

Online Appendix
Decision Making under Uncertainty: An Experimental
Study in Market Settings

Federico Echenique Taisuke Imai Kota Saito

Contents

A	Implementation of Revealed Preference Tests	2
A.1	Exact Revealed Preference Tests	2
A.2	Approximate Revealed Preference Tests	8
B	Supplementary Figures and Tables	10
B.1	Laboratory Data	10
B.2	Panel Data	14
B.3	Sample Comparison in the Panel Study	18
C	Power Calculation	20
D	Design Detail	23
D.1	The Set of Budgets	23
D.2	Simulated Price Paths for the Market-Stock Task	24
D.3	Post-Experiment Survey in the Laboratory Study	26
E	Instructions for the Experiments	27
	References	39

A Implementation of Revealed Preference Tests

A.1 Exact Revealed Preference Tests

We are able to check whether a given dataset is consistent with SEU or MEU by solving a linear programming problem that is equivalent to the axiom characterizing the model under consideration. The construction of linear programming problems closely follows the argument in the proofs of Theorems that appear in [Echenique and Saito \(2015\)](#) and [Chambers et al. \(2016\)](#).

For example, [Echenique and Saito \(2015\)](#) prove in Lemma 7 that a dataset $(x^k, p^k)_{k=1}^K$ is SEU rational if and only if there are strictly positive numbers v_s^k , λ^k , and μ_s for $s = 1, \dots, S$ and $k = 1, \dots, K$ such that

$$\mu_s v_s^k = \lambda^k p_s^k, \quad x_s^k > x_s^{k'} \implies v_s^k \leq v_s^{k'},$$

or equivalently,

$$\log v_s^k + \log \mu_s - \log \lambda^k - \log p_s^k = 0, \quad x_s^k > x_s^{k'} \implies \log v_s^k \leq \log v_s^{k'},$$

in a log-linearized form.

Testing SEU rationality boils down to checking for existence of a solution to the above system, which can be expressed as a system of linear equalities and inequalities:

$$\begin{cases} A \cdot z = 0 \\ B \cdot z \geq 0 \\ E \cdot z > 0 \end{cases} . \quad (\text{A.1})$$

A system of linear equalities and inequalities. We now construct three key ingredients of the system (A.1), matrices A , B , and E for testing SEU.

The first matrix A has $K \times S$ rows and $K \times S + S + K + 1$ columns, defined as follows: We have one row for every pair (k, s) ; one column for every pair (k, s) ; one column for every s , one column for each k ; and one last column. In the row corresponding to (k, s) the matrix has zeroes everywhere with the following exceptions: it has a 1 in the column for (k, s) ; it has a 1 in the column for s ; it has a -1 in the column for k ; and $-\log p_s^k$ in the very last column. This finalizes

the construction of A . The resulting matrix looks as follows:

$$(1,1) \begin{array}{c} \vdots \\ (k,s) \\ \vdots \\ (K,S) \end{array} \begin{array}{c} (1,1) \quad \dots \quad (k,s) \quad \dots \quad (K,S) \\ \left[\begin{array}{ccccc|ccccc|ccccc} 1 & \dots & 0 & \dots & 0 & 1 & \dots & 0 & \dots & 0 & -1 & \dots & 0 & \dots & 0 & -\log p_1^1 \\ \vdots & & \vdots & & \vdots & \vdots & & \vdots & & \vdots & \vdots & & \vdots & & \vdots & \vdots \\ 0 & \dots & 1 & \dots & 0 & 0 & \dots & 1 & \dots & 0 & 0 & \dots & -1 & \dots & 0 & -\log p_s^k \\ \vdots & & \vdots & & \vdots & \vdots & & \vdots & & \vdots & \vdots & & \vdots & & \vdots & \vdots \\ 0 & \dots & 0 & \dots & 1 & 0 & \dots & 0 & \dots & 1 & 0 & \dots & 0 & \dots & -1 & -\log p_S^K \end{array} \right] \end{array} \begin{array}{c} p \\ -\log p_1^1 \\ \vdots \\ -\log p_s^k \\ \vdots \\ -\log p_S^K \end{array}.$$

Next, we construct matrix B that has $K \times S + S + K + 1$ columns and there is one row for every pair (k, s) and (k', s') for which $x_s^k > x_{s'}^{k'}$. In the row corresponding to $x_s^k > x_{s'}^{k'}$, we have zeroes everywhere with the exception of a -1 in the column for (k, s) and a 1 in the column for (k', s') .

Finally, we prepare a matrix that captures the requirement that the last component of a solution be strictly positive. The matrix E has a single row and $K \times S + S + K + 1$ columns. It has zeroes everywhere except for 1 in the last column.

In order to test MEU, we need to modify matrices A , B , and E appropriately, following the characterization provided by [Chambers et al. \(2016\)](#) for the case of two states of the world. Let $K^0 = \{k : x_1^k = x_2^k\}$, $K^1 = \{k : x_1^k < x_2^k\}$ and $K^2 = \{k : x_1^k > x_2^k\}$. The first-order conditions are:

$$\mu_s^k v_s^k = \lambda^k p_s^k,$$

for $s = 1, 2$ and $k \in \{1, \dots, K\}$, where $\mu_1^k = \bar{\mu}_1$ if $k \in K^1$, $\mu_1^k = \underline{\mu}_1$ if $k \in K^2$, $\mu_1^k \in [\underline{\mu}_1, \bar{\mu}_1]$ if $k \in K^0$. We now use $\pi = \mu_1/\mu_2$ instead of μ_1 . Then we can rewrite the first-order conditions:

$$\pi^k v_1^k = \lambda^k p_1^k \quad \text{and} \quad v_2^k = \lambda^k p_2^k,$$

for $k \in \{1, \dots, K\}$, where $\pi^k = \bar{\pi}$ if $k \in K^1$, $\pi^k = \underline{\pi}$ if $k \in K^2$, $\pi^k \in [\underline{\pi}, \bar{\pi}]$ if $k \in K^0$.

Let A be a matrix with $2K + 2 + |K^0| + K + 1$ columns. The first $2K$ columns are labeled with a different pair (k, s) . The next two columns are labeled $\bar{\pi}$ and $\underline{\pi}$. The next $|K^0|$ columns are for choices on the 45-degree line. The next K columns are labeled with k . Finally the last column is labeled p .

For each $(k, 2)$, A has a row with all zero entries with the following exception: It has a 1 in the column labeled $(k, 2)$; It has a -1 in the column labeled k ; It has $-\log p_s^k$ in the column labeled p . For each $(k, 1)$ with $k \in K^1$, A has a row with all zero entries with the following exception: It has a 1 in the column labeled $(k, 1)$; It has a -1 in the column labeled k ; it has $-\log p_s^k$ in the column labeled p ; It has a 1 in the column labeled $\bar{\pi}$. For each $(k, 1)$ with $k \in K^2 \cup K^0$, A has a row defined as above. The only difference is that it has a 1 in the column labeled $\underline{\pi}$ if $k \in K^2$ and in the column labeled π^k if $k \in K^0$, instead of having a 1 in the column labeled $\bar{\pi}$.

The resulting matrix A looks as follows:

$$\begin{array}{c}
\vdots \\
(k,s) \in (K,2) \\
(k,s) \in (K^1,1) \\
(k,s) \in (K^2,1) \\
(k,s) \in (K^0,1) \\
\vdots
\end{array}
\begin{array}{c}
(1,1) \quad \dots \quad (k,s) \quad \dots \quad (K,S) \\
\left[\begin{array}{cccc|ccc|cccc|c}
\vdots & & \vdots & & \vdots & \bar{\pi} & \underline{\pi} & \pi^k & \dots & 1 & \dots & k & \dots & K & p \\
\vdots & & \vdots & & \vdots & \vdots & \vdots & \vdots & & \vdots & & \vdots & & \vdots & \vdots \\
0 & \dots & 1 & \dots & 0 & 0 & 0 & 0 & \dots & 0 & \dots & -1 & \dots & 0 & -\log p_s^k \\
0 & \dots & 1 & \dots & 0 & 1 & 0 & 0 & \dots & 0 & \dots & -1 & \dots & 0 & -\log p_s^k \\
0 & \dots & 1 & \dots & 0 & 0 & 1 & 0 & \dots & 0 & \dots & -1 & \dots & 0 & -\log p_s^k \\
0 & \dots & 1 & \dots & 0 & 0 & 0 & 1 & \dots & 0 & \dots & -1 & \dots & 0 & -\log p_s^k \\
\vdots & & \vdots & & \vdots & \vdots & \vdots & \vdots & & \vdots & & \vdots & & \vdots & \vdots
\end{array} \right].
\end{array}$$

Let B be a matrix with the same number of columns as A . The columns of B are labeled like those of A . B has a row for each pair $(x_s^k, x_{s'}^{k'})$ with $x_s^k > x_{s'}^{k'}$. The row for $x_s^k > x_{s'}^{k'}$ has all zeroes except for a 1 in column (k', s') and a -1 in column (k, s) . Finally, B has a row which has a 1 in the column for $\bar{\pi}$ and a -1 in the column for $\underline{\pi}$ and $2|K^0|$ additional rows to capture $\pi^k \in [\underline{\pi}, \bar{\pi}]$ for $k \in K^0$. The resulting matrix B looks as follows:

$$\begin{array}{c}
\vdots \\
x_s^k > x_{s'}^{k'} \\
\vdots \\
\bar{\pi} \geq \underline{\pi} \\
\pi^k \geq \underline{\pi} \\
\pi^k \leq \bar{\pi}
\end{array}
\begin{array}{c}
(1,1) \quad \dots \quad (k,s) \quad \dots \quad (k',s') \quad \dots \quad (K,S) \\
\left[\begin{array}{cccc|ccc|cccc|c}
\vdots & & \vdots & & \vdots & \bar{\pi} & \underline{\pi} & \pi^k & \dots & 1 & \dots & k & \dots & K & p \\
\vdots & & \vdots & & \vdots & \vdots & \vdots & \vdots & & \vdots & & \vdots & & \vdots & \vdots \\
0 & \dots & -1 & \dots & 1 & \dots & 0 & 0 & 0 & 0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \\
\vdots & & \vdots & & \vdots & & \vdots & \vdots & \dots & \vdots & & \vdots & & \vdots & & \vdots & \vdots \\
0 & \dots & 0 & \dots & 0 & \dots & 0 & 1 & -1 & 0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \\
0 & \dots & 0 & \dots & 0 & \dots & 0 & 0 & -1 & 1 & \dots & 0 & \dots & 0 & \dots & 0 & 0 \\
0 & \dots & 0 & \dots & 0 & \dots & 0 & 1 & 0 & -1 & \dots & 0 & \dots & 0 & \dots & 0 & 0
\end{array} \right].
\end{array}$$

Solve the system. Our task is to check if there is a vector z that solves the system (A.1) of linear inequalities corresponding to model $M \in \{\text{SEU}, \text{MEU}\}$. If there is a solution z to this system, we say that the dataset is “M rational.”

Extension. There are three underlying states of the world, $S = \{\omega_1, \omega_2, \omega_3\}$, in the experiments. There are two types of questions: in type 1 questions, two events are $s_1 = \{\omega_1\}$ and $s_{23} = \{\omega_2, \omega_3\}$; in type 2 questions, two events are $s_{12} = \{\omega_1, \omega_2\}$ and $s_3 = \{\omega_3\}$. Let $S_1 = \{s_1, s_{23}\}$ denote the set of events in type 1 questions and $S_2 = \{s_{12}, s_3\}$ denote the set of events in type 2 questions. See Figure A.1.

Suppose we have K observations in the data $(x^k, p^k)_{k=1}^K$. Let $k_1 \in K_1$ and $k_2 \in K_2$ denote indices for type 1 and type 2 questions, respectively (thus $K = K_1 \cup K_2$). Note that there is no type 1 question with state s_3 . Therefore, indices for observations (k) and states (s) need to be consistent, i.e., $(k, s) \in K_i \times S_i$ for each $i = 1, 2$.

Type 1 question	s_1	s_{23}	
State of the world	ω_1	ω_2	ω_3
Type 2 question	s_{12}		s_3

FIGURE A.1: Event structure in the experiment.

In order to test SEU in this environment, we use the following proposition.

Proposition A.1. *There exist strictly positive numbers $\mu_1, \mu_{23}, \mu_{12}, \mu_3, v_1^{k_1}, v_{23}^{k_2}, v_{12}^{k_1}, v_3^{k_1}, \lambda^{k_1}, \lambda^{k_2}$ such that*

$$\mu_1 v_1^{k_1} = \lambda^{k_2} p_1^{k_1} \text{ for each } k_1, \quad (\text{FOC1})$$

$$\mu_{23} v_{23}^{k_1} = \lambda^{k_2} p_{23}^{k_1} \text{ for each } k_1, \quad (\text{FOC2})$$

$$\mu_{12} v_{12}^{k_2} = \lambda^{k_1} p_{12}^{k_2} \text{ for each } k_2, \quad (\text{FOC3})$$

$$\mu_3 v_3^{k_2} = \lambda^{k_1} p_3^{k_2} \text{ for each } k_2, \quad (\text{FOC4})$$

$$\mu_{12} + \mu_3 = 1, \quad (\text{NO1})$$

$$\mu_1 + \mu_{23} = 1, \quad (\text{NO2})$$

$$\mu_{12} \geq \mu_1, \quad (\text{MO1})$$

$$\mu_{23} \geq \mu_3, \quad (\text{MO2})$$

$$\mu_{12} - \mu_1 = \mu_{23} - \mu_3. \quad (\text{EQ})$$

if and only if there exist strictly positive numbers $\tilde{\mu}_{23}, \tilde{\mu}_{12}, v_1^{k_1}, v_{23}^{k_2}, v_{12}^{k_2}, v_3^{k_2}, \tilde{\lambda}^{k_1}, \tilde{\lambda}^{k_2}$ such that

$$v_1^{k_1} = \tilde{\lambda}^{k_1} p_1^{k_1} \text{ for each } k_1, \quad (\text{FOC1}')$$

$$\tilde{\mu}_{23} v_{23}^{k_1} = \tilde{\lambda}^{k_1} p_{23}^{k_1} \text{ for each } k_1, \quad (\text{FOC2}')$$

$$\tilde{\mu}_{12} v_{12}^{k_2} = \tilde{\lambda}^{k_2} p_{12}^{k_2} \text{ for each } k_2, \quad (\text{FOC3}')$$

$$v_3^{k_2} = \tilde{\lambda}^{k_2} p_3^{k_2} \text{ for each } k_2, \quad (\text{FOC4}')$$

$$\tilde{\mu}_{23} \tilde{\mu}_{12} \geq 1. \quad (\text{MO1}')$$

Proof. Define $\mu_1 = 1/(1 + \tilde{\mu}_{23})$, $\mu_{23} = \tilde{\mu}_{23}/(1 + \tilde{\mu}_{23})$, $\mu_{12} = \tilde{\mu}_{12}/(1 + \tilde{\mu}_{12})$, $\mu_3 = 1/(1 + \tilde{\mu}_{12})$, $\lambda^{k_1} = \tilde{\lambda}^{k_1}/(1 + \tilde{\mu}_{23})$, and $\lambda^{k_2} = \tilde{\lambda}^{k_2}/(1 + \tilde{\mu}_{12})$. Then, conditions FOC1-FOC4 are equivalent to FOC1'-FOC4' since, for example,

$$\mu_{12} v_{12}^{k_2} = \lambda^{k_2} p_{12}^{k_2} \iff \frac{\tilde{\mu}_{12}}{1 + \tilde{\mu}_{12}} v_{12}^{k_2} = \frac{\tilde{\lambda}^{k_2}}{1 + \tilde{\mu}_{12}} p_{12}^{k_2} \iff \tilde{\mu}_{12} v_{12}^{k_2} = \tilde{\lambda}^{k_2} p_{12}^{k_2}.$$

Condition **MO1** is equivalent to **MO1'** since

$$\mu_{12} \geq \mu_1 \iff \frac{\tilde{\mu}_{12}}{1 + \tilde{\mu}_{12}} \geq \frac{1}{1 + \tilde{\mu}_{23}} \iff \tilde{\mu}_{12} + \tilde{\mu}_{12}\tilde{\mu}_{23} \geq 1 + \tilde{\mu}_{12} \iff \tilde{\mu}_{12}\tilde{\mu}_{23} \geq 1,$$

and similarly **MO2** is equivalent to **MO1'**. Condition **EQ** is satisfied since

$$\mu_{12} - \mu_1 = \frac{\tilde{\mu}_{12}}{1 + \tilde{\mu}_{12}} - \frac{1}{1 + \tilde{\mu}_{23}} = \frac{\tilde{\mu}_{12}\tilde{\mu}_{23} - 1}{(1 + \tilde{\mu}_{12})(1 + \tilde{\mu}_{23})} = \frac{\tilde{\mu}_{23}}{1 + \tilde{\mu}_{23}} - \frac{1}{1 + \tilde{\mu}_{12}} = \mu_{23} - \mu_3.$$

□

In order to implement the test, we first assemble matrices A (capturing v , μ , and λ ; equality constraints in the linear programming problem) and B (capturing concavity of u ; weak inequality constraints). The above proposition has two implications: (i) We need to find only two strictly positive numbers capturing subjective beliefs, $\tilde{\mu}_{23}$ and $\tilde{\mu}_{12}$, instead of four numbers μ_1 , μ_{23} , μ_{12} , and μ_3 . (ii) We need to add one row in B to take care of additional weak inequality constraint $\tilde{\mu}_{23}\tilde{\mu}_{12} \geq 1$ (or equivalently, $\log \tilde{\mu}_{23} + \log \tilde{\mu}_{12} \geq 0$).

Let us now consider MEU. Suppose that in the first m_1 observations we have a partition $\{\{\omega_1\}, \{\omega_2, \omega_3\}\}$ (i.e., type 1 questions), and in the second m_2 observations we have a partition $\{\{\omega_1, \omega_2\}, \{\omega_3\}\}$ (i.e., type 2 questions).

- Partition 1: $\{\{\omega_1\}, \{\omega_2, \omega_3\}\}$. Let $O^0 = \{k : x_1^k = x_{23}^k\}$, $O^1 = \{k : x_1^k < x_{23}^k\}$ and $O^2 = \{k : x_1^k > x_{23}^k\}$. Afriat inequalities are now:

$$\theta^k v_1^k = \lambda^k p_1^k \quad \text{and} \quad v_{23}^k = \lambda^k p_{23}^k,$$

for $k \in \{1, \dots, m_1\}$, where $\theta^k = \bar{\theta}$ if $k \in O^1$, $\theta^k = \underline{\theta}$ if $k \in O^2$, and $\theta^k \in [\underline{\theta}, \bar{\theta}]$ if $k \in O^0$.

- Partition 2: $\{\{\omega_1, \omega_2\}, \{\omega_3\}\}$. Let $T^0 = \{k : x_{12}^k = x_3^k\}$, $T^1 = \{k : x_{12}^k < x_3^k\}$ and $T^2 = \{k : x_{12}^k > x_3^k\}$. Afriat inequalities are now:

$$\pi^k v_{12}^k = \lambda^k p_{12}^k \quad \text{and} \quad v_3^k = \lambda^k p_3^k,$$

for $k \in \{m_1 + 1, \dots, m_1 + m_2\}$, where $\pi^k = \bar{\pi}$ if $k \in T^1$, $\pi^k = \underline{\pi}$ if $k \in T^2$, and $\pi^k \in [\underline{\pi}, \bar{\pi}]$ if $k \in T^0$.

The unknowns are

$$\underline{\theta}, \bar{\theta}, \theta^k, v_s^k, \lambda^k$$

for all $k = 1, \dots, m_1$, and $s \in \{\{\omega_1\}, \{\omega_2, \omega_3\}\}$, and

$$\underline{\pi}, \bar{\pi}, \pi^k, v_s^k, \lambda^k$$

for all $k = m_1 + 1, \dots, m_1 + m_2$, $s \in \{\{\omega_1, \omega_2\}, \{\omega_3\}\}$. The system of inequalities are:

$$\left\{ \begin{array}{ll} \theta^k v_1^k = \lambda^k p_1^k & \text{if } k \in O^0 \\ \bar{\theta} v_1^k = \lambda^k p_1^k & \text{if } k \in O^1 \\ \underline{\theta} v_1^k = \lambda^k p_1^k & \text{if } k \in O^2 \\ v_{23}^k = \lambda^k p_{23}^k & \text{if } k \in O^0 \cup O^1 \cup O^2 \\ \underline{\theta} \leq \theta^k \leq \bar{\theta} & \text{if } k \in O^0 \cup O^1 \cup O^2 \end{array} \right. , \quad \left\{ \begin{array}{ll} \pi^k v_{12}^k = \lambda^k p_{12}^k & \text{if } k \in T^0 \\ \bar{\pi} v_{12}^k = \lambda^k p_{12}^k & \text{if } k \in T^1 \\ \underline{\pi} v_{12}^k = \lambda^k p_{12}^k & \text{if } k \in T^2 \\ v_3^k = \lambda^k p_3^k & \text{if } k \in T^0 \cup T^1 \cup T^2 \\ \underline{\pi} \leq \pi^k \leq \bar{\pi} & \text{if } k \in T^0 \cup T^1 \cup T^2 \end{array} \right.$$

and, in addition, the constraints $\underline{\theta} \leq \bar{\theta}$, $\underline{\pi} \leq \bar{\pi}$, $\underline{\theta} \leq \underline{\pi}$, and $\bar{\theta} \leq \bar{\pi}$.

Note that this system of inequalities is linear after we take the log of each variable. In particular the constraint that $\pi^k \in [\underline{\pi}, \bar{\pi}]$ is written as $\log(\underline{\pi}) \leq \log(\pi^k) \leq \log(\bar{\pi})$.

Proposition A.2. *A solution to the previous Afriat inequalities gives a solution to the FOCs.*

Proof. Define

$$\mu_1^k = \theta^k / (1 + \theta^k), \quad \mu_{23}^k = 1 / (1 + \theta^k)$$

if $k = 1, \dots, m_1$, and

$$\mu_{12}^{k'} = \pi^{k'} / (1 + \pi^{k'}), \quad \mu_3^{k'} = 1 / (1 + \pi^{k'})$$

if $k' = m_1 + 1, \dots, m_1 + m_2$. Then

$$1 = \mu_1^k + \mu_{23}^k = \mu_{12}^{k'} + \mu_3^{k'}.$$

Observe that:

(a) $\underline{\theta} \leq \bar{\theta} \implies \underline{\mu}_1 \leq \bar{\mu}_1$;

(b) $\underline{\pi} \leq \bar{\pi} \implies \underline{\mu}_{12} \leq \bar{\mu}_{12}$;

(c) $\underline{\theta} \leq \underline{\pi} \implies \underline{\mu}_1 \leq \underline{\mu}_{12}$; and

(d) $\bar{\theta} \leq \bar{\pi} \implies \bar{\mu}_1 \leq \bar{\mu}_{12}$.

Define $\underline{\mu}_2 = \underline{\mu}_{12} - \underline{\mu}_1$. Note that $\underline{\mu}_2 = \bar{\mu}_{23} - \bar{\mu}_3$ because

$$1 = \underline{\mu}_{12} + \bar{\mu}_3 = \underline{\mu}_1 + \bar{\mu}_{23} \implies \underline{\mu}_{12} - \underline{\mu}_1 = \bar{\mu}_{23} - \bar{\mu}_3.$$

Note also that $\underline{\mu}_2 \geq 0$, as (c) implies that $\underline{\mu}_{12} \geq \underline{\mu}_1$. Similarly, if we define $\bar{\mu}_2 = \bar{\mu}_{12} - \bar{\mu}_1$. Then using (d) we obtain that

$$0 \leq \bar{\mu}_2 = \bar{\mu}_{23} - \bar{\mu}_3.$$

□

A.2 Approximate Revealed Preference Tests

We can characterize e -price-perturbed SEU (Fact 3 in Section 2) in the environment of the experiment.

Proposition A.3. *Given $e \in \mathbf{R}_+$, a dataset $(x^k, p^k)_{k=1}^K$ is e -price-perturbed SEU rational if and only if there exist strictly positive numbers v_s^k , λ^k , μ_s , and ε_s^k such that:*

1. for all $(k, s), (k', s') \in \cup_{i=1}^2 (K_i \times S_i)$,

$$\mu_s v_s^k = \lambda^k \varepsilon_s^k p_s^k, \quad x_s^k > x_s^{k'} \implies v_s^k \leq v_s^{k'},$$

2. for all $i = 1, 2$,

$$\sum_{s \in S_i} \mu_s = 1,$$

3. $\mu_{12} \geq \mu_1$ and $\mu_{23} \geq \mu_3$,

4. $\mu_{12} - \mu_1 = \mu_{23} - \mu_3$, and

5. for all $k, l \in K$ and $s, t \in S$,

$$\frac{\varepsilon_s^k / \varepsilon_t^k}{\varepsilon_s^l / \varepsilon_t^l} \leq 1 + e.$$

Following the same reasoning as Proposition A.1, we obtain an equivalent characterization which is useful for setting up a linear programming problem.

Proposition A.4. *Given $e \in \mathbf{R}_+$, a dataset $(x^k, p^k)_{k=1}^K$ is e -price-perturbed SEU rational if and only if there exist strictly positive numbers v_s^k , $\tilde{\lambda}^k$, $\tilde{\mu}_s$, and ε_s^k such that:*

1. for all $k_1 \in K_1$,

$$v_1^{k_1} = \tilde{\lambda}^{k_1} \varepsilon_1^{k_1} p_1^{k_1}, \quad \text{and} \quad \tilde{\mu}_{23} v_{23}^{k_1} = \tilde{\lambda}^{k_1} \varepsilon_{23}^{k_1} p_{23}^{k_1}, \quad (e\text{-FOC1})$$

2. for all $k_2 \in K_2$,

$$\tilde{\mu}_{12} v_{12}^{k_2} = \tilde{\lambda}^{k_2} \varepsilon_{12}^{k_2} p_{12}^{k_2} \quad \text{and} \quad v_3^{k_2} = \tilde{\lambda}^{k_2} \varepsilon_3^{k_2} p_3^{k_2}, \quad (e\text{-FOC2})$$

3. for all $(k, s), (k', s') \in \cup_{i=1}^2 (K_i \times S_i)$,

$$x_s^k > x_s^{k'} \implies v_s^k \leq v_s^{k'}, \quad (e\text{-CON})$$

4. $\tilde{\mu}_{23} \tilde{\mu}_{12} \geq 1$ (e -MON), and

5. for all $k, l \in K$ and $s, t \in S$,

$$\frac{\varepsilon_s^k / \varepsilon_t^k}{\varepsilon_s^l / \varepsilon_t^l} \leq 1 + e.$$

Definition A.1. Given a dataset $(x^k, p^k)_{k=1}^K$, minimal e for SEU, e_*^{SEU} , is the solution to the following problem:

$$\min_{(\tilde{\mu}_s, v_s^k, \tilde{\lambda}^k, \varepsilon_s^k)_{k,s}} \max_{k, l \in K, s, t \in S} \frac{\varepsilon_s^k / \varepsilon_t^k}{\varepsilon_s^l / \varepsilon_t^l} \quad (\star)$$

subject to (e-FOC1), (e-FOC2), (e-CON), and (e-MON).

Remark A.1. Notice that in the objective function of the problem (\star),

$$\frac{\varepsilon_s^k / \varepsilon_t^k}{\varepsilon_s^l / \varepsilon_t^l},$$

two states s, t are fixed and observations k, l are different. In our experimental setup, it means that either $k, l \in K_1$ or $k, l \in K_2$.

Remark A.2. By log-linearizing and substituting equality constraints in the objective function in the problem (\star), we obtain

$$\begin{aligned} \log \left(\frac{\varepsilon_s^k / \varepsilon_t^k}{\varepsilon_s^l / \varepsilon_t^l} \right) &= \log \varepsilon_s^k - \log \varepsilon_t^k - \log \varepsilon_s^l + \log \varepsilon_t^l \\ &= (\log \tilde{\mu}_s + \log v_s^k - \log \lambda^k - \log p_s^k) - (\log \tilde{\mu}_t + \log v_t^k - \log \lambda^k - \log p_t^k) \\ &\quad - (\log \tilde{\mu}_s + \log v_s^l - \log \lambda^l - \log p_s^l) + (\log \tilde{\mu}_t + \log v_t^l - \log \lambda^l - \log p_t^l) \\ &= (\log \tilde{\mu}_s + \log v_s^k - \log p_s^k) - (\log \tilde{\mu}_t + \log v_t^k - \log p_t^k) \\ &\quad - (\log \tilde{\mu}_s + \log v_s^l - \log p_s^l) + (\log \tilde{\mu}_t + \log v_t^l - \log p_t^l) \\ &= (\log v_s^k - \log p_s^k) - (\log v_t^k - \log p_t^k) - (\log v_s^l - \log p_s^l) + (\log v_t^l - \log p_t^l). \end{aligned}$$

B Supplementary Figures and Tables

B.1 Laboratory Data

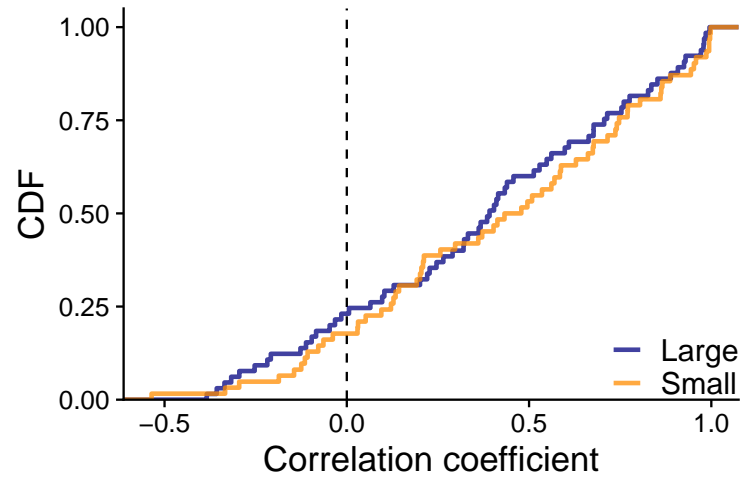


FIGURE B.1: Empirical CDF of within-subject (Spearman's) correlation between allocations in the market-stock task and the market-Ellsberg task. The two distributions are not significantly different (two-sample Kolmogorov-Smirnov test, $p = 0.91$).

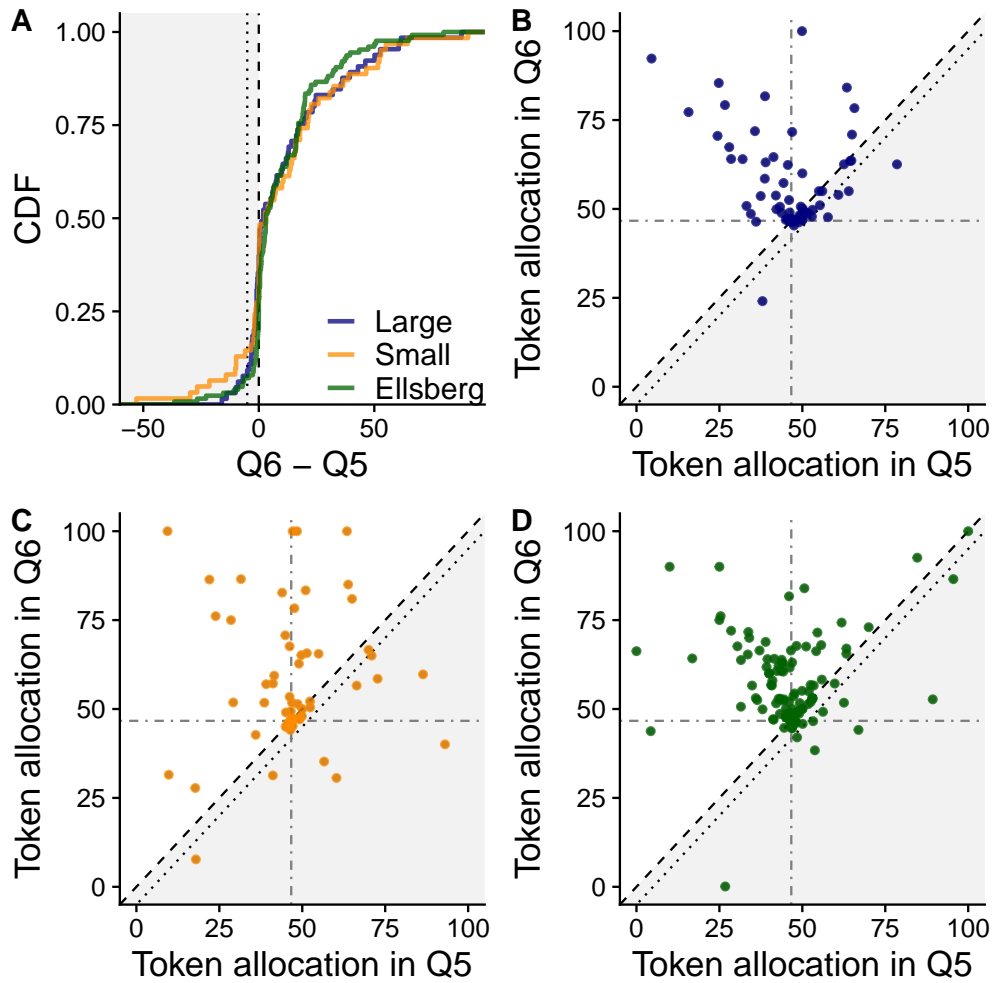


FIGURE B.2: Event monotonicity. (A) Empirical CDFs of token allocation difference. The dotted line represents a 5-token margin. No two pairs of distributions is significantly different (two-sample Kolmogorov-Smirnov test). (B-D) Token allocations in two questions. The dot-dashed lines at 46.67 indicate the number of tokens which equalizes payouts in two events.

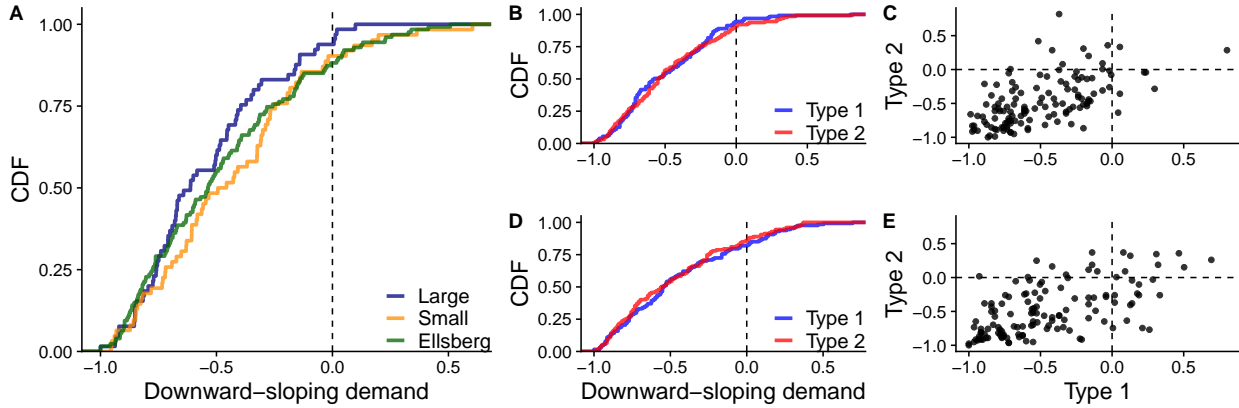


FIGURE B.3: Downward-sloping demand at the individual level (measured by ρ^{dsd}). (A) Empirical CDFs comparing across tasks. (BC) Comparing two question types in market-stock. (DE) Comparing two question types in market-Ellsberg.

TABLE B.1: Pass rates. (C.f. Table 2.)

Task	GARP			PS		
	Type 1	Type 2	Joint	Type 1	Type 2	Joint
Market-stock	0.7638	0.6850	0.5827	0.7323	0.8110	0.4803
Market-Ellsberg	0.8268	0.7480	0.6693	0.8110	0.8346	0.6220
Task	SEU			MEU		
	Type 1	Type 2	Joint	Type 1	Type 2	Joint
Market-stock	0.0472	0.0157	0.0000	0.0472	0.0157	0.0000
Market-Ellsberg	0.0787	0.0315	0.0157	0.0787	0.0315	0.0157

Note: A subject satisfies GARP “jointly” if the subject passes GARP for both types. A subject is not inconsistent with PS “jointly” if the subject is not inconsistent with PS in the sense of Epstein for both types, and satisfies event monotonicity. Since Epstein’s (2000) condition is only necessary for probabilistic sophistication, the numbers reported here capture the fraction of the subjects who are not inconsistent with probabilistic sophistication.

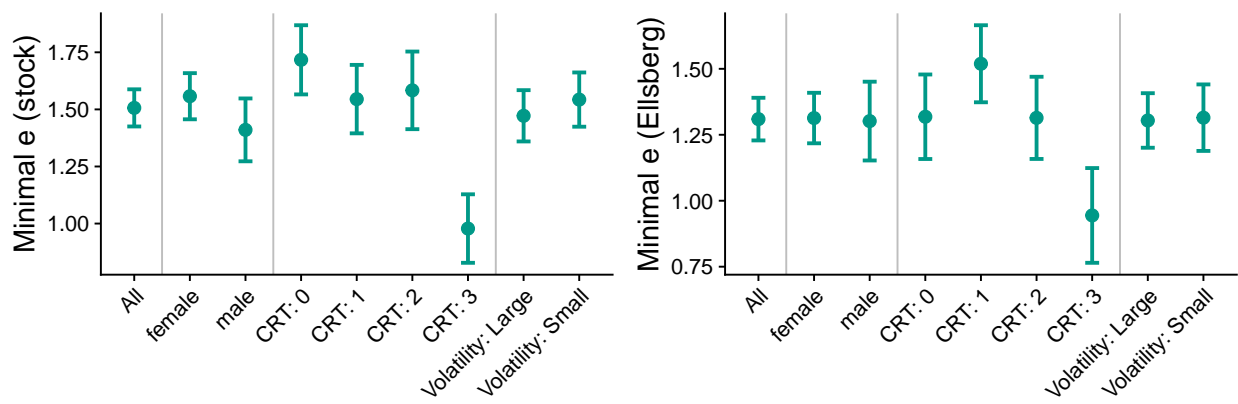


FIGURE B.4: Average e^* for SEU in each group of subjects. *Notes:* Bars indicate standard errors of means.

B.2 Panel Data

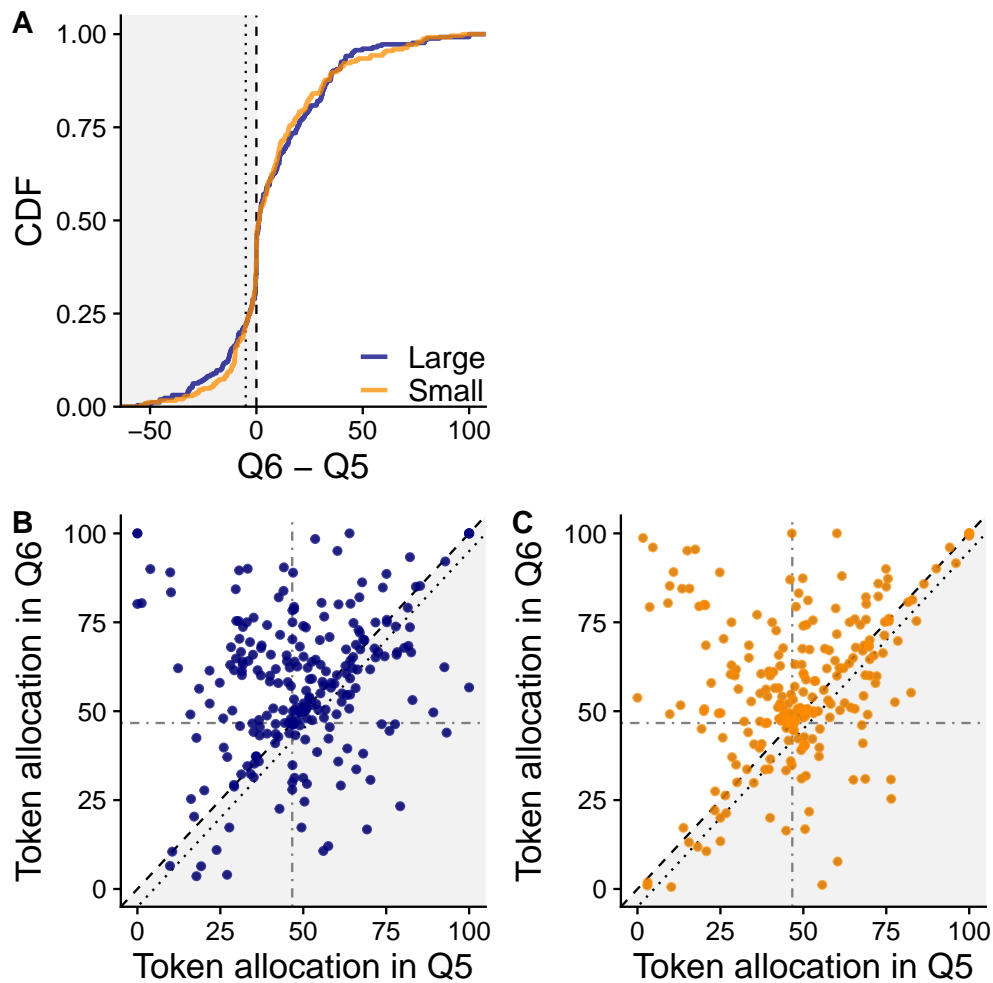


FIGURE B.5: Event monotonicity. (A) Empirical CDFs of token allocation difference. The dotted line represents a 5-token margin. No two pairs of distributions are significantly different (two-sample Kolmogorov-Smirnov test). (B-C) Token allocations in two questions. The dot-dashed lines at 46.67 indicate the number of tokens which equalizes payouts in two events.

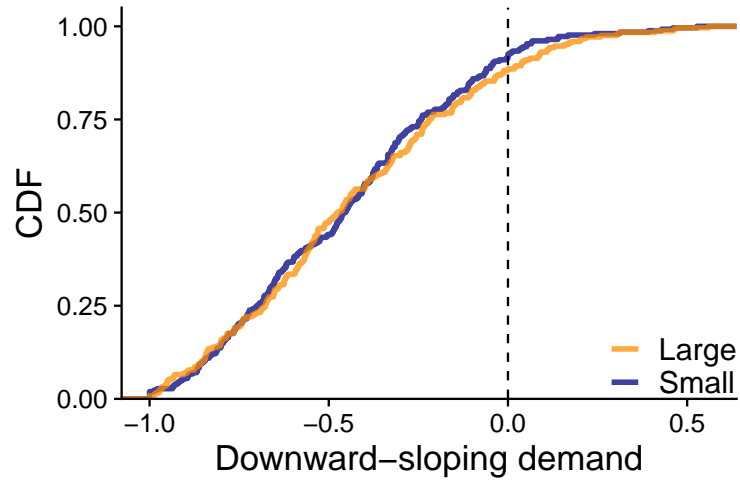


FIGURE B.6: Downward-sloping demand at the individual level (measured by ρ^{dsd}).

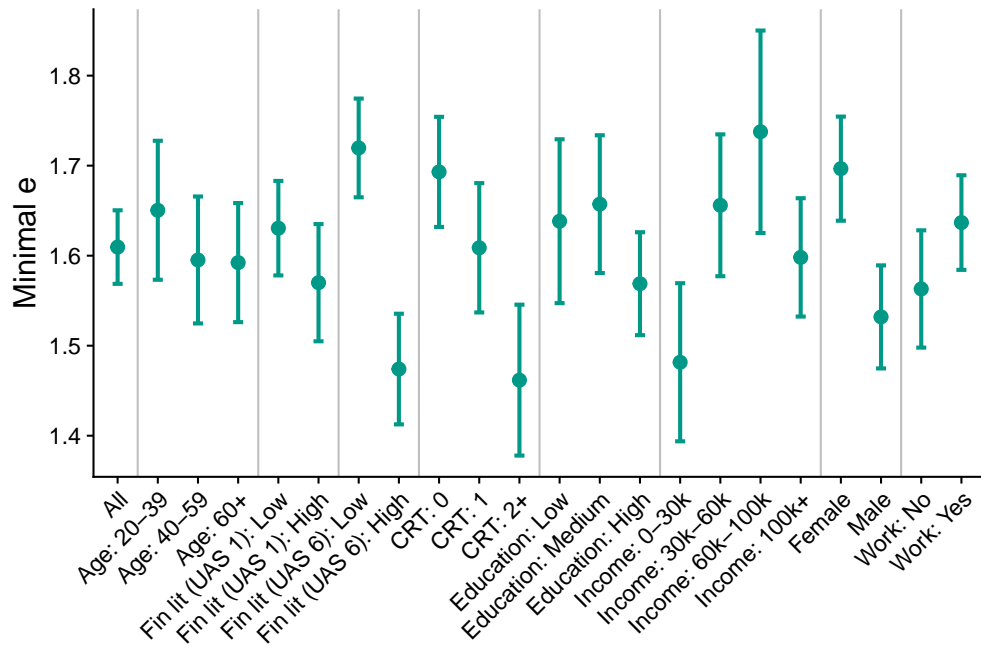


FIGURE B.7: Average e_* for SEU in each group of subjects. *Notes:* Bars indicate standard errors of means.

TABLE B.2: Pass rates. (C.f. Table 5.)

Treatment	N	GARP			PS		
		Type 1	Type 2	Joint	Type 1	Type 2	Joint
Large volatility	245	0.6653	0.5918	0.4367	0.6776	0.8041	0.3959
Small volatility	256	0.6523	0.6016	0.4492	0.6680	0.7812	0.3945
Combined	501	0.6587	0.5968	0.4431	0.6727	0.7924	0.3952

Treatment	N	SEU			MEU		
		Type 1	Type 2	Joint	Type 1	Type 2	Joint
Large volatility	245	0.0735	0.0490	0.0122	0.0735	0.0490	0.0122
Small volatility	256	0.0508	0.0547	0.0234	0.0508	0.0547	0.0273
Combined	501	0.0619	0.0519	0.0180	0.0619	0.0519	0.0200

Note: A subject satisfies GARP “jointly” if the subject passes GARP for both types. A subject is not inconsistent with PS “jointly” if the subject is not inconsistent with PS in the sense of Epstein for both types, and satisfies event monotonicity. Since Epstein’s (2000) condition is only necessary for probabilistic sophistication, the numbers reported here capture the fraction of the subjects who are not inconsistent with probabilistic sophistication.

TABLE B.3: Sociodemographic information. Treatment assignments (small volatility or large volatility) are balanced.

Variable	Treatment			Test
	All	Small volatility	Large volatility	
<i>Gender</i>				
Female	0.496	0.487	0.505	$\chi^2(1) = 0.19$
Male	0.504	0.513	0.495	$p = 0.6666$
<i>Age group</i>				
20-39	0.319	0.317	0.322	
40-59	0.353	0.366	0.340	$\chi^2(2) = 0.62$
60+	0.327	0.317	0.338	$p = 0.7342$
<i>Education level</i>				
Less than high school	0.258	0.256	0.261	
Some college	0.219	0.235	0.202	
Assoc./professional degree	0.187	0.189	0.186	$\chi^2(3) = 1.51$
College or post-graduate	0.336	0.320	0.351	$p = 0.6806$
<i>Household annual income</i>				
– \$25k	0.211	0.247	0.173	
\$25k – \$50k	0.258	0.245	0.271	
\$50k – \$75k	0.202	0.196	0.207	
\$75k – \$150k	0.262	0.240	0.285	$\chi^2(4) = 7.34$
\$150k –	0.068	0.072	0.064	$p = 0.1188$
<i>Occupation type</i>				
Full-time	0.497	0.474	0.521	$\chi^2(2) = 2.45$
Part-time	0.102	0.098	0.106	$p = 0.2935$
Not working	0.401	0.428	0.372	
<i>Marital status</i>				
Married/live with partner	0.690	0.673	0.707	$\chi^2(1) = 0.92$
Other	0.310	0.327	0.293	$p = 0.3369$
# of observations in the sample	764	388	376	

B.3 Sample Comparison in the Panel Study

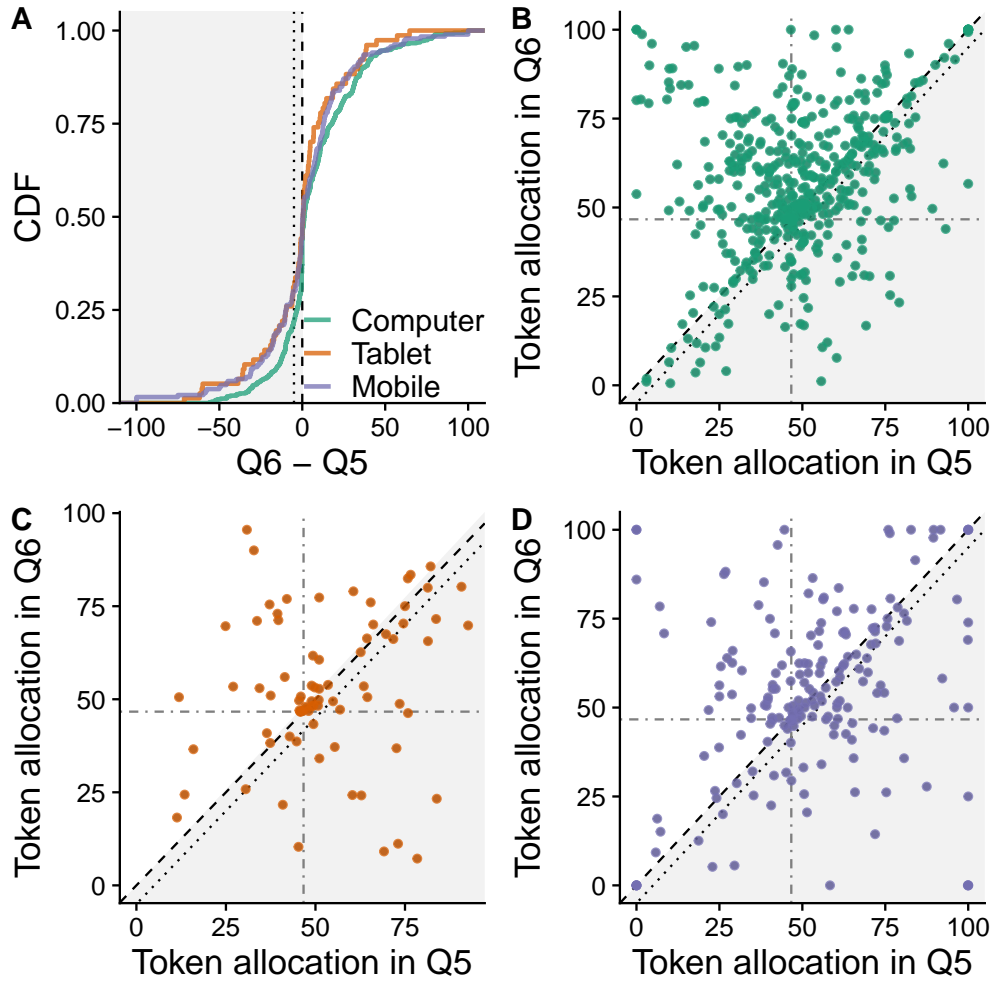


FIGURE B.8: (Panel) Event monotonicity. (A) Empirical CDFs of token allocation difference. The dotted line represents 5-token margin. Two-sample Kolmogorov-Smirnov test p -values: Computer vs. Tablet, $p = 0.116$; Computer vs. Mobile, $p = 0.044$; Tablet vs. Mobile, $p = 0.575$. (B-D) Token allocations in two questions. The dot-dashed lines at 46.67 indicate the number of tokens which equalizes payouts in two events.

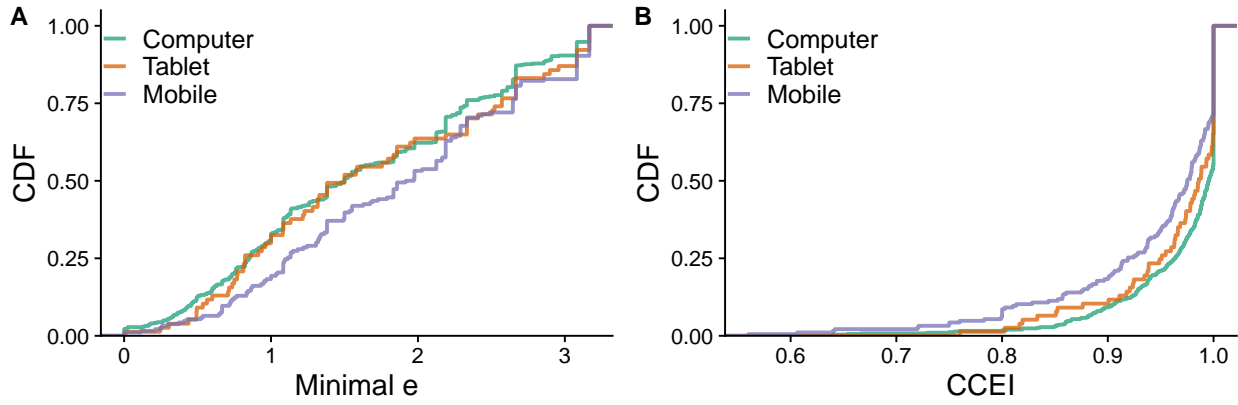


FIGURE B.9: Distribution of measures, by subjects using computer, tablet, or mobile. Two-sample Kolmogorov-Smirnov tests between the “computer” sample and the “mobile” sample: $p = 0.007$ for e_* and $p < 0.001$ for CCEI.

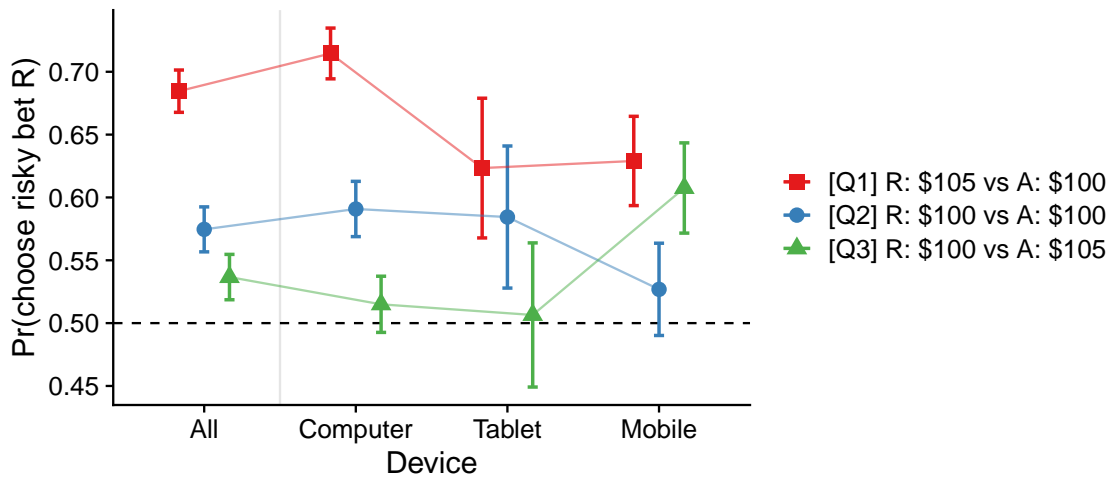


FIGURE B.10: (Panel) Probability of choosing a risky bet in each question in the standard-Ellsberg task, by subjects using computer, tablet, or mobile.

C Power Calculation

It is well known that tests in revealed preference theory can have low power when used on certain configurations of budget sets. As a result, it is common to assess the power of a test by comparing the pass rates (the fraction of choices that pass the relevant revealed preference axiom) of the observed choice data from some benchmark behavior such as purely random choices.¹

We assess the power of the tests using two kinds of data-generating processes. In the first benchmark, we use the simple bootstrap procedure to look at the power from an ex-post perspective (Andreoni and Miller, 2002). More precisely, for each budget set, we randomly pick one choice from the set of choices observed in the experiment. We repeat this to generate 10,000 synthetic choice data. In the second benchmark, we generate 10,000 datasets in which choices are made at random and uniformly distributed on the frontier of the budget set (Method 1 of Bronars, 1987). Table C.1 report pass rates. The simulated choices almost always violate SEU and MEU. Pass rates for GARP test range from 0.23 to 0.68, depending on the underlying data-generating process. These numbers are higher than those reported in other studies (e.g., Choi et al., 2007, 2014), but given that each type of problem has only 10 budgets, the configuration of budgets in our design has reasonable power to detect GARP violations.

¹The idea of using random choices as a benchmark is first applied to revealed preference theory by Bronars (1987). This approach is the most popular in empirical application: see, among others, Andreoni and Miller (2002), Fisman et al. (2007), Choi et al. (2007), Crawford (2010), Beatty and Crawford (2011), Adams et al. (2014), and Dean and Martin (2016). For overview of power calculation, see discussion in Andreoni et al. (2013) and Crawford and De Rock (2014).

TABLE C.1: Pass rates under different data generating process. Simulation sample size $N = 10,000$.

Data-generating process	Device	GARP			PS			SEU			MEU		
		Type 1	Type 2	Joint	Type 1	Type 2	Joint	Type 1	Type 2	Joint	Type 1	Type 2	Joint
Bootstrap: Laboratory													
Market-stock (Large)		0.4591	0.5577	0.2562	0.5762	0.8742	0.3913	0.0007	0.0001	0.0000	0.0011	0.0001	0.0000
Market-stock (Small)		0.4769	0.4005	0.1934	0.6689	0.7269	0.4003	0.0002	0.0000	0.0000	0.0002	0.0000	0.0000
Market-Ellsberg		0.4712	0.5365	0.2560	0.7429	0.8373	0.5196	0.0002	0.0002	0.0000	0.0002	0.0004	0.0000
Bootstrap: Panel													
Market-stock (Large)	All	0.3642	0.3162	0.1172	0.4894	0.7299	0.2545	0.0001	0.0000	0.0000	0.0001	0.0000	0.0000
from Market-stock (Small)	All	0.3184	0.2842	0.0881	0.4857	0.7136	0.2521	0.0001	0.0000	0.0000	0.0001	0.0000	0.0000
Market-stock (Large)	Desktop/laptop	0.3940	0.3533	0.1389	0.4878	0.7319	0.2661	0.0002	0.0000	0.0000	0.0002	0.0000	0.0000
Market-stock (Small)	Desktop/laptop	0.3314	0.2908	0.0967	0.5106	0.7245	0.2789	0.0001	0.0001	0.0000	0.0001	0.0001	0.0000
Uniform random		0.2270	0.1440	0.0332	0.5002	0.5350	0.1925	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

TABLE C.2: CCEI and e^* calculated with randomly generated choice data. Simulation sample size $N = 10,000$.

	CCEI			$e^*(\text{SEU})$			$e^*(\text{MEU})$		
	Type 1	Type 2	Joint	Type 1	Type 2	Joint	Type 1	Type 2	Joint
Mean	0.9123	0.9194	0.8716	1.2476	1.3770	1.7121	1.2217	1.3770	1.7012
Median	0.9256	0.9436	0.8841	1.0833	1.5510	1.7639	1.0804	1.5510	1.7580
SD	0.0829	0.0817	0.0855	0.5968	0.6523	0.5293	0.6060	0.6523	0.5410

D Design Detail

D.1 The Set of Budgets

TABLE D.1: The set of 20 budgets. The numbers indicate “exchange value” for each account (z_1, z_2).

	Type	Order	Lab		Panel	
			Account 1	Account 2	Account 1	Account 2
1	1	random	0.30	0.18	3.0	1.8
2	1	random	0.30	0.24	3.0	2.4
3	1	random	0.38	0.30	3.8	3.0
4	1	random	0.40	0.40	4.0	4.0
5	1	random	0.50	0.12	5.0	1.2
6	1	random	0.50	0.24	5.0	2.4
7	1	random	0.50	0.34	5.0	3.4
8	1	random	0.50	0.44	5.0	4.4
9	1	random	0.60	0.30	6.0	3.0
10	1	fixed (5 th)	0.32	0.28	3.2	2.8
11	2	random	0.14	0.50	1.4	5.0
12	2	random	0.24	0.50	2.4	5.0
13	2	random	0.28	0.32	2.8	3.2
14	2	random	0.30	0.36	3.0	3.6
15	2	random	0.30	0.42	3.0	4.2
16	2	random	0.30	0.56	3.0	5.6
17	2	random	0.38	0.52	3.8	5.2
18	2	random	0.40	0.50	4.0	5.0
19	2	random	0.50	0.56	5.0	5.6
20	2	fixed (6 th)	0.32	0.28	3.2	2.8

D.2 Simulated Price Paths for the Market-Stock Task

In order to simulate price paths, we use a Geometric Brownian Motion (GBM):

$$dS_t = \mu S_t dt + \sigma S_t dW_t,$$

where W_t is a Wiener process, μ is a drift parameter, and σ is a volatility parameter. To simulate trajectories of GBM, we calculate increments of S :

$$S_{t+h} = S_t \times \exp\left((\mu - \sigma^2/2)h + \sigma\sqrt{h}Z\right),$$

with $Z \sim N(0, 1)$.

As a first step, we generated N paths of GBM, where each path $P^n = (P_0^n, P_1^n, \dots, P_T^n)$ has the common starting price P_0 and T periods of prices. We then group these N paths into several categories, based on several observable features: (i) absolute movement within T periods; (ii) final price is higher than the initial price; (iii) final price is lower than the initial price; (iv) trends such as up-down, down-up, straight-gain, straight-loss, and cycle.

After visually inspecting the pattern of each price path, we handpicked 28 paths and then asked workers on Amazon Mechanical Turk what they believed the future price of each path would be. We used a “bins-and-balls” belief elicitation task (also known as a histogram elicitation method) introduced by [Delavande and Rohwedder \(2008\)](#) to elicit subjective belief distribution. The method, later refined by [\(Delavande et al., 2011\)](#) and [Rothchild \(2012\)](#), is simple and easy to understand. It has been shown to work well in experiments conducted at developing countries [\(Delavande et al., 2011\)](#) and online survey [\(Breunig et al., forthcoming\)](#).

The idea of the task is as follows. First, the (continuous) state of the world (ranges of future prices) is partitioned into 20 disjoint and exhaustive bins. Second, subjects are asked to place 20 “balls,” each representing 5% probability mass, into these bins. The subjects were then asked to express how likely they believed that the price to be in each or the 20 ranges. [Figure D.1](#) illustrates the task.

The elicited belief distributions were then averaged across subjects. Some price paths, especially those with clear upward or downward trend, tend to be associated with skewed distributions. Others have more symmetric distributions. We thus selected two relatively “neutral” ones from the latter set for the main experiment.

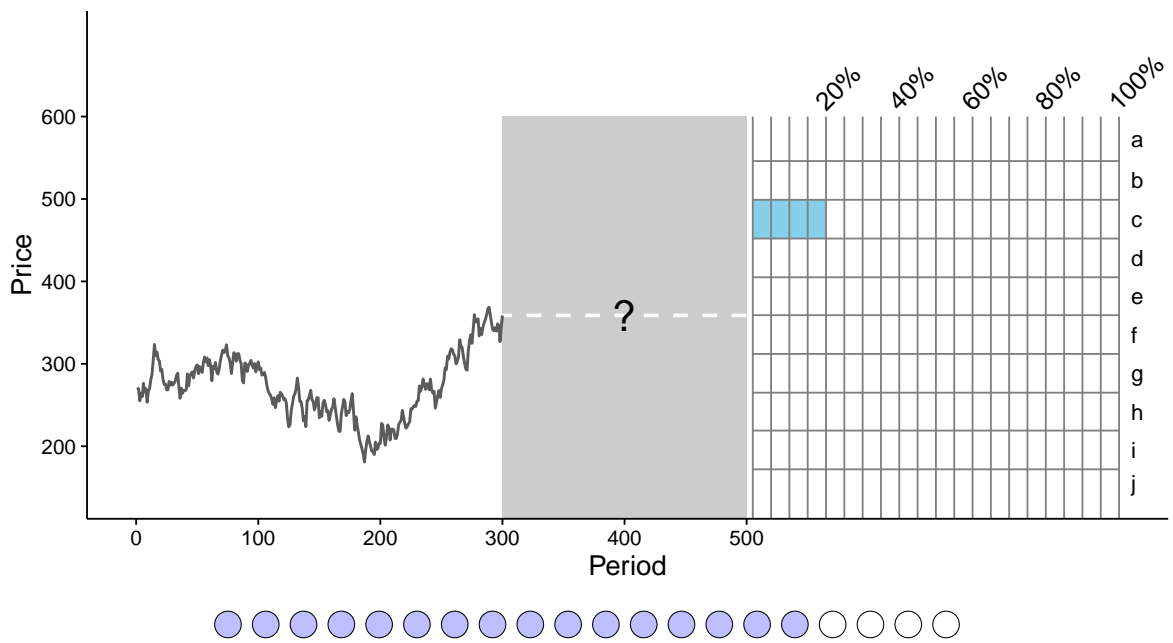


FIGURE D.1: Illustration of the bins-and-balls belief elicitation task.

D.3 Post-Experiment Survey in the Laboratory Study

Demographic information.

1. What is your age?
2. What is your gender?
3. What is your ethnicity?
4. What is your major?

Three-item cognitive reflection test.

1. If it takes 5 people 5 months to save a total of \$5,000, how many months would it take 100 people to save a total of \$100,000?
2. A TV and a radio cost \$110 in total. The TV costs \$100 more than the radio. How much does the radio cost?
3. In a lake, there is a patch of lily pads. Each day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?

E Instructions for the Experiments

Welcome!

Thank you for participating in today's experiment.

Please turn off all electronic devices, especially phones and tablets. During the experiment you are **not** allowed to open or use any other applications on these laboratory computers, except for the interface of the experiment.

This experiment is designed to study decision making. You will be paid for your participation in cash privately at the end of the session. Please follow the instructions carefully and do not hesitate to ask the experimenter any questions by raising your hand. The experimenter will then come to your desk.

Structure of the experiment

The experiment consists of 3 tasks and a survey. We will hand out specific instructions for each of the tasks just before you are to perform that task.

At the front of this laboratory you will see several opaque bags labeled **A**, **B**, and so on, which we will use in some of the tasks during the experiment. Each of these bags contains colored chips. The exact composition of chips in each bag (for example, how many of them are red) may or may not be announced to you. If you wish, you can inspect these bags **after** completing all sections of the experiment.

Payment

In order to determine the payment, **one task** and **one question from that task** will be randomly selected. Your payoff in the experiment will consist of the amounts you earned in the selected question plus a \$10 show-up fee if you complete the experiment as announced. The specific rules applied to determine payoffs for each section will be described in detail in the instructions for that part.

To select **one task** and **one question** that will determine your payment, the assistant rolled two fair dice for each participant. The assistant wrote down two numbers, one indicating the task and another indicating the question in that particular task that counts for payment. The note was placed into a sealed envelope. Please write your participant ID on the envelope once you receive it. Please do not open the envelope until you are instructed by the experimenter.

Remember that the question determining your payment is selected before you make any decisions in the experiment. This protocol of determining payments suggests that you should make a decision in each question as if it is the question that determines your payment.

Important rules

In the experiment we use a web browser. It is important that you ...

1. do not close or refresh the browser,
2. do not open other windows/tabs on the browser,
3. do not exit the full screen mode, and
4. do not open other applications and programs.

If you exit the full screen mode, please click the button at the top right corner to enter the full screen mode again.

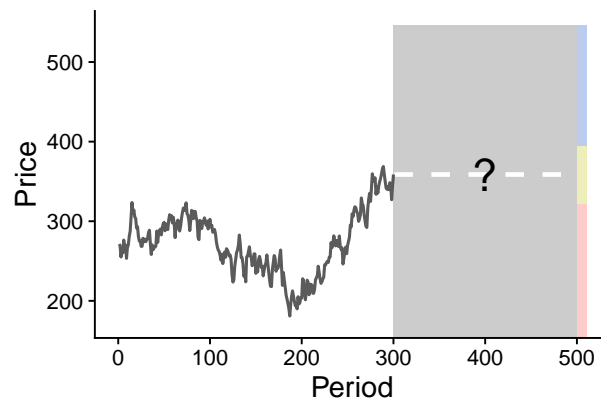
Please raise your hand if you have any questions regarding the structure of the experiment.

Task 1

Overview

In this part of the experiment, you will be asked a total of 20 independent questions that share a common structure. Your goal is to invest tokens in two different accounts. The accounts pay off according to the value of a stock.

There is a **hypothetical** company which we refer to as **Company X**. We simulated a history of stock prices of this company using a model frequently used in financial economics. You will be presented a chart plotting the history of Company X's stock prices. The figure below is an illustration of such chart. Note that the price history presented in the image is meant to be an example, and is not the same one as you will see in the task.



The chart shows stock prices from period 1 to 300 (imagine that period 300 is “today”). You do not know the movement beyond period 300, the area shaded in gray. Your payoff in this task depends on the “future” value of Company X's stock price at period 500, i.e., at the end of the chart. More precisely, it depends on whether the final price lies in the Blue area (increase by more than the threshold), Yellow area (change up to the threshold), or Red area (decrease by more than the threshold). In this example, the threshold is set to 10%.

How it works

Now we will explain the task in detail.

You will be asked a total of 20 independent questions. In each decision problem, you will be endowed with 100 tokens and asked to choose the portion of this amount (between 0 and 100 tokens, inclusive and divisible) that you wish to allocate between two accounts. Tokens allocated to each account may have different monetary values. Your payoff in this task will be determined by the following three components:

- (i) the monetary value of tokens in each account, which is given in the question,
- (ii) your allocation of tokens in each of the two accounts, and
- (iii) in which colored area Company X's stock price lies at period 500.

Two types of questions

There are two types of questions.

In Type 1 questions, two accounts are

Account **Blue-or-Yellow** : Stock price increases by a positive percentage
or decreases by at most 10%.

Account **Red** : Stock price decreases by more than 10%.

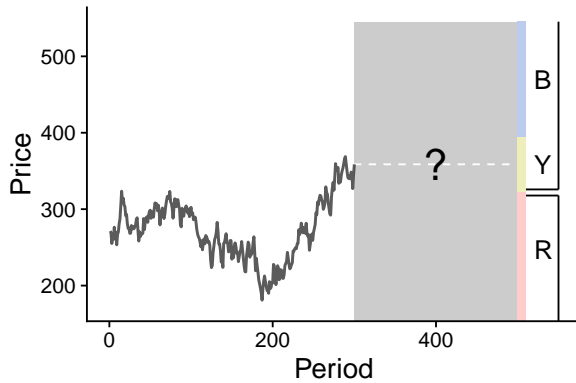
In Type 2 questions, two accounts are

Account **Blue** : Stock price increases by more than 10%.

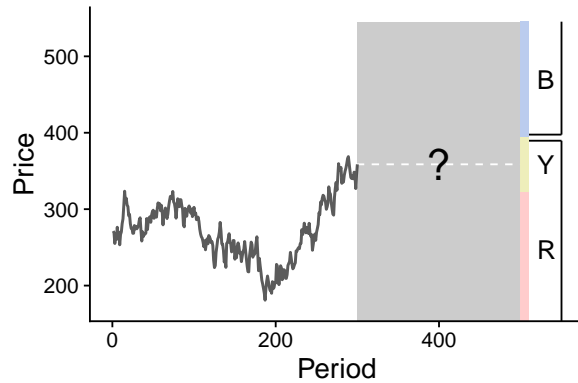
Account **Yellow-or-Red** : Stock price decreases by any percentage
or increases at most 10%.

These two types of questions appear in random order. To understand the decision problem for the given trial correctly, it would be of your best interest to check the type of the question (1 or 2) on the right of the stock chart and also at the top of the "allocation table" which will be explained below.

The "allocation table" at the bottom block of the screen shows information on the monetary values of tokens. In the example of Type 1 question below, each token you allocate to the **Blue-or-Yellow** account is worth \$0.30 (30 cents), while each token you allocate to the **Red** account is worth \$0.25 (25 cents). Notice that monetary values of tokens may change across questions.



(A) Example: Type 1 question



(B) Example: Type 2 question

	B	Y	R
Token value	\$0.30		\$0.25
Tokens	75		25
Account value	\$22.50		\$6.25

How to make a decision

You can allocate 100 tokens between two accounts using the slider. The table will be updated instantly once you move the slider, showing current allocations of tokens and their implied payment amounts if the stock ends up in the corresponding color region. No cursor appears at the start of the experiment—you need to click anywhere on the slider line to activate it.

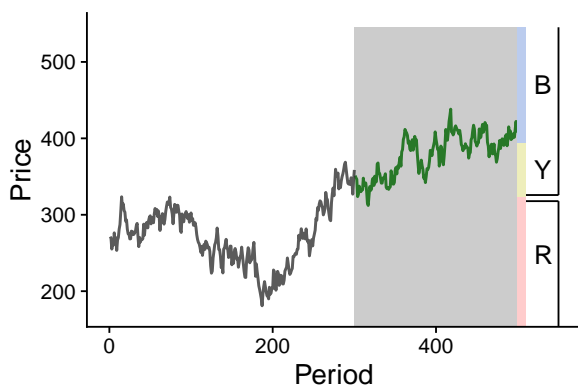
Alternatively, you can allocate tokens by directly putting numbers in one of the boxes, or clicking **up/down** arrow (which appears when you mouse-over the box) to make small adjustments.

How your payoff for this task is determined

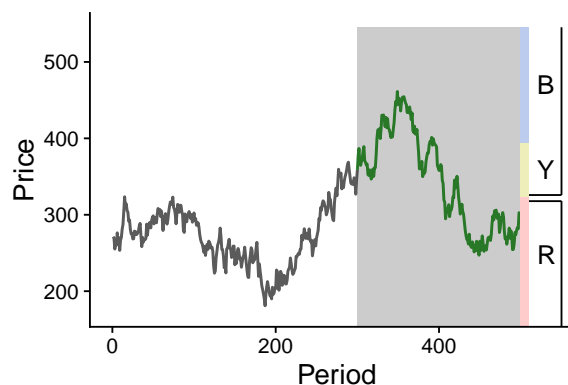
Your payoff is determined by the number of tokens in your two accounts, and the “future” value of stock X at the end of the chart (period 500), which will be simulated after you complete all questions.

Suppose you allocated 75 tokens to account **Blue-or-Yellow** and 25 tokens to account **Red** as in the above example. If this question has been chosen to determine your payoff, your payoff will be determined by the price of company X’s stock in period 500. If stock X hits blue or yellow area at period 500 (as in panel (a) below), then you will earn $75 \times \$0.30 = \22.50 (22 dollars 50 cents). On the other hand, if stock X hits red area (as in panel (b) below), then you will earn

$25 \times \$0.25 = \6.25 (6 dollars 25 cents). Amount below one cent will be rounded up.



(A) Example: Stock price hits Blue area



(B) Example: Stock price hits Red area

Important

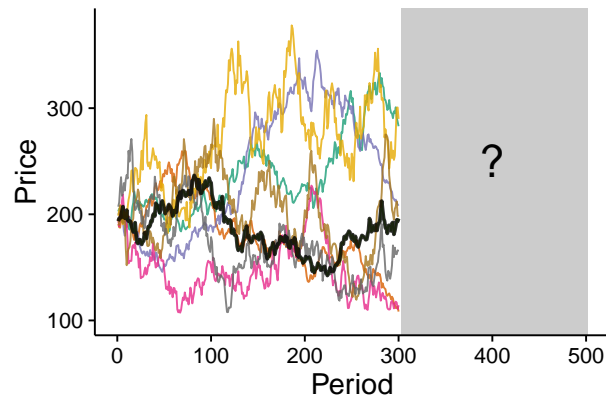
- The history of stock prices of Company X up to period 300 (“today”) is the same throughout this task.
- You will not know “future” prices (between period 301 and period 500) until you complete all tasks in the experiment.
- Token values and question types can vary between questions.
- Once you hit the Proceed button, you cannot change your decision. You **cannot** go back to previous pages, either. Note also that you **cannot** change the question by refreshing the browser once it is displayed.
- Remember that the question that will determine your payment has already been selected at the start of the experiment. It is your best interest to treat each question as if it is the question that determines you payment.

Hypothetical Stock Market

As we mentioned before, we simulated a history of stock prices of this company using a model frequently used in financial economics. The following chart illustrates eight such simulated stocks in our “hypothetical stock market”.

Let's imagine that we are at period 300 ("today") and we do not know the "future" stock prices (periods 301 to 500).

The black solid line represents the price history of our Company X. You will see ONLY this price history during this task.



Task 2

Overview

In this part of the experiment, you will be asked a total of 20 independent questions that share a common structure. Your goal is to invest tokens in two different accounts. The accounts pay off according to the color of a chip drawn from a bag at the end of the experiment.

There is an opaque **bag Z** which contains 30 colored chips. Each chip is either Blue, Yellow, or Red. The number of chips of each color is unknown to you: There can be anywhere from 0 to 30 Blue chips, anywhere from 0 to 30 Yellow chips, and anywhere from 0 to 30 Red chips, as long as the total number of Blue, Yellow, and Red chips sums to 30. Your payoff in this task depends on the color of a chip you will draw at the end of the experiment.

Bag Z: Total 30 chips



The contents of bag Z has already been determined by an assistant at the beginning of the experiment. If you wish, you can inspect the contents of the bag **after** completing the experiment.

How it works

Now we will explain the task in detail.

You will be asked a total of 20 independent questions. In each decision problem, you will be endowed with 100 tokens and asked to choose the portion of this amount (between 0 and 100 tokens, inclusive and divisible) that you wish to allocate between two accounts. Tokens allocated to each account may have different monetary values. Your payoff in this task will be determined by the following three components:

- (i) the monetary value of tokens in each account,
- (ii) your allocation of tokens in each of the two accounts, and
- (iii) the color of the chip you will draw from the bag at the end of the experiment.

Two types of questions

There are two types of questions.

In Type 1 questions, two accounts are

Account **Blue-or-Yellow** : The color of chip drawn from the bag is either Blue or Yellow.

Account **Red** : The color of chip drawn from the bag is Red.

In Type 2 questions, two accounts are

Account **Blue** : The color of chip drawn from the bag is Blue.

Account **Yellow-or-Red** : The color of chip drawn from the bag is either Yellow or Red.

These two types of questions appear in random order. To understand the decision problem for the given trial correctly, it would be of your best interest to check the account structure at the top of the “allocation table” which will be explained below.

The “allocation table” at the bottom block of the screen shows information on the monetary values of tokens. In the example of Type 2 question below, each token you allocate to the **Blue** account is worth \$0.36 (36 cents), while each token you allocate to the **Yellow-or-Red** account is worth \$0.24 (24 cents). Notice that monetary values of tokens may change across questions.

	B	Y	R
Token value	\$0.36	\$0.24	
Token	30	70	
Account value	\$10.80	\$16.80	

How to make a decision

You can allocate 100 tokens between two accounts using the slider. The table will be updated instantly once you move the slider, showing current allocations of tokens and their implied payment amounts. No cursor appears at the start of the experiment—you need to click anywhere on the slider line to activate it.

Alternatively, you can allocate tokens by directly putting numbers in one of the boxes, or clicking **up/down** arrow (which appears when you mouse-over the box) to make small adjustments.

How your payoff for this task is determined

Your payoff is determined by the number of tokens in your two accounts, and the color of a chip you will draw from the bag at the end of the experiment.

Suppose you allocated 30 tokens to account **Blue** and 70 tokens to account **Yellow-or-Red** as in the above example. If this question has been chosen to determine your payoff, your payoff will be determined by the color of a chip you will draw at the end of the experiment. If it is Blue, then you will earn $30 \times \$0.36 = \10.80 (10 dollars 80 cents). On the other hand, if it is Yellow or Red, then you will earn $70 \times \$0.24 = \16.80 (16 dollars 80 cents). Amount below one cent will be rounded up.

Important

- The composition of the bag (how many chips are blue, yellow, or red) is the same throughout this task.
 - You will not know the actual composition until you complete all tasks in the experiment.
 - Token values and question types can vary between questions.
 - Once you hit the Proceed button, you cannot change your decision. You **cannot** go back to previous pages, either. Note also that you **cannot** change the question by refreshing the browser once it is displayed.
 - Remember that the question that will determine your payment has already been selected at the start of the experiment. It is your best interest to treat each question as if it is the only question that determines your payment.
-

Task 3

There are two bags, bag A and bag B, each of which contains 30 chips. Each chip is either orange or green. The contents of each bag is as follows:

- Bag A contains 10 orange chips and 10 green chips.
- Bag B contains 20 chips. Each chip is either orange or green. The number of chips of each color is unknown to you: There can be anywhere from 0 to 20 orange chips, and anywhere from 0 to 20 green chips, as long as the total number of orange and green chips sums to 20.

Bag A: Total 20 chips



Bag B: Total 20 chips



The contents of bag B has already been determined at the beginning of the experiment. If you wish, you can inspect the contents of each bag **after** completing the experiment.

You will now answer several questions, each of which offers you a choice between bets on the color of a chip that you will draw from one of two bags at the end of the experiment (if this section is chosen for payment).

You will first be asked to choose one of the two colors. We will call this **Your Color**. You will be paid only if a chip of this color is drawn from the bag at the end of the experiment.

You will then be asked to answer the following three questions.

- Question: Please select a bet
 1. \$10.50 if a chip drawn from bag A is of **Your Color** and \$0 otherwise.
 2. \$10.00 if a chip drawn from bag B is of **Your Color** and \$0 otherwise.
- Question: Please select a bet
 1. \$10.00 if a chip drawn from bag A is of **Your Color** and \$0 otherwise.
 2. \$10.00 if a chip drawn from bag B is of **Your Color** and \$0 otherwise.
- Question: Please select a bet
 1. \$10.00 if a chip drawn from bag A is of **Your Color** and \$0 otherwise.
 2. \$10.50 if a chip drawn from bag B is of **Your Color** and \$0 otherwise.

How your payoff for this section is determined

Suppose one of the three questions in this section is selected for determining your payment. If you chose bet 1 in that particular question, you will draw a chip from bag A. On the other hand, if you chose bet 2 in that particular question, you will draw a chip from bag B. In either case, you will get payment if the color of the drawn chip matches with Your Color.

How to make a decision

You will see four questions on the screen. The first one asks which color you want to use as **Your Color** and the following three questions ask which bet you would like to play.

For each question, you can make your selection by clicking on the check box for the option you would like to choose. You can change your selection as many times as you want, and there is no time limit. Once you make your selections for all three questions, you can submit them by clicking Proceed. You will not be able to change your decision after that.

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