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Piercing the 'Payoff Function' Veil: Tracing Beliefs and Motives

By Guidon Fenig, Giovanni Gallipoli and Yoram Halevy

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Guidon Fenig † Giovanni Gallipoli ‡ Yoram Halevy §

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Abstract

This paper develops an experimental methodology that allows the identification of decision-making processes in interactive settings using tracking of non-choice data. This non-intrusive and indirect approach provides essential information for the characterization of beliefs. The analysis reveals significant heterogeneity, which is reduced to two broad types, differentiated by the importance of pecuniary rewards in agents' payoff function. Most subjects maximize monetary rewards by best responding to beliefs shaped by recent history. Others are able to identify profit-maximizing actions but choose to systematically deviate from them. The interaction among different types is key to understanding aggregate outcomes.

JEL classifications: C9, C92, C72, D9, H41.

Keywords: non-choice data, typology, tracking, response-time, coordination, public goods, complementarity, altruism, joy of giving, competitiveness, joy of winning, laboratory experiment.

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†Department of Economics, University of Saskatchewan. http://www.guidonfenig.com.

‡Vancouver School of Economics, UBC. http://giovanni-gallipoli.ca/

§Department of Economics, University of Toronto. http://uoft.me/halevy.

1 Introduction

There is growing acceptance among researchers that the decision-making processes that agents employ in interactive settings are heterogeneous and often diverge from the principles of standard textbook game theory. Empirical identification of the decision processes adopted by players requires the examination of observed choices in conjunction with richer data that convey information about the way these choices are made.

We develop a simple framework to study, within an experimental setting, the interactions among agents utilizing heterogeneous decision procedures. To identify interactive decision-making processes one needs to posit an environment in which agents' beliefs about other agents' actions affect their pecuniary payoffs. The environment must be such that these beliefs are elicited in a non-intrusive and credible way. The setting must also feature a role for agents to learn about the environment and about the motives and procedures of other agents. An environment with such attributes and that exhibits multiple equilibria, would be naturally suited to provide new insights into coordination problems. Finally, fine-tuning the pecuniary incentives toward coordination would enable the researcher to assess the intensity of alternative behavioral motives.

This paper proposes an environment that satisfies the key requirements outlined above. We study a joint investment problem in which private investments are made by individual group members, without communication, to generate income that is equally shared. In this problem, an agent's beliefs about the investment of others play a key role in determining her own investment because of the presence of *complementarity* among individual investments. Finding the optimal investment is facilitated by the usage of a calculator whose in-

puts, which are recorded by the experimenter, provide valuable and reliable information about each subject's thought process and her conjectures regarding other players' investments. We do not elicit beliefs explicitly but we do collect data on the inputs subjects enter in the payoff calculator. These include conjectures about other group members' investments. In Section 5 we describe these data extensively. While this type of analysis is not regularly used by behavioral economists, online retailers, like Amazon, and advertising platforms, such as Facebook or Google, routinely track both the choices (e.g. purchases, likes, shares) and the search and browsing history of their users before quoting a price or presenting an advert.

We consider a model with a continuous strategy space. However, the joint investment problem may exhibit two equilibria, one at each endpoint of the strategy space. This allows one to examine coordination and equilibrium selection. Moreover, manipulating a single parameter within our setting alters the potential gains from coordination, making it possible for the researcher to quantify the monetary cost of pursuing non-pecuniary incentives.

For low levels of complementarity, the unique Nash equilibrium (assuming agents are selfish) is a zero-investment equilibrium. When complementarity is sufficiently high, a second full-investment equilibrium emerges, transforming the selection of equilibrium into a coordination problem.

Our experimental design varies the degree of complementarity and includes, as a special case, the well-studied linear public good game. When we introduce complementarity, subjects visibly respond to it. With strong complementarity, subjects are able to move closer to the high-investment level. When complementarity is sizable but insufficient to support a second selfish-equilibrium, subjects persistently invest above zero and we observe little or no convergence towards the unique equilibrium.

Combining choice and non-choice data allows us to examine several aspects of the interactive decision-making of subjects. Are conjectures influenced by past experience? Do subjects use the calculator more or less intensively depending on the complexity of the environment? Do subjects adjust their behavior over time and do they use history-dependent best-response strategies? How do they experiment with hypothetical investments and are they able to find the profit-maximizing strategy, given their conjectures? Can we classify subjects according to the processes they adopt to make choices? And how does heterogeneity matter for response times?

To answer these questions, we rely on a wealth of non-choice data, including accurate information about calculations made by each subject before submitting a choice and how long it takes one to submit a choice. We document a variety of facts about the way subjects form conjectures about other players' investments, whether subjects are able to identify profit-maximizing responses to their conjectures, and how these calculations relate to their choices.

Analysis of both choice and non-choice data suggests that one can reduce the rich heterogeneity in observed investments to two *modus operandi*, which we associate with two different types of agents. We denote these two types as, respectively, *Homo pecuniarius* and *Homo behavioralis*. *Homo pecuniarius* maximizes money-profits by best responding to his or her beliefs, which are shaped by recent history. *Homo behavioralis*, on the other hand, is able to identify the profit-maximizing choice but chooses to systematically deviate from it. We do not find strong evidence of confusion: *Homo behavioralis* subjects appear willing to sacrifice some pecuniary rewards to pursue other goals. When complementarity is low, some agents may have altruistic motives and they invest above their monetary best response. When complementarity is high, altruistic behavior is indistinguishable from profit maximization, but a

new competitive motive surfaces: by lowering their investment below the pecuniary best response, some subjects are able to make relatively higher profits than other participants.[1] We quantify the magnitude of these behavioral motives and show that, while relatively modest, they may lead to significant and systematic deviations from the pecuniary best response.

These two types of agents coexist and are able to best respond to each other in equilibrium. Their dynamic interactions shape aggregate outcomes and provide a way to interpret the choices we observe under alternative degrees of complementarity.

The experimental methodology we propose, together with the exogenous variation in the degree of complementarity, provides a transparent way to study heterogeneity in response times and its relationship to altruism or other potential motives. We show that the time it takes subjects to make a decision depends on the complexity of the environment, on their type (as described above) and on the intensity of complementarity. This implies that analyzing response times while not allowing for sufficient variation in the environment may provide only a partial view on the heterogeneity of the decision-making process.

Although we are primarily interested in the interactive decision making process of (possibly heterogeneous) agents, our work touches on three other areas of research. First, our analysis of rich data describing the agents' decision-making activities is naturally related to a small but fast-growing literature using non-choice data to investigate the way individuals process available information to reach decisions. Furthermore, our experimental setting posits a risky investment problem which includes as a special case the linear voluntary

[1] In the low-complementarity treatment, competition is indistinguishable from profit-maximizing behavior.

contribution mechanism (LVCM) studied in the extensive literature on public good games. Finally, the presence of multiple equilibria in some of our experimental parameterizations introduces coordination issues that are typically examined in work on equilibrium selection using order-statistic and stag-hunt games. We discuss how our work relates to these important areas of research in Section 7.

The paper is organized as follows. Section 2 presents an overview of the model and selfish-equilibrium predictions. The experimental design and laboratory procedures are described in Section 3. In Section 4 we report results from aggregate data and show how investment behavior varies depending on the degree of complementarity in the environment. Section 5 explores individual-specific behaviors. The combined use of choice and non-choice data is instrumental in explaining deviations from the profit-maximizing strategies and to classify subjects into types. In this section, we also estimate the magnitude of altruistic and competitive motives. In Section 6 we provide an extensive analysis of response times, processing speed and intensity of calculator usage by different subjects. Section 8 summarizes results and concludes.

2 The Joint Investment Problem

Consider a set of n individuals indexed by $i \in \{1, ..., n\}$, each endowed with $\omega > 0$, who must decide whether—and how much—to invest in a joint account that transforms private investments into income that is equally shared among all group members. Let g_i denote individual i's investment. The remainder of the endowment $(\omega - g_i)$ is consumed privately by player i. Individual investments are aggregated through a constant elasticity of substitution production function that exhibits constant returns to scale. Player i's preferences are

additively separable between the private and joint accounts:

$$\pi_i = \omega - g_i + \beta \left(\sum_{i=1}^{n} g_i^{\rho} \right)^{1/\rho}, \tag{2.1}$$

where $\rho \leq 1$ denotes the degree of complementarity and $\beta > 0$ is a constant. This joint investment problem encompasses as a special case (when $\rho = 1$) the standard Linear Voluntary Contribution Mechanism (LVCM). The individual return from investing depends on the investments of all n players and on the degree of complementarity in production.[2]

Equilibrium

The best response (BR) of agent i, denoted as $g_i^*(g_{-i})$ is

$$g_i^*\left(g_{-i}\right) = \begin{cases} kM_{\rho}(g_{-i}) & \text{if } \; kM_{\rho}(g_{-i}) \leq \omega \\ \omega & \text{otherwise.} \end{cases} \tag{2.2}$$

The BR is a linear function of the generalized ρ-mean of his or her conjecture about the investments of other group members,[3] denoted by the vector $g_{-i} \in \Re_{+}^{n-1}$. Here, $k \equiv \left(\frac{n-1}{\beta^{\frac{\rho}{\rho-1}} - 1} \right)^{\frac{1}{\rho}}$ is a constant that depends on the model's parameters.[4] If $k > 0$, the investments are complementary; moreover, as the degree of complementarity diminishes (ρ increases), k decreases as well. In the limit, when ρ approaches 1, k goes to zero and the BR of player i is to invest

[2] The marginal per capita return (MPCR) on investments is equal to $\beta \left(\sum_{i=1}^{n} g_i^{\rho} \right)^{\frac{1-\rho}{\rho}} g_i^{\rho-1}$. This reduces to the customary β in the linear case. In standard LVCM experiments it is usually assumed that $\frac{1}{n} < \beta < 1$.

[3] The generalized ρ-mean of g_{-i} is $M_{\rho}(g_{-i}) \equiv \left(\frac{\sum_{i=1}^{n-1} g_{-i}^{\rho}}{n-1} \right)^{1/\rho}$. The arithmetic mean is a special case of the generalized mean when $\rho = 1$. The arithmetic and the generalized means are identical when all investments are equal, that is when $g_{-i} = g\mathbf{1}_{n-1}$.

[4] Details on the derivation of the BR can be found in Appendix A.

zero in the joint account regardless of other players' contributions. Because agent i's BR depends on the generalized mean of g_{-i}, it depends also on the dispersion of other players' investments: for a given arithmetic mean, player i's optimal investment decreases as the dispersion of other players' investments increases. Put simply, there is an additional benefit from coordination. Figure 2.1 summarizes the BR $g_i^*(g_{-i})$ for different values of the complementarity parameter ρ (each used in the experiments that follow).

Imposing the symmetry condition $g_i + \sum_{j \neq i} g_j = n g_i$ in Equation (2.2) and solving for g_i, we characterize the symmetric equilibria:

$$g_i^{eq} = \begin{cases} 0 & \text{if } k < 1 \\ \{0, \omega\} & \text{if } k > 1. \end{cases} \tag{2.3}$$

Thus, for given β and n and with sufficiently high complementarity,[5] there exist two equilibria.[6] It is worth noting that when there are two equilibria, only the full-investment equilibrium is stable.

[5] Alternatively, $k \gtreqless 1$ if and only if $\rho \lesseqgtr \frac{\ln(n)}{\ln(n/\beta)}$.

[6] It is straightforward to verify that only symmetric equilibria in pure strategies exist: suppose that there exists a non-symmetric equilibrium g^* and denote by $g^*_{min} = min\{g^*\} < max\{g^*\} = g^*_{max}$. For the case of $k \leq 1$, let $(n) = \{i : g_i > g_j \forall j \in N\}$, then if $g^*_{-(n)}$ denotes the vector of investment values different from $g^*_{(n)}$, it follows that $kM_\rho\left(g^*_{-(n)}\right) < g^*_{max}$, which is a contradiction. Similarly, if $k \geq 1$, and $(m) = \{i : g_i < g_j \forall j \in N\}$ it follows that $kM_\rho\left(g^*_{-(m)}\right) > g^*_{min}$, which is a contradiction. Also, there are no symmetric Nash equilibria in mixed strategies. The proof can be found in Appendix A.1. Finally, when $k = 1$, any symmetric strategy profile is a Nash equilibrium.

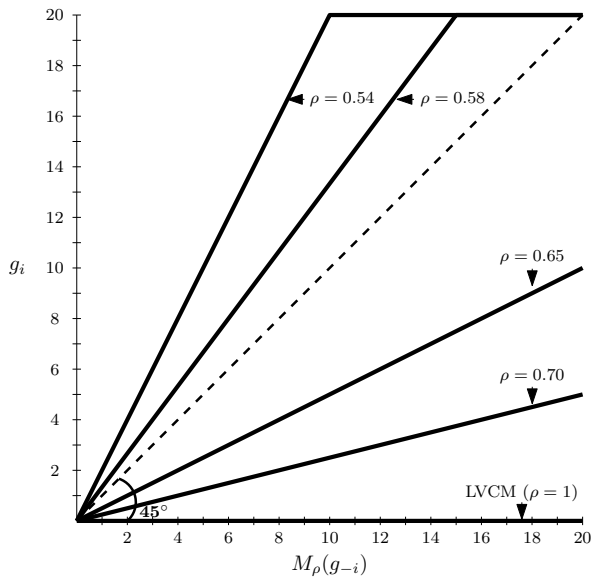


Figure 2.1. Best-response functions. In this figure the x-axis shows the generalized mean of others' investments; the y-axis displays player i's investments. The figure shows the BR as a function of others' investments, $g_i^*(g_{-i})$. The solid lines represent $g_i^*(g_{-i})$ of player i.

3 Experimental Design

The baseline parameters are chosen so that the linear treatment ($\rho = 1$) is easily comparable to similarly parameterized LVCM experiments.[7] Specifically, the group size is $n = 4$, initial token endowment of $\omega = 20$ and $\beta = 0.4$. The latter is a commonly assumed value of the MPCR in the linear case. In the nonlinear case, however, the MPCR also depends on the curvature parameter ρ and on investments of other players.

Given the above parameters, the threshold value of ρ that generates an additional full-investment equilibrium is approximately 0.602. Our treatments consist of variations in the degree of complementarity, ρ. Table 3.1 presents

[7] See, among others, Fehr and Gächter (2000), Kosfeld et al. (2009), and Fischbacher and Gächter (2010).

an overview of the experimental design. Treatments are classified as LC (low-complementarity) if ρ equals to 0.65 or 0.70, which are above the threshold and support a unique equilibrium of 0 investment. If ρ equals 0.54 or 0.58, which are below the threshold and support the additional full-investment equilibrium, the treatments are classified as HC (high-complementarity).

Table 3.1
Experimental Treatments

Treatment Group	ρ	Number of Sessions	Equilibrium Investment
LVCM	1	2	{0}
LC	0.70	2	{0}
	0.65	2	{0}
HC	0.58	2	{0,20}
	0.54	3	{0,20}

3.1 Experimental Procedures

In each experimental session, we recruited 16 subjects with no prior experience in any treatment of our experiment. Subjects were recruited from the broad undergraduate population of the University of British Columbia using the online recruitment system ORSEE (Greiner, 2015). The subject pool includes students with many different majors.

Each session was developed in the following way: upon arriving at the lab, subjects received a set of instructions (see Appendix J). After reading the instructions, subjects were required to answer a set of incentivized control questions.[8] The experiment started after all participants answered all control

[8]The questions' goal was to facilitate subjects' learning of the main features of the framework. Relevant features included (a) decreasing marginal productivity in the group account given a fixed level of others' investments, (b) efficiency gains due to coordination, and (c) absence of a dominant strategy (for treatments in which $\rho < 1$). Subjects were credited

questions correctly. At the beginning of each round of the experiment, subjects were matched with three other participants. They then played the static game described in Section 2. This process was repeated 20 times.[9]

All sessions were computerized using the software z-Tree (Fischbacher, 2007). Given the difficulty of computing potential earnings using the nonlinear payoff function, we provided subjects with a computer interface which eliminated the need to make calculations. Through this interface subjects were able to enter as many hypothetical choices and conjectures of other group members' investments as they wanted, visualizing the potential payoff associated with each combination.[10] In each round, subjects had 95 seconds to submit their chosen investment. At the end of each round, they were informed about their own earnings and the investment choices of other group members.[11] At the end of the experiment, subjects were paid the payoff they obtained in a single randomly selected round.

The sessions were conducted at the Experimental Lab of the Vancouver School of Economics (ELVSE) at the University of British Columbia, in January 2015 and March 2017. The experiments lasted 90 minutes. Subjects were paid in Canadian dollars (CAD). On average, participants earned $30.60.[12]

$0.20, $0.15 or $0.10 for each question answered correctly in the first, second and third attempt, respectively. There were 19 control questions, which can be found in Appendix I.

[9] To avoid reputation effects we used an extreme version of the stranger matching protocol. The group composition was predetermined and unknown to the participants. We pre-selected the groups so that the subjects were matched with a given participant in only four rounds. Each time a subject was matched with a participant he or she had encountered before, all other group members were different. This meant that any given grouping of four players never occurred more than once.

[10] Figure H.1 in Appendix H displays a screenshot of the main interface.

[11] Figure H.2 in Appendix H shows the screenshot of the feedback given to subjects at the end of each round. Subjects were shown their overall income, as well as the breakdown between their private account income and group account income. Since group income is the same for each group member, subjects could easily infer the earnings of each of the other group members by looking at their investments, reported on the same screen.

[12] This amount includes a $5 show-up fee and the cash received for the control questions.

4 Average Investment by Treatment

This section examines how changes in the degree of complementarity are reflected in the level and evolution of aggregate investment. Manipulating the degree of complementarity induces stark changes in subjects' behavior.[13]

Each solid line in Figure 4.1 represents the evolution of the average investment over the 20 rounds of each specific treatment. Figure 4.1 clearly shows that average investment increases with complementarity. With the exception of the LVCM treatment ($\rho = 1$), in which average investment converges towards the zero-investment selfish-equilibrium, there is no evidence of convergence to selfish-equilibrium for the LC (low complementarity) treatments. Analogously, there is no evidence of convergence to the full-investment equilibrium in the HC (high complementarity) treatments.

The difference in investments across treatments is substantial, even in the first round when subjects have yet to receive any feedback from other players. This may be attributed to the training subjects receive before deciding on investments: their understanding of the rules of the game is reflected in their initial beliefs about others' investments, and these beliefs appear to be treatment-specific. To verify the role of training we compare the initial conjectures concerning others' investments across different treatments. Table 4.1 shows the average of the generalized mean of the conjectures in each treatment. As discussed in the Introduction and will be analyzed extensively in Section 5, we did not elicit beliefs. Instead, we collected data on the inputs subjects entered in the payoff calculator. We use conjectures about other

The exchange rate used in each treatment was adjusted so that expected payoffs in Pareto efficient allocation were similar across treatments. The exchange rate (tokens per CAD) was set to: 1 for $\rho = 1$, 2 for $\rho = 0.65$ and $\rho = 0.70$, 2.5 for $\rho = 0.58$, and 3 for $\rho = 0.54$.

[13] We concentrate here on average investment. Dispersion in investments is analyzed in Appendix B.

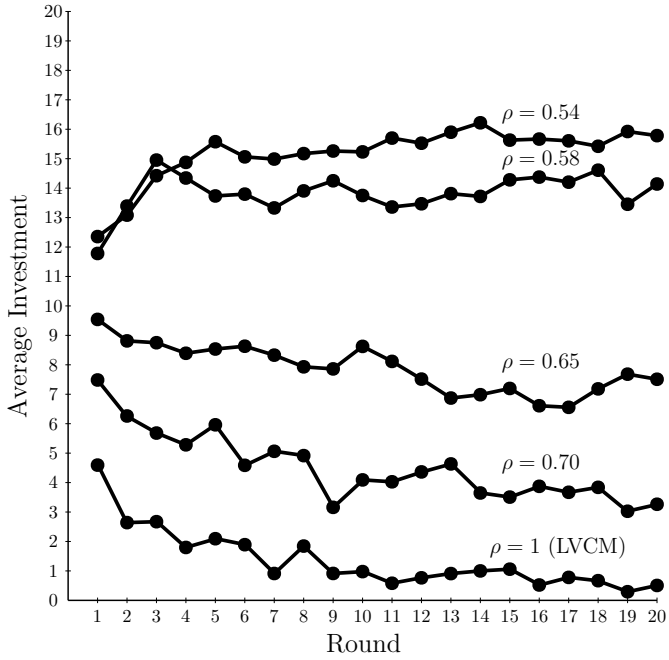


Figure 4.1. Average investment over time.

group members' investments to describe beliefs about others. As can be seen from the second column of Table 4.1, there is no differences across treatments in conjectures made during the practice period before the experiment started, as subjects are still learning about the payoff space. However, starting from round 1 (column 3) we observe significant differences across treatments. When a subject chooses to best respond to beliefs, his or her investments decrease as the degree of complementarity diminishes (that is, as ρ increases).

5 How Do Players Choose Their Investments?

So far the analysis has highlighted two main findings: (a) the linear environment exhibits diminishing investments, approaching the unique zero-investment selfish-equilibrium; and (b) in the LC or HC treatments, there

Table 4.1
Average Conjecture About Others' Investments

Treatment	Practice	Round 1	Round 2	Round 5	Round ≥ 10
LVCM	9.2	6.6	5.2	3.7	3.0
	(5.5)	(5.3)	(5.6)	(5.8)	(5.8)
$\rho = 0.70$	9.0	8.5	6.9	4.4	5.0
	(6.3)	(5.2)	(5.2)	(5.7)	(5.9)
$\rho = 0.65$	9.4	10.0	10.1	6.9	6.8
	(5)	(4.9)	(4.4)	(4.7)	(5.3)
$\rho = 0.58$	9.2	10.6	9.8	11.9	11.7
	(4.6)	(4.4)	(4.1)	(4.6)	(4.1)
$\rho = 0.54$	8.9	11.0	12.6	14.8	14.9
	(4.6)	(4.6)	(5)	(5.3)	(5.4)
No. of conjectures	5,213	357	249	204	961

Note: Each cell reports the average value for the generalized mean of the conjectures of others' investments (standard deviations are reported in parentheses).

appears to be no visible convergence to equilibrium over 20 rounds, as some subjects persistently deviate from their money-maximizing strategies. We find recurrent over-investment in LC treatments and under-investment in HC treatments.

In what follows we use a combination of choice and non-choice data to document several important aspects of the choice process. In particular, we examine the scope of history dependence in subjects' decision making and document how investments of partners in previous rounds shape the subject's current choice. This history dependence allows us to define a notion of best response (BR) to past investments and assess to what extent subjects' choices can be rationalized as profit-maximizing behavior.

5.1 Grouping Subjects into Types

There exist large differences in the behavior of subjects within each treatment. Some invest consistently more than others; many change their choices repeatedly, while others do not. Also, as we document in Section 6 below, and in Appendix E, there is substantial heterogeneity in the intensity of calculator usage by different subjects. This suggests that not all agents conduct themselves in the same way when it comes to choosing an investment in particular or making decisions more generally. To facilitate the analysis, we classify subjects into two broad groups, or types, based on the discrepancy between the payoff associated with the history-dependent BR and the payoff from the actual investment. A larger discrepancy indicates larger foregone earnings. We then examine whether there are differences in the calculator usage of different subject types.

Appendix C provides evidence for history dependence of subjects' beliefs about others' investments. This is an essential preliminary step that provides support for the usage of history-dependent BR as our benchmark. In assessing the length of the subjects' memory span we try to account for variation in conjectures as a function of lagged investments by others. We find that using memory of length 2 accounts for approximately 47% of the variation in conjectures and that further lags are insignificant in accounting for conjectures.[14]

[14] To confirm the results of the regression analysis included in Appendix C, we consider all conjectures from round 2 onwards and find that roughly 16% coincide exactly with previous round investments by other group members. In 30% of the cases, the conjecture matches exactly with one of the 10 possible combinations that can be formed from the group members' investments in the prior round. Finally, in 36% of the cases, the conjecture matches exactly one of the 56 possible combinations that can be formed from group members' investments in the two previous rounds. These relative frequencies are extremely high when compared to the three most recurring individual conjectures, namely $(10, 10, 10)$, $(0, 0, 0)$ and $(20, 20, 20)$, which were considered in only 3%, 4%, and 5% of the cases, respectively. Agents clearly appear to make conjectures based on past experiences.

Rationalization of choices and the measurement deviations. How should one use information about investments in the previous two rounds to define a BR? Restricting subjects to respond to the specific investments observed in a given round seems unreasonable because subjects are well aware that they will not be matched with the same set of individuals in subsequent rounds. Instead, we ask if a subject's investment can be rationalized based on recent history. We posit that subjects may respond to any possible combination that can be obtained by combining group members' investments in rounds $t-1$ and $t-2$. Then, for each subject/round and for every combination of the partners' investments, we compute the difference between the profit associated with the BR ($\pi_{i,t}^{BR}$) and the profit associated with the actual choice ($\pi_{i,t}^{ACT}$). We keep only the lowest such difference per subject/round and denote it by $Min\ Loss_{i,t} = \min\left\{\pi_{i,t}^{BR} - \pi_{i,t}^{ACT}\right\}$.[15] Next, we define the proportional loss as $\frac{Min\ Loss_{i,t}}{\pi_{i,t}^{BR}}$. This is a money-metric index that measures how close actual investments are to the money-maximizing investments, conditional on conjectures. If the lowest proportional loss is zero, then the choice can be rationalized through the lens of pecuniary-profit-seeking behavior. The final step is to compute the average proportional loss of each subject.

For each treatment group – LVCM ($\rho = 1$), LC ($\rho \in \{0.65, 0.70\}$), HC ($\rho \in \{0.54, 0.58\}$) – we classify subjects into two subgroups by applying the clustering method developed by Ward (1963). The goal of the method is to minimize the within-cluster variance. Subjects are denoted as Type 1 if they belong to the cluster with lower individual proportional loss, otherwise they are denoted as Type 2. Table 5.1 displays the distribution of types by the

[15] We sort the $\pi_{i,t}^{BR}$ values from highest to lowest. We then remove the two lowest and highest values. We do this to avoid bias due to outlying investments, whether unusually high or unusually low.

intensity of complementarity.[16] It is worth stressing again that this grouping criterion requires the joint use of choice and non-choice data.

Table 5.1
Distribution of Types

Type	Treatment Group			Total
	LVCM	LC	HC	
1	17	39	54	114
2	15	25	24	60
Total	32	64	78	174

5.2 Patterns of Individual Investments

Valuable information about individual decision making can be elicited from the evolution of individual investments. Crucially, one can measure how close investments are to the notion of history-dependent pecuniary BR, as defined in Section 5.1. In HC treatments, despite much heterogeneity, a remarkable 42% of all investments are consistent with BR behavior. Even when a deviation exists, it is often small. Most deviations are due to under-investments: in HC treatments subjects under-invest in 44% of the cases and over-invest in only 14% of cases.

In contrast, in LC treatments only 12% of investments are consistent with BR and, when deviations occur, they mostly result in over-investments. In 70% of all cases subjects over-invest, while under-investments occur in only 18% of cases.

In Appendix D we present plots of the complete sequence of investments made by each subject. Investments are juxtaposed to the rationalizable set (gray)—an area consisting of the set of BRs computed using the steps described

[16] For the case of HC treatments we had to exclude two subjects for which their individual proportional loss was significantly higher than the average of subjects classified as Type 2.

in Section 5.1. This allows one to visualize whether a subject's investment can be rationalized by pecuniary-profit-maximizing motives, and to appreciate how investments drift into and out of the BR range. In these same figures, we superimpose a dashed red line representing the myopic BR; that is, the best response function to the investments by members of the group to which the subject belonged in the previous round. This provides a direct counterpart to assess the path dependence of actual investments.

5.3 Linking Types to Behavioral Categories

What drives Type 2 subjects to deviate from profit-maximizing strategies? One possibility is that over-investment in LC treatments reflects motives that are beyond simple profit-seeking. For example, when optimal investments become smaller, some agents may find joy in the act of contributing to a group account. Such joy of giving would be harder to identify when complementarity is high and profit-seeking behavior dictates high investments.

On the other hand, under-investment in HC treatments is consistent with competitive motives, as suggested by Fershtman et al. (2012); when other subjects invest relatively high amounts, marginally reducing one's own investment may guarantee the highest payoff in the group. This motive would be indistinguishable from pecuniary-profit-maximizing when complementarity is low, as both usually lead to lower investments relative to other group members.

It is conceivable that subjects—even profit-seeking ones—may deviate from the profit-maximizing strategy because they do not understand the rules of the game. Given their conjectures, they may fail to calculate the profit-maximizing choices. To discriminate between confusion and alternative behavioral motives we examine what we call "payoff-relevant" use of the calculator. That is, we

identify whether subjects are able to compute the BR to their conjectures using the calculator and whether they systematically play a BR strategy after they identify it.

We adopt two measures of payoff-relevant use of the calculator: (a) the difference between hypothetical investments and the BR to conjectures about other players' choices, defined as $\hat{g}_i - g_i^*(\hat{g}_{-i})$. We denote this difference as the *Calculated Deviation from BR*;[17] (b) the difference between actual investments and the BR to conjectures, defined as $g_i - g_i^*(\hat{g}_{-i})$. We call this the *Actual Deviation from BR*.

5.3.1 *Homo pecuniarius* versus *Homo behavioralis*

It is informative to examine how the payoff-relevant measures *Calculated Deviation from BR* and *Actual Deviation from BR* are distributed among participants. When a subject identifies the pecuniary-profit-maximizing strategy using the calculator, the discrepancy between her own hypothetical investment and the BR to her conjectures (*Calculated Deviation from BR*) is close to zero. Similarly, a value of *Actual Deviation from BR* close to zero indicates that a participant has actually pursued the pecuniary-profit-maximizing strategy for a given conjecture. Figure 5.1 displays a scatter plot of the average value of *Calculated Deviation from BR* and *Actual Deviation from BR* for each subject.

[17] We consider all conjectures and hypothetical investments starting from the practice session. For cases in which an individual entered multiple hypothetical investments for the same conjecture, we set a rule to match a hypothetical investment with a conjecture: namely, we select the current or past hypothetical investment that maximizes the monetary payoff given the conjecture. We consider past hypothetical investments (in addition to current ones) because we find evidence of subjects selecting a given conjecture and then adjusting their hypothetical investments over several rounds. Finally, to simplify the analysis we group conjectures within different bins based on their generalized ρ-mean. The bins, B, are defined as follows: if $M_\rho \leq 0.5$ then $M_\rho \in \{B = 1\}$; if $M_\rho \geq 19.5$ then $M_\rho \in \{B = 21\}$; if $j - 1.5 < M_\rho \leq j - 0.5$ then $M_\rho \in \{B = j\}$ for $j = 2, \ldots, 20$. When $\rho = 0.54$ ($\rho = 0.58$) we group in the same bin all conjectures for which $M_\rho \geq 10$ ($M_\rho \geq 15$).

Black circles and gray squares refer to Type 1 and Type 2 subjects, respectively. The plot confirms that, except in the LVCM treatment, both types are usually capable of finding the profit-maximizing investment using the calculator (*Calculated Deviation from BR* is never very far from zero). This means that confusion cannot account for most of the observed choices.[18]

To further examine this issue we calculate, for each treatment and type, a weighted average of *both Calculated Deviation from BR* and *Actual Deviation from BR*.[19] The ratio of the former to the latter captures the proportion of the total deviation due to confusion. For the LVCM, confusion accounts for 54% of the actual deviation for Type 2 subjects (relative to Type 1 subjects). In contrast, for LC and HC confusion is much lower, at 19% and 14%, respectively. Considering actual choices (*Actual Deviation from BR*), significant differences become apparent: Type 1 subjects (*Homo pecuniarius*) clearly pursue the pecuniary-profit-maximizing strategy, whereas Type 2 individuals (*Homo behavioralis*) often choose to deviate from it. Type 2 subjects exhibit altruistic behavior in LC treatments, while in HC environments they appear to pursue a competitive motive.[20]

Crucially, variation in the degree of complementarity and the magnitude of optimal investments, may play a role for the occurrence of non-pecuniary motives. When BR choices are very low (LC treatments) some agents may enhance their payoff through altruistic over-investments. Such joy of giving could be tainted, or less salient, in an environment where a high payoff is

[18] This is also confirmed when looking at the performance on the control questions. There is a negligible difference between the payoffs each type obtained from answering the control questions correctly. Type 1 subjects earned \$3.73, whereas Type 2 received \$3.63.

[19] Weights are with respect to the number of rounds the calculator was activated.

[20] Because we use a between-subject design, we make no claim as to the identity of types across treatments. That is, an agent may appear as *Homo pecuniarius* in LC treatments (since competitive behavior coincides with profit maximizing) while under-contributing in HC treatments—like a *Homo behavioralis*. The opposite pattern may emerge as well.

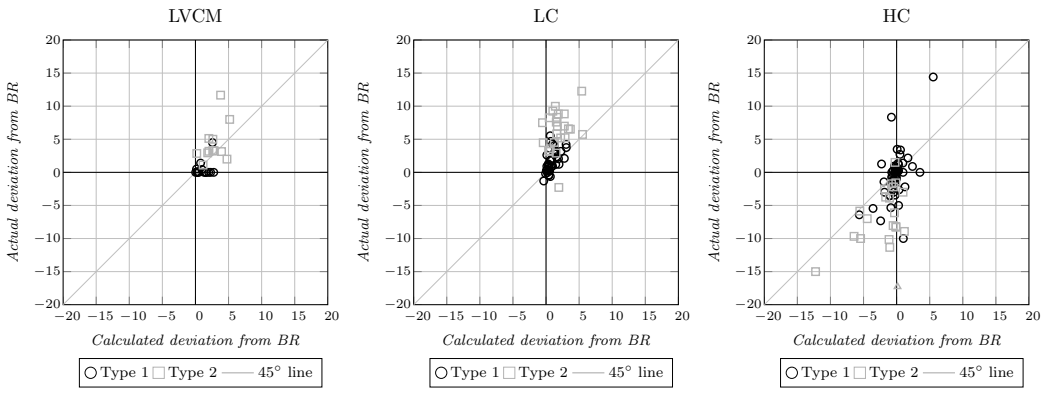


Figure 5.1. *Calculated Deviation from BR* versus *Actual Deviation from BR.* The black circles display the average *Calculated Deviation from BR* and *Actual Deviation from BR* for each Type 1 subject. The gray squares display the average *Calculated Deviation from BR* and *Actual Deviation from BR* for each Type 2 subject. The triangle on the right panel represents one of the subjects that we excluded on the clustering procedure (the second one did not activate the calculator).

associated with a high investment. When the optimal investment is high, a competitive motive may become more appealing as agents recognize that small reductions in investment are both costly to other players and useful to boosting relative performance within a group. This competitive motive is indistinguishable from pecuniary-profit-maximizing in LC environments.

Behavioral motives may operate side by side with profit-seeking behavior as agents consider all these aspects in their decision making. This observation motivates the analysis in the next section.

5.4 Non-Pecuniary Motives

Given that deviations from profit-maximizing strategies cannot be simply attributed to confusion, *Homo behavioralis* subjects appear to pursue a combination of monetary and non-monetary rewards. In what follows we attempt to quantify the magnitude of non-pecuniary motives by estimating how much money these subjects are willing to forego in the process of making gifts (in LC treatments) or to obtain a relatively higher payoff within their group (in

HC treatments).

5.4.1 Gauging the Extent of Non-Pecuniary Motives

Individual's payoff function can be written as $U_i = \pi(g_i, g_{-i}, \rho) + \gamma$, where the augend describes the monetary payoff and γ captures the joy-of-giving (or warm-glow) motive (Andreoni et al., 2008) that balances the forgone pecuniary payoff. We use observed choices by *Homo behavioralis* to estimate γ for each treatment. By definition, γ is the difference between the pecuniary-profit-maximizing investment and the pecuniary profits from the actual investment of *Homo behavioralis* subjects.

$$\pi(g_i^*(\bar{g}), \bar{g}, \rho) - \pi(\bar{g}_{Type2}, \bar{g}, \rho) = \gamma, \tag{5.1}$$

where $\bar{g}$ is the average investment observed among all players and $\bar{g}_{Type2}$ is the observed average investment of *Homo behavioralis* subjects.[21] Equation (5.1) describes the choice of a *Homo behavioralis* subject: when other subjects invest $\bar{g}$, she prefers to invest $\bar{g}_{Type2}$ tokens rather than $g_i^*(\bar{g})$. We assume that the warm-glow compensates the subject for the pecuniary loss. Table 5.2 reports the estimated average magnitude of γ within each treatment; the estimates are roughly similar when comparing across treatments (between 2 and 1.35 tokens). The forgone monetary payoffs only accounts for between 2% and 5% of the maximum monetary payoffs given other players' average investment.

[21] We assume that $g_{-i} = \bar{g}$. To account for possible early learning of the game and the environment, we concentrate on the last 10 rounds.

Table 5.2
Joy of Giving Estimates

ρ	$\bar{g}$	$g_i^*(\bar{g})$	$\bar{g}_{Type2}$	γ
1	0.7	0	1.4	0.84
0.70	3.8	0.9	6.3	1.35
0.65	7.2	3.6	9.7	0.87

Note: The first column displays the degree of complementarity, $\bar{g}$ is the overall average investment, $g_i^*(\bar{g})$ is the BR given the average investment, $\bar{g}_{Type2}$ is the average investment of *Homo behavioralis* (Type 2) subjects, and γ captures the joy of giving. We only consider the last 10 rounds.

Given our joint investment technology, the cost of a constant deviation from the money-maximizing strategy changes with the degree of complementarity. As ρ decreases, the monetary payoff function becomes flatter and any marginal change in strategy has a smaller effect on the final reward. This implies that rationalizing similar deviations from profit-maximizing behavior requires a higher joy of giving value (γ) as ρ increases. This observation helps explain the investments of *Homo behavioralis* (Type 2) subjects when $\rho = 0.65$ as opposed to when $\rho = 0.70$. This comparative static is further explored in Appendix G.

Using similar reasoning, one can quantify the intensity of competitive motives in HC treatments; that is, the pecuniary payoff a subject is willing to sacrifice in exchange for a higher income rank within a group. We define the individual utility function as $U_i = \pi(g_i, g_{-i}, \rho) + \kappa$, where κ measures the joy of winning. Table 5.3 reports estimates for κ. The competitive motive is estimated to be higher for $\rho = 0.54$ than for $\rho = 0.58$. This is consistent with two observations: (a) *Homo behavioralis* deviations are marginally larger in $\rho = 0.54$, and (b) for any given κ, the cost of deviating is non-trivially higher when complementarity is stronger. In the next subsection we discuss the latter point in some detail.

Table 5.3
Competitive-Motive Estimates

ρ	$\bar{g}$	$g_i^*(\bar{g})$	$\bar{g}_{Type2}$	κ
0.58	13.9	18.6	8.1	1.27
0.54	15.7	20	11.6	2.14

Note: The first column displays the degree of complementarity, $\bar{g}$ is the overall average investment, $g_i^*(\bar{g})$ is the BR given the average investment, $\bar{g}_{Type2}$ is the average investment of *Homo behavioralis* (Type 2) subjects, and κ captures the competitive motives. We only consider the last 10 rounds.

In Appendix F we examine the distribution of estimated γ and κ for *Homo behavioralis* (Type 2) subjects. We consistently find that for more than 80% of *Homo behavioralis* subjects the non-pecuniary motive is at most 2 tokens, which is fairly low given the monetary stakes in the game as this only accounts for between 2% and 3% of the maximum monetary payoffs given other players' average investment.

5.4.2 Conditional Cooperation

It is conceivable that one goal for some *Homo behavioralis* subjects is to match other group members' investments, behavior similar to conditional cooperators (Fischbacher et al., 2001; Fischbacher and Gächter, 2010). The standard procedure to detect conditional cooperation is to elicit subjects' beliefs about others' investments. Our experimental setting delivers valuable non-choice data (conjectures about others' investments) to identify this behavior. In Table *5.4* we report results from a regression in which the dependent variable is the investment made by each subject and the right-hand-side variable is the average conjecture about others' investments. For the linear case (LVCM) these results suggest that subjects are willing to match up to 50 percent of what they expect to be the average investment of others. Moreover, and quite remarkably, for the case of LC, subjects are willing to invest an amount that is close to what

they predict to be the average investment of others.[22] But perhaps the most interesting results are those in the case of HC: in these treatments the average (and expected) investments are also higher, as cooperation motives should be reinforced by the monetary reward subjects obtain when they coordinate on high investment levels. However, while we find a positive association between investments and conjectures, we also find that investments match only about 60% of the average conjecture. It is apparent that conditional cooperation cannot fully account for the choices made by *Homo behavioralis* subjects in HC settings, suggesting that these individuals are likely to have alternative non-pecuniary motives, as competitiveness.

Table 5.4
Response of Subjects' Investments to Conjectures about Others' Investments

Variable	Coefficient	Number of observations
$\hat{g}_{-i}$	0.566 (0.087)	94
$D_{LC} \times \hat{g}_{-i}$	0.462 (0.115)	232
$D_{HC} \times \hat{g}_{-i}$	0.056 (0.151)	155
Hypothesis	F	$p > F$
$H_0: \hat{\delta}_{LC} = 0$	16.24	0.0001
$H_0: \hat{\delta}_{HC} = 0$	0.14	0.7117
$H_0: \hat{\delta}_{HC} = \hat{\delta}_{LC}$	7.88	0.0068

Note: Results for the regression*:* $g_{i,t} = \beta \hat{g}_{-i,t} + \sum \delta_k (D_k \times \hat{g}_{-i,t})$, where $g_{i,t}$ is the investment of a Type 2 subject i in round t, $\hat{g}_{-i,t}$ the arithmetic mean of conjectures of Type 2 subject i in round t, D_k is a dummy variable for each complementarity degree ($k \in \{LC, HC\}$), when the baseline is the LVCM treatment.This means that the total effect on LC is 1.028 and the total effect on HC is 0.622. The standard errors (reported in parentheses) are clustered at the individual level. At the bottom part of the table we test for equality of the coefficients.

[22] We cannot reject the hypothesis that in LC treatment Type 2 subjects make investments that match exactly their average conjecture (A t-test of $H_0: \hat{\beta} + \hat{\delta}^{\beta}_{LC} = 1$ results in F=0.14 and $p > F = 0.709$).

6 Evidence from Response Times

Using non-choice data we obtain precise measures of subjects' response times and intensity of calculator usage. This information is a valuable way to peek at the mechanics of individual decision making. Analyzing decision times in public good games has become increasingly popular since Rand et al. (2012) reported that in a one-shot LVCM experiment shorter response times are positively correlated with higher contributions. This finding was interpreted as evidence that humans are instinctively generous. However, this interpretation has been challenged by, among others, Recalde et al. (2018), who point out that in the LVCM the only possible deviation is to over-contribute, making it hard to distinguish between subjects who instinctively over-contribute and those who rush and make genuine mistakes.[23]

6.1 Response Times in the First Round

First, we replicate the analysis of Rand et al. (2012). For comparability, we consider only the first-round investments in the LVCM treatment. The results confirm the findings of Rand et al. (2012): subjects who invest zero wait 34 seconds, on average, before logging their choice. In contrast, it takes an average of just 25 seconds to select a positive investment. Our experimental design allows us to go beyond the one-shot game and the case of no complementarity. The analysis of sequential rounds makes it feasible to assess how response times change with both size and direction of investments' deviations from

[23] Recalde et al. (2018) design a voluntary investment experiment in which the dominant strategy is in the interior of the strategy space, and they replicate the finding of Rand et al. (2012) when the equilibrium investment is below the midpoint of the choice space. However, when the equilibrium is located above the midpoint, they find a negative correlation between response time and investments.

pecuniary BRs. We combine non-choice data and response-time information to illustrate how some of the conclusions about instinctive generosity drawn by Rand et al. (2012) are inconsistent with our findings. More generally we argue that valuable information can be elicited from differences in the length of time it takes subjects to enter their investments and from the intensity of their calculator usage over that interval.

6.2 Differences across Treatments and Types

By analyzing the patterns of response time over several periods it is clear that subjects respond faster on average as rounds elapse (Figure 6.1). This is not surprising given that participants become more familiar with the game as time progresses.

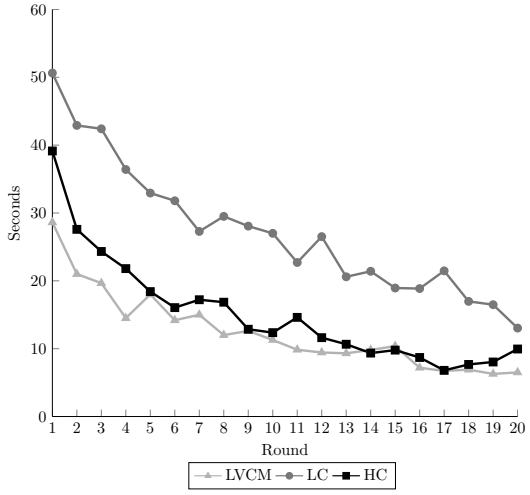
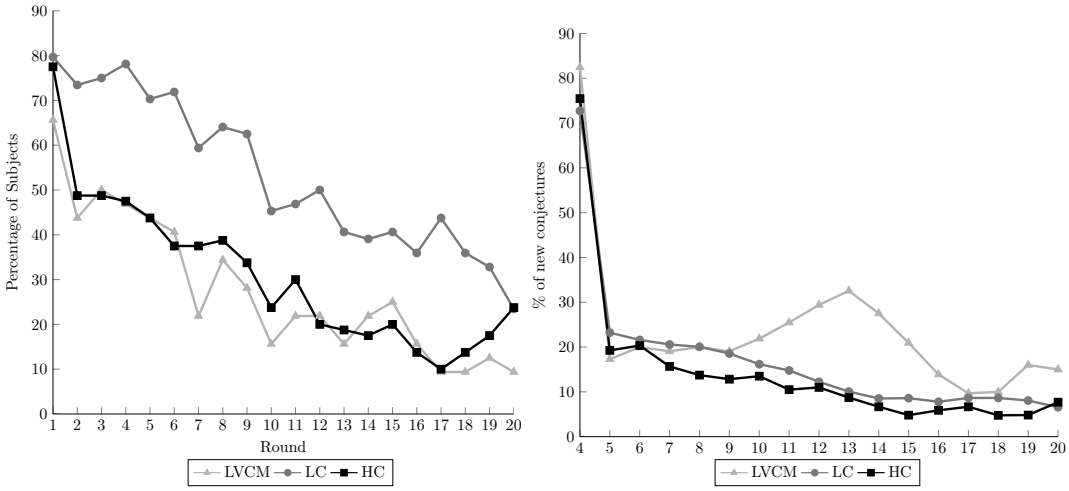


Figure 6.1. Average response time over time. This figure shows the evolution of the average response in each treatment.

This increase in speed is closely related to usage of the calculator,[24] which

[24]For this reason, in the last part of this section we combine these two measures to compute the average processing speed for each treatment.

declines as rounds progress. This can be seen in the left panel of Figure 6.2. The right panel of Figure 6.2 shows the five-round moving average of the number of new conjectures as a share of the overall number of conjectures considered in all previous rounds. A steep drop in the percentage of new conjectures is visible after the first few rounds: this is consistent with the hypothesis that most subjects form conjectures early in the experiment and that they stop updating such conjectures fairly early.



(a) Use of the calculator (b) New conjectures

Figure 6.2. Use of the calculator over time. The left panel reports the proportion of subjects who activated the calculator by treatment. The right panel displays the five-round moving average of the number of new conjectures as a percentage of overall conjectures. Notice that for period 4 we include data from the practice round, for which the percentage of new conjectures is 100%.

As shown in Figure 6.3 and Table 6.1, we observe considerable differences in the average response time across treatments. Subjects in LVCM treatments take significantly less time than in the LC treatments (t-test: p-value=0.000), suggesting that more complex environments, like LC, elicit more pondering of potential choices. The HC response times lie between those of the the two other treatments, suggesting that high complementarity settings are less challenging than low complementarity ones.

We also examine our non-choice data through the lens of the typology described in Section 5.3.1. This unveils interesting discrepancies in both the quantity and quality of time usage between types. In the LVCM and HC treatments *Homo pecuniarius* (Type 1) subjects seem to respond faster (t-test: LVCM, p-value=0.0643 and t-test: HC, p-value=0.1195). Differences are, at most, marginally significant and we take them with some caution. Nonetheless, the disparity in estimated time use clearly indicates that in one set of treatments (LVCM) the marginally faster subjects are those who invest little or nothing, while in another set (HC) the quicker subjects are those who get closer to full-investment. Hence, both response time and the direction of deviations from pecuniary BR seem to depend on the specific environment. More importantly, we find little or no evidence that speedy choices systematically and significantly imply over-investment.

In contrast, in LC treatments *Homo pecuniarius* subjects take more time before submitting their choices, possibly because calculating the optimal level of (pecuniary) investment with precision is harder when complementarity is low.[25] However, differences in raw time usage across types in the LC case are poorly identified (t-test: LC, p-value=0.4251). For this reason we resort to additional measurements to examine the hypothesis that Type 1 agents may try harder to figure out pecuniary best responses; as we show below, agents who play close to pecuniary BR in the LC treatments not only take longer to log a choice but also use the calculator more intensively and consider a higher number of potential combinations.[26]

[25] Rubinstein (2007) obtains similar results. He finds that it takes more time to make decisions that require cognitive reasoning than to make instinctive choices.

[26] The response times of Type 1 and Type 2 subjects in the LC treatments are consistent with the typology described in Rubinstein (2016). He divides subjects into two types according to their response time, arguing that subjects who make quick decisions are more instinctive while those who are slower often make strategic considerations.

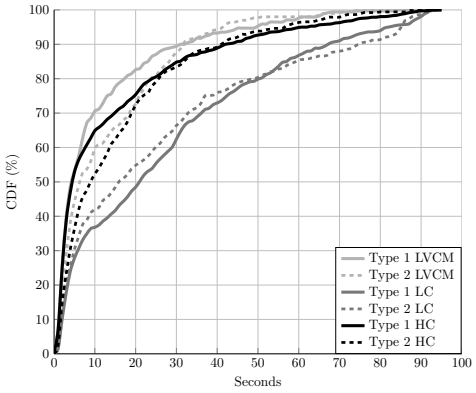


Figure 6.3. Response-time frequencies. Each solid line represents the cumulative distribution function for Type 1 subjects for each of the treatments. Each dashed line represents the cumulative distribution function for Type 2 subjects for each of the treatments. The y-axis is displayed in percentage terms
.

6.3 Processing Speed

Given the evidence presented so far on raw time use data, it is crucial to distinguish between subjects who spend much of their time idly staring at the screen and those who do try to get the most out of the calculator. To identify this difference we compute the average amount of time subjects spend entering any given combination in the calculator. This is done by dividing the total time spent on the calculator by the number of combinations that are considered during that time interval.[27] The resulting statistic is a proxy for the speed at which information is processed. The bottom panel of Table 6.1 shows that, across all treatments, *Homo pecuniarius* subjects process more combinations per unit of time than *Homo behavioralis* subjects (the difference is not significant for LVCM, but p-values of t-test are 0.026 and $<$0.0001 for LC and HC, respectively).

[27] This statistic can only be computed for those who actually use the calculator.

Moreover, regardless of their type, all subjects process combinations significantly faster in the LC treatment (t-test: LVCM vs LC, p-value=0.008; t-test: LC vs HC p-value=0.029). This provides further evidence in support of the hypothesis that in more complex environments, like the LC ones, subjects tend to exert more effort when choosing an investment. This is especially true for *Homo pecuniarius* subjects, who not only devote more time to the choice problem but appear to be significantly more efficient in their time usage.

Table 6.1
Response Times, by Type and Treatment

	Type 1			Type 2			Overall		
	Avg. seconds	(SD)	obs.	Avg. seconds	(SD)	obs.	Avg. seconds	(SD)	obs.
LVCM	11.4	15.1	340	13.6	14.4	300	12.5	14.8	640
LC	27.8	25.5	780	26.6	27.0	500	27.3	26.1	1280
HC	14.7	19.7	1080	16.3	17.4	520	15.2	19.0	1600

Processing Speed, by Type and Treatment
(Response Time Divided by Number of Combinations Entered in the Calculator)

	Type 1			Type 2			Overall		
	Avg. seconds	(SD)	obs.	Avg. seconds	(SD)	obs.	Avg. seconds	(SD)	obs.
LVCM	18.2	(17.8)	79.0	19.6	(14.7)	98.0	19.0	(16.1)	177
LC	14.3	(15.3)	430.0	17.1	(16.9)	254.0	15.4	(15.9)	684
HC	14.9	(14.5)	328.0	22.0	(15.2)	170.0	17.3	(15.1)	498

7 Discussion of Related Literature

It is often challenging to interpret decision-making through the examination of choice data alone. For this reason, several studies have started collecting non-choice data to shed light on the decision process of players. Throughout

each session, we give participants access to a payoff calculator. By using the calculator subjects can see the monetary payoff associated with as many hypothetical investments as they wish, including different hypothetical values of their own choice. We record every trial that subjects enter in the calculator during both the practice period and the experiment. These non-choice data are different from information collected using "mouse lab" (see, among others, Camerer et al., 1993; Costa-Gomes et al., 2001; Johnson et al., 2002; Costa-Gomes and Crawford, 2006; and Brocas et al., 2014), "eyetracking" (see, among others, Knoepfle et al., 2009; Wang et al., 2010; Reutskaja et al., 2011; and Arieli et al., 2011), analysis of response times (see Spiliopoulos and Ortmann, 2017 for a literature review), rational inattention analysis (see, among others, Caplin and Dean, 2015; and Dean and Neligh, 2017), or fMRI techniques (see Bhatt and Camerer, 2005; Smith et al., 2014). When employing these techniques participants are aware that experimenters are gathering data and this may influence their choices. Finding the optimal strategy in our investment problem makes the use of the calculator often necessary, as payoff functions are nonlinear and individual gains are affected by the dispersion of players' investments. For these reasons subjects depend on the calculator to evaluate alternative strategies and to make informed choices. The input they enter into the calculator delivers a valuable description of their beliefs about the investments of other agents. In this sense, our method provides a non-intrusive way to collect high-quality non-choice data. A further advantage of this approach is that data collection is simple and requires no special technology or equipment; thus, it can be applied easily to the analysis of most individual or group decision problems.

Crucially, agents are able to use the calculator as they wish. They can change one or more conjectures about other agents' investments and/or adjust

their own hypothetical investment in whichever order, by any amount and as many times as they want. In this sense subjects are let free to explore the payoff space in countless ways. Cherry et al. (2015) use a related method. They implement an output-sharing game with negative externalities in which they provide subjects a payoff calculator and analyze non-choice data. A key difference is that, in their case, subjects must enter a conjecture before they are allowed to see a table reporting the payoffs associated with a subset of hypothetical choices, given the conjecture. This limits both the number of payoffs that can be visualized for any set of conjectures and, more importantly, removes the possibility to quantify how a marginal change in subject's hypothetical own investment, or in the conjecture about other agents, affects the payoff. Our experimental design allows agents to exactly reproduce and modify investments observed in previous rounds, or to consider significantly different scenarios since they face no constraint in the number and type of combinations they are allowed to evaluate. Furthermore, Cherry et al. (2015) analyze only the last conjecture used before making a choice, while in our analysis we consider all conjectures and hypothetical choices given that the exploration of the payoff function can be gradual as subjects adjust both their conjectures and hypothetical investments over time.

Second, our analysis concentrates on the joint investment problem of agents facing non-linear returns. We model these returns as the product of complementary investments and consider treatments with different levels of gains from cooperation. A constrained version of our problem corresponds to the LVCM. This game emphasizes the tension between private incentives and social efficiency, examining how individual choices shape group outcomes. The LVCM assumes a production technology of the public good which is linear and

additively separable in agents' investments.[28] Hence, this linear specification focuses on the choice problem of an agent whose optimal (profit-maximizing) choice is independent of other agents' choices.[29,30] Yet, complementarity is key in many environments in which individual investments entail costly effort. For example, a family may be viewed as a group in which individual efforts are strong complements in generating positive group outcomes. Similarly, modern charities often rely on matching efforts by different stakeholders to raise funds and reach a socially valuable objective. Crucially, in several joint endeavors such as school funding activities, neighborhood improvement initiatives and even scientific research projects, the return on a participant's effort depends on the level of effort that all other participants choose to exert, and too much heterogeneity in individual investments may be detrimental. Identifying how subjects coordinate in such joint investment environments is essential to make sense of empirical observations. In practice, a provision technology featuring complementarity in individual investments captures two essential features of joint investment problems. First, an increase in one's investment raises the marginal return on others' investments and, second, the provision is more efficient when agents' investments are relatively homogeneous.[31]

[28] Under this key assumption, and assuming that the marginal per capita return (MPCR) is lower than one, the dominant strategy for agents with self-regarding preferences is to invest nothing at all (i.e., to free ride) rather than make a positive investment that results in a private cost and a social benefit.

[29] The experimental literature is much too vast and thoughtful to be covered fairly here. An interested reader is referred to Ledyard, 1995 for an older but very helpful survey and a more recent survey by Vesterlund (2016). The robust experimental finding is that contributions are significantly higher than zero in early rounds but diminish over time. Positive contributions have been interpreted (among other explanations) as reflecting confusion, altruism, or willingness to cooperate if others do.

[30] Andreoni (1993) considers complementarity between the private and public good; Keser (1996) studies utility that is non-linear in the private good; Harrison and Hirshleifer (1989); Croson et al. (2005) study public good experiments based on the weakest-link mechanism of Hirshleifer (1983).

[31] Steiger and Zultan (2014) compare the linear case and a case in which the marginal

Lastly, this paper focuses on the experimental literature that studies coordination failures in games with strategic complementarities in players' decisions. The classic example is the two-by-two stag hunt game in which there are two Nash equilibria in pure strategies, one payoff dominant and the other risk dominant (see Cooper et al., 1992). In this type of coordination game, the Pareto superior (payoff-dominant) outcome is not always chosen; the equilibrium selection depends on the basin of attraction and the optimization premium (see Battalio et al., 2001; Van Huyck, 2008). The current study introduces coordination considerations in a public good game. Our experimental result of no convergence to the unique Nash equilibrium in the case of weak complementarity is in sharp contrast to experimental results in binary-action games and suggests that a richer strategy space may induce interesting behavioral dynamics.

When the degree of complementarity supports two equilibria, our game superficially resembles order-statistic games (see Devetag and Ortmann (2007) for a survey of experimental results). The n players in these games select integer number between 1 to k, and their payoff is decreasing in the distance between their chosen number and some order statistic. Order statistic games have multiple Pareto-ranked equilibria, and have been studied experimentally in the context of coordination. For example, in the extreme weakest-link game the agent's payoff depends on the minimum of all the chosen numbers. Van Huyck et al. (1990) show that subjects fail to coordinate on the efficient outcome when groups are large. However, there are important differences between

return from the public good increases as the number of contributors increases (through increasing returns to scale). Subjects have a binary choice: either to contribute or not. In the increasing returns to scale treatment, there are two equilibria: zero-investment and full-investment. The authors implement a partner-matching protocol and find that only groups that cooperate in early rounds are able to converge to the full-investment equilibrium.

order-statistic games and our joint investment framework. First, order-statistic games do not enable free-riding. Second, in our framework, the earnings from the joint account depend on the investments and on the investments' dispersion, whereas order-statistics games do not account for heterogeneity in players' choices. In terms of equilibrium selection: in order-statistic games, coordination is challenging because there exist $k-1$ equilibria that are relatively fragile, whereas in our environment, only the Pareto-efficient equilibrium is stable.

8 Conclusion

In this paper we examine and compare the dynamic decision processes of individuals who participate in a joint investment problem. We carry out our analysis in an environment featuring complementarity between private investments into a common account. The environment can exhibit multiple equilibria.

Our experimental setting is such that agents' beliefs about other agents' actions affect their pecuniary payoffs. The setting allows us to gather rich information about the way agents learn about the environment and about the motives and procedures of other agents. We do not elicit beliefs explicitly but, rather, collect data on the inputs subjects enter in the payoff calculator. These include conjectures about other group members' investments.

Consistent with theoretical predictions we find a positive relationship between aggregate investments and the degree of complementarity. In HC environments subjects learn to coordinate, moving towards the socially preferable equilibrium, but do not reach the Pareto efficient outcome. Similarly, when complementarity is very low, investments decrease but do not reach the unique zero-investment equilibrium. Subjects also seem to respond to complementar-

ity when its intensity is sizable but not sufficiently high to introduce a second full-investment equilibrium; in this case, they persistently over-invest and show little or no tendency towards the unique zero investment.

The use of detailed non-choice data, together with the manipulation of the intensity of complementarity, allows us to identify the empirical relevance of non-pecuniary motives in the decision-making process. We find that deviations from the profit-maximizing strategy cannot be attributed to confusion and that different types of non-pecuniary motives emerge when we change the intensity of complementarity among individual investments.

Crucially, not all subjects are equally sensitive to non-pecuniary motives. We find evidence that while some individuals (*Homo Pecuniarius*) can be clearly described as profit seekers who are willing to make cognitive efforts to find pecuniary best response strategies, others (*Homo Behavioralis*) are able to calculate the payoff-maximizing strategy but deliberately deviate from it. The interaction of different types of participants is key to understanding how groups behave and why we observe different aggregate patterns under different levels of complementarity. The fact that *Homo Behavioralis* subjects are willing to sacrifice some monetary rewards to deviate from pecuniary-best-response strategies may lead to imperfect convergence to equilibrium, not only because their strategic decisions but also because *Homo Pecuniarius* are aware of their choices and best-respond to them. The presence of *Homo Behavioralis* increases social welfare when complementarity is low, as it restrains group investments from collapsing to zero, but it reduces welfare when complementarity is high and full investments would be optimal.

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For Online Publication

A Derivation of the Best-Response Function

Player i's payoff is

$$\pi_i = \omega - g_i + \beta \left(\sum_{i=1}^{n} g_i^{\rho} \right)^{1/\rho},$$

where $\rho \leq 1$ denotes the degree of complementarity, g_i denotes individual i's investment in the group account, ω is the endowment, and β is a constant. The best response of player i is a unique solution, $g_i^*(g_{-i})$, to the first order condition (FOC)

$$\begin{aligned}
0 = \frac{\partial \pi_i}{\partial g_i} &= \beta \left(g_i^{\rho} + \sum g_{-i}^{\rho} \right)^{\frac{1-\rho}{\rho}} \left(g_i^{\rho-1} \right) - 1 \\
\beta \left(g_i^{\rho} + \sum g_{-i}^{\rho} \right)^{\frac{1-\rho}{\rho}} &= g_i^{1-\rho} \\
g_i^{\rho} + \sum g_{-i}^{\rho} &= g_i^{\rho} \beta^{\frac{\rho}{\rho-1}} \\
g_i^{\rho} \left(\beta^{\frac{\rho}{\rho-1}} - 1 \right) &= (n-1) \frac{\sum g_{-i}^{\rho}}{n-1}.
\end{aligned}$$

In the last line we multiply and divide the right hand side by $(n-1)$ so the best response of player i is defined as a function of $M_{\rho} = \left(\frac{\sum g_{-i}^{\rho}}{n-1}. \right)^{1/\rho}$. Finally, defining $k \equiv \left(\frac{n-1}{\beta^{\frac{\rho}{\rho-1}} - 1} \right)^{\frac{1}{\rho}}$ yields:

$$g_i^* \left(g_{-i} \right) = k \left(\frac{\sum g_{-i}^{\rho}}{n-1} \right)^{1/\rho}.$$

The second order condition (SOC)

$$\begin{aligned}\frac{\partial^2 \pi_i}{\partial g_i^2} &= (1-\rho)\beta\left(g_i^\rho + \sum g_{-i}^\rho\right)^{\frac{1-\rho}{\rho}-1} g_i^{2(\rho-1)} + (\rho-1)\beta\left(g_i^\rho + \sum g_{-i}^\rho\right)^{\frac{1-\rho}{\rho}} g_i^{\rho-2} \\ &= (\rho-1)\beta\left(g_i^\rho + \sum g_{-i}^\rho\right)^{\frac{1-\rho}{\rho}} g_i^{\rho-2}\left(1 - \frac{g_i^\rho}{g_i^\rho + \sum g_{-i}^\rho}\right) < 0,\end{aligned}$$

implies concavity of π_i.

A.1 Absence of symmetric Nash equilibrium in mixed strategies

A symmetric NE in mixed strategies is a joint distribution μ^{n-1} over g_{-i} such that i is indifferent between all $g_i \in supp(\mu)$. In other words, for any two strategies, g_i' and g_i'', in the support of μ, it must be that:

$$\omega - g_i' + \beta \int_{supp(\mu^{n-1})} \left(g_i'^{\rho} + \sum g_{-i}^\rho\right)^{1/\rho} d\mu^{n-1}(g_{-i}) = \omega - g_i'' + \beta \int_{supp(\mu^{n-1})} \left(g_i''^{\rho} + \sum g_{-i}^\rho\right)^{1/\rho} d\mu^{n-1}(g_{-i})$$

We will show that g_i^* - the BR of player i to μ^{n-1} is a singleton, and therefore there is no symmetric NE in mixed strategies. The first order condition is:

$$\frac{\partial \pi_i\left(g_i, \mu^{n-1}(g_{-i})\right)}{\partial g_i} = -1 + \beta \int_{supp(\mu^{n-1})} g_i''\left(g_i^\rho + \sum g_{-i}^\rho\right)^{\frac{1-\rho}{\rho}} g_i^{\rho-1} d\mu^{n-1}(g_{-i}) = 0$$

The second derivative of player's i payoff is:

$$
\begin{aligned}
&\frac{\partial^2 \pi_i\left(g_i, \mu^{n-1}\left(g_{-i}\right)\right)}{\partial g_i^2} = \\
= \quad & \beta \int_{supp\left(\mu^{n-1}\right)} \left(\left(\frac{1-\rho}{\rho} \right) \left(g_i^\rho + \sum g_{-i}^\rho \right)^{\frac{1}{\rho}-2} \rho g_i^{\rho-1} g_i^{\rho-1} + \left(g_i^\rho + \sum g_{-i}^\rho \right)^{\frac{1-\rho}{\rho}} (\rho-1) g_i^{\rho-2} \right) d\mu^{n-1}\left(g_{-i}\right) \\
= \quad & \beta \int_{supp\left(\mu^{n-1}\right)} \left((1-\rho) \frac{g_i^\rho}{\left(g_i^\rho + \sum g_{-i}^\rho \right)} \left(g_i^\rho + \sum g_{-i}^\rho \right)^{\frac{1}{\rho}-1} g_i^{\rho-2} + \left(g_i^\rho + \sum g_{-i}^\rho \right)^{\frac{1}{\rho}-1} (\rho-1) g_i^{\rho-2} \right) d\mu^{n-1}\left(g_{-i}\right) \\
= \quad & \beta \int_{supp\left(\mu^{n-1}\right)} \left((1-\rho) \left(g_i^\rho + \sum g_{-i}^\rho \right)^{\frac{1}{\rho}-1} g_i^{\rho-2} \left(\frac{g_i^\rho}{\left(g_i^\rho + \sum g_{-i}^\rho \right)} - 1 \right) \right) d\mu^{n-1}\left(g_{-i}\right) < 0.
\end{aligned}
$$

That is, $\pi_i\left(g_i, \mu^{n-1}\left(g_{-i}\right)\right)$ is globally strictly concave and g_i^* is a singleton. It follows that there is no symmetric NE in mixed strategies.

B Coordination and Complementarity

B.1 Distribution of investments

Figure B.1 displays the cumulative distribution of investments by treatment (i.e., by complementarity). The plots confirm the finding of Section 4: the median investment in LVCM is zero even in the early rounds; in the case of the HC treatments, there is not much difference between the distributions under $\rho = 0.58$ and $\rho = 0.54$. investments concentrate at the extremes as sessions progress towards the end.

By contrast, when ρ is set to 0.65 or to 0.70, the mass distribution is more heavily concentrated in the interior of the strategy space. Subjects choose to invest nontrivial amounts even after 10 rounds. For example, in rounds 11 to 20, more than half of all investments are larger than 5 tokens. Investments are range-bound and show little tendency towards convergence.

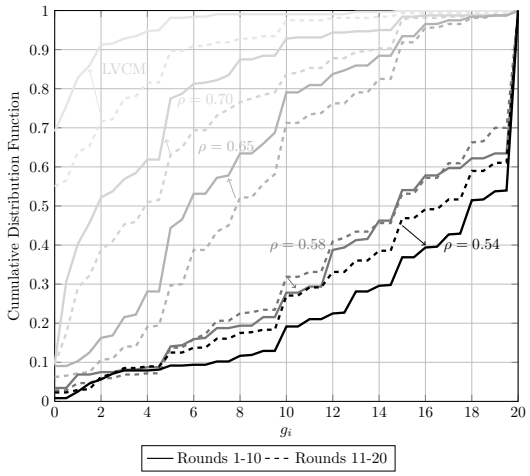


Figure B.1. Cumulative distribution functions. The dashed lines display the cumulative distribution function for the individual investments from rounds 1 to 10. The solid lines show the cumulative distribution function for the individual investments from rounds 11 to 20

.

A key feature of the production technology is that individuals not only benefit from others' investments but also enjoy incremental gains as coordination improves. The cost of less-than-perfect coordination depends on the degree of complementarity; in the linear case there is no additional loss due to lack of coordination. As complementarity increases, the impact of dispersion grows and it becomes more costly to forego coordination; on the other hand, when complementarity is high, a potential obstacle to coordination is the multiplicity of equilibria. Next subsection contrasts the cost of incoordination in environments with a single equilibrium and multiple equilibria.

B.2 Dispersion Loss Index

We measure coordination in each treatment by capturing the loss due to dispersion. We define the dispersion loss index (DLI) for group k in round t as

$$DLI_{k,t} = \frac{\frac{1}{4}\sum_{i=1}^{4} g_{i,t} - \left(\frac{1}{4}\sum_{i=1}^{4} g_{i,t}^{\rho}\right)^{1/\rho}}{10 - \left(\frac{20}{2^{1/\rho}}\right)}.$$

The numerator of the $DLI_{k,t}$ identifies the dispersion loss, as it measures the difference between actual group account output and hypothetical output under perfect coordination. The denominator is just a normalization factor making the index comparable across treatments. When the investments of the four group members are identical (zero dispersion) the arithmetic mean and the generalized mean are identical for any ρ, and $DLI_{k,t} = 0$; when dispersion is highest, $DLI_{k,t} = 1$.[32] This index may be sensitive to outliers because there are only four groups in each session. To account for this sensitivity, in each

[32] This is achieved at the vector of investments $(0, 0, 20, 20)$ in which the discrepancy between the arithmetic and the generalized mean is maximized.

round/session we take the 16 actual investments and average over all possible combinations of investments that can be made by groups of four players; for any such combination we compute $DLI_{k,t}$ and, finally, we record the median $DLI_{k,t}$ for that round.[33]

Figure B.2 reports median DLI by treatment, averaged over five-round intervals,[34] and its 95% confidence interval.[35] This analysis illustrates that in HC treatments, despite the multiplicity of equilibria, dispersion decreases over time. This is reflected in significantly lower DLI, after multiple rounds, than in LC treatments and lends support to the evidence in Figure B.1. Subjects in HC treatments manage to better coordinate their actions.

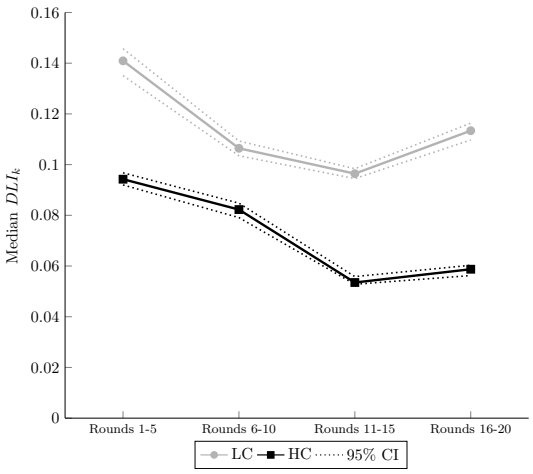


Figure B.2. Dispersion loss index (DLI). This figure reports the median DLI for HC, and LC treatments, averaged over five-round intervals. The dotted lines display the 95% confidence interval.

[33] The total number of possible combinations is $\frac{16!}{12!\times 4!} = 1,820$.

[34] We pool together LC treatments ($\rho = 0.70$ and $\rho = 0.65$) and HC ones ($\rho = 0.58$ and $\rho = 0.54$).

[35] Confidence intervals are calculated using a binomial-based method. We also compute confidence intervals by randomly selecting 500 samples with replacement of the 1,820 combinations in each round/session. We obtain very similar results.

C History-dependent Conjectures

This Appendix provides evidence of history dependence of subjects' beliefs about others. We assess the length of the subjects' memory span by regressing the conjectures about others' investments on the actual investments by group partners in the previous five rounds. Table C.1 reports the results, showing that subjects' conjectures respond significantly to investments made by other members in the previous two rounds.

Table C.1
Response of Subjects' Conjectures to Others' Investments

	$\left(\frac{1}{n-1}\sum g_{-i}^{\rho}\right)^{1/\rho}$	$\frac{1}{n-1}\sum g_{-i}$
$F\left(g_{-i,t-1}\right)$	0.541***	0.557***
	(0.05)	(0.06)
$F\left(g_{-i,t-2}\right)$	0.209***	0.211***
	(0.07)	(0.07)
$F\left(g_{-i,t-3}\right)$	0.035	0.023
	(0.04)	(0.04)
$F\left(g_{-i,t-4}\right)$	-0.008	-0.009
	(0.05)	(0.05)
$F\left(g_{-i,t-5}\right)$	0.072*	0.067
	(0.04)	(0.04)
Constant	1.414***	1.358***
	(0.45)	(0.44)
Observations	1,603	1,605

Note: We estimate the following least-squares specification: $F\left(\hat{g_{i,t}}\right) = C + \sum_{L=1}^{5} A_L F\left(g_{-i,t-L}\right) + u_{i,t}$, where $\hat{g_i}$ is a vector of player i's conjectures about other group members' investments, $g_{-i,t-L}$ contains the vector of investments made by other members in round $t-L$, C is a common constant, and $u_{i,t}$ is an idiosyncratic error. We let the function $F(\cdot)$ be either the arithmetic or the generalized mean of degree ρ. The standard errors (reported in parentheses) are clustered by individuals and obtained by bootstrap estimations with 1,000 replications. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. As a robustness check, we also estimate this specification including dummy variables to control for different treatments. Results are very similar.

D Best-Response Range and Investments

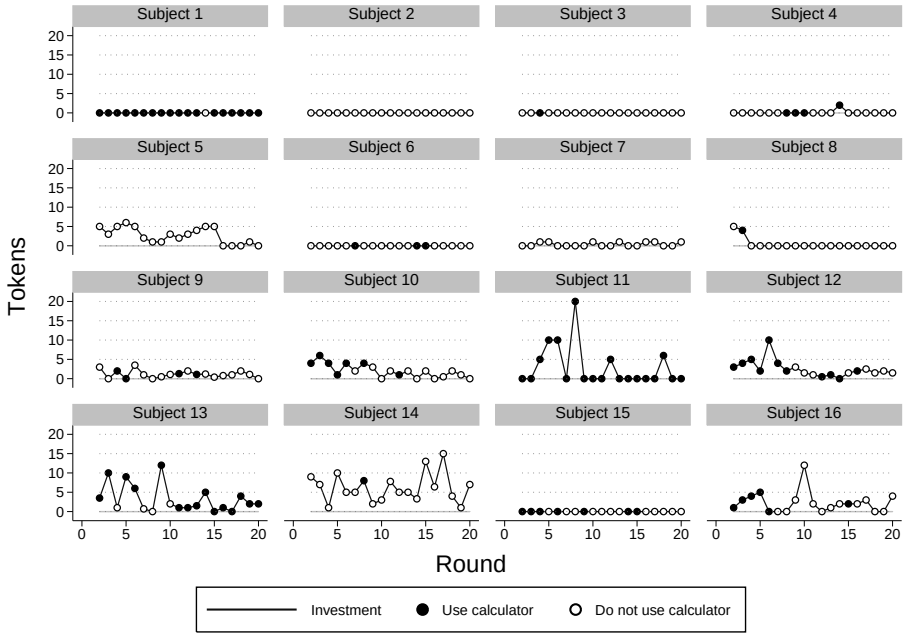


Figure D.1. Session 1 (LVCM)

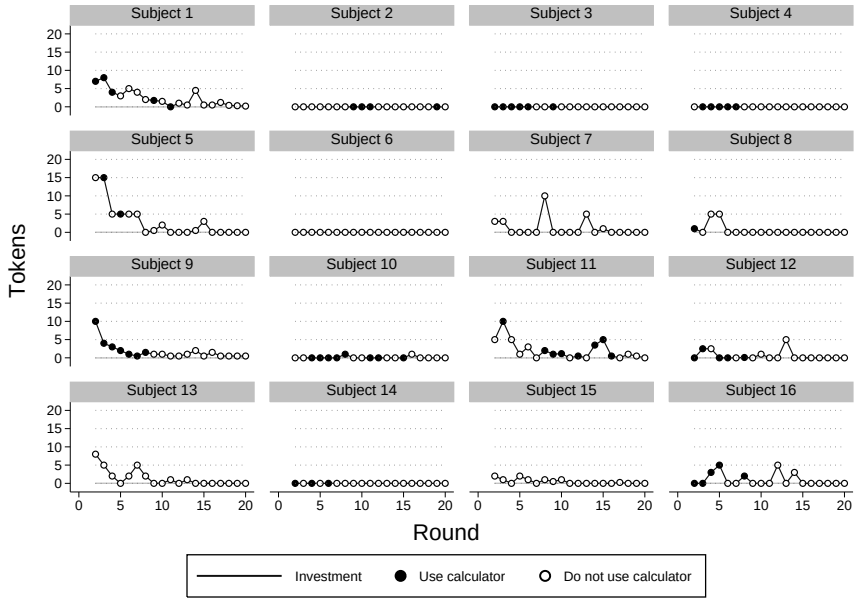


Figure D.2. Session 2 (LVCM)

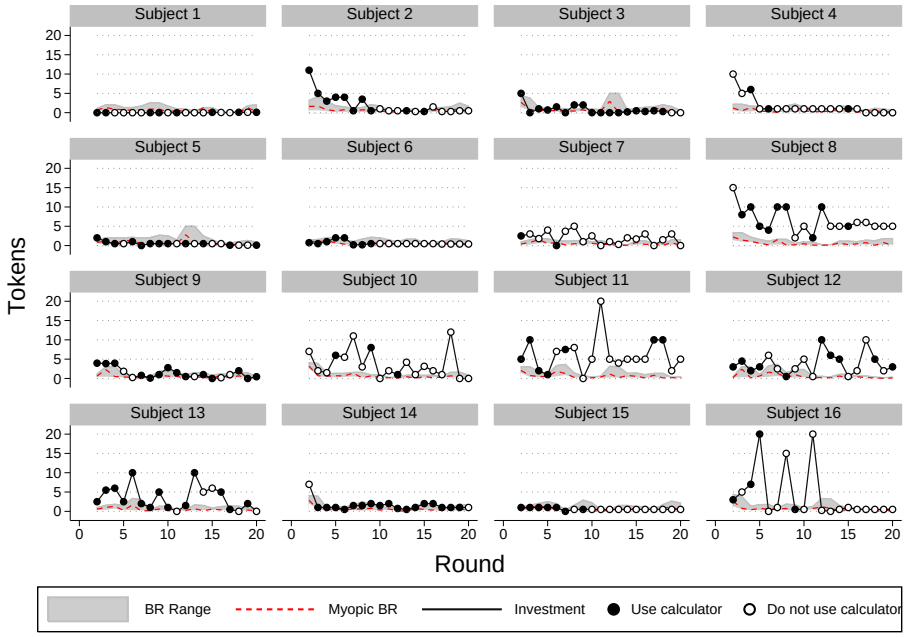


Figure D.3. Session 3 ($\rho = 0.70$)

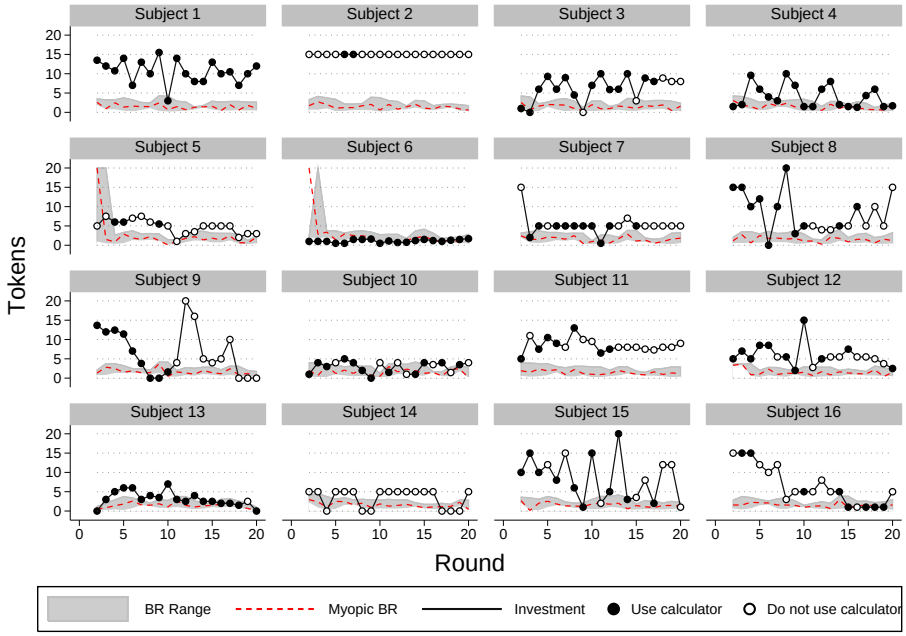


Figure D.4. Session 4 ($\rho = 0.70$)

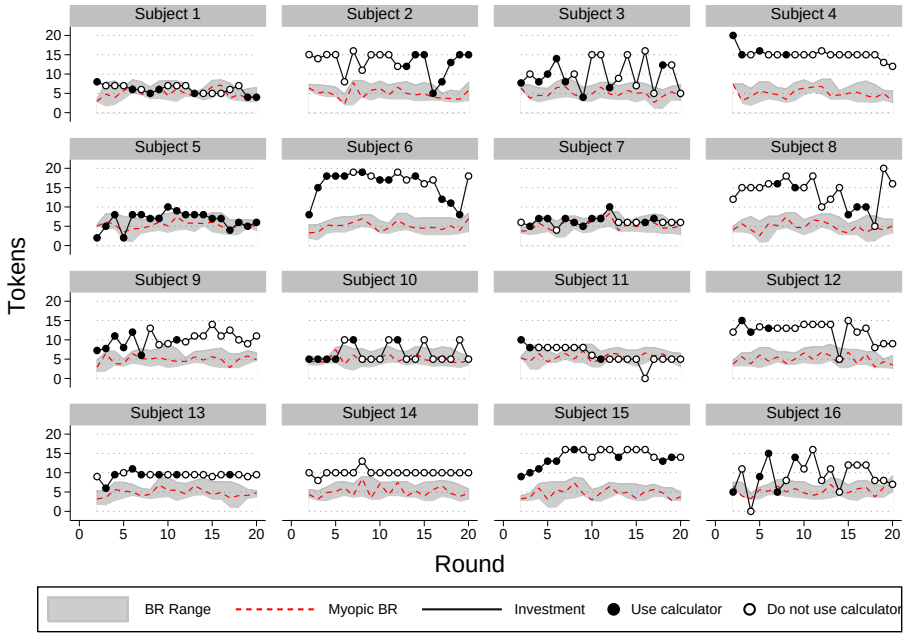


Figure D.5. Session 5 ($\rho = 0.65$)

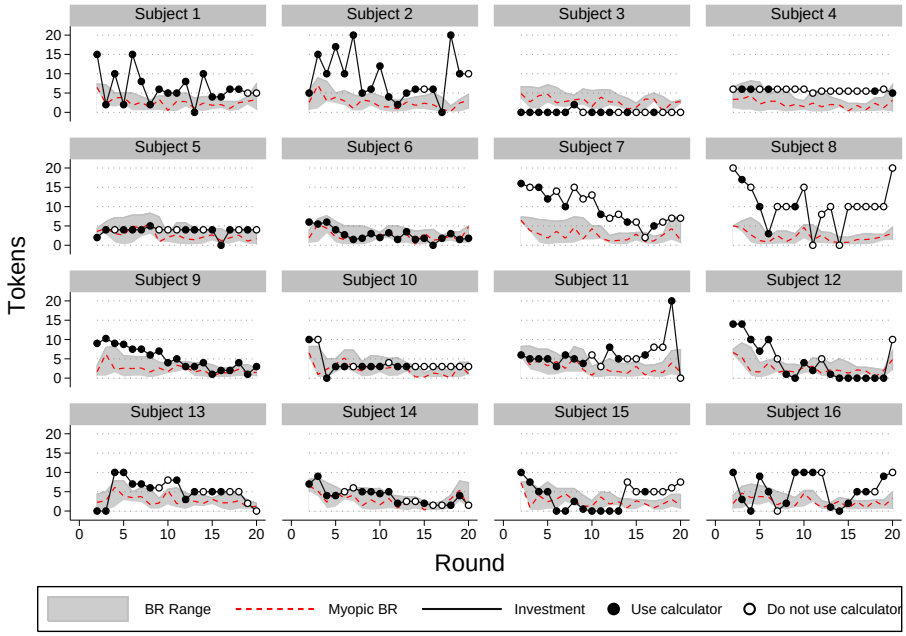


Figure D.6. Session 6 ($\rho = 0.65$)

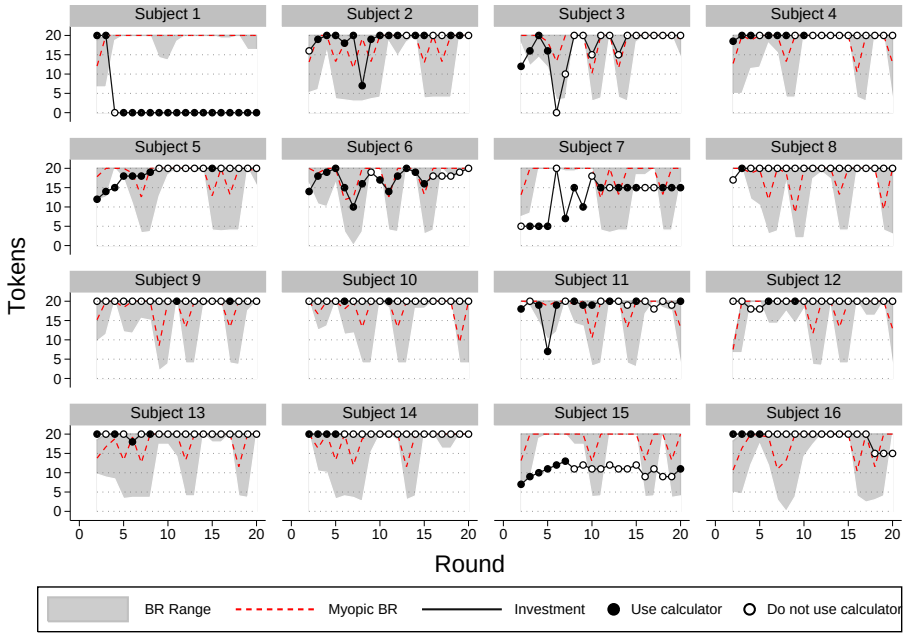


Figure D.7. Session 7 ($\rho = 0.58$)

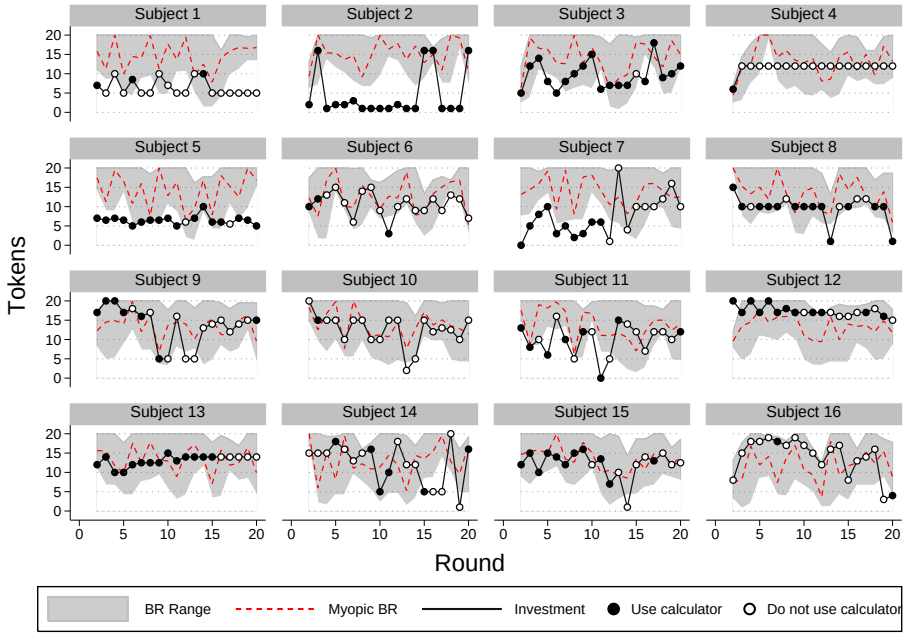


Figure D.8. Session 8 ($\rho = 0.58$)

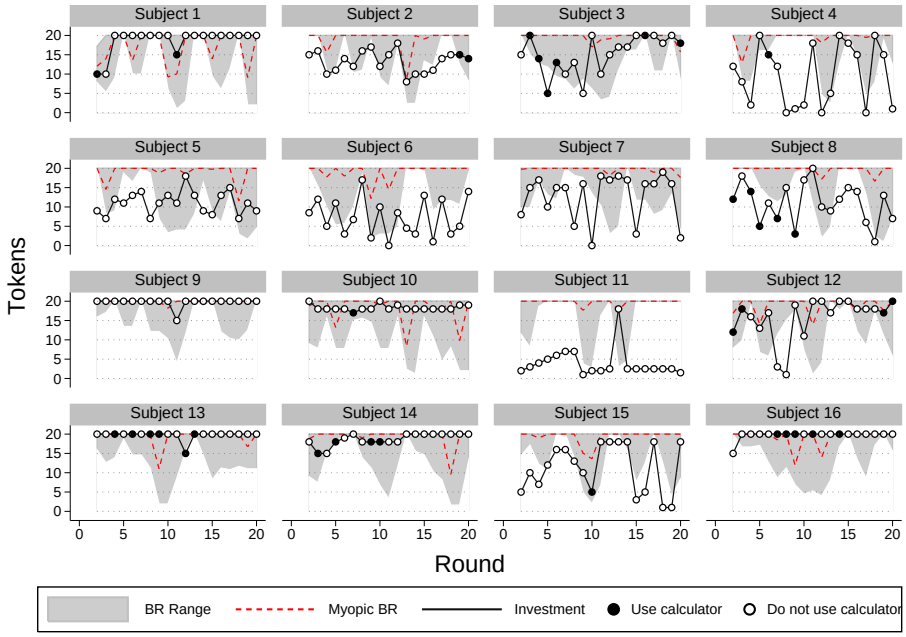


Figure D.9. Session 9 ($\rho = 0.54$)

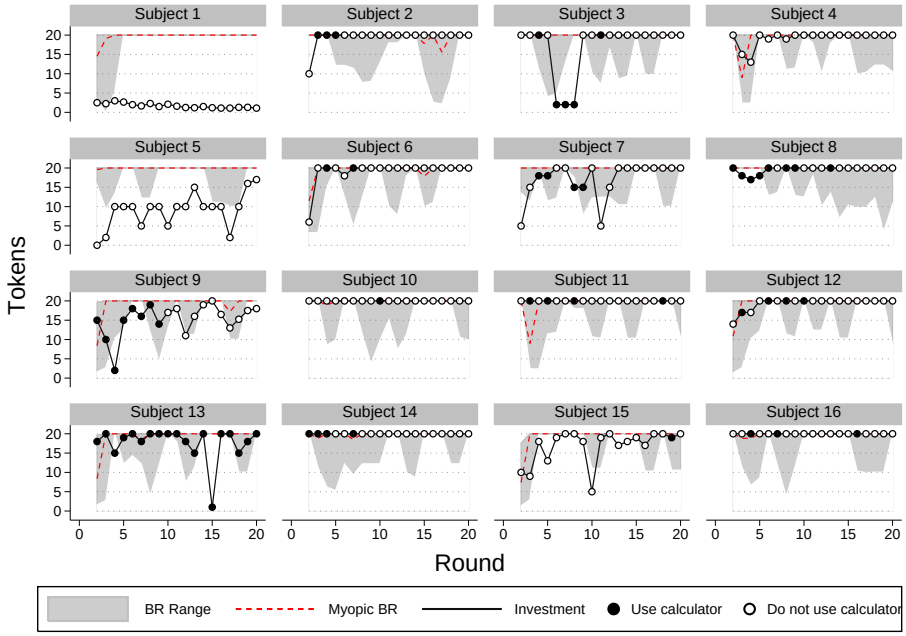


Figure D.10. Session 10 ($\rho = 0.54$)

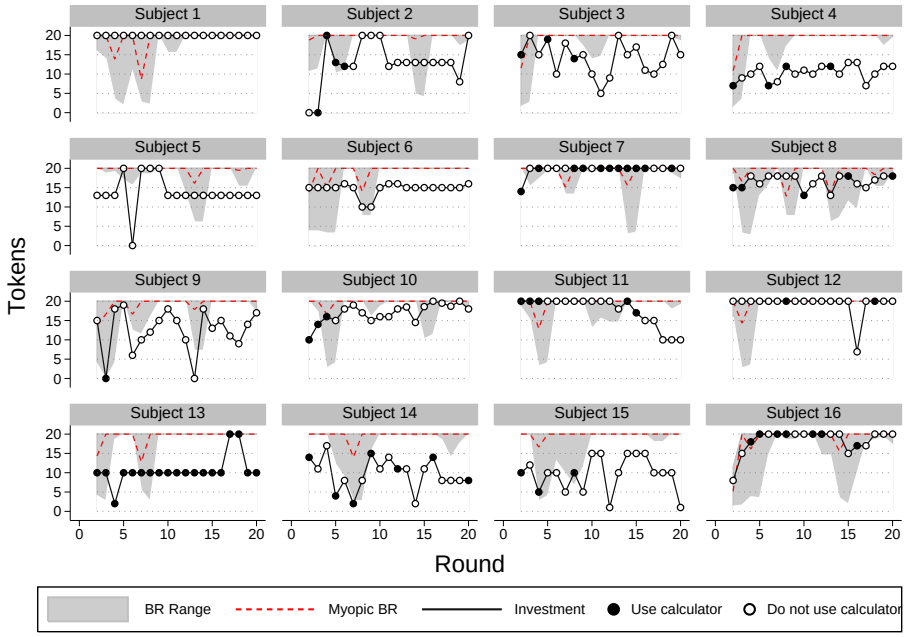


Figure D.11. Session 11 ($\rho = 0.54$)

E Mechanical Use of the Calculator

In what follows we report additional information about the way subjects use the calculator. In Table E.1 we show the summary statistics of the mechanical use of the calculator for different types and treatments. We examine the following variables: (a) *CalcRound*, number of rounds the calculator was used by a subject, (b) *Hyp*, number of own hypothetical investments entered in the calculator, (c) *Conj*, number of conjectures about other players' investments that were entered into the calculator, and (d) *Hyp per Conj*, number of own hypothetical investments entered, given a conjecture about other players' investments.

Number of rounds. Table E.1 confirms that the LVCM is arguably the easiest environment for Type 1 subjects: they end up using the calculator very little (in only 4.6 rounds).[36] In contrast, Type 2 agents use the calculator in the LVCM as much as in other LC treatments. This suggests that Type 1 may use the calculator to identify the BR and then mechanically play it to maximize pecuniary rewards.

The degree of complementarity noticeably affects calculator usage: subjects in LC treatments use the calculator in twice as many rounds as subjects in HC sessions. This supports the view that subjects find it easier to calculate BR strategies in HC treatments.[37] For example, when $\rho = 0.54$, the BR is to invest the whole endowment in the group account if other group members invest at least half of their endowment; this means that, after a few rounds, agents may effectively adopt something close to a high-investment strategy, which requires no further refinement through the use of the calculator. In LC

[36] Three Type 1 participants did not even activate the calculator after the practice round.
[37] Six subjects in the HC treatment did not use the calculator after the practice period.

treatments, instead, choosing a strategy that maximizes payoff requires more fine tuning. For example, when $\rho = 0.70$, a subject would optimally choose to invest one quarter of the average investment made by others to maximize his or her payoff, assuming all other players invest the same amount. Hence, it may be harder to identify a BR strategy in LC treatments.

Conjectures and hypothetical choices. Looking at conjectures, and at the number of own hypothetical choices per conjecture, there is no significant difference across types in LVCM and LC. Subjects in LC and HC treatments enter more hypothetical choices than in LVCM. A Type 1 subject enters on average slightly more hypothetical investments per conjecture than does a Type 2 subject in the LC and the HC sessions. One may expect this behavior from an individual who is very concerned about maximizing her money earnings.

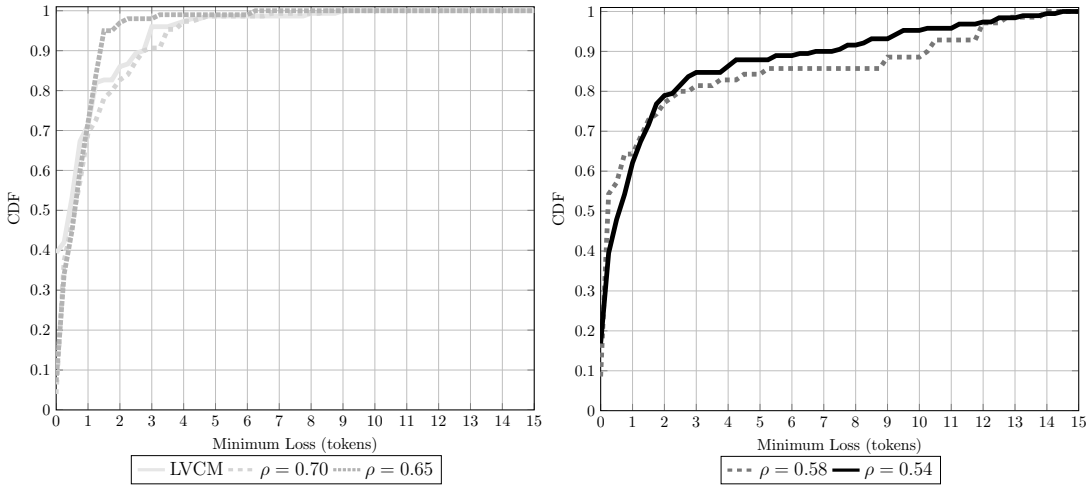
Table E.1
Differences in Mechanical Use of the Calculator, by Subject Type Within Complementarity Level

	LVCM			LC			HC		
	Type 1	Type 2	t-test (p-value)	Type 1	Type 2	t-test (p-value)	Type 1	Type 2	t-test (p-value
CalcRound	4.6 (1.1)	6.5 (1.5)	0.3	11.0 (0.9)	10.2 (0.9)	0.5	6.1 (0.6)	6.3 (1.3)	0.7
Hyp	17.2 (2.4)	22.1 (3.4)	0.2	30.1 (2.1)	31.2 (2.9)	0.8	29.4 (2.4)	14.9 (1.4)	0
Conj	14.1 (1.0)	14.0 (1.2)	1.0	15.0 (0.6)	16.4 (0.7)	0.1	10.9 (0.4)	9.1 (0.7)	0
Hyp Per Conj	3.7 (0.4)	4.3 (0.5)	0.3	7.2 (0.5)	6.6 (0.6)	0.24	8.2 (0.7)	5.1 (0.6)	0
Observations	17	15		39	25		54	24	

Note: Each cell reports the average value for the respective category (standard errors are reported in parentheses). The t-tests of the means are reported in the third column of each treatment. *CalcRound*, number of rounds in which subjects used the calculator; *Hyp*, number of hypothetical own investments; *Conj*, number of conjectures about others; *Hyp per Conj,* number of own hypothetical investments entered, given a conjecture about other players' investments. We include the practice rounds.

F Distribution of the minimum loss index

In this Appendix we examine the distribution of estimated γ and κ for f *Homo behavioralis* (Type 2) subjects subjects. To do this, we use the *Min Loss* criterion defined in Section 5.1. Figure F.1 displays the cumulative distribution of the individual *Min Loss* values for rounds 11 to 20 in the LC, LVCM, and HC treatments. We consistently find that for more than 80% of *Homo behavioralis* subjects the non-pecuniary motive is at most 2 tokens, which is fairly low given the monetary stakes in the game as this only accounts for between 2% and 3% of the maximum monetary payoffs given other players' average investment.



(a) LVCM and LC (b) HC

Figure F.1. Cumulative distribution of the individual minimum loss. Each line of the left panel displays the cumulative distribution of the per-round *Min Loss* of *Homo behavioralis* (Type 2) subjects for the LC and LVCM treatments, whereas each line of the right panel displays cumulative distribution of the per-round *Min Loss* of Type 2 subjects for the HC treatments. We consider the minimum loss per subjects for rounds 11 to 20.

G The Costs of Deviating from Pecuniary Best-Response

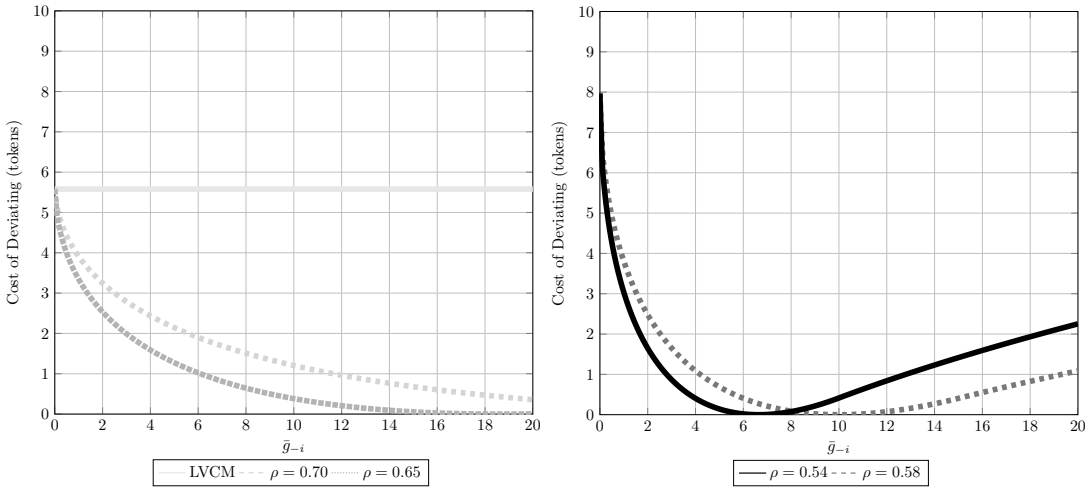
Given our joint investment technology, the cost of a constant deviation from the money-maximizing strategy changes with ρ. As ρ decreases, the monetary payoff function becomes flatter and any marginal change in strategy has a smaller effect on the final reward. This implies that rationalizing similar deviations from profit-maximizing behavior requires a higher joy of giving value (γ) as ρ increases. This observation helps explain the investments of *Homo behavioralis* (Type 2) subjects when $\rho = 0.65$ as opposed to when $\rho = 0.70$.

To illustrate this point we assume that subject i chooses an investment that equals the average investment of *Homo behavioralis* subjects when $\rho = 0.65$.[38] Then we calculate the difference between the money earnings that subject i would make following this strategy and that obtained when best responding (monetarily) to group members' investments.[39] This difference measures the monetary cost of deviating from the profit-maximizing strategy, which is plotted in the left panel of Figure G.1. The x-axis displays the investments of others ($\bar{g}_{-i}$), and the y-axis reports the cost for each treatment. When $\bar{g}_{-i} = 0$, the cost is the same irrespective of complementarity; as the investment by other players grows, over-contributing becomes generally less costly. Comparing between treatments in panel (a), as complementarity increases, the cost of over-investing is reduced. This implies that in treatments with higher complementarity it is less expensive to behave altruistically, which accounts for the different behavior of players in the $\rho = 0.65$ and $\rho = 0.70$ treatments. For the LVCM the cost is constant and it is higher than in LC treatments. In

[38] Type 2 subjects invest an average of 9.2 tokens when $\rho = 0.65$ (last 10 rounds).
[39] To facilitate the analysis we assume that other members' investments are equal.

other words, an identical value of the joy-of-giving motive is translated into a higher over-investment as complementarity increases (from LVCM to $\rho = 0.7$ to $\rho = 0.65$).

The right panel of Figure G.1 displays the cost of deviating in HC treatments. Here we assume that player i makes an investment that equals the average investment of Type 2 subjects in HC treatments, which is 13.3 tokens. In HC the cost function does not monotonically decrease in other players' investments, and losses start mounting if one does not best respond to high investments by others. In these cases, if ρ decreases (that is, complementarity increases), the competitive motive κ must become stronger to justify similar deviations below pecuniary BR.



(a) LVCM and LC (b) HC

Figure G.1. Cost of deviating from the money-profit-maximizing strategy. Each line of the left panel displays the cost of deviating from the profit-maximizing strategy (in tokens) for the LC and LVCM treatments when subject i invests 9.3 tokens (the observed average investment of Type 2 when $\rho = 0.65$). Each line of the right panel displays the cost of deviating from the profit-maximizing strategy (in tokens) for the HC treatments when subject i invests 13.3 tokens (the observed average investment of Type 2 in HC). The cost is equal to: $\pi(\rho, g_i^*, \bar{g}_{-i}) - \pi(\rho, g_i, \bar{g}_{-i})$.

H Computer Interface

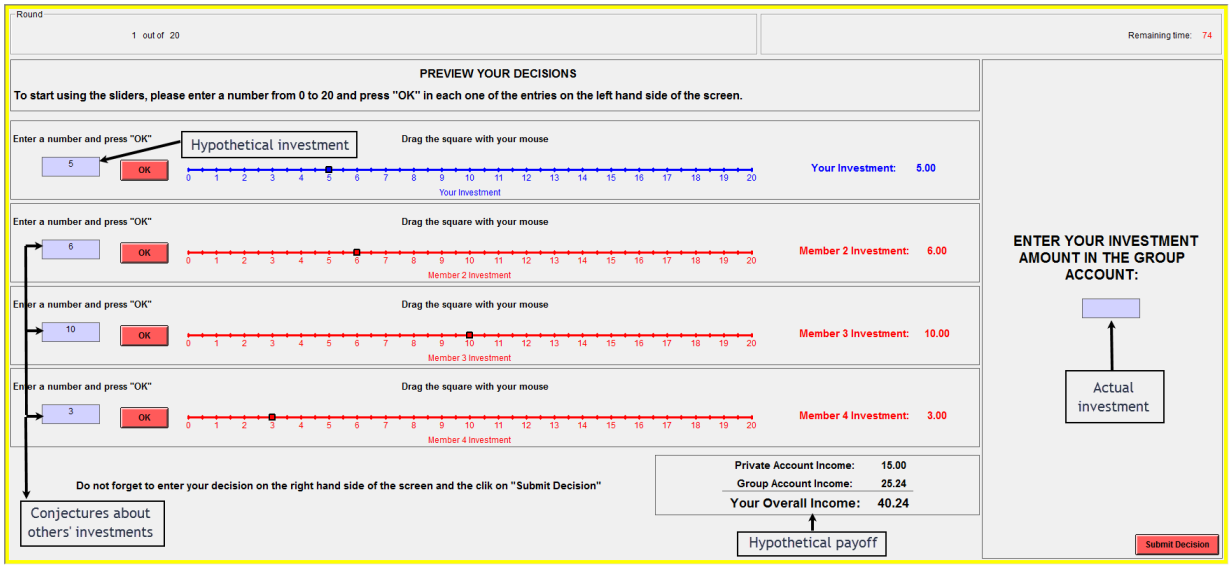


Figure H.1. Main computer interface

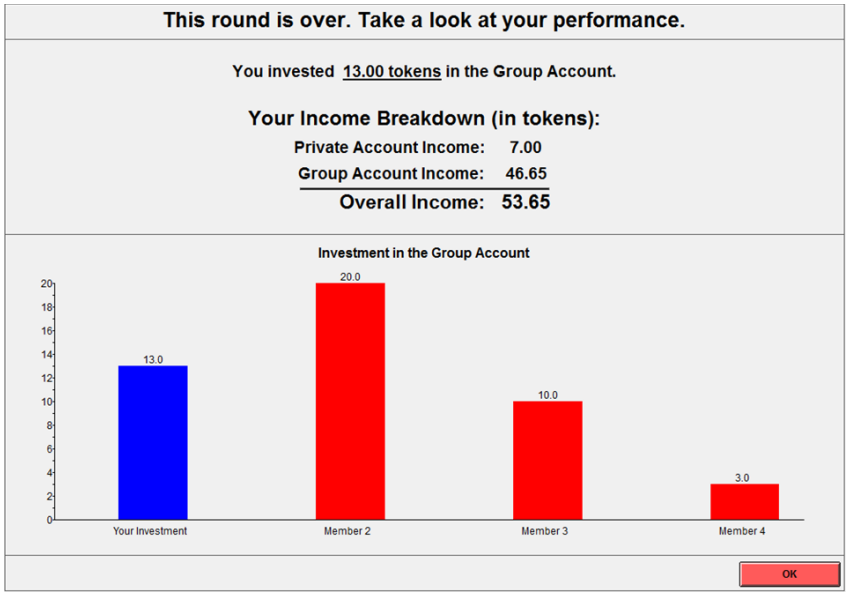


Figure H.2. Feedback

I Control Questions

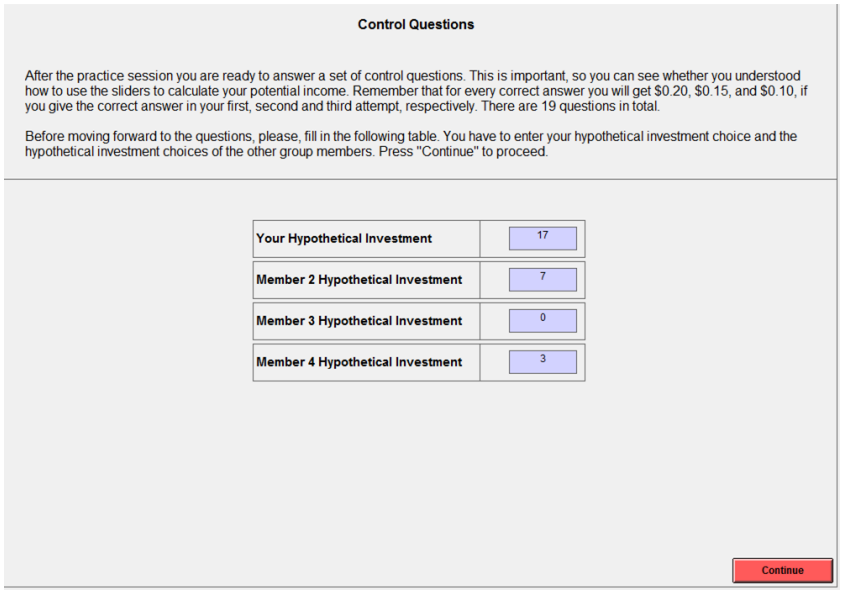


Figure I.1. Control question 1/7

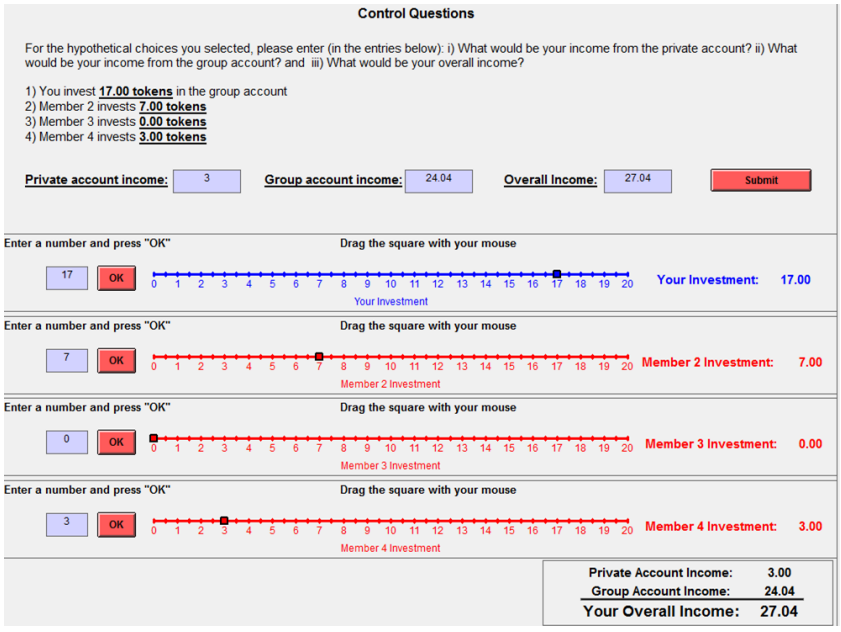


Figure I.2. Control question 2/7

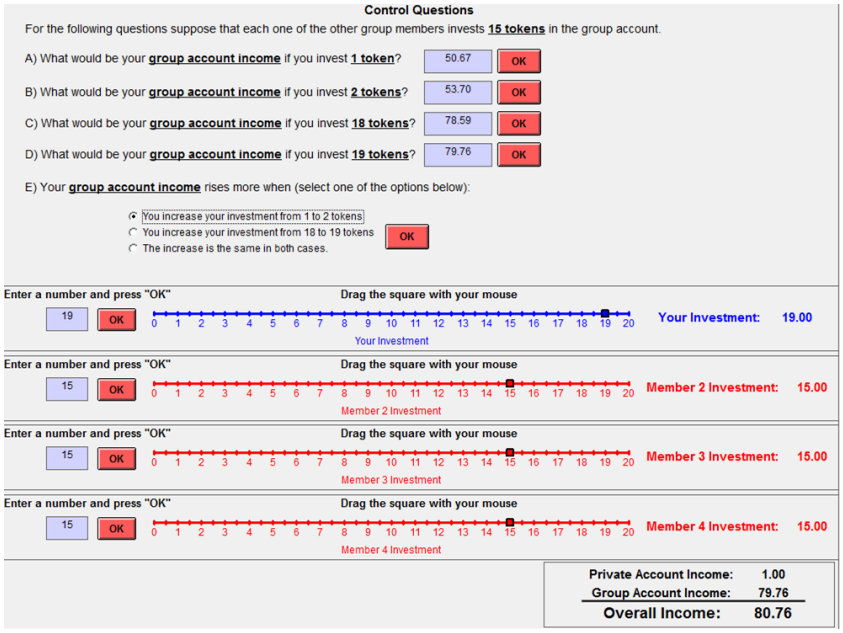


Figure I.3. Control question 3/7

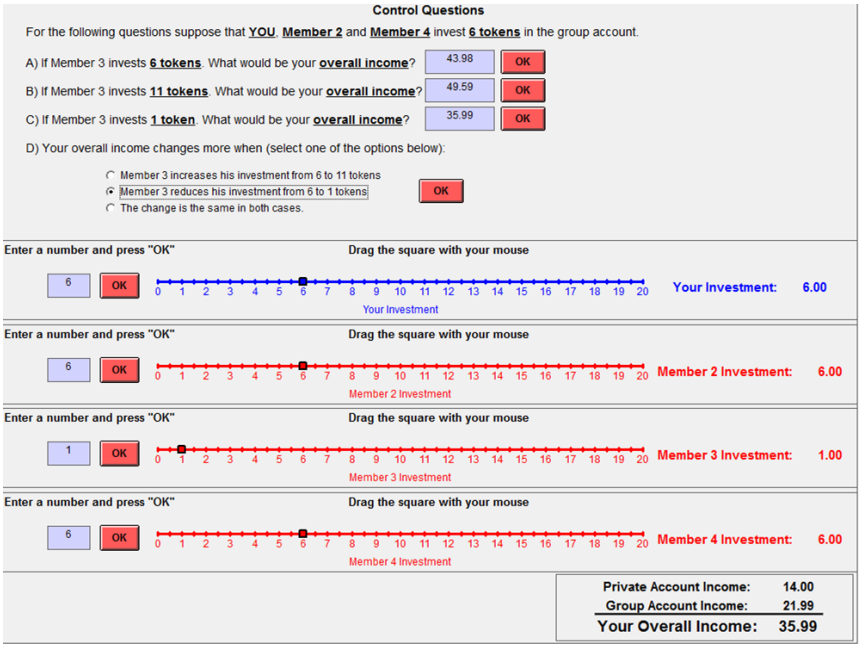


Figure I.4. Control question 4/7

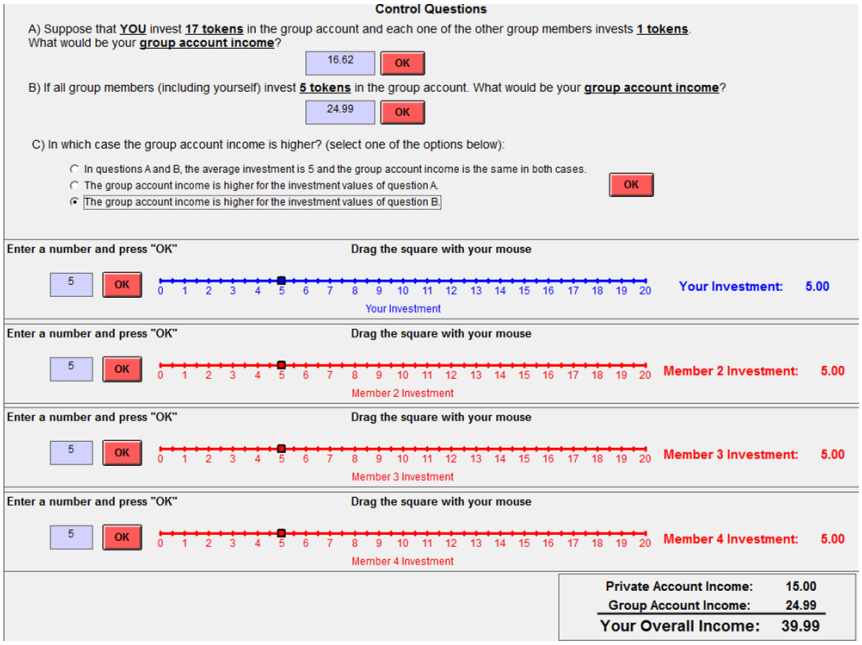


Figure I.5. Control question 5/7

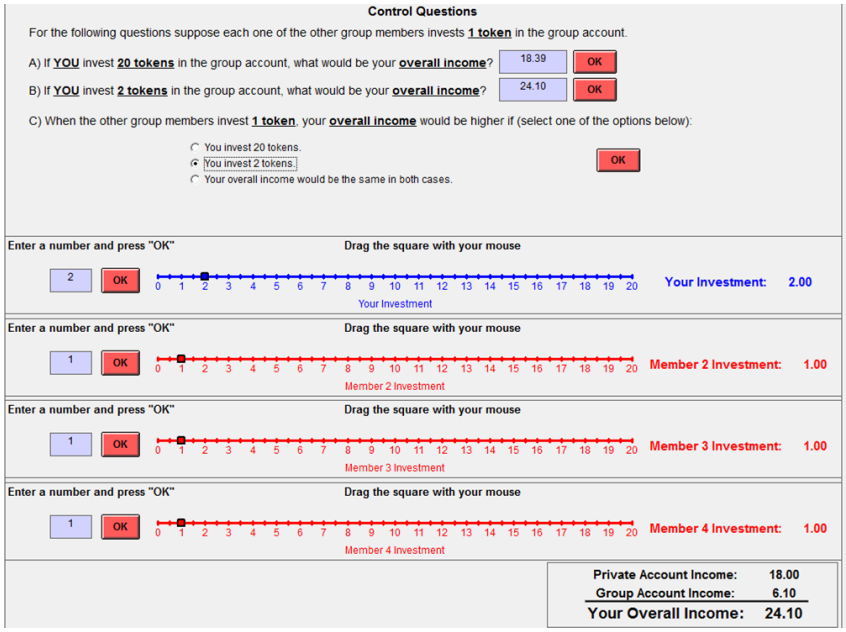


Figure I.6. Control question 6/7

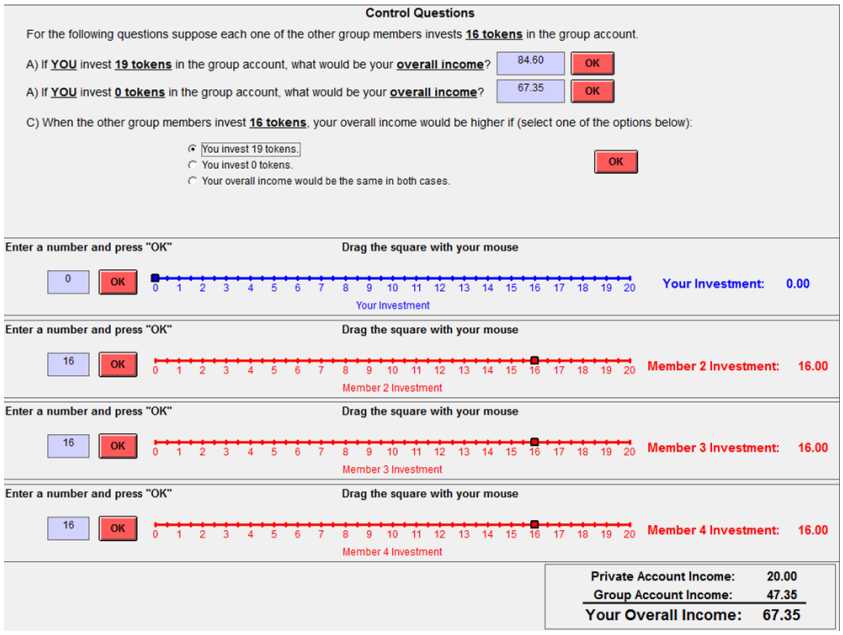


Figure I.7. Control question 7/7

J Instructions

The instructions distributed to subjects in all the treatments are reproduced on the following pages. All subjects received the same set of instructions except that those in the LVCM treatment received the following explanation about how the income from the group account was calculated:

> The total group income depends on the investments of all group members, and it is shared equally among all group members. This means that each group member receives one quarter (1/4) of the total group income. Some important points to keep in mind:
> a. The more you and others invest in the group account, the higher the total group income.
> b. The group income is obtained by multiplying the sum of the investments of all group members by 1.6 (remember that the resulting group income is shared equally among group members).

Also, the exchange rate was adjusted so that the average expected payoff was the same across all treatments.

Vancouver School of Economics
#997 - 1873 East Mall
Vancouver, B.C. Canada V6T 1Z1
Tel: (604) 822-2876 Fax: (604) 822-5915
Website: http://www.econ.ubc.ca

January, 2015

Instructions

You are taking part in an economic experiment in which you will be able to earn money. Your earnings depend on your decisions and on the decisions of the other participants with whom you will interact. It is therefore important to read these instructions with attention. You are not allowed to communicate with the other participants during the experiment.

All the transactions during the experiment and your entire earnings will be calculated in terms of tokens. At the end of the experiment, the total amount of tokens you have earned during this session will be converted to CAD and paid to you in cash according to the following rules:

1. The game will be played for 20 rounds. At the end of the experiment, the computer will randomly select one of your decision rounds for payment. That is, there is an equal chance that any decision you make during the experiment will be the decision that counts for payment.

2. The amount of tokens you get in the randomly selected round will be converted into CAD at the rate: 2 tokens = $1.

3. You will get $0.20 for every control question you answer correctly in the first attempt; $0.15 for every question you answer correctly in the second attempt; and $0.10 for every question you answer correctly in the third attempt.

4. In addition, you will get a show-up fee of $5.

Introduction

This experiment is divided into different rounds. There will be 20 rounds in total. In each round you will obtain some income in tokens. The more tokens you get, the more money you will be paid at the end of the experiment.

During all 20 rounds the participants are divided into groups of four. Therefore, you will be in a group with 3 other participants. **The composition of the groups will change every round.** You will meet each of the participants only four times, in randomly chosen rounds. However, each time you are matched with a participant that you encountered before, the other group members will be different. This means that the group composition will never be identical in any two rounds. Moreover, **you will never be informed of the identity of the other group members.**

Description of the rounds

At the beginning of the rounds each participant in your group receives 20 tokens. We will refer to these tokens as the initial endowment. Your only decision will be on how to use your initial endowment. You will have to choose how many tokens you want to invest in a group account and how many of them

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#997 - 1873 East Mall
Vancouver, B.C. Canada V6T 1Z1
Tel: (604) 822-2876 Fax: (604) 822-5915
Website: http://www.econ.ubc.ca

you'll want keep for yourself in a private account. You can invest any amount of your initial endowment in the group account.

The decision on how many tokens to invest is up to you. Each other group member will also make such a decision. All decisions are made simultaneously. That is, nobody will be informed about the decision of the other group members before everyone made his or her decision.

End of the rounds

At the end of each round (after all choices are submitted), you will see: (i) your investment choice, (ii) the investment choices of the other members in your group, and (iii) your income. Then, next round starts automatically and you will receive a new endowment of 20 tokens.

Income calculation

Each round, your total earnings will be calculated by adding up the income from your private account and the income from the group account:

1. Income from your private account. You will earn 1 token for every token you keep in you private account. If for example, you keep 10 tokens in your private account your income will be 10 tokens.

2. Income from the group account. The total group income depends on the investments of all group members, and it is shared **equally** among all of them. That is, each group member receives one quarter (1/4) of the total group income.

Some important points to keep in mind:

a. The more you and others invest, the higher the **total** group income.
b. Taking as given the investments of all other group members, consider two levels for your investment in the group account (say, low investment and high investment). Next, increase both the low investment and the high investment by 1 token. The total group income will increase in both cases. However, the increase is smaller in the case of the higher investment level.
c. When you increase your investment in the group account, the total income will not increase at a constant rate. The rate depends on the value of all participants' investments in the group account.
d. For the same average investment in the group account, the total group income would be higher if there is not much difference between the investments chosen by each one of the group members.
e. If all other members in your group invest zero, the total group income will be determined by multiplying your investment in the group account by **1.6**; the resulting amount is the group income and it will be shared equally among all group members.

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#997 - 1873 East Mall
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Using the calculator to compute your income

To calculate your potential income you will have access to a calculator (look at the picture below).

To activate the calculator, you will be asked to fill in a hypothetical value for your own investment and for the other group members' investment; then, you will be able to visualize your income for such hypothetical investment choices. You can consider as many hypothetical investment combinations as you want.

Before the experiment starts you'll understand how to use the calculator; you will be able to practice with it; and finally, you will have to answer some control questions. For every correct answer you will get $0.20, $0.15, $0.10 if you give the correct answer in the first, second and third attempt, respectively.

Remember that your actual investment decision has to be entered on the right hand side of the screen. Every round you will have 95 seconds to do that.

Screen-shot of the experiment interface