Information Redundancy Neglect versus Overconfidence: A Social Learning Experiment

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Online Appendix

A Proofs

Proof of Proposition 4

The proposition can be proven in a recursive way. Agent 1 only observes his signal and chooses

$$\frac{a_1^{OC}}{100-a_1^{OC}}=\frac{a_1^{****}(s_1)}{100-a_1^{****}(s_1)}=\left(\frac{q_1}{1-q_1}\right)^{2s_t-1}.$$

Agent 2 observes a_1^{OC} and infers the signal realization, since an action greater (lower) than 50 can only be taken after observing a good (bad) signal. By the assumption of "k-overconfidence," he has subjective expectations on the predecessor's signal precision, and the likelihood ratio after observing the action is $\left(\frac{q_1}{1-q_1}\right)^{(2s_1-1)k}$ rather than $\left(\frac{q_1}{1-q_1}\right)^{(2s_1-1)}$. Hence,

$$\frac{a_2^{OC}}{100-a_2^{OC}}=\frac{a_2^{****}(s_1,s_2)}{100-a_2^{****}(s_1,s_2)}=\left(\frac{q_1}{1-q_1}\right)^{(2s_1-1)k}\left(\frac{q_2}{1-q_2}\right)^{2s_2-1}.$$

Note that this is equivalent to attributing precision $\frac{\left(\frac{q_1}{1-q_1}\right)^k}{1+\left(\frac{q_1}{1-q_1}\right)^k}$ to the predecessor's signals. Since k-overconfidence is common knowledge, agent 3 infers the signal realizations from the observation of a_1^{OC} and a_2^{OC} (since $a_2^{OC}>a_1^{OC}$ is only possible after observing a signal $s_2=1$, and $a_2^{OC} < a_1^{OC}$ after observing a signal $s_2 = 0$) and again uses subjective expectations for the precision of both, thus choosing a_3^{OC} such that

$$\frac{a_3^{OC}}{100 - a_3^{OC}} = \frac{a_3^{****}(s_1, s_2, s_3)}{100 - a_3^{****}(s_1, s_2, s_3)} = \Pi_{i=1}^{2} \left(\frac{q_i}{1 - q_i}\right)^{(2s_i - 1)k} \left(\frac{q_3}{1 - q_3}\right)^{2s_3 - 1}.$$

The same steps apply to any further agent $t = 4, 5, ..., T$.

Proof of Proposition 5

Let us define $l(x) := \log \frac{x}{1-x}$. First, observe that, for each $t \geq 2$, the β coefficients are determined by the following equations:

$$\begin{aligned}
l(a_1^2) &= (2s_1 - 1)\, l(q_1), \\
l(a_2^2) &= \beta_{2,1}\, (2s_1 - 1)\, l(q_1) + (2s_2 - 1)\, l(q_2) \\
&\vdots \\
l(a_t^2) &= \beta_{t,1}\, (2s_1 - 1)\, l(q_1) + \cdots + \beta_{t,t-1}(2s_t - 1) l(q_{t-1}) + (2s_t - 1)\, l(q_t).
\end{aligned}$$

In matrix notation,

$$\begin{pmatrix} l(a_1^2) \\ l(a_2^2) \\ \vdots \\ l(a_t^2) \end{pmatrix} = B \cdot \begin{pmatrix} (2s_1 - 1) l(q_1) \\ (2s_2 - 1) l(q_2) \\ \vdots \\ (2s_t - 1) l(q_2) \end{pmatrix}, \tag{A.1}$$

where B is the $t \times t$ lower triangular matrix

$$B = \begin{pmatrix} 1 & 0 & \cdots & \cdots & 0 \\ \beta_{2,1} & 1 & 0 & \cdots & 0 \\ \beta_{3,1} & \beta_{3,2} & 1 & & 0 \\ \vdots & \vdots & & \ddots & \vdots \\ \beta_{t,1} & \beta_{t,2} & \cdots & \beta_{t,t-1} & 1 \end{pmatrix}.$$

Similarly, the γ coefficients are defined by the following equations:

$$
\begin{aligned}
l(a_1^2) &= (2s_1 - 1)\, l(q_1), \\
l(a_2^2) &= \gamma_{2,1} l(a_1^2) + (2s_2 - 1)\, l(q_2), \\
&\vdots \\
l(a_t^2) &= \gamma_{t,1} l(a_1^2) + \cdots + \gamma_{t,t-1}(2s_t - 1) l(a_{t-1}^2) + (2s_t - 1)\, l(q_t).
\end{aligned}
$$

In matrix notation,

$$
\Gamma \begin{pmatrix} l(a_1^2) \\ l(a_2^2) \\ \vdots \\ l(a_t^2) \end{pmatrix} = \begin{pmatrix} (2s_1 - 1) l(q_1) \\ (2s_2 - 1) l(q_2) \\ \vdots \\ (2s_t - 1) l(q_2) \end{pmatrix},
$$

where Γ is the $t \times t$ lower triangular matrix containing γ coefficients,

$$
\Gamma = \begin{pmatrix} 1 & 0 & \cdots & \cdots & 0 \\ -\gamma_{2,1} & 1 & 0 & \cdots & 0 \\ -\gamma_{3,1} & -\gamma_{3,2} & 1 & & 0 \\ \vdots & \vdots & & \ddots & \vdots \\ -\gamma_{t,1} & -\gamma_{t,2} & \cdots & -\gamma_{t,t-1} & 1 \end{pmatrix}. \tag{A.2}
$$

By comparing (A.1) with (A.2), one can see that, since B is nonsingular, $\Gamma = B^{-1}$ must hold. Hence, for $l < t$, $-\gamma_{t,l}$ is given by the $[t, l]$-element of B^{-1}.

The closed form solutions for $\gamma_{y,i}$ for each theory can also be obtained in a recursive way.

For the PBE, note that agent t chooses action a_t^{PBE} such that

$$
\frac{a_t^*(s_1, s_2, .., s_t)}{100 - a_t^*(s_1, s_2, .., s_t)} = \Pi_{i=1}^{t} \left(\frac{q_i}{1 - q_i} \right)^{2s_i - 1} =
$$
$$
\Pi_{i=1}^{t-1} \left(\frac{q_i}{1 - q_i} \right)^{2s_i - 1} \left(\frac{q_t}{1 - q_t} \right)^{2s_t - 1} =
$$
$$
\frac{a_{t-1}^*(s_1, s_2, .., s_{t-1})}{100 - a_{t-1}^*(s_1, s_2, .., s_{t-1})} \left(\frac{q_t}{1 - q_t} \right)^{2s_t - 1}.
$$

1. For BRTNI, observe that, by assumption, agent t chooses action a_t^{BRTNI} such that

$$\frac{a_t^{BRTNI}}{100 - a_t^{BRTNI}} = \prod_{i=1}^{t-1} \frac{a_{t-i}^{BRTNI}}{100 - a_{t-i}^{BRTNI}} \left(\frac{q_t}{1 - q_t}\right)^{2s_t - 1}.$$

(Indeed, Eyster and Rabin (2009) derive the β coefficients from this formula).

In the OC model, agent 2 chooses action a_2^{OC} such that

$$\begin{aligned}\frac{a_2^{OC}}{100 - a_2^{OC}} &= \left(\frac{q_1}{1 - q_1}\right)^{(2s_1-1)k} \left(\frac{q_2}{1 - q_2}\right)^{2s_2-1} = \\ &\left(\frac{a_1^{OC}}{100 - a_1^{OC}}\right)^{k} \left(\frac{q_2}{1 - q_2}\right)^{2s_2-1}.\end{aligned}$$

Agent 3 chooses action a_3^{OC} such that

$$\begin{aligned}\frac{a_3^{OC}}{100 - a_3^{OC}} &= \Pi_{i=1}^{2} \left(\frac{q_i}{1 - q_i}\right)^{(2s_i-1)k} \left(\frac{q_3}{1 - q_3}\right)^{2s_3-1} = \\ &\left(\frac{a_1^{OC}}{100 - a_1^{OC}}\right)^{k} \left(\frac{q_2}{1 - q_2}\right)^{(2s_2-1)k} \left(\frac{q_3}{1 - q_3}\right)^{2s_3-1} = \\ &\left(\frac{a_1^{OC}}{100 - a_1^{OC}}\right)^{k} \left(\frac{a_2^{OC}}{100 - a_2^{OC}}\right)^{k} \left(\frac{a_1^{OC}}{100 - a_1^{OC}}\right)^{-k^2} \left(\frac{q_3}{1 - q_3}\right)^{2s_3-1} = \\ &\left(\frac{a_1^{OC}}{100 - a_1^{OC}}\right)^{k(1-k)} \left(\frac{a_2^{OC}}{100 - a_2^{OC}}\right)^{k} \left(\frac{q_3}{1 - q_3}\right)^{2s_3-1}.\end{aligned}$$

The same steps apply to any further agent $t = 4, 5, ..., T$.

Finally, let us consider the ABEE. First of all, recall that in the ABEE $\beta_{t,i} = t - i$, that is, $\beta_{t,t-k} = k$ for all $t = 2, 3, \ldots,$ and $k = 1, 2, \ldots, (t-1)$.

Consider now the system of equations $\Gamma B = I$. For $t = 2, 3, 4 \ldots,$ the product of the t-th row vector of Γ and the $(t-1)$-th column vector of B gives

$$-\gamma_{t,t-1} + \beta_{t,t-1} = 0,$$

from which we obtain that $\gamma_{t,t-1} = 1$. For $t = 3, 4, 5, \ldots,$ the product of the t-th row vector of Γ and the $(t-2)$-th column vector of B gives

$$-\gamma_{t,t-2} - \gamma_{t,t-1}\beta_{t-1,t-2} + \beta_{t,t-2} = 0,$$

from which we obtain that $\gamma_{t,t-2} = 1$. For $t = 4, 5, 6, ...$, the product of the t-th row vector of Γ and the $(t-3)$-th column vector of B gives

$$-\gamma_{t,t-3} - \gamma_{t,t-2}\beta_{t-2,t-3} - \gamma_{t,t-1}\beta_{t-1,t-3} + \beta_{t,t-3} = 0,$$

from which we obtain that $\gamma_{t,t-3} = 0$.

Now, let us consider all $t = 5, 6, 7, \ldots,$ and $k = 4, 5, 6, \ldots, (t-1)$. The product of the t-th row vector of Γ and the $(t-k)$-th column vector of B gives

$$\begin{aligned} \gamma_{t,t-k} &= -\sum_{j=1}^{k-1} \gamma_{t,t-k+j}\beta_{t,t-j} + \beta_{t,t-k} \\ &= -\sum_{j=1}^{k-1} \gamma_{t,t-k+j} j + k. \end{aligned}$$

On the basis of this equation, observe that the difference of $\gamma_{t,t-k-1}$ and $\gamma_{t,t-k}$ gives

$$\gamma_{t,t-k-1} - \gamma_{t,t-k} = -\gamma_{t,t-k} - \gamma_{t,t-k+1} - \gamma_{t,t-k+2} - \cdots - \gamma_{t,t-1} + 1.$$

Similarly, the difference between $(\gamma_{t,t-k-2} - \gamma_{t,t-k-1})$ and $(\gamma_{t,t-k-1} - \gamma_{t,t-k})$ gives

$$\gamma_{t,t-k-2} = \gamma_{t,t-k-1} - \gamma_{t,t-k}.$$

Moreover, the sum of $\gamma_{t,t-k-2}$ and $\gamma_{t,t-k-3}$ gives

$$\gamma_{t,t-k-3} = -\gamma_{t,t-k}.$$

Hence, starting from the three initial values, $\gamma_{t,t-1} = \gamma_{t,t-2} = 1$ and $\gamma_{t,t-3} = 0$, this equation iteratively pins down the whole sequence of $(\gamma_{t,t-1}, \gamma_{t,t-2}, \ldots, \gamma_{t,1})$. Specifically, $(\gamma_{t,t-4}, \gamma_{t,t-5}, \gamma_{t,t-6}) = (-1, -1, 0)$, $(\gamma_{t,t-7}, \gamma_{t,t-8}, \gamma_{t,t-9}) = (1, 1, 0)$, $(\gamma_{t,t-10}, \gamma_{t,t-11}, \gamma_{t,t-12}) = (-1, -1, 0)$, and so on. For instance, for subject 10, the weights are $(\gamma_{10,1}, \gamma_{10,2}, \gamma_{10,3}, \ldots, \gamma_{10,9}) = (0, 1, 1, 0, -1, -1, 0, 1, 1)$.

Finally note that, given its cyclical feature, the sequence of weights can be expressed as $\gamma_{t,t-k} = sign\left(\sin(\frac{k}{3}\pi)\right)$, or $\gamma_{t,i} = sign\left(\sin(\frac{t-i}{3}\pi)\right)$.

B Testing Differences across Treatments

Table B.1: Differences across Treatments:
Median Rank-sum Test for Action 1 (p-value)

	SL1 vs. SL2	SL1 vs. SL3	SL2 vs. SL3
Period 1	0.999	0.999	0.999
Period 2	0.136	0.520	0.738
Period 3	0.317	0.881	0.317
Period 4	0.738	0.597	0.829
Period 5	0.881		
Period 6	0.911		
Period 7	0.316		
Period 8	0.289		
Period 9	0.435		
Period 10	0.420		

For each period, the test is performed using session-specific medians.

Table B.2: Differences across Treatments:
Median Rank-sum Test for Action 2 (p-value)

	SL1 vs. SL2	SL1 vs. SL3	SL2 vs. SL3
Period 1	0.459	0.834	0.751
Period 2	0.220	0.999	0.243
Period 3	0.218	0.345	0.914
Period 4	0.281	0.244	0.117
Period 5	0.911		
Period 6	0.599		
Period 7	0.023		
Period 8	0.590		
Period 9	0.529		
Period 10	0.805		

For each period, the test is performed using session-specific medians.

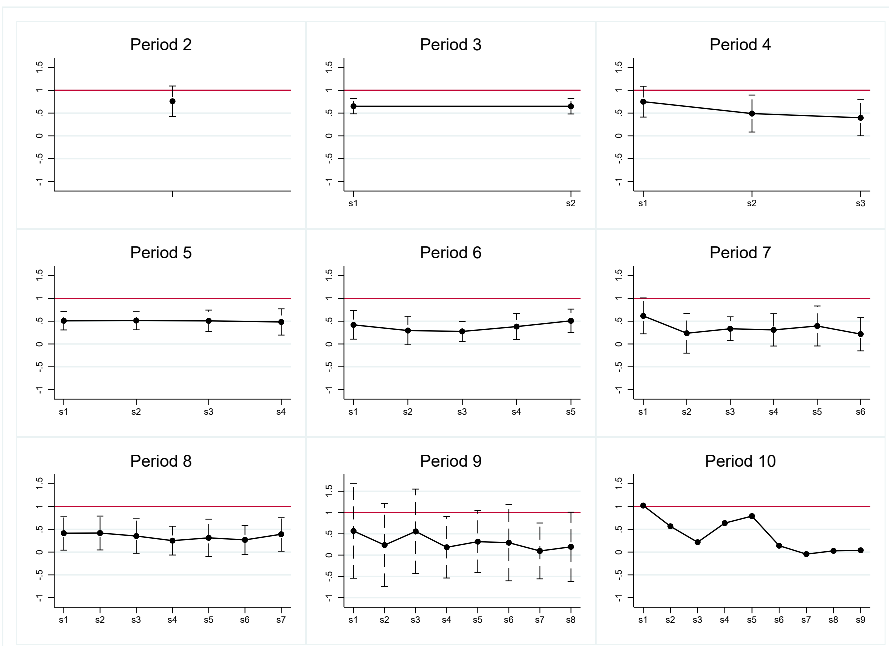
C Factoring Out Uninformative Actions

In this section we offer a robustness check, by factoring out actions that are, presumably, uninformative. In particular, as a first step, we define an action at time i as uninformative according to the criterion:

$$(a^2_{i=1} = 50) \text{ or } (a^2_i = a^2_{i-1}) \text{ for } i = 2, \cdots, t-1.$$

To factor out these actions, we eliminate them and renumber the entire sequence (e.g., if action 3 is uninformative, then action 3 is eliminated, period 4 becomes period 3, period 5 becomes period 4 and so on).

Figure C.1: Quantile Regressions of Action 1 on Predecessors' Signals Eliminating Uninformative Periods (Estimated Weights)



The figure shows the estimated coefficients from a median regression of first action loglikelihood ratios on predecessors' signal loglikelihood ratios after eliminating uninformative periods. For each period $t = 1, \ldots, 10$, predecessors' signals, $s_i, i = 1, \ldots, t-1$, are on the x-axis; corresponding point estimates and 95% confidence intervals are on the y-axis, represented by black dots and dashed capped lines, respectively. Confidence intervals are computed by bootstrap (500 replications), clustering at the session level.

Table C.1: Hypothesis Testing: Weights on Predecessors' Signals (p-values)
Dependent Variable: Action 1 (loglikelihood ratio)
Eliminating Uninformative Periods

	H_0^{PBE} : $\beta_{t,1} = \cdots = \beta_{t,t-1} = 1$	H_0^{BRTNI} : $\beta_{t,i} = 2^{t-i-1}\ \forall i = 1, \ldots, t-1$
Period 2	0.159	0.159
Period 3	0.000	0.000
Period 4	0.025	0.000
Period 5	0.000	0.000
Period 6	0.000	0.000
Period 7	0.000	0.000
Period 8	0.000	0.000
Period 9	0.000	0.000
	H_0^{ABEE} : $\beta_{t,i} = t - i\ \forall i = 1, \ldots, t-1$	H_0^{OC} : $\beta_{t,1} = \cdots = \beta_{t,t-1}$
Period 2	0.159	.
Period 3	0.000	0.999
Period 4	0.000	0.079
Period 5	0.000	0.993
Period 6	0.000	0.582
Period 7	0.000	0.291
Period 8	0.000	0.996
Period 9	0.000	0.986

The table reports tests based on bootstrap standard errors (500 replications), clustering at the session level.

It is worth noting that this procedure implies a loss of observations for later periods. In particular, the available observations for $t = 10$ are 47. Coefficients for this period are not reliably estimated. We report them without confidence intervals and only for the sake of completeness. For the same reason, we do not report hypothesis testing p-values and estimates of k for this period.

We have repeated the analysis using a more stringent criterion according to which an action i is classified as uninformative if and only if

$$(a^2_{i=1} = 50) \text{ or } (a^2_i = a^2_{i-1}) \text{ or } (a^2_{i-1} = 0 \text{ or } a^2_{i-1} = 100) \text{ for } i = 2, \cdots, t-1.$$

Table C.2: Quantile Regressions of Action 1 on Predecessors' Signals: Estimation of k under $H_0^{OC}: \beta_{t,1} = \cdots = \beta_{t,t-1}$
Eliminating Uninformative Periods

	$\hat{k}$	95% Confidence Interval lower limit	upper limit
Period 2	0.752	0.462	0.992
Period 3	0.650	0.518	0.818
Period 4	0.559	0.438	0.997
Period 5	0.508	0.332	0.647
Period 6	0.422	0.250	0.545
Period 7	0.327	0.183	0.528
Period 8	0.332	0.200	0.508
Period 9	0.272	0.098	0.437
All	0.463	0.317	0.626

The table reports 95% confidence intervals obtained with bootstrap (500 replications), clustering at the session level.

The results are similar to those presented here and available upon request.

We have also used a different methodology, by attributing the value $s_i = 0.5$ (uninformative signal) to any uninformative action. The results are again broadly similar to those presented here and available upon request.

D Distance between a_t^1 and a_{t-1}^2

As we mention in footnote 27, the theoretical models have strikingly different predictions about the difference between the first action chosen by a subject at time t and the second action (i.e., the observable action) chosen by his immediate predecessor at time $t-1$. By combining expressions (1) and (2) one obtains the following difference in loglikelihood ratios:

$$\Delta^{llr}_{a1,a2} \equiv \ln\left(\frac{a^1_t}{100-a^1_t}\right) - \ln\left(\frac{a^2_{t-1}}{100-a^2_{t-1}}\right) =$$
$$= (\beta_{t,1}-\beta_{t-1,1})\ln\left(\frac{q_1}{1-q_1}\right)^{2s_1-1} + (\beta_{t,2}-\beta_{t-1,2})\ln\left(\frac{q_2}{1-q_2}\right)^{2s_2-1} + \dots$$
$$\dots + (\beta_{t,t-1}-\beta_{t-1,t-1})\ln\left(\frac{q_{t-1}}{1-q_{t-1}}\right)^{2s_{t-1}-1} + \varepsilon^1_t - \varepsilon^2_{t-1}. \tag{D.1}$$

According to the PBE, all differences in the β coefficients on the right-hand-side are equal to 0. This gives the well known result that, in the PBE, the agent simply imitates the immediate predecessor's action, as this is a sufficient statistics for all the private information up to that period. In the OC equilibrium, the differences in the β coefficients are all equal to 0, except for the last one, $(\beta_{t,t-1} - \beta_{t-1,t-1})$, which is negative and constant over time. This is because $\beta_{t-1,t-1} = 1$ and $\beta_{t,t-1} < 0$ (e.g., 0.488 in our estimation).[1] In the BRTNI and ABEE models, the distance between the loglikelihood ratios is increasing over time, since the terms of the sum on the right hand side are strictly greater from zero (except the last one). For instance, in the ABEE the differences in the β coefficients are all equal to 1, except for the last one which is 0. Hence, if the value of the good is 100 (0), the difference in equation (D.1) becomes, in expectation, larger and positive (negative) over time.

In the figure below, we report the median of the difference

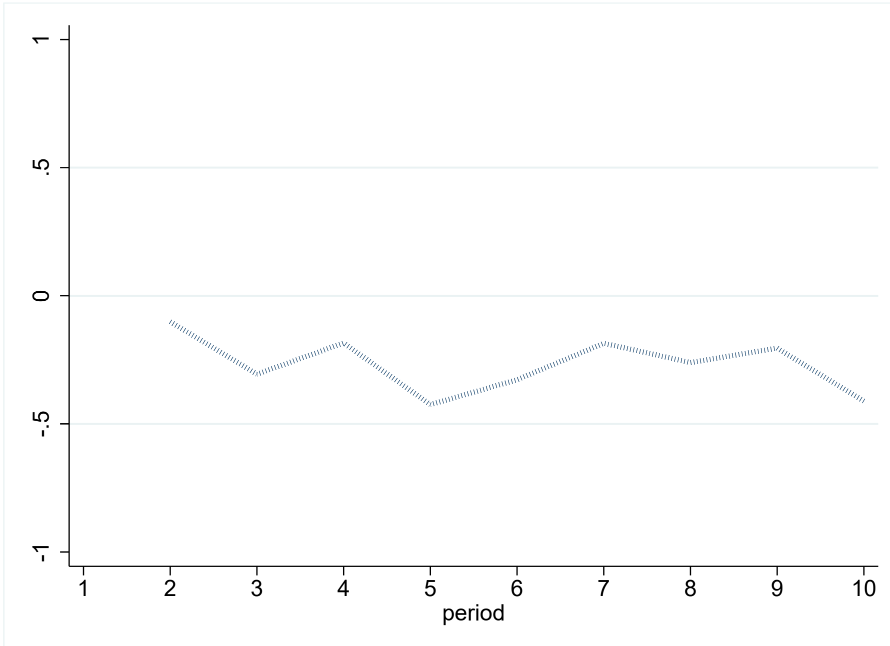
$$\Delta = \begin{cases} \Delta^{llr}_{a1,a2}, & \text{if } s_{t-1} = 1 \\ -\Delta^{llr}_{a1,a2}, & \text{if } s_{t-1} = 0 \end{cases}$$

as observed in the data across periods. Under the assumption that $(\varepsilon^1_t - \varepsilon^2_t)$ has median 0 conditional on the history of signals, we would expect the median of this difference to be about 0 if the data generating model were the PBE, negative and roughly constant in the case of the OC, and to exhibit a tendency to increase, in the case of BRTNI and ABEE.

As one can seen, the median difference Δ is negative and roughly constant, in agreement

[1] One may be tempted to think that an alternative model (or heuristic) with the same implication is a simple model in which the agent neglects the entire sequence, only looks at the immediate predecessor's action and "discounts it". Note, however, that to "discount" an action one would need to know the predecessor's signal realization, which with this heuristic would not be available.

Figure D.1: Median Difference of Loglikelihood Ratios of Action 1 and 2 across Periods



with the OC model.

E Instructions

Welcome to our experiment! We hope you will enjoy it.

You are about to take part in a study on decision making with 9 other participants. Everyone in the experiment has the same instructions. If something in the instructions is not clear and you have questions, please, do not hesitate to ask for clarification. We will be happy to answer your questions privately.

Depending on your choices, the other participants' choices and some luck you will earn some money. You will receive the money immediately after the experiment.

E.1 The Experiment

The experiment consists of 15 rounds of decision making. In each round you will make two consecutive decisions. All of you will participate in each round.

What you have to do

In each round, you have simply to choose a number between 0 and 100. You will make this choice twice, before and after receiving some information. The reason for these choices is the following. There is a good whose value can be either 0 or 100 units of a fictitious currency called "lira." You will not be told whether the good is worth 0 or 100 liras, but will receive some information about which value is more likely to have been chosen by a computer. We will ask you to predict the value of the good, that is, to indicate the chance that the value is 100 liras.

The value of the good

Whether the good will be worth 0 or 100 liras will be determined randomly at the beginning of each round: there will be a probability of 50% that the value is 0 and a probability of 50% that it is 100 liras, like in the toss of a coin. The computer chooses the value of the good in each round afresh. The value of the good in one round never depends on the value of the good in one of the previous rounds.

What you will know about the value

Although you will not be told the value of the good, you will, however, receive some information about which value is more likely to have been chosen. For each of you, the computer will use two "virtual urns" both containing green and red balls. The proportion of the two types of balls in each urn, however, is different. One urn contains more red than green balls, whereas the other urn contains more green than red balls. If the value of the good is 0, you will observe a ball drawn from an urn containing more red balls. If the value is 100, instead, you will observe a ball drawn from an urn containing more green balls. To recap:

- If the value is 100, then there are more GREEN balls in the urn.
- If the value is 0, then there are more RED balls in the urn.

Therefore, the ball color will give you some information about the value of the good. Below we will tell you more about how many balls there are in the urns. First, though, let us see more precisely what will happen in each round.

E.2 Procedures for each round

In each of the 15 rounds you will make decisions in sequence, one after the other. There will be 10 periods. Each of you will make her/his two choices only in one period, randomly chosen. Since there are 10 participants, this means that all of you will participate in each round.

The precise sequence of events is the following:

First: the computer program will decide randomly if the good for that round is worth 0 or 100 liras. You will not be told this value. On your screen you will read "Round 1 of 15. The computer is deciding the value of the good by flipping a coin."

Second: the computer program will randomly select who is the first person who has to make a choice. Each of you has the same ($1/10th$) chance of being selected.

Third: the computer will draw a ball from the "virtual urn" and inform the first person (only the first person) of the drawn ball color. The first person will see this information on the screen. No one else will see it. The other participants will be waiting.

Fourth: after the person sees this information, (s)he has to choose a number between 0 and 100. This can be done by moving a slider on the screen (to select a precise number, please, use the arrows on your keyboard). The decision made will be visible to all participants.

Fifth: the computer will now randomly choose another person. Again, all the remaining 9 people have the same ($1/9th$) chance of being chosen.

Sixth: this second person, having observed the first person's prediction, will be asked to make her/his prediction, choosing a number between 0 and 100. This decision will not be visible to other participants.

Seventh: after the decision, the computer will draw a ball from the "virtual urn" and inform (only) the second person of its color.

Eighth: the second person, after observing the ball color, will now make a new prediction, choosing again a number between 0 and 100. This choice is visible to all participants.

Ninth: the computer will choose a third person. This person will have to make two predictions, before and after receiving information, exactly as the second person. The first decision is after having observed the first two persons' predictions. The second prediction is after having observed the ball color too. The decision made after seeing the ball color will be visible to everyone. Then the computer will choose the fourth person and so on, until all ten people have had the opportunity to participate.

Tenth: the computer will reveal the value of the good for the round and the payoff you earned in the round.

Observation 1: All 10 participants have to make the same type of decision, predicting the value of the good. However, the first person in the sequence is asked to make only one prediction, while the others will make two. The reason is simple. Since the first person knows nothing, the only sensible prediction is 50, given that there is a $50-50$ chance that the value is 0 or 100 liras. Therefore, if you are the first, we do not ask you to make the prediction before seeing the ball color. Instead, if you are a subsequent person, we will ask you to make a prediction even before seeing the ball color, just after observing the predecessors' predictions. **Always recall that the predecessors' predictions that you will observe are the second predictions that they made, that is, the predictions they made after receiving information about the ball color.**

Observation 2: As we said, when it is your turn, the computer will draw a ball from one of two virtual urns: the urn containing more red than green balls if the value is zero; and the urn containing more green than red balls if the value is 100. But, exactly how many red and green balls are there in the urns? If the value is 0, then there are 70 red balls and 30 green balls. If the value is 100, then there are 70 green balls and 30 red balls.

E.3 Your per-round payoff

Your earnings depend on how well you predict the value of the good. If you are the first person in the sequence, your payoff will depend on the only prediction that you are asked to make. If you are a subsequent decision maker, your payoff will depend on the first or the second prediction you make, with the same chance (like in the toss of a coin).

If you predict the value exactly, you will earn 100 liras. If your prediction differs from the true value by an amount x, you will earn $100 - 0.01x^2$. This means that the further your prediction is from the true value, the less you will earn. Moreover, if your mistake is small, you will be penalized only a small amount; if your mistake is big, you will be penalized more than proportionally.

To make this rule clear, let us see some examples.

Example 1: Suppose the true value is 100. Suppose you predict 80. In this case you made a mistake of 20. We will give you $100 - 0.01 * 20^2 = 96.0$ liras.

Example 2: Suppose the true value is 0. Suppose you predict 10. In this case you made a mistake of 10. We will give you $100 - 0.01 * 10^2 = 99$ liras.

Example 3: Suppose the true value is 100. Suppose you predict 25. In this case you made a mistake of 75. We will give you $100 - 0.01 * 75^2 = 43.75$ liras.

Example 4: Suppose the true value is 0. Suppose you predict 50. In this case you made a mistake of 50. We will give you $100 - 0.01 * 50^2 = 75$ liras.

Note that the worst you can do under this payoff scheme is to state that you believe that there is a 100% chance that the value is 100 when in fact it is 0, or you believe that there is a 100% chance that the value is 0 when in fact it is 100. Here your payoff from prediction would be 0. Similarly, the best you can do is to guess correctly and assign 100% to the value which turns out to be the actual value of the good. Here your payoff will be 100 liras.

Note that with this payoff scheme, the best thing you can do to maximize the expected size of your payoff is simply to state your true belief about what you think the true value of the good is. Any other prediction will decrease the amount you can expect to earn. For instance, suppose you think there is a 90% chance that the value of the good is 100 and, hence, a 10% chance that value is 0. If this is your belief about the likely value of the good, to maximize your expected payoff, choose 90 as your prediction. Similarly, if you think the value is 100 with chance 33% and 0 with chance 67%, then select 33.

E.4 The other rounds

We will repeat the procedures described in the first round for 14 more rounds. As we said, at the beginning of each new round, the value of the good is again randomly chosen by the computer. Therefore, the value of the good in round 2 is independent of the value in round 1 and so on.

E.5 The final payment

To compute your payment, we will randomly choose (with equal chance) one round among the first five, one among the rounds $6 - 10$ and one among the last five rounds. For each of these round we will then choose either prediction 1 or prediction 2 (with equal chance), unless you turn was 1, in which case there is nothing to choose since you only made one prediction. We will sum the payoffs that you have obtained for those predictions and rounds. We will then convert your payoff into pounds at the exchange rate of 100 liras $= \pounds 7$. That is, for every 100 liras you earn, you will get 7 pounds. Moreover, you will receive a participation fee of $\pounds 5$ just for showing up on time. You will be paid in cash, in private, at the end of the experiment.