 in Appendix B). These subjects were chosen because their behaviors corresponded to several prototypical preferences which exhibit striking regularities within subjects and heterogeneity across subjects.

The first six subjects made similar decisions in lottery and VoI treatment. Subject 89 always chose (50%, 50%) allocations in two treatments, which is consistent with the Leontief utility function ($U(x, y) = min(x, y)$). He may possess infinite risk aversion in Lottery treatment or infinite inequality aversion in VoI treatment. Subject 22 allocated all tokens to High Reward which maximized the total pie size. This behavior is consistent with perfect substitution utility function ($U(x, y) = x + y$), indicating he may have been risk neutral in the Risk task and demonstrated utilitarian social preference in the VoI task. Subject 56 chose allocations with the same expenditures on both rewards, which is consistent with maximizing Cobb-Douglas utility function ($U(x, y) = xy$). Subject 48 chose fixed proportions for High Reward and Low Reward. In addition, Subject 61 and Subject 79 preferred certain fixed amounts for one of two available commodities (High Reward for Subject 61 and Low

Reward for Subject 79) and allocated the rest of the money to another commodity. These behaviors imply that the subjects preferred floors and ceilings while choosing consumptions of two state-dependent commodities or of income distribution for the pair.

We also found that some subjects displayed certain mixed-type preferences. For example, Subject 74 always chose an equal split when the price for Low Reward was one but allocated all of the money to High Reward when the price was higher than one. This behavior is consistent with maximizing expected utility in Lottery treatment. It also indicated that this subject cared about distributive efficiency in VoI treatment.

The rest of the illustrative subjects exhibited distinct behaviors in two treatments. To save some space, we will report only four subjects with remarkable changes. Subject 4 allocated almost all the money to High Reward in the Lottery treatment, which clearly indicates risk-loving preference. But in VoI treatment, this subject chose an equal split of pie, which indicates that the subject was inequality averse when his decision might determine payments of another subject. Moreover, the inequality aversion Subject 4 demonstrated was strong enough to dominate the risk loving motivation. The direction of behavioral change is totally the opposite for Subject 46. In the Lottery treatment, his choice was quite consistent with the Cobb-Douglas utility function, meaning that this subject tried to balance risk by spending the same money on two rewards. However, in VoI treatment, utilitarianism dominated risk preference and the prior motivation of this subject was to obtain the biggest pie for the pair. For Subject 58, his choices in Lottery treatment were consistent with maximizing Cobb-Douglas utility, but he chose more equal distributions in a VoI environment.

Of course, there are cases wherein the regularities are less clear. We found some subjects whose choices exhibited different mixed-type preferences in both treatments and thus defied easy classification. However, an overall review of the data set reveals striking regularities within and marked heterogeneity across subjects, which may be covered within pooled data, so in the following section, we focus mainly on individual behaviors. With our rich individual-level data set, we can further investigate these regularities and heterogeneity and answer questions such as whether choices made by subjects are consistent, whether preferences are homothetic and whether the difference in two treatments can be justified by structured models.

5 Testing Consistency and Homotheticity

In this section, we turn to the problem of recovering underlying preferences using revealed preference techniques. First, we answer the question of whether observed choices in each of the two environments can be rationalized in the sense of maximizing a well-behaved utility function. Then we check whether the utility function is homothetic, which is important to econometric analysis because a homothetic preference can be described by a single indifference curve. Based on the results, we provide a rough classification of preferences in two treatments.

5.1 Consistency

We first examine whether choices made in our experiment can be generated by the process of maximizing a well-defined utility function for each individual. For linear budget sets (as the case of our experiment), Afriat [1967] and Varian [1982, 1983] provide a well-constructed nonparametric approach based on revealed preference relationships in the data. One of the most important concepts is the Generalized Axiom of Revealed Preference (GARP). As Varian shows, satisfying GARP is both a necessary and sufficient condition for the existence of well-behaved (that is, piecewise linear, continuous, increasing, and concave) utility function in the framework of linear budget constraints. Hence, violations of GARP for each subject are a direct method to see whether individuals choose rationally. Since our subjects make choices in a wide range of budget sets, our data is rich enough for the test. We check every pair of allocation choices and test whether they are satisfied with GARP for each subject. The media violations for GARP is 4 in Lottery treatment and 5 in the VoI environment, which is very low compared to other studies. Over 30% of the subjects violated GARP only once or less both in Lottery and VoI treatment.

Since most subjects had violations of GARP, the frequency of violations doesn't tell the extent of violations. If the violation was caused by a trembling hand, then it may be less severe. So the second question regarding individual rationality is how severe are the violations? One measure of the extent of a violation is Afriat [1972]'s Critical Cost Efficiency Index (CCEI). The basic idea of CCEI is to measure how much the budget constraint must be adjusted in order to avoid violations of GARP. The value of this index is bounded between zero and one. The closer it is to one, the smaller the budget constraints have to shrink in order to remove violations and thus the closer the data are to satisfying GARP. If CCEI score equals to 1, then there is no need to move budget lines. Thus, CCEI for each subject is a summary statistic of overall consistency. Varian [1991] also provides a similar idea to test the severity of violations. The difference with CCEI is that he selects the minimum adjustment required to eliminate the violations of GARP. In another words, Varian [1991]'s index is a lower bound on CCEI.

We list the frequency of violations of the Weak Axiom of Revealed Preference (WARP) and GARP, the efficiency indices of Afriat and Varian for all 92 subjects in Table C1 (see Appendix C). We only briefly summarize here. For CCEI scores (Afri_L or Afri_V) of 92 subjects, the media is as high as 0.982 in Lottery and 0.977 in VoI treatment. 70 subjects (76%) have CCEI scores above 0.95 in both treatments and among them around 55% are above 0.98. This result confirms that individual behaviors can indeed be rationalized by maximizing a well-behaved utility function for majority of subjects.

Although these scores look satisfactory, they don't necessary prove subjects are close enough to satisfying GARP that they can be regarded as utility maximizers. So the third question is how strong the test is when compared with natural benchmarks of the consistency level. Varian [1991] suggests a threshold of 0.95 for the CCEI, but the idea of Bronars [1987] is more appealing. He proposed to use the choices made by hypothetical subjects who randomly choose allocations as a benchmark. Using the same budget sets in our experiment, we simulated 4,600 subjects whose choices were uniformly distributed on budget lines and calculated violations of WARP, GARP and Afriat and Varian efficiency indices. Figure 3 compares histograms of CCEI scores generated by experimental subjects and 4600 hypothetical subjects. The graph clearly shows that the consistency levels of actual subjects are much higher than those of randomly-generated subjects. Although the comparisons with other studies imply that our budget sets favor higher consistency levels for random individuals, the test is sufficiently powerful to exclude the possibility that the overall high consistency level in our experiment is the accidental result of random behavior.

5.2 Homotheticity

We also want to determine whether preferences are compatible with a homogeneous utility function. If preferences are homothetic, then we can describe individual preferences by a single indifference curve. According to several previously described

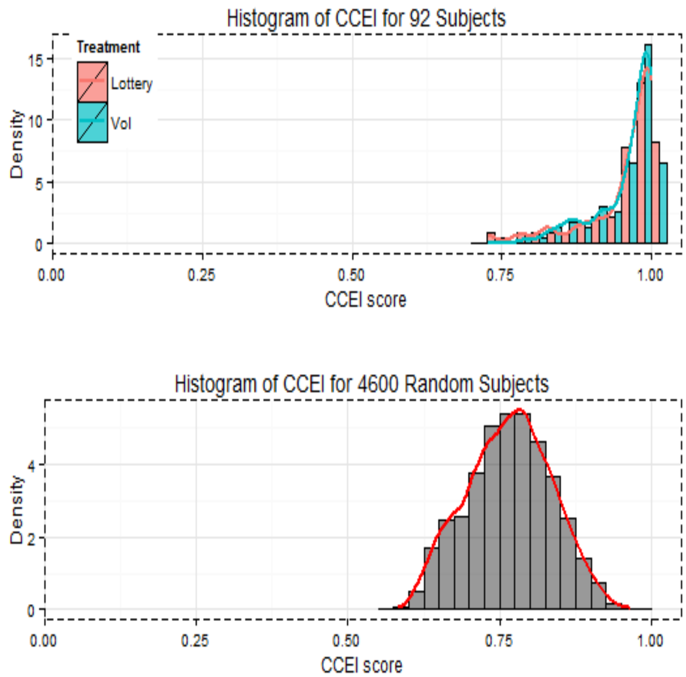

Figure 3: Distributions of CCEI for Experimental and Random Subjects

behavioral patterns, we can also apply some special types of utility functions to reveal individual preference.

A utility function is homothetic if there is a positive monotonic transformation of a function that is homogeneous of degree of 1. Varian [1983] refined Afriat [1972] homogeneity inequalities and proposed a non-parametric test of homotheticity – Homothetic Axiom of Revealed Preference (HARP). Heufer [2013] introduced Pairwise Homothetic Axiom of Revealed Preference (PHARP) for two dimensional commodity spaces and showed that satisfying PHARP is both a necessary and sufficient condition for the existence of a homothetic utility function which rationalizes the data. She also proposed the homothetic efficiency index (HEI) to measure the extent of deviation from homothetic utility maximization. This efficiency index is an analogy to the CCEI score, which describes how much budget lines should shrink in order to remove HARP violations. To examine the power of the test, we also employed the efficiency indices of 4600 hypothetical subjects as a benchmark for comparison.

Table D1 in Appendix D shows the results of the numbers of HARP violations and Homothetic Efficiency Index (HEI) for each subject. The results are not as satisfying as in testing consistency. The average HARP violations are 230 in Lottery treatment and 238 in VoI treatment. The mean HEI are around 0.73 in two treatments. It clearly shows that, on average, subjects do not choose the same proportional allocations for budget lines with same slope, even though our experimental design makes it more easily. We also compare the distribution of efficiency indices with random subjects (see Figure D1 in Appendix D). The significant difference confirms that experimental subjects are generally consistent with maximizing homothetic utility, however, the difference is not distinct as that in the consistency case, implying that large numbers of subjects do not behave in accordance with homothetic utility function. This may have some implications for real life situations. For example, some subjects consume more risky assets when the total pie size increases and some subjects prefer more equal distributions in a more wealthy society.

5.3 Classification

Since subjects' behaviors are consistent and weakly homothetic, we provide a rough classification of utility forms for all subjects here. By calculating the Euclidean distance between experimental choices and optimal choices predicted by one particular utility function, we can assign each subject into one particular group which has the minimized distance compared to other groups.

As we described in section 4, there are several behavioral types which can be easily identified. We consider three types of utility functions: Rawlsian (Leontief): $U(x,y) = min(x,y)$; Utilitarian (perfect substitution): $U(x,y) = x + y$; Cobb-Douglas(Nash): $U(x,y) = xy$. These three types of utility functions are particularly chosen for several reasons. Firstly, they describe the majority of choice behavioral types we have discussed. Secondly, they display explanatory powers both in Lottery and in VoI treatment. For example, in the Lottery environment, trade-offs between two state-contingent commodities can be described by function forms of max-min, perfect substitution or Cobb-Douglas; while in the VoI treatment, these three types of utility functions are coincident with social welfare functions of Raulsian, Utilitarian and Nash. The third function is called Nash because it is a transformation of a utility function which maximizes the product of utilities of the dictator and the beneficiary if both have the same concave Bernoulli utility function for money.

The results of the classification are discussed at Table 3. The strong classifications illustrate that the experimental choices exactly follow one particular utility function and the weak classifications are more general. Since Leontief (Rawlsian) and perfect substitution (Utilitarian) are two extreme cases, a majority of subjects (78% in Lottery treatment and 67% in VoI treatment) chose the Cobb-Douglas (Nash) utility function that are between two boundary cases. We also found there are more boundary utility types in VoI treatment than in Lottery treatment, which implies that there are subjects who exhibit different behavioral types in two treatments, as shown by subjects 4, 46 and 58. More importantly, these findings demonstrate that there is a great deal of heterogeneity across and within subjects. Individuals differed in risk attitude, sense of fairness and efficiency concerns and for the same subject, these motivations differed in two environments. In the following section, we will try to capture heterogeneity both across and within subjects through structured models.

Table 3: Preference Classification

	Lottery		
	Strong	Weak	Sum
Rawls	1(1.09%)	14(15.22%)	15(16.30%)
Utilitarian	1(1.09%)	4(4.35%)	5(5.43%)
Nash	0(0.00%)	72(78.26%)	72(78.26%)
	VoI		
	Strong	Weak	Sum
Rawls	1(1.09%)	17(18.48%)	18(1957%)
Utilitarian	1(1.09%)	10(10.87%)	11(11.96%)
Nash	0(0.00%)	62(67.39%)	62(67.39%)

6 Econometric Analysis

Since the nonparametric approach makes no assumptions about the form of utility function, it provides relatively little information about the structure of preferences. In this section, we utilize several structure models to try to capture the underlying preferences in two environments. We begin with a simple constant relative risk aversion (CRRA) utility function based on individual data, hoping to get an overview of risk aversion / inequality aversion among subjects. We then move a non-expected utility model to try to decompose different motivations with more precision.

6.1 Expected Utility Model

Suppose the utility functions are independent of states of nature and individual preferences over probability distributions of monetary payoffs satisfy the Savage axioms, then the preference ordering over lotteries (x, y) in Lottery treatment can be expressed by the following expected utility function:

$$\pi u(x) + (1-\pi)u(y)$$

where $u(x)$ is the utility function that is decided only by monetary payoffs. By maximizing the utility function subject to budget constraints $y + px = z$, a rational subject will choose the optimal pair of allocations (x^*, y^*), which satisfies the first-order condition:

$$\frac{\pi}{(1-\pi)}\frac{u'(x^*)}{u'(y^*)} = p$$

We assume $u(x)$ follows constant relative risk aversion (CRRA) model, which is commonly used to describe preferences under uncertainty. The functional form of $u(x)$ often adopts the following power utility function:

$$u(x) = \frac{x^{1-\rho}}{(1-\rho)}$$

where ρ is the Arrow-Pratt measure of relative risk aversion. The larger the ρ is, the more risk averse the individual will be. As ρ approaches 0, the individual will be risk neutral. When ρ equals to 1, the power utility degenerates to $\ln(x)$. In this case, the fraction of the money spent on each reward is independent of the price ratio.
By calculating the first order condition of the power function, we get the following optimization equation:

$$\frac{\pi}{(1-\pi)}\left(\frac{y^*}{x^*}\right)^{\rho} = p$$

Taking logs for each side will generate econometric specification for subject with ID i:

$$\log\left(\frac{y_j^i}{x_j^i}\right) = \alpha^i + \beta^i \log(p_j^i) + \epsilon_j^i$$

where ϵ_j^i is assumed to follow normal distribution with zero mean and variance of σ_i^2. The simple ordinary least squares (OLS) will generate parameters α^i and β^i and we can thus infer relative risk aversion $\rho^i = 1/\beta^i$and subjective probability $\pi^i = 1/(1 + e^{\alpha^i/\beta^i})$.

However, this approach builds solely upon theories of decision-making under uncertainty, and thus can only be applied to experimental data in Lottery treatment. To incorporate data in VoI treatment and further to decompose various motivations behind these two environments, we assume social preference in the VoI scenario can also be represented by a parameter that is similar to relative risk aversion (RRA). We call this parameter Relative Inequality Aversion (RIA). Unlike in a traditional Harsanyi framework where the analogy between risk aversion and inequality aversion is based on risk neutral assumption, our approach takes heterogeneous risk attitudes into consideration. By controlling risk considerations exhibited in lottery scenarios, we can estimate inequality aversion with more precision and thus provide a better description of social preference.

We achieve this by replacing ρ^i in the regression specification above with a simple additive form:

$$\rho_1^i + \rho_2^i T$$

where T is the treatment indicator. This replacement is based on the assumption that underlying preference in VoI treatment is a combination of unchanged risk preference in Lottery treatment and another preference that is an analogy to decision-making under uncertainty. For experimental data in VoI treatment, T equals to 1 and thus ρ_1^i and ρ_2^i jointly depicts the underlying preference. Among them, ρ_1^i is pure risk preference of individual i and ρ_2^i describes social preference. If it is positive, then it makes the indifference curve more concave than in risk treatment, suggesting that this individual is inequality averse, and vice versa.

We report the estimation results, by subject, in Table E1 (see Appendix E). It should be noted that we have estimated only 66 (72%) out of total 92 subjects. First, we have omit subjects whose behaviors are not consistent with utility maximization. More specifically, we excluded 6 subjects (ID 2, 26, 35, 72, 86, 92) with CCEI scores lower than 0.95 in two treatments. Since the power function is not well defined in boundary allocations $(0, y)$, we then discarded boundary choices for the rest of the subjects. This further excludes 6 subjects (ID 12, 22, 69, 78, 87) who chose so many boundary allocations that the remaining samples were not large enough for estimation. Another point is that sample variations are essential to OLS estimation;

hence, we also discarded 13 subjects (ID 6, 11, 13, 14, 24, 32, 36, 44, 48, 49, 55, 75, 85, 89) who always chose similar allocations for various budget sets. For example, subject 6 always distributed 20$ to low reward no matter what the budget line was; Subject 48 preferred allocating 75% of the pie to high reward, which made the dependent variable in the regression a constant.

Observation of relative risk aversion (ρ_1) and relative inequality aversion (ρ_2) reveals considerable heterogeneity in risk attitude across subjects. The median Arrow-Pratt measure of relative risk aversion (2.125) is too high compared to other studies in literature (often around 0.5). One possible reason for this is the relatively larger price changes in our experiment, which may discourage risk-taking. Another conjecture is that omitting boundary observations may overestimate individual risk aversion. The relative inequality aversion (ρ_2) is more moderate with median 0.12, however, it varies significantly from -17.260 to 9.650. Among total 66 subjects, 39 (59%) exhibited positive RIA, which clearly indicated that they were willing to pay for a more equal distribution between a pair of subjects. More interestingly, a large number of subjects were found to be inequality loving, which on the other hand proved that these subjects cared more about efficiency because the more unequal the distribution was, the larger the total pie the pair would receive from the experimenter.

We also found that risk attitude and sense of inequality are two different and, most likely, independent concepts. The correlation coefficient between RRA and RIA is -0.278, which is quite contradictory to results in the literature. We provide a scatter plot of these two estimators in Figure 4. One notable feature of the graph is that preference over inequality is more heterogeneous than risk preference. Most subjects of our experiment are risk averse, which has been proved in a great amount of literature. Although there are heterogeneities across subjects with regard to risk attitude, the estimation results show that they are narrowed around 2. However, attitudes regarding income distribution are much more dispersive. More importantly, they seem to be independent of risk attitudes.

Another point worth attention is subjective probability π_i. Theoretically, they should be around the actual probability 0.5. But here we find many of them fall on a boundary point of 0. Sixty (91%) out of 66 subjects have subjective probability below 0.5 and among them, 31 (47%) are lower than 0.3. According to the expected utility function and optimal condition, we can infer $u'(x) > u'(y)$, that is, subjects are willing to assign more money to low reward. This result clearly demonstrates the existence of loss aversion of subjects.

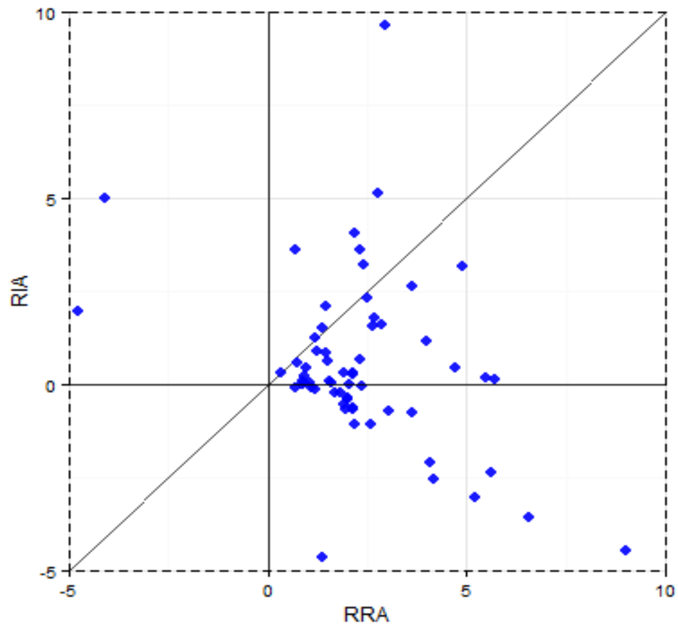

Figure 4: Scatterplot of RRA and RIA for Expected Utility Model

In summary, we found that a simple expected utility model based on a CRRA utility function provides an overview of individual risk aversion and inequality aversion, as well as of the relationship between them. The considerable heterogeneity of risk preference and more distinctly, of inequality attitude are recovered by a structured OLS regression. A large number of boundary estimations of subjective probability, however, suggest that a more complex formulation, which can also explain loss aversion, is necessary to fully interpret the data. Consequently, in the next session, we will turn to a non-expected utility model.

6.2 Non-expected Utility Model

The distinct loss aversion shown in subjective probabilities forces us to a more meticulous model in order to reveal underlying motivations. To account for loss aversion, we adopt Gul [1991]'s utility function, which takes the following form:

$$\min\{\alpha u(x) + u(y), u(x) + \alpha u(y)\}$$

where $\alpha >= 1$ is a parameter measuring loss aversion and u(x) is the utility function of monetary amounts. If $\alpha = 1$, we have a standard expected utility specification and if $\alpha > 1$, then there will be a kink at the point where $x = y$. This model is quite general in that it embeds the expected utility model as a special case and thus allows for flexible estimation.

Suppose the utility function still takes the form of Constant Relative Risk Aversion (CRRA), then parameters α and ρ will jointly determine individual preference. As noted previously, the power function is not well defined for boundary allocations $(x, y) = (0, z)$. However, these boundary choices also contain information about underlying preference. So instead of discarding boundary choices, we incorporate them by replacing zero values with a small number of $\omega = 0.001$. Even with replacement, we still need to exclude 14 subjects since 6 of them did not behave rationally (ID 2, 26, 35, 72, 86, 92) and 8 of them (ID 12, 13, 22, 69, 74, 76, 87, 89) always chose the same decisions. This leaves us 78 (85%) subjects for analysis.

By maximizing the utility function subject to budget constraint $y+px = z$, we arrive at the following optimization conditions:

$$\ln(x^*/y^*) = f[ln(p); \alpha, \rho, \omega]$$

$$= \begin{cases} \ln \omega & \text{if} \ln(p) \leq \ln \alpha - \rho \ln \omega, \\ -\frac{1}{\rho}[\ln(p) - \ln(\alpha)], & \text{if} \ln \alpha < \ln(p) < \ln \alpha - \rho \ln \omega, \\ 0 & \text{if} -\ln \alpha \leq \ln(p) \leq \ln(alpha), \\ -\frac{1}{\rho}[\ln(p) + \ln(\alpha)], & \text{if} -\ln \alpha + \rho \ln \omega < \ln(p) < -\ln \alpha, \\ -\ln \omega, & \text{if} \ln(p) \leq -\ln \alpha + \rho \ln \omega, \end{cases}$$

Among optimization conditions, two of them are interior solutions derived from first order conditions. We also have two corner solutions that can characterize boundary observations. In addition, the third condition describes loss aversion. The advantage of this specification is that it incorporates almost all observations and thus can provide a more precise estimation for various motivations including loss aversion, risk aversion and inequality aversion. For each subject, we can minimize the square sums between their true choices and their optimal choices to estimate parameters ρ and α:

$$\sum_{j=1}^{80}[\ln(\frac{x_j}{y_j}) - \ln(\frac{x_j^*}{y_j^*})]^2 = \sum_{j=1}^{80}[\ln(\frac{x_j}{y_j}) - f(ln(p_j); \alpha, \rho, \omega)]^2$$

Similarly, to compare data in two treatments, we replace both ρ and α with forms of $\rho_1 + \rho_2 T$ and $\alpha_1 + \alpha_2 T$. As in the previous section, parameter ρ_2 is still called Relative Inequality Aversion (RIA). The additional parameter α_2 characterizes a concept similar to loss aversion in distributive framework. In the risk framework, the risk aversion (α_1 larger than 1) parameter describes the aversion of being allocated to a less preferred outcome. This aversion is shown by the kink of indifference curve because subjects chose an equal split more often. In the VoI environment, besides the aversion to loss, the aversion can be larger because there are other people who will receive a high reward. Thus we call α_2 the "Jealousy" parameter because it describes the part of aversion to get low reward that do not result from disappointment, but from the comparison with other people. The larger the α_2, the more jealous the subject is.

The estimation results for each subject are shown in table F1 (see Appendix F). We only list the summary statistics here in Table 4. Our first finding is that relative risk aversion (ρ_1) estimations are much smaller than those of the expected utility model. Although the median RRA is still as high as 1.09, the result is quite comparable to that found in literature given the large variation of budget sets in our experiment. All RRAs are positive and over 75% of them are significant with t values larger than 2. The relative inequality aversion (ρ_2) estimations in the new model are bigger than in the previous model. The median value is 0.53 and ranges broadly from -3.72 to 13.05. Among a total of 78 subjects, 54 (70%) exhibited positive RIA, clearly showing preferences over equal distribution or over other-regarding. The percentage of subjects who favored equality was higher than estimations from the expected utility model. One possibility is that it may absorb some of the effects of loss aversion. In our estimation of loss aversion, 63 (81%) subjects have $\alpha_1 = 1$. Since a majority of them do not follow expected utility, we can only attribute it to the effect of curvature parameters (ρ_1)

The relationship between risk attitude and the inequality concept is similar to previous analysis. The correlation coefficient is -0.176. We also plot their relationship in the following Figure 4. We can still find attitudes over income distribution are much more dispersive than risk aversion. More importantly, similarities between the two pictures robustly prove that risk attitude and sense of inequality are two different concepts, and they jointly determine distributive preferences behind VoI.

Another interesting finding is that people are generally not jealous behind VoI. We found 58 (74%) subjects had negative Jealousy parameters and the median was around -0.39. This result shows that subjects are generally less disappointed when

Table 4: Summary of NLLS Estimation

Stats	Mean	Sd	Min	Pctl(25)	Median	Pctl(75)	Max
α_1	1.09	0.24	1.00	1.00	1.00	1.00	2.60
$sd(\alpha_1)$	0.56	0.35	0.18	0.38	0.48	0.66	2.86
α_2	-0.32	0.62	-2.48	-0.67	-0.39	-0.02	2.26
$sd(\alpha_2)$	0.72	0.46	0.23	0.48	0.62	0.78	2.90
ρ_1	1.28	0.85	0.20	0.71	1.08	1.67	5.58
$sd(\rho_1)$	0.71	1.47	0.03	0.28	0.40	0.72	12.84
ρ_2	0.80	2.11	-3.71	-0.08	0.38	0.84	13.05
$sd(\rho_2)$	2.56	8.40	0.03	0.47	0.86	1.31	62.71
R2	0.39	0.51	0.00	0.17	0.30	0.50	4.26

there is another subject who will receive high reward. In the Lottery environment, receiving low reward is similar to losing a gamble. However, this analogy cannot sustain in VoI treatment where instead payoffs of both members in a pair are taken into consideration, thus incurring less jealous motivation. To confirm the result, we check the relationship between relative inequality aversion and the Jealousy parameter. Theoretically, inequality aversion and jealousy are two related concepts. The more other-regarding the subject is, the less likely the subject will be jealous about allocating high reward to another subject. The correlation between these two parameters is -0.58, which confirms our conjecture. We also show the scatter plot of RIA and the Jealousy parameter in Figure 6. The clearly negative relationship between these two estimations further supports the finding that VoI incurs less jealous motivations.

In summary, we employed a Non-linear Least Square estimation on a general non-expected utility model in this section. The combination of kink parameters and curvature parameters jointly results in a plausible estimation of motivations like inequality aversion, risk aversion, loss aversion and jealousy consideration. Furthermore, we estimated two treatments together, which allowed us to decompose different motivations in two treatments. The results further support the heterogeneity of inequality attitudes across subjects and further confirmed that inequality aversion and risk aversion are two distinct concepts in decision-making behind VoI. We also found that only 25% of subjects exhibit jealousy in VoI treatment.

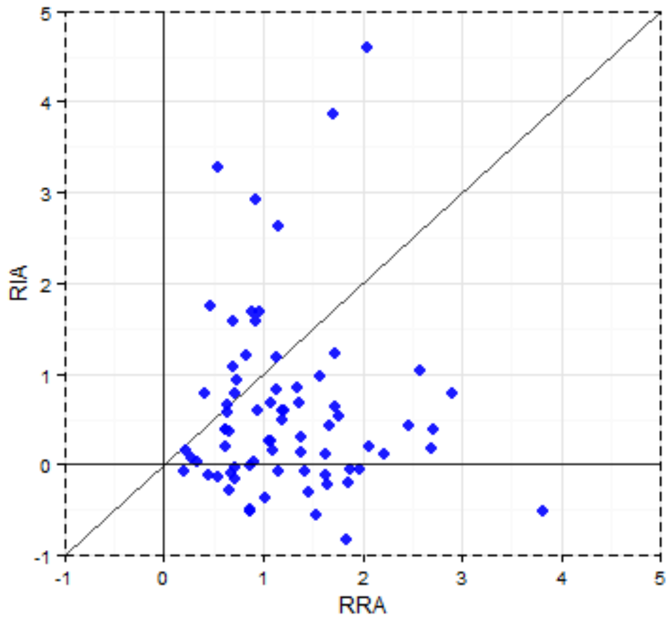

Figure 5: Scatterplot of RRA and RIA for Non-expected Utility Model

7 Future Work

We want to take several additional steps down the path in the following aspects: First, we plan to explore other econometric models to decompose risk attitude and social preference more precisely. Although our expected and non-expected utility model reveals several exciting findings, the simplicity of our first model and the computational load on our second model reduce their estimating power. Since the utility functions in two environments fundamentally belong to different frameworks, it's very difficult to find a suitable model to incorporate preference in two environments. One direction we want to explore is the difference lie in demand curves in two treatments. Since demand curves are the outcome of utility maximization, we can ignore the underlying utility function and identify the difference shown in outcomes. Approaches in empirical demand theory like Almost Ideal Demand Systems Deaton and Muellbauer [1980] can be an attractive choice for further investigation.

Second, we want to incorporate demographic characteristics such as age, major, sex, self-reported income level and risk attitude into analysis based on aggregate data.

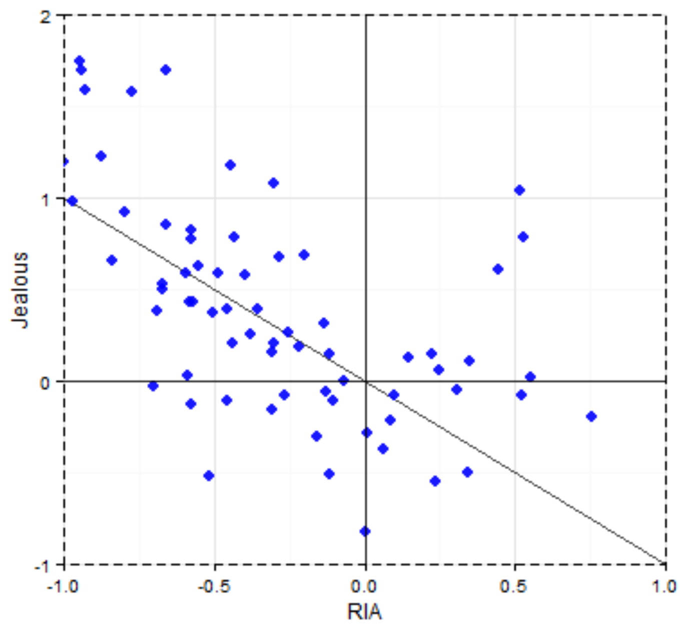

Figure 6: Scatterplot of RRA and Jealousy for Non-expected Utility Model

In the experiment, we collected detailed individual socio-economic data sets. We hope this will provide control over some individual characteristics and thus give a more convincing distribution of risk attitude and inequality attitude of population. Another attractive point is the experiment conducted among subjects of different socio-economic status. Since our interface is intuitive and easy to understand, we can design applications on smart phones to collect more relevant real world responses.

Third, we want to try non-linear budget sets. Afriat [1967] has shown that linear budget lines will inherently introduce the tendency for consistency. We would like to try non-linear budget lines like step-shaped or constant efficiency loss budget sets. These nonlinear budget sets with changing slopes and curvatures will provide more general scenarios in revealing underlying preference. In addition, our experimental design is especially suited to nonlinear budgets because we didn't directly present subjects with budget lines but rather vividly displayed them graphically via a pie and tables where all division information was available. We believe this experimental design will be suitable for numerous budget settings without introducing confusion or framing effects for subjects.

8 Conclusion

In this paper, we have attempted to identify and decompose risk preference and social preference behind VoI. We designed graphical representations of choices made in both pure lottery environment and a distributive environment behind the veil of ignorance. This allows for the collection of a rich individual-level data set that provides variations for testing individual consistency and homotheticity. The decompositions of underlying motivations are estimated by a simple expected utility model and a general non-expected utility model.

The results are summarized in the following: First, we found that almost all decision choices made by individuals in two treatments can be rationalized by a well-behaved utility function both in the sense of satisfying GARP and of the severity of violations. Second, the homothetic tests for utility functions are relatively poor because a large number of subjects changed decisions when same budget sets moved upward. This finding implies that the individual sense of equality changes with total income levels. The third point is that individual preferences over equality are highly heterogeneous and are not related to risk attitudes. Controlling risk aversion for each subject in our simple expected utility model, estimations of inequality aversion in VoI treatment show that individual inequality aversion varies at a larger range and does not display a clear relationship with risk aversion. This finding is confirmed by the similar estimation approach in a more complex model. We also found that a significant majority of subjects demonstrated other-regarding preference in the sense of positive inequality aversion and negative jealousy parameter. In addition, the experimental techniques that were developed allowed us to decompose various motivations of risk and distributive concerns and furthermore to characterize the distribution of them in the population. We hope our studies stimulate new ideas and methodologies for understanding behaviors and underlying motivations behind VoI.

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