# Appendices

equationsection

# A Sample Instructions $(\pi = 2/3)$

#### Introduction

This is an experiment in decision-making. Research foundations have provided funds for conducting this research. Your payoffs will depend partly only on your decisions and partly on chance. It will not depend on the decisions of the other participants in the experiments. Please pay careful attention to the instructions as a considerable amount of money is at stake.

The entire experiment should be complete within an hour and a half. At the end of the experiment you will be paid privately. At this time, you will receive \$5 as a participation fee (simply for showing up on time). Details of how you will make decisions and receive payments will be provided below.

During the experiment we will speak in terms of experimental tokens instead of dollars.

Your payoffs will be calculated in terms of tokens and then translated at the end of the experiment into dollars at the following rate:

2 Tokens = 1 Dollar

#### A decision problem

In this experiment, you will participate in 50 independent decision problems that share

a common form. This section describes in detail the process that will be repeated in all decision problems and the computer program that you will use to make your decisions.

In each decision problem you will be asked to allocate tokens between two accounts, labeled x and y. The x account corresponds to the x-axis and the y account corresponds to the y-axis in a two-dimensional graph. Each choice will involve choosing a point on a line representing possible token allocations. Examples of lines that you might face appear in Attachment A1.

### [Attachment A1 here]

In each choice, you may choose any x and y pair that is on the line. For example, as illustrated in Attachment A2, choice A represents a decision to allocate q tokens in the x account and x tokens in the y account. Another possible allocation is B, in which you allocate x tokens in the x account and x tokens in the y account.

### [Attachment A2 here]

Each decision problem will start by having the computer select such a line randomly from the set of lines that intersect with at least one of the axes at 50 or more tokens but with no intercept exceeding 100 tokens. The lines selected for you in different decision problems are independent of each other and independent of the lines selected for any of the other participants in their decision problems.

To choose an allocation, use the mouse to move the pointer on the computer screen to the allocation that you desire. When you are ready to make your decision, left-click to enter your chosen allocation. After that, confirm your decision by clicking on the Submit button. Note that you can choose only x and y combinations that are on the line. To move on to the next round, press the OK button. The computer program dialog window is shown in Attachment A3.

### [Attachment A3 here]

Your payoff at each decision round is determined by the number of tokens in your x account and the number of tokens in your y account. At the end of the round, the computer will randomly select one of the accounts, x or y. For each participant, account y will be selected with 1/3 chance and account x will be selected with 2/3 chance. You will only receive the number of tokens you allocated to the account that was chosen.

Next, you will be asked to make an allocation in another independent decision. This process will be repeated until all 50 rounds are completed. At the end of the last round, you will be informed the experiment has ended.

#### **Earnings**

Your earnings in the experiment are determined as follows. At the end of the experiment, the computer will randomly select one decision round from each participant to carry out (that is, 1 out of 50). The round selected depends solely upon chance. For each participant, it is equally likely that any round will be chosen.

The round selected, your choice and your payment will be shown in the large window that appears at the center of the program dialog window. At the end of the experiment, the tokens will be converted into money. Each token will be worth 0.5 Dollars. Your final earnings in the experiment will be your earnings in the round selected plus the \$5 show-up fee. You will receive your payment as you leave the experiment.

#### Rules

Your participation in the experiment and any information about your payoffs will be kept strictly confidential. Your payment-receipt and participant form are the only places in which your name and social security number are recorded.

You will never be asked to reveal your identity to anyone during the course of the experiment. Neither the experimenters nor the other participants will be able to link you to any of your decisions. In order to keep your decisions private, please do not reveal your choices to any other participant.

Please do not talk with anyone during the experiment. We ask everyone to remain silent until the end of the last round. If there are no further questions, you are ready to start, an instructor will approach your desk and activate your program.

### B Individual-level Data

The portfolio choices  $(x_1, x_2)$  as points in a scatterplot (left panel); the relationship between  $\ln(p_1/p_2)$  and  $x_1/(x_1+x_2)$  (middle panel); and the relationship between  $\ln(p_1/p_2)$  and  $p_1x_1$  (left panel).

# A. Symmetric Treatment $(\pi = 1/2)$

[Attachment B1 here]

## B. Asymmetric Treatment ( $\pi = 1/3$ and $\pi = 2/3$ )

[Attachment B2 here]

## C Testing rationality

Let  $\{(p^i,x^i)\}_{i=1}^{50}$  be the data generated by some individual's choices, where  $p^i$  denotes the i-th observation of the price vector and  $x^i$  denotes the associated portfolio. A portfolio  $x^i$  is directly revealed preferred to a portfolio  $x^j$ , denoted  $x^iR^Dx^j$ , if  $p^i \cdot x^i \geq p^i \cdot x^j$ . A portfolio  $x^i$  is revealed preferred to a portfolio  $x^j$ , denoted  $x^iRx^j$ , if there exists a sequence of portfolios  $\{x^k\}_{k=1}^K$  with  $x^1 = x^i$  and  $x^K = x^j$ , such that  $x^kR^Dx^{k+1}$  for every k = 1, ..., K-1. The Generalized Axiom of Revealed Preference (GARP), which requires that if  $x^iRx^j$  then  $p^j \cdot x^j \leq p^j \cdot x^i$  (i.e. if  $x^i$  is revealed preferred to  $x^j$ , then  $x^i$  must cost at least as much as  $x^j$  at the prices prevailing when  $x^j$  is chosen). It is clear that if the data are generated by a non-satiated utility function, then they must satisfy GARP. Conversely, the following result due to Afriat (1967) tells us that if a finite data set generated by an individual's choices satisfies GARP, then the data can be rationalized by a well-behaved utility function.

**Afriat's Theorem** If the data set  $\{(p^i, x^i)\}$  satisfies GARP, then there exists a piecewise linear, continuous, increasing, concave utility function u(x) such that for each observation  $(p^i, x^i)$ 

(1) 
$$u(x) \le u(x^i)$$
 for any  $x$  such that  $p^i \cdot x \le p^i \cdot x^i$ .

Hence, in order to show that the data are consistent with utility-maximizing behavior we must check whether it satisfies GARP. Since GARP offers an exact test, it is desirable to measure the *extent* of GARP violations. We report measures of GARP violations based on three indices: Afriat (1972), Varian (1991), and Houtman and Maks (1985).

Afriat (1972) Afriat's critical cost efficiency index (CCEI) measures the amount by which each budget constraint must be adjusted in order to remove all violations of GARP. For any number  $0 \le e \le 1$ , define the direct revealed preference relation  $R^D(e)$  as  $x^i R^D(e) x^j$  if  $ep^i \cdot x^i \ge p^i \cdot x^j$ , and define R(e) to be the transitive closure of  $R^D(e)$ . Let  $e^*$  be the largest value of e such that the relation R(e) satisfies GARP. Afriat's CCEI is the value of  $e^*$  associated with the data set  $\{(p^i, x^i)\}$ . It is bounded between zero and one and can be interpreted as saying that the consumer is 'wasting' as much as  $1 - e^*$  of his income by making inefficient choices. The closer the CCEI is to one, the smaller the perturbation of the budget constraints required to remove all violations and thus the closer the data are to satisfying GARP. Although the CCEI provides a summary statistic of the overall consistency of the data with GARP, it does not give any information about which of the observations  $(p^i, x^i)$  are causing the most severe violations. A single large violation may lead to a small value of the index while a large number of small violations may result in a much larger efficiency index.

Varian (1991) Varian refined Afriat's CCEI to provide a measure that reflects the minimum adjustment required to eliminate the violations of GARP associated with each observation  $(p^i, x^i)$ . In particular, fix an observation  $(p^i, x^i)$  and let  $e^i$  be the largest value of e such that R(e) has no violations of GARP within the set of portfolios  $x^j$  such that  $x^iR(e)x^j$ . The value  $e^i$  measures the efficiency of the choices when compared to the portfolio  $x^i$ . Knowing the efficiencies  $\{e^i\}$  for the entire set of observations  $\{(p^i, x^i)\}$  allows us to say where the inefficiency is greatest or least. These numbers may still overstate the extent of inefficiency, however, because there may be several places in a cycle of observations where an adjustment of the budget constraint would remove a violation of GARP and the

above procedure may not choose the 'least costly' adjustment. Varian (1991) provides an algorithm that will select the least costly method of removing all violations by changing each budget set by a different amount. When a single number is desired, as here, one can use  $e^* = \min\{e^i\}$ . Thus, Varian's (1991) index is a lower bound on the Afriat's CCEI. Houtman and Maks (1985) (HM) HM find the largest subset of choices that is consistent with GARP. This method has a couple of drawbacks. First, some observations may be discarded even if the associated GARP violations could be removed by small perturbations of the budget constraint. Further, since the algorithm is computationally very intensive, we were unable to compute the HM index for a small number of subjects (ID 211, 324, 325, 406, 504 and 608) with a large number of GARP violations. In those few cases we report upper bounds on the consistent set.

Table C1 lists, by subject, the number of violations of the Weak Axiom of Revealed Preference (WARP) and GARP, and also reports the values of the three indices. We allow for small mistakes resulting from the imprecision of a subject's handling of the mouse. The results presented in Table C1 allow for a narrow confidence interval of one token (i.e. for any i and  $j \neq i$ , if  $d(x^i, x^j) \leq 1$  then  $x^i$  and  $x^j$  are treated as the same portfolio).

### [Table C1 here]

Figure C1 compares the distributions of the Varian efficiency index generated by the sample of hypothetical subjects (gray) and the distributions of the scores for the actual subjects (black). The horizontal axis shows the value of the index and the vertical axis measures the percentage of subjects corresponding to each interval. The histograms show that actual subject behavior has high consistency measures compared to the behavior of

the hypothetical random subjects. Figure C2 shows the distribution of the HM index. Note that we cannot generate a distribution of this index for random subjects because of the computational load.

[Figure C1 here]

[Figure C2 here]

# D Constant Relative Risk Aversion (CRRA)

[Table D1 here]

- **E** The relationship between  $\ln(p_1/p_2)$  and  $\ln(\widehat{x}_1, \widehat{x}_2)$
- A. Symmetric Treatments ( $\pi = 1/2$ )

[Attachment E1 here]

B. Asymmetric Treatments ( $\pi = 1/3$  and  $\pi = 2/3$ )

[Attachment E2 here]

F Risk measures and OLS expected-utility model

[Table F1 here]

# G Constant absolute risk aversion (CARA)

We could also have estimated the model with the assumption of constant absolute risk aversion (CARA). The CARA utility function has two advantages. First, it allows us to get rid of the nuisance parameter  $\omega_0$ . Secondly, it easily accommodates boundary portfolios. To implement this approach, we assume the exponential form

$$(2) u(x) = -e^{-Ax}$$

where  $A \geq 0$  is the coefficient of absolute risk aversion (we assume without loss of generality that  $\omega_0 = 0$ ). By direct calculation, the first-order conditions that must be satisfied at each observation  $(\bar{x}_1^i, \bar{x}_2^i, x_1^i, x_2^i)$  are given by

$$(3) \ x_2^i - x_1^i = f\left[\bar{x}_1^i, \bar{x}_2^i; \alpha, A\right] = \begin{cases} \bar{x}_2^i & \ln\left(\frac{\bar{x}_2^i}{\bar{x}_1^i}\right) \ge \ln\alpha + A\bar{x}_2^i, \\ \frac{1}{A}\left[\ln\left(\frac{\bar{x}_2^i}{\bar{x}_1^i}\right) - \ln\alpha\right] & \ln\alpha < \ln\left(\frac{\bar{x}_2^i}{\bar{x}_1^i}\right) < \ln\alpha + A\bar{x}_2^i, \\ 0 & -\ln\alpha \le \ln\left(\frac{\bar{x}_2^i}{\bar{x}_1^i}\right) \le \ln\alpha, \\ \frac{1}{A}\left[\ln\left(\frac{\bar{x}_2^i}{\bar{x}_1^i}\right) + \ln\alpha\right] & -\ln\alpha + A\bar{x}_1^i < \ln\left(\frac{\bar{x}_2^i}{\bar{x}_1^i}\right) < -\ln\alpha, \\ -\bar{x}_1^i & \ln\left(\frac{\bar{x}_2^i}{\bar{x}_1^i}\right) \le -\ln\alpha + A\bar{x}_1^i. \end{cases}$$

Then, for each subject n, we choose the parameters,  $\alpha$  and A, to minimize

(4) 
$$\sum_{i=1}^{50} \left[ \left( x_2^i - x_1^i \right) - f\left( \bar{x}_1^i, \bar{x}_2^i; \alpha, A \right) \right]^2.$$

The problem with CARA is that it implies a (non-linear) relationship between  $\log(p_1/p_2)$  and  $x_1 - x_2$ . Since the variation in  $\log(p_1/p_2)$  is quite small relative to the variation in  $x_1 - x_2$ , the estimated individual-level regression coefficients are bound to be small. This implies that the estimated coefficients of absolute risk aversion  $\hat{A}_n$ , as well as  $\hat{\alpha}_n$ , will be small too. Of course, it may be true that the  $\hat{A}_n$  are close to zero, but this seems unlikely

given the behavior of the subjects, which suggests a non-negligible degree of risk aversion. The individual-level estimation results,  $\hat{\alpha}_n$  and  $\hat{A}_n$ , are also presented in Table F1.

# H Maximum likelihood estimation (ML)

### A. Constant relative risk aversion (CRRA)

In order to have a well defined likelihood function, we need to define the error structure. To this end, we assume the power form  $u(x) = x^{1-\rho}/(1-\rho)$  and consider the following stochastic utility function,

(5) 
$$\min \left\{ \alpha \frac{x_1^{1-\rho}}{1-\rho} e^{\varepsilon_1} + \frac{x_2^{1-\rho}}{1-\rho} e^{\varepsilon_2}, \frac{x_1^{1-\rho}}{1-\rho} e^{\varepsilon_1} + \alpha \frac{x_2^{1-\rho}}{1-\rho} e^{\varepsilon_2} \right\}.$$

Recall that the data generated by an individual's choices are  $\{(\bar{x}_1^i, \bar{x}_2^i, x_1^i, x_2^i)\}_{i=1}^{50}$ , where  $(x_1^i, x_2^i)$  are the coordinates of the choice made by the subject and  $(\bar{x}_1^i, \bar{x}_2^i)$  are the endpoints of the budget constraint, (so we can calculate the relative prices  $p_1^i/p_2^i = \bar{x}_2^i/\bar{x}_1^i$  for each observation i). The first-order conditions that must be satisfied at each observation  $(\bar{x}_1^i, \bar{x}_2^i, x_1^i, x_2^i)$  can thus be written as follows:

$$\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) \geq \ln\alpha + \rho\ln\left(\frac{1}{\omega}\right) + \varepsilon^{i} \text{ for } \frac{x_{1}^{i}}{x_{2}^{i}} = \omega, \\
\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) = \ln\alpha + \rho\ln\left(\frac{x_{2}^{i}}{x_{1}^{i}}\right) + \varepsilon^{i} \text{ for } \omega < \frac{x_{1}^{i}}{x_{2}^{i}} < 1, \\
-\ln\alpha + \rho\ln\left(\frac{x_{2}^{i}}{x_{1}^{i}}\right) + \varepsilon^{i} \leq \ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) \leq \ln\alpha + \rho\ln\left(\frac{x_{2}^{i}}{x_{1}^{i}}\right) + \varepsilon^{i} \text{ for } \frac{x_{1}^{i}}{x_{2}^{i}} = 1, \\
\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) = -\ln\alpha + \rho\ln\left(\frac{x_{2}^{i}}{x_{1}^{i}}\right) + \varepsilon^{i} \text{ for } 1 < \frac{x_{1}^{i}}{x_{2}^{i}} < \frac{1}{\omega}, \\
\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) \leq -\ln\alpha + \rho\ln(\omega) + \varepsilon^{i} \text{ for } \frac{x_{1}^{i}}{x_{2}^{i}} = \frac{1}{\omega},$$

where  $\varepsilon^i \equiv \varepsilon_2^i - \varepsilon_1^i$ . When the first order condition is an equation, it defines a unique value of  $\varepsilon^i$  that satisfies the expression and hence the likelihood  $\varphi\left(\varepsilon^i\right)$  is well defined, where  $\varphi\left(\cdot\right)$  is the p.d.f. of  $\varepsilon^i$ . When the first order condition is an inequality, there is an interval of values of  $\left[\underline{\varepsilon}^i, \overline{\varepsilon}^i\right]$  that satisfy the first order condition and the probability  $\Phi\left(\overline{\varepsilon}^i\right) - \Phi\left(\underline{\varepsilon}^i\right)$  is well defined, where  $\Phi\left(\cdot\right)$  is the c.d.f. of  $\varepsilon^i$ . Further, we assume that  $\varepsilon^i$  is distributed normally with mean zero and variance  $\sigma^2$ .

With these terms we can define the likelihood function:

$$(7) \qquad \mathcal{L}\left(\left\{\left(\bar{x}_{1}^{i}, \bar{x}_{2}^{i}, x_{1}^{i}, x_{2}^{i}\right)\right\}_{i=1}^{50}; a, \rho\right) \\ = \prod_{\substack{\frac{x_{1}^{i}}{x_{2}^{i}} = \omega}} \Phi\left[\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) - \ln\alpha - \rho\ln\left(\frac{1}{\omega}\right)\right] \\ \times \prod_{\substack{\alpha < \frac{x_{1}^{i}}{x_{2}^{i}} < 1}} \varphi\left[\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) - \ln\alpha - \rho\ln\left(\frac{x_{2}^{i}}{x_{1}^{i}}\right)\right] \\ \times \prod_{\substack{\frac{x_{1}^{i}}{x_{2}^{i}} = 1}} \left[\Phi\left[\ln\alpha + \rho\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right)\right] - \Phi\left[-\ln\alpha + \rho\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right)\right]\right] \\ \times \prod_{1 < \frac{x_{1}^{i}}{x_{2}^{i}} < \frac{1}{\omega}} \varphi\left[\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) + \ln\alpha - \rho\ln\left(\frac{x_{2}^{i}}{x_{1}^{i}}\right)\right] \\ \times \prod_{1 < \frac{x_{1}^{i}}{x_{2}^{i}} < \frac{1}{\omega}} 1 - \Phi\left[\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) + \ln\alpha - \rho\ln(\omega)\right].$$

We incorporate the boundary observations  $(\bar{x}_1, 0)$  or  $(0, \bar{x}_2)$  into our estimation using strictly positive portfolios where the zero component is replaced by a small consumption level such that the demand ratio  $x_1/x_2$  is either  $1/\omega$  or  $\omega$ , respectively. The minimum ratio is chosen to be  $\omega = 10^{-3}$ . Table H1 presents the CRRA results of the ML estimation for the full set of subjects. Table H2 displays summary statistics, and compares the results of the ML and nonlinear least squares (NLLS) estimations.

[Table H1 here]
[Table H2 here]

Constant absolute risk aversion (CARA) We assume the exponential form  $u(x) = -e^{-Ax}$  and consider the following stochastic utility function,

(8) 
$$U(x_1, x_2; a, A) = \min\{-ae^{-Ax_1-\varepsilon_1} - e^{-Ax_2-\varepsilon_2}, -e^{-Ax_1-\varepsilon_1} - ae^{-Ax_2-\varepsilon_2}\}.$$

The first-order conditions that must be satisfied at each observation  $(\bar{x}_1^i, \bar{x}_2^i, x_1^i, x_2^i)$  can be written as follows:

(9) 
$$\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) \geq \ln a + A\bar{x}_{2}^{i} + \varepsilon^{i} \text{ for } 0 = x_{1}^{i} < x_{2}^{i},$$

$$\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) = \ln a + A\left(x_{2}^{i} - x_{1}^{i}\right) + \varepsilon^{i} \text{ for } 0 < x_{1}^{i} < x_{2}^{i},$$

$$-\ln a + \varepsilon^{i} \leq \ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) \leq \ln a + \varepsilon^{i} \text{ if } x_{1}^{i} = x_{2}^{i},$$

$$\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) = -\ln a + A\left(x_{2}^{i} - x_{1}^{i}\right) + \varepsilon^{i} \text{ for } x_{1}^{i} > x_{2}^{i} > 0,$$

$$\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) \leq -\ln a - A\bar{x}_{1}^{i} + \varepsilon^{i} \text{ for } x_{1}^{i} > x_{2}^{i} = 0.$$

With these terms we can define the likelihood function:

$$\mathcal{L}\left(\left\{\left(\bar{x}_{1}^{i}, \bar{x}_{2}^{i}, x_{1}^{i}, x_{2}^{i}\right)\right\}_{i=1}^{50}; a, A\right)$$

$$= \prod_{0=x_{1}^{i} < x_{2}^{i}} \Phi\left[\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) - \ln a - A\bar{x}_{2}^{i}\right]$$

$$\times \prod_{0< x_{1}^{i} < x_{2}^{i}} \varphi\left[\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) - \ln a - A\left(x_{2}^{i} - x_{1}^{i}\right)\right]$$

$$\times \prod_{x_{1}^{i} = x_{2}^{i}} \left[\Phi\left[\ln \alpha + \ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right)\right] - \Phi\left[-\ln \alpha + \ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right)\right]\right]$$

$$\times \prod_{x_{1}^{i} > x_{2}^{i} > 0} \varphi\left[\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) + \ln a - A\left(x_{2}^{i} - x_{1}^{i}\right)\right]$$

$$\times \prod_{x_{1}^{i} > x_{2}^{i} = 0} 1 - \Phi\left[\ln\left(\frac{\bar{x}_{2}^{i}}{\bar{x}_{1}^{i}}\right) + \ln a + A\bar{x}_{1}^{i}\right].$$

Table H3 presents the CARA results of the ML estimation for the full set of subjects.

Table H4 displays summary statistics, and compares the results of the ML and NLLS estimations.

[Table H3 here]

[Table H4 here]