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November 15, 2015

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JEL classifications: C92, C72, D83, H41.

Keywords: Public goods, Voluntary Contribution Mechanism, Complementarity, Coordination, Altruism, Competitiveness, Warm-Glow, Joy of Winning, Laboratory Experiment.

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1 Introduction

The standard economic models of private provision of public goods by selfish agents often predict an inefficient level of contributions. These theoretical predictions appear to be inconsistent with empirical behavior.[1]

In an attempt to understand this discrepancy, economists use lab and field experiments to investigate the factors shaping the voluntary provision of public goods. The Linear Voluntary Contribution Mechanism (LVCM) has been the most common experimental design employed. It assumes a production technology of the public good which is linear and additively separable in agents' contributions. Under this key assumption the dominant strategy for agents with self-regarding preferences is to contribute nothing at all (i.e., to free-ride) rather than make a positive contribution which results in a private cost and a social benefit.[2] 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.[3]
Identifying why subjects may want to coordinate in voluntary contribution contexts is essential to understanding empirical observations. In this study we generalize the linear mechanism used in most public good experiments by letting agents' contributions be complements in production. This provision technology captures two essential features. First, an increase in one's contribution raises the marginal return on others' contributions, and second - the provision is more efficient when agents' contributions are relatively homogeneous.

Complementarity is fundamental when the provision is performed through effort. Through evolution, *Homo sapiens* has learned to coordinate efforts in order to hunt

[1] In the US, for example, donations accounted for over 2% of GDP in 2014 (Giving USA, 2015).

[2] Assuming that the marginal per capita return (MPCR) is lower than one.

[3] 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 (Forthcoming). Typically, changes in the environment have been shown to increase cooperation, e.g. allowing communications between participants, increasing the group size, setting a higher marginal per capita return on total contributions, and introducing the ability to administer punishment.

and guard. A family (household) may be viewed as an environment in which public goods are provided through effort, and in which complementarity is instrumental. Similarly, many modern charities that provide for public goods rely on efforts by stakeholders (mainly board members) in order to raise funds and produce their public good of choice. Crucially, in several joint endeavors such as school funding activities, neighborhood improvement initiatives and even some scientific research projects, the return to a participant's effort depends on the level of effort that all other participants choose to exert.

For low levels of complementarity, the unique Nash equilibrium remains the zero-contribution equilibrium (though in the non-linear case it is not in dominant strategies). When complementarity is sufficiently high a new (second) full-contribution equilibrium emerges, transforming the selection of equilibrium into a coordination problem.

Our experimental design varies the degree of complementarity, encompassing the special linear case. For the linear (no-complementarity) benchmark, we replicate the usual result of positive but diminishing contributions. When we introduce complementarity, subjects visibly respond to it. With strong complementarity subjects are able to coordinate on the full contribution equilibrium. When complementarity is sizable but insufficient to support a new equilibrium, subjects persistently contribute above the unique zero contribution selfish-equilibrium and we observe little or no convergence towards this equilibrium.

To understand what motivates subjects to make these choices, we investigate the decision-making processes underlying their choices. This analysis relies on a wealth of unique non-choice data, including accurate information about calculations made by each subject before submitting a choice and how long it took to submit a choice. We document a variety of facts about the way subjects form conjectures about other players' contributions, whether subjects are able to identify profit-maximizing responses to their conjectures, and how these calculations relate to their choices.

The examination of choice and non-choice data allows us to reduce the rich heterogeneity in observed contributions to two *modus operandi*, which we associate to two different types of agents denoted respectively as *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 find no 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 contribute 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 contribution below the pecuniary best-response some subjects are able to make relatively higher profits than other participants.[4] We quantify the magnitude of these behavioral motives and show that they are relatively modest but lead to significant and systematic deviations from the pecuniary best-response.

These two types of agents co-exist and are able to best respond to each other in equilibrium. Over time their interaction shapes aggregate dynamics and provides a way to interpret the patterns observed under different degrees of complementarity.

The paper is organized as follows. Section 2 overviews the theoretical model and equilibrium predictions. The experimental design and laboratory procedures are described in Section 3. In Section 4 we report results from aggregate data and show that contribution behavior converges towards equilibrium values, with one conspicuous exception which we examine in detail. Section 5 explores individual-level behavior. The combined use of choice and non-choice data is instrumental in explaining deviations from the profit-maximizing strategies. We then classify subjects into two types, *Homo pecuniarius* and *Homo behvaioralis*, and we estimate the magnitude of altruistic and competitive motives. Section 6 provides a summary of related research, and Section 7 concludes.

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

2 The Voluntary Contribution Mechanism with Complementarity

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 public good which maps private contributions into an output that is equally shared among all group members. Let g_i denote individual i's contribution to the public good. The remainder of the endowment that is not allocated to the public good ($\omega - g_i$), is consumed privately by player i. Individual investments in the public good 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 public goods:

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

where $\rho \leq 1$ denotes the degree of complementarity and $\beta > 0$ is a constant. The voluntary contribution mechanism with complementarity (VCMC) encompasses, as a special case when $\rho = 1$, the standard LVCM. The individual return from an investment in the public good depends on the contributions of all n players and on the degree of complementarity between their investments.[5]

2.1 Best-response function

In the well studied special case of LVCM ($\rho = 1$), the unique dominant strategy is to contribute zero whenever β is below one, or allocate the entire endowment to the public good when β is greater than one. In the general VCMC environment, the best response (BR) of agent i, denoted as $g_i^*(g_{-i})$, is a linear function of the generalized ρ-mean of his or her conjecture about the contributions of other group members, denoted by the vector $g_{-i} \in \Re_+^{n-1}$. Denote by $M_\rho(g_{-i})$ the generalized ρ-mean of g_{-i}:

[5]The marginal per capita return on contributions to the public good (MPCR) 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 $\frac{1}{n} < \beta < 1$.

$M_\rho(g_{-i}) \equiv \left(\frac{\sum_{i=1}^{n-1} g_{-i}^\rho}{n-1}\right)^{1/\rho}$.[6] To see this, consider the first order condition with respect to g_i:[7]

$$\frac{\partial \pi_i}{\partial g_i} = \beta\left((g_i^*)^\rho + \sum g_{-i}^\rho\right)^{\frac{1-\rho}{\rho}}\left((g_i^*)^{\rho-1}\right) - 1 = 0. \tag{2.2}$$

Rearranging terms, we obtain $g_i^*(g_{-i})$;

$$g_i^*(g_{-i}) = \begin{cases} kM_\rho(g_{-i}) & \text{if } \; kM_\rho(g_{-i}) \leq \omega \\ \omega & \text{otherwise,} \end{cases} \tag{2.3}$$

where $k \equiv \left(\frac{n-1}{\beta^{\frac{\rho}{\rho-1}}-1}\right)^{\frac{1}{\rho}}$ is a constant that depends on the model's parameters. If $k > 0$, the contributions are complementary; moreover, as the degree of complementarity diminishes (ρ increases), k decreases as well. In the limit, when ρ approaches one, k goes to zero and the BR of player i is to invest zero in the public good regardless of other players' actions. As agent i's BR depends on the generalized mean of g_{-i}, it depends also on the dispersion of other players' contributions: for a given arithmetic mean, player i's optimal contribution decreases as the dispersion of other players' contributions 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). The generalized $\rho-$mean of other group members' contributions is measured on the horizontal axis, and player i's contribution is shown on the vertical-axis. The solid lines represent the BR of player i.

Imposing the symmetry condition $g_i + G_{-i} = ng_i$ in Equation (2.2)[8] and solving for g_i, we characterize the symmetric equilibria:

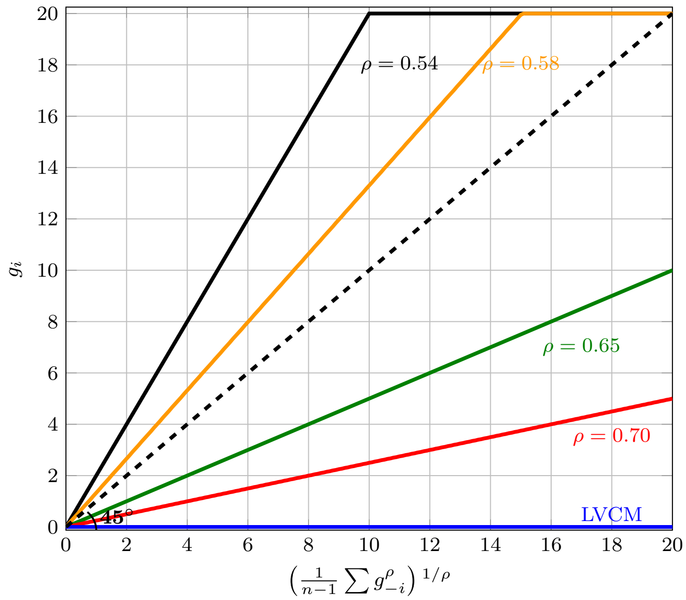
$$g_i^{eq} = \begin{cases} 0 & \text{if } \; k < 1 \\ \{0, \omega\} & \text{if } \; k > 1. \end{cases} \tag{2.4}$$

[6] The arithmetic mean is a special case of the generalized mean (when $\rho = 1$). The arithmetic and the generalized means are identical when all contributions are equal, that is when $g_{-i} = g\mathbf{1}_{n-1}$.

[7] Details on the derivation of the best response can be found in Appendix A.

[8] Where $G_{-i} = \sum_{j \neq i} g_j$.

Figure 2.1: Best-Response Functions



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

Thus, for given β and n and with sufficiently high complementarity, there exist two equilibria.[9] When $k = 1$, any symmetric strategy profile is a Nash equilibrium.[10]

3 Experimental Design

The baseline parameters are chosen so that the linear treatment ($\rho = 1$) is easily comparable to similarly parameterized LVCM experiments.[11] Specifically, we assign the following values: (i) number of players in a group, $n = 4$; (ii) initial token

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

[10]It is immediate to verify that only symmetric equilibria 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 $k \leq 1$ it follows that $kM_\rho\left(g^*_{-max}\right) < g^*_{max}$ which is a contradiction. Similarly, if $k \geq 1$ it follows that $kM_\rho\left(g^*_{-min}\right) > g^*_{min}$ which is a contradiction.

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

endowment, $\omega = 20$; and (iii) $\beta = 0.4$. The latter is a commonly assumed value of the MPCR in the linear case. In the non-linear case, however, the MPCR also depends on the curvature parameter ρ and on contributions of other players.

Our treatments consist of variations in the degree of complementarity, ρ. Table 3.1 presents an overview of each treatment design, highlighting key aspects for each value of ρ. The equilibrium contribution is displayed in the third column. For sufficiently large values of ρ there exists a unique equilibrium of zero contribution. There also exists a threshold value of ρ below which the equilibrium contribution is either zero or the whole endowment ω (given the baseline parameters, this happens when $\rho < 0.602$). Finally, the fourth column reports the exchange rate used in each treatment, adjusted so that expected payoffs were similar across treatments.

Table 3.1: Experimental Treatments

Degree of Complementarity	Number of Sessions	Equilibrium Contribution	Exchange Rate (tokens per CAD)
$\rho = 1$	2	{0}	1
$\rho = 0.70$	1	{0}	2
$\rho = 0.65$	2	{0}	2
$\rho = 0.58$	1	{0,20}	2.5
$\rho = 0.54$	2	{0,20}	3

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 were seated at individual computer stations and given a set of written instructions; at the same time the instructions were displayed on their computer screens.[12] After read-

[12]The instructions can be found in Appendix I.

ing the instructions subjects were required to answer a set of control questions. The goal of the control questions was to verify and measure subjects' basic understanding of how to use the tools in their computer interfaces and how to interpret information displayed on the screens. Subjects received cash for answering control questions correctly.[13] The experiment did not proceed any further until all participants had answered all control 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 game was repeated 20 times.

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 only in four rounds and each time someone was matched with a participant he or she had encountered before, all other group members were different. This means that any given grouping of four players never occurred more than once.

All eight sessions were computerized, using the software z-Tree (Fischbacher, 2007). Given the difficulty of computing potential earnings using the non-linear 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 member's contributions as they wanted, visualizing the potential payoff associated with each combination.[14] In each round subjects had 95 seconds to submit their chosen contribution. At the end of each round they were informed about their own earnings and the contribution choices of other group members.[15] At the end of the experiment, subjects were paid

[13] The questions' goal was to facilitate subjects' learning of the main features of the VCMC. Relevant features included are: (i) decreasing marginal productivity in the group account given a fixed level of others' contributions, (ii) efficiency gains due to coordination, and (iii) absence of a dominant strategy (for treatments in which $\rho < 1$). Subjects were credited \$0.20, \$0.15 or \$0.10 for each question answered correctly in, respectively, the first, second, and third attempt. There were 19 control questions, which can be found in Appendix E.

[14] Figure D.1 of Appendix D displays a screenshot of the main interface.

[15] Figure D.2 of Appendix D 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. Given that group income is the same for each

the payoff they obtained in a single randomly selected round.

The sessions were conducted at the Experimental Lab of the Vancouver School of Economics, at the University of British Columbia (ELVSE), in January 2015. The experiments lasted 90 minutes. Subjects were paid in Canadian dollars (CAD). On average, participants earned \$30.60. This amount includes \$5 show-up fee and the additional cash received for the control questions.

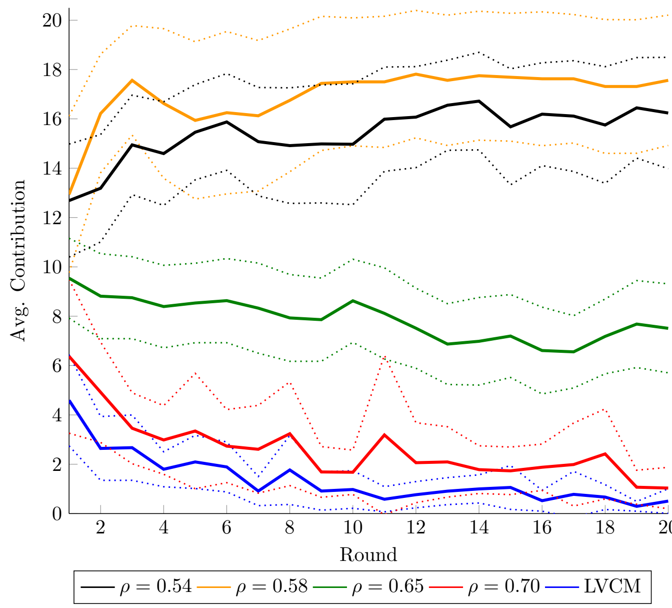
In what follows we begin by examining how changing the degree of complementarity in different treatments is reflected in both the level and the evolution of individual contributions. Next, using a combination of choice and non-choice data, we document various interesting aspects of the choice process: we examine the scope of history dependence in subjects' decision-making, and document how past contributions by past group players shape the subject's current choice. This history-dependence allows us to define a notion of BR to past contributions and assess to what extent subjects' choices can be framed as rational (profit-maximizing) behavior, both in the cross section and over time. Non-choice data also reveal differences in calculator usage and response time, showing how subjects process information and make choices in different ways.

4 Results

Manipulating the degree of complementarity induces stark changes in subjects' behavior. This is reflected in the average contribution chosen by subjects, as well as in the heterogeneity among contributions. In this section we study how changes in complementarity affect the level and evolution of individual contributions.

group member, subjects could easily infer the earnings of each one of the other group members by looking at their contributions, reported in the same screen.

Figure 4.1: Average Contribution over Time



Notes: This figure shows the evolution of the average contribution in each treatment (solid lines). The dotted lines identify confidence intervals at the 95% confidence level.

4.1 Average contributions

Each solid line in Figure 4.1 represents the evolution of the average contribution over the 20 rounds of an individual treatment (dotted lines identify 95% confidence intervals). Figure 4.1 clearly shows that average contributions increase with complementarity.[16] With the exception of $\rho = 0.65$, average contributions converge towards the socially inefficient equilibrium when the degree of complementarity supports only one zero-contribution equilibrium. In contrast, they converge towards the socially efficient equilibrium when complementarity introduces an additional full-contribution equilibrium.

[16] Average contributions when $\rho = 0.58$ look marginally higher than average contributions when $\rho = 0.54$. However, this difference is not statistically significant.

4.1.1 Initial contributions

The average contribution in the first round is significantly higher than zero in all treatments. This is not surprising given existing evidence about LVCM experiments. Some variation exists in first-round contributions across treatments: subjects in high-complementarity (HC) treatments, with ρ equal to 0.54 or 0.58, contribute 4.3 tokens more, on average, than subjects in low-complementarity (LC) ones, with ρ equal to 0.65 or 0.70. The difference in contributions across treatments is substantial, even in the first round when subjects have yet to receive any feedback. This may be attributed to the training subjects receive before deciding on contributions: subjects' understanding of the rules of the game is reflected in their initial beliefs about others' contributions, and these beliefs are likely to be treatment specific. To verify the role of the training we can compare the initial conjectures on others' contributions across different treatments. Table 4.1 shows the average of the generalized mean of the conjectures in each treatment.[17] Column 2 reports conjectures made during the practice period, before the experiment started: unsurprisingly no significant difference across treatments is apparent at this stage, as subjects are still learning about the payoff space and may experiment with any conjectures that come to mind. 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 contributions will become lower as the degree of complementarity diminishes (ρ increases).

4.1.2 Treatment-specific dynamics

In the LVCM environment we observe a pattern consistent with many previous experiments. Initially the average contribution is significantly larger than zero; as the rounds progress, there is a progressive decline in contributions.

In the linear case the dominant strategy is to contribute zero.[18] The treatment

[17]We did not elicit beliefs. Rather, we collected data on the inputs subjects entered in the payoff calculator. This includes conjectures about other group members' contributions, which are a proxy of beliefs about others' contributions. In Section 5 we describe these data extensively.

[18]The linear treatment is also useful to benchmark our experimental design. While differences exist in the instructions and experimental interface, the aggregate results appear remarkably similar

Table 4.1: Average Conjecture about Others' Contributions[1]

Treatment	Practice	Round 1	Round 2	Round 5	Round≥10
LVCM	10.3	6.6	5.2	3.7	3
	(5.6)	(6.3)	(5)	(4.6)	(4.6)
$\rho = 0.70$	10.1	7.6	5.3	2.8	4.6
	(5.2)	(5)	(4.5)	(3)	(6.3)
$\rho = 0.65$	10.7	10	10.1	6.9	6.8
	(5.3)	(5.1)	(4.4)	(5.6)	(5)
$\rho = 0.58$	11.1	11.7	12.1	17.7	15.4
	(5.6)	(5.3)	(4.5)	(2.8)	(5.5)
$\rho = 0.54$	10.3	10.3	12.3	14.5	13.8
	(5.7)	(5.8)	(6.1)	(4.3)	(6.1)
No. of conjectures	2,339	264	150	140	537

[1]Each cell reports the average value for the generalized mean of the conjectures of others' contributions (standard deviations are reported in parentheses).

with $\rho = 0.70$ introduces very slight complementarity in contributions. Yet, the pattern remains quite similar to that of the LVCM treatment despite the fact that a zero contribution is no longer the dominant strategy.

By contrast, when complementarity is sufficiently strong to generate an additional full-contribution equilibrium ($\rho = 0.58$ and $\rho = 0.54$), the evolution of the average contribution exhibits the opposite pattern, as contributions tend to grow. In other words, intense complementarity changes the way agents interact, and they find a way to move towards the full-contribution equilibrium.

Finally, a unique pattern emerges when $\rho = 0.65$, a value which supports only a unique equilibrium of zero contribution but is closer to the threshold at which a full-contribution equilibrium arises. Experimental results show little or no evidence of variation in the average contribution as rounds elapse; it is apparent that contributions remain range-bound even as players gain experience in advanced rounds. It is important to note that at this level of complementarity, the unique equilibrium

to those from standard LVCM experiments, albeit with slightly lower contributions (probably due to the extensive control questions that minimized confusion).

of zero-contribution has a full basin of attraction. Even if an agent believes that all other group members will fully contribute, her best response is to contribute only half of her endowment. The dynamics observed in this experiment are possible only if many subjects contribute significantly above their pecuniary best response.

4.2 Distribution and dispersion of contributions

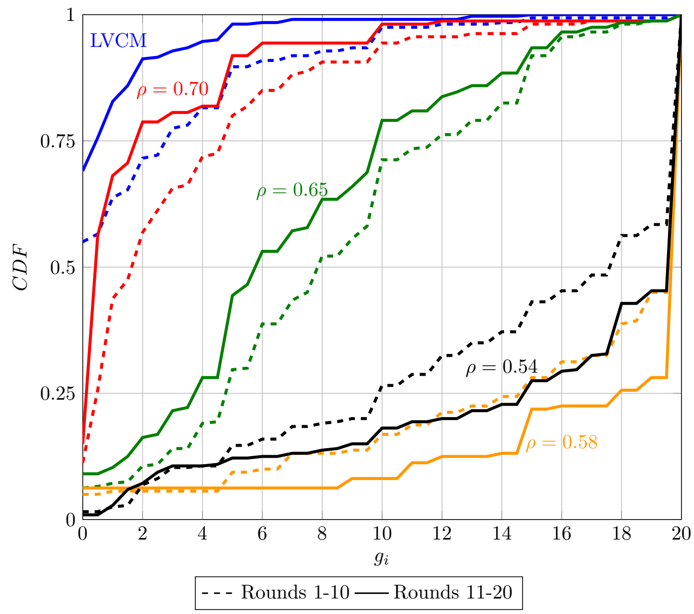
The confidence intervals reported in Figure 4.1 suggest that there is substantial heterogeneity in contributions. In this section we start by examining how the distribution of contributions varies over time and across treatments, and we conclude the analysis by investigating the patterns of contributions' dispersion. Specifically we study (i) whether subjects are able to coordinate and (ii) the effect of complementarity on coordination rates.

4.2.1 Distribution of contributions

Figure 4.2 displays the cumulative distribution of contributions by treatment (i.e., by complementarity). Individual contributions fall into one of two categories: dashed lines show the cumulative distribution for rounds 1 to 10, and solid lines show the cumulative distribution for rounds 11 to 20. The plots confirm the finding of the previous subsection: the distributions in the LVCM and $\rho = 0.70$ treatment look similar; the same is true for HC treatments, with not much difference between the distributions under $\rho = 0.58$ and $\rho = 0.54$. Contributions concentrate at the extremes as sessions progress towards the end.

By contrast, when ρ is set to 0.65, the mass distribution is more heavily concentrated in the interior of the strategy space. Subjects choose to contribute non-trivial amounts even after 10 rounds: for example, in rounds 11 to 20, more than half of all contributions are larger than 5 tokens. Contributions are range-bound, and show little tendency towards convergence. In Section 5 we examine these patterns in detail.

Figure 4.2: Cumulative Distribution Function



Notes: The dashed lines display the cumulative distribution function for the individual contributions from rounds 1 to 10. The solid lines show the cumulative distribution function for the individual contributions from rounds 11 to 20.

4.2.2 Coordination and complementarity

A key feature of the VCMC production technology is that individuals not only benefit from others' contributions 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.

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 ($DLI_k(t)$) 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 contributions 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, $DLI_k(t) = 1$.[19] This index may be sensitive to outliers because there are only four groups in each session. To account for this sensitivity, in each round/session we take the 16 actual contributions and average over all possible combinations of contributions 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.[20]

Figure 4.3 reports median DLI by treatment, averaged over five-round intervals,[21] and its 95% confidence interval.[22] 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 supports the evidence from Figure 4.2. Subjects in HC treatments manage to better coordinate their actions.

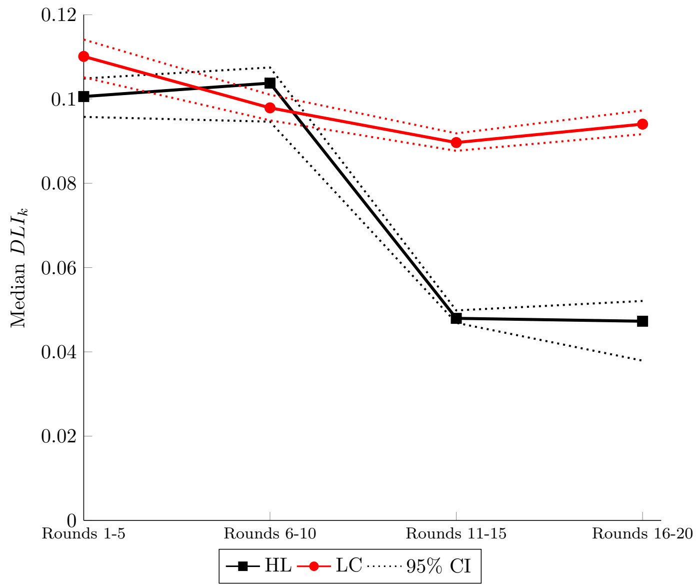
[19]This is achieved at the vector of contributions $(0, 0, 20, 20)$ in which the discrepancy between the arithmetic and the generalized mean is maximized.

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

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

[22]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 ech round/session. We obtain very similar results.

Figure 4.3: Dispersion Loss Index



Notes: This figure reports the median dispersion loss index (DLI), for high complementarity (HC) and low complementarity (LC) treatments, averaged over 5-round intervals. The dotted lines display the 95% confidence interval.

5 How Do Players Choose Their Contribution?

So far the analysis has highlighted three main findings: (i) when complementarity is sufficiently strong, subjects coordinate on the socially efficient equilibrium; (ii) similarly, when complementarity is sufficiently weak, contributions converge to the unique zero-equilibrium; (iii) in the middling case of $\rho = 0.65$, there appears to be no visible convergence to equilibrium over 20 rounds, as some subjects persistently deviate from their money-maximizing strategies.

In addition, we find recurrent over-contribution in LC treatments, and under-contribution in HC treatments. While observed choices provide some support for the complementarity hypothesis, this is not sufficient evidence to ascribe individual actions to profit-seeking motives. This is especially true in the case of $\rho = 0.65$.

It is very hard to interpret individual choices through the examination of choice data alone; therefore we complement the analysis by resorting to non-choice data.

Throughout each session participants were given access to a payoff calculator. By using the calculator subjects could see the monetary payoff associated with as many hypothetical contributions as they wished, including different hypothetical values of their own choice. We recorded every trial that subjects entered in the calculator during both the practice period and the experiment.

This non-choice data is different from information collected using "mouse lab" techniques. In the latter, participants may be aware that experimenters are gathering data and this may influence their choices. Moreover, finding the optimal strategy in the VCMC makes the use of the calculator often necessary, as payoff functions are non-linear and individual gains are affected by the dispersion of players' contributions. For these reasons subjects depend on the calculator to evaluate different strategies and to make informed choices, and the input they enter into the calculator can be considered in many instances a good proxy of their beliefs about the contribution of others.[23]

Combining choice and non-choice data makes it possible to ask questions like these: Are conjectures influenced by the history of other players' contributions? How do subjects adjust their behavior from one round to the next? Do they use history-dependent best-response strategies? If so, how is this reflected in the use of the calculator? Do subjects in specific treatments use the calculator more or less intensively? How do they experiment with hypothetical contributions? Are they able to find the profit-maximizing strategy given their conjectures? How does this relate to their actual contribution? And can we classify subjects according to the way they use the calculator?

5.1 Classifying subjects into types

Large differences exist in subjects' behavior within each treatment: some contribute consistently more than others; many change their choices repeatedly, while others

[23] Cherry et al. (2015) also provide subjects a payoff calculator and analyze non-choice data. A key difference with respect to our design is that, in their case, subjects have to enter a conjecture first, and then the experimenters display a table with the payoffs associated with each hypothetical choice given that conjecture.

Table 5.1: Dependent variable: current conjecture. Explanatory variable: contributions by other group members in previous rounds[1]

	Generalized Mean	Arithmetic Mean
$F(g_{-i,t-1})$	0.564^{***}	0.574^{***}
	(0.07)	(0.08)
$F(g_{-i,t-2})$	0.140^{**}	0.171^{***}
	(0.07)	(0.06)
$F(g_{-i,t-3})$	0.054	0.050
	(0.06)	(0.06)
$F(g_{-i,t-4})$	-0.011	-0.034
	(0.07)	(0.07)
$F(g_{-i,t-5})$	0.100^{*}	0.090
	(0.06)	(0.06)
Constant	1.707^{***}	1.666^{***}
	(0.46)	(0.45)
Observations	963	963

[1] We estimate the following least-squares specification: $F(\hat{g_{i,t}}) = C + \sum_{L=1}^{5} A_L F(g_{-i,t-L}) + u_{i,t}$. Where $\hat{g_i}$ is a vector of player i's conjectures about other group members' contributions, $g_{-i,t-L}$ contains the vector of contributions 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 looks very similar.

do not. Also, as we document below, the calculator is used with different intensity. This suggests that not all agents conduct themselves in the same way when it comes to choosing a contribution. 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 contribution. A larger discrepancy indicates larger foregone earnings. Then we examine whether there are differences in the calculator usage of different subject types.

Our grouping criterion considers the payoff associated with the history-dependent BR. Thus, we begin by showing evidence of history dependence of subjects' beliefs about others, buttressing the choice of history-dependent BR as our benchmark.

Next, we assess the length of subjects' memory span; to do this we regress the conjectures about others' contributions on the actual contributions by group partners in the previous five rounds. Table 5.1 reports the results, showing that subjects' conjectures respond to other members' contributions in the previous two rounds.[24]

How should one use information about contributions in the previous two rounds to define a BR? Restricting subjects to respond to the specific contributions 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 posit that subjects may respond to any possible combination that can be obtained by combining group members' contributions in rounds $t-1$ and $t-2$. Then for each subject/round, and for every combination of the partners' contributions, we compute the difference between the profit associated with the BR and the profit associated with the actual choice; we only keep the lowest such difference per subject/round and we call it *Min Loss*.[25,26] Next, we define the proportional loss as $\frac{Min\ Loss_{i,t}}{\pi_{i,t}^{BR}}$. This is a money index that measures how close actual contributions are to the money maximizing contributions (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. Then for each treatment group (LVCM, LC, HC) we obtain a median proportional loss, by selecting the median value among all the individual averages in that treatment group. Subjects are denoted as Type 1 if their individual proportional loss is not higher than the median value for their group. The remaining subjects are denoted as

[24]To confirm the results of Table 5.1, we consider all conjectures from round 2 onwards, and find that roughly 11% coincide exactly with previous round contributions by other group members. In 28% of the cases the conjecture matches exactly with one of the 10 possible combinations that can be formed from the prior round group members' contributions. Finally, in 38% of the cases the conjecture matches exactly one of the 56 possible combinations that can be formed from group members' contributions in the two previous rounds. These relative frequencies are extremely high when compared to the three most recurring individual conjectures, namely $(0,0,0)$, $(20,20,20)$ and $(10,10,10)$, which were considered in only 9%, 7%, and 3% of the cases, respectively. Agents clearly appear to make conjectures based on past experiences.

[25]$Min\ Loss_{i,t} = \min\left(\pi_{i,t}^{BR} - \pi_{i,t}^{ACT}\right)$.

[26]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 contributions, whether unusually high or low.

Type 2. It is worth stressing again that this grouping criterion requires the joint use of choice and non-choice data.

5.2 Patterns of individual contributions

Valuable information about individual decision-making can be elicited from the evolution of individual contributions. Crucially one can measure how close contributions are to the notion of history-dependent pecuniary-BR, as defined in Section 5.1. In HC treatments, despite much heterogeneity, a remarkable two thirds of all contributions are consistent with BR behavior. Moreover, subjects commit a full 20 tokens in over half of the cases in which a full contribution is within the range classified as BR. Even when a deviation exists, it is often small. Most deviations are due to under-contributions: in HC treatments subjects under-contribute in 30% of the cases, but over-contribute in only 5% of them.

In LC treatments just 42% of contributions are consistent with BR and, when deviations occur, they mostly result in over-contributions: in over half of all cases subjects over-contribute, while under-contributions occur in only 3% of cases.

In Appendix B we present plots of the complete sequence of contributions made by each subject. Contributions are juxtaposed to the rationalizable set (gray) – an area consisting of the set of BRs computed using the steps described in Section 5.1. This allows one to visualize whether a subject's contribution can be rationalized by pecuniary-profit maximizing motives, and to appreciate how contributions drift into and out of the BR range. In these same figures we superimpose a red line representing the myopic BR, that is a function of contributions by members of the group to which the subject belonged in the previous round: this provides a more direct counterpart to assess the path dependence of actual contributions. In Appendix C we include a graphical representation of the patterns of deviation for either type of subject.

5.3 Linking types to behavioral categories

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

On the other hand, under-contribution in HC treatments might be due to competitive motives; when other subjects contribute relatively high amounts, marginally reducing one's own contributions 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 contributions 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 both the mechanical use of the calculator (number of rounds the calculator is activated and the number of hypothetical contributions and conjectures about other players) and what we call payoff-relevant use of it. We exploit this information to 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.[27]

We adopt two measures of payoff relevant use: (i) the difference between hypothetical contributions and the BR to conjectures about other players' choices ($\hat{g}_i - g_i^*(\hat{g}_{-i})$), denoted as *Difference1*;[28,29] (ii) the difference between actual contributions and the

[27]To analyze mechanical use of the calculator we examine the following variables: (i) CalcRound, number of rounds the calculator was used by a subject, (ii) Hyp, number of own hypothetical contributions entered in the calculator, (iii) Conj, number of conjectures about other players' contributions that were entered in the calculator, and (iv) Hyp per Conj, number of own hypothetical contributions entered, given a conjecture about other players' contributions.

[28]We consider all conjectures and hypothetical contributions starting from the practice session.

[29]When there are multiple hypothetical contributions per conjecture for the same subject, we keep only the current or past hypothetical contributions that maximize the monetary payoff given that conjecture. We consider past hypothetical own contributions because we find evidence of persistence in conjectures. In other words, some subjects might select a given conjecture and adjust their hypothetical own contributions over several rounds (more details can be found in Appendix G). Finally, 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

BR to conjectures ($g_i - g_i^*(\hat{g}_{-i})$), called *Difference2*.

5.3.1 Mechanical use of the calculator

We begin by reporting in Table 5.2 the summary statistics of the mechanical variables for different types and treatments.[30]

Number of rounds. Table 5.2 confirms that the LVCM is arguably the easiest environment for Type 1 subjects: they end up using the calculator very little (in only 4.4 rounds).[31] 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 (roughly, in 10 versus 5 rounds). This supports the view that subjects find it easier to calculate BR strategies in HC treatments.[32] 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 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 contribution made by others to maximize his or her payoff, assuming all other players contribute 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

$j - 1.5 < M_\rho \leq j - 0.5$ 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 $M_\rho \geq 10$ ($M_\rho \geq 15$).

[30] As a robustness check for the results in Table 5.2, Appendix F contains a table displaying results for a grouping of subjects based on the assumption that subjects respond only to other group members' contributions in the previous round.

[31] Three Type 1 participants did not even activate the calculator after the practice round.

[32] Six subjects in the HC treatment did not use the calculator after the practice period.

across types. However, subjects in LC and HC treatments enter more hypothetical choices than in LVCM. A Type 1 subject enters on average slightly more hypothetical contributions 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. The difference, however, is not significant, possibly because a Type 2 subject may be able to approximate the monetary BR. The next subsection provides evidence to that effect.

Table 5.2: Differences in Mechanical Use of the Calculator, by Subject Type within Complementarity Level[1]

	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	4.4	9.5	0.0	11.1	9.5	0.3	5.0	5.4	0.8
	(1.2)	(1.9)		(1.1)	(0.9)		(0.7)	(1.2)	
Hyp	14.1	19.7	0.2	28.7	26.3	0.5	24.5	21.3	0.5
	(2.3)	(3.3)		(3.0)	(2.3)		(3.6)	(3.2)	
Conj	12.6	13.6	0.5	14.6	14.8	0.9	9.0	9.4	0.7
	(1.3)	(1.1)		(0.9)	(0.8)		(0.7)	(0.6)	
Hyp Per Conj	3.2	4.1	0.1	6.9	5.9	0.1	8.0	6.5	0.3
	(0.4)	(0.4)		(0.5)	(0.4)		(1.1)	(0.9)	
Observations	16	16		24	24		24	24	

[1]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 subjects used the calculator; *Hyp.* number of hypothetical own contributions; *Conj.* No. of conjectures about others; *Hyp per Conj.* number of own hypothetical contributions entered, given a conjecture about other players' contributions. We include the practice rounds.

5.3.2 *Homo pecuniarius* versus *Homo behavioralis*

Next, we examine the way payoff-relevant measures *Difference1* and *Difference2* are distributed among participants. When a subject identifies the pecuniary-profit-maximizing strategy using the calculator, the discrepancy between hypothetical and BR contribution levels (*Difference1*) is close to zero. Similarly, a value of *Difference2* close to zero indicates that a participant has pursued the pecuniary-profit-maximizing strategy for a given conjecture. Figure 5.1 displays a scatter plot of the average value of *Difference1* and *Difference2* for each subject. Blue circles and red squares refer to Type 1 and Type 2 subjects, respectively. The plot confirms that both types are usually capable of finding the profit-maximizing contribution using the calculator (*Difference1* is never very far from zero). This means that confusion cannot account for most of the observed choices.[33] Considering actual choices (*Difference2*), significant differences become apparent: Type 1 subjects (*Homo pecuniaris*) clearly pursue the pecuniary-profit-maximizing strategy, whereas Type 2 individuals (*Homo behavioralis*) often choose to deviate from it. Type 2 subjects seem to exhibit altruistic behavior in LC treatments, while in HC environments Type 2 subjects act as if they have a competitive motive.[34] Crucially, variation in the degree of complementarity and the magnitude of optimal contributions may play a role in the occurrence of different behavioral motives. When BR choices are very low (LC treatments) some agents may enhance their payoff through altruistic over-contributions; such joy-of-giving could be tainted, or less salient, in an environment where a high payoff is associated with a high contribution. When the magnitude of the optimal contribution is large, a competitive motive may become more appealing as agents recognize that small reductions in contribution 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 low complementarity environments.[35]

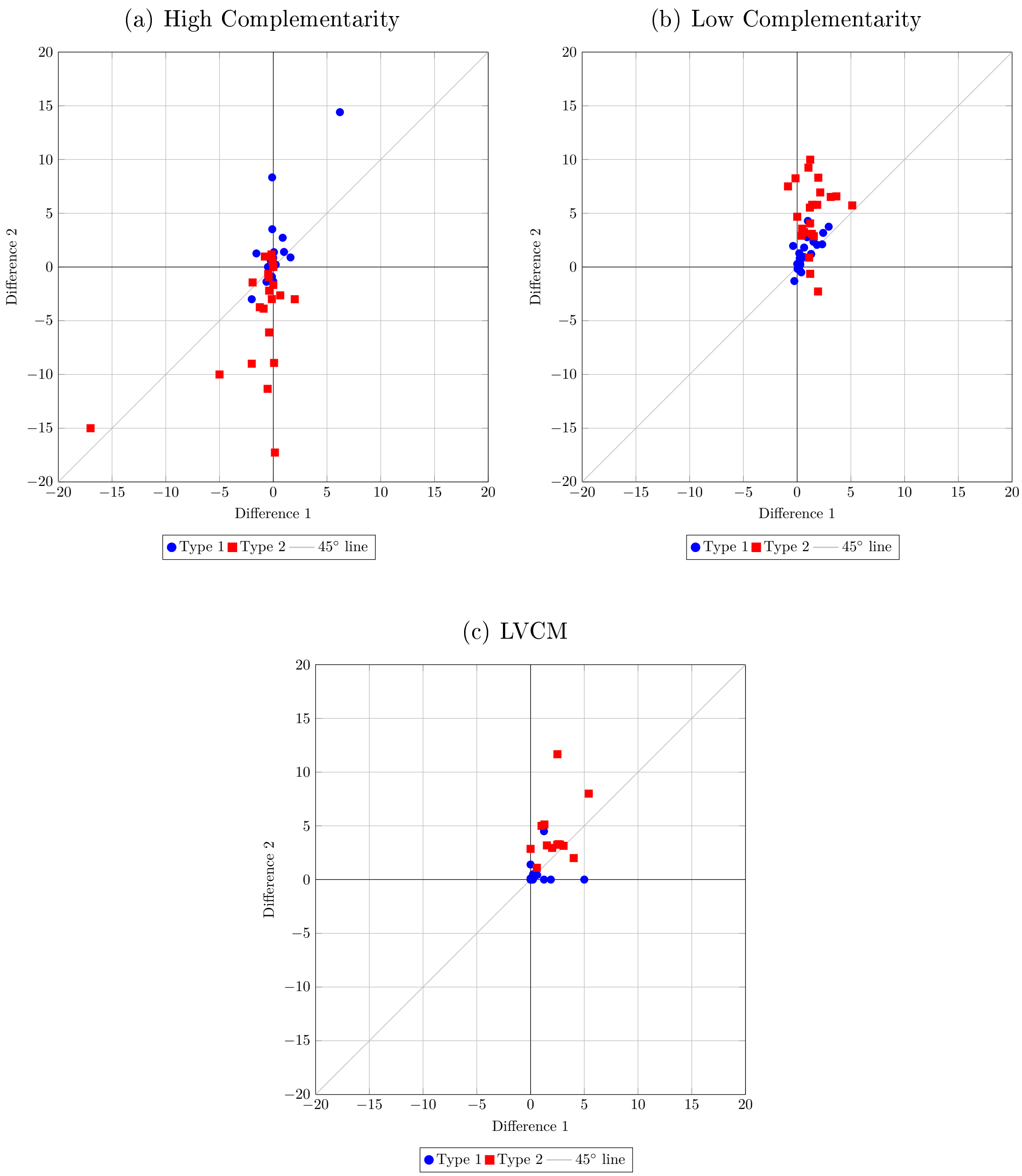
Behavioral motives may operate side by side with profit-seeking behavior as agents consider all these aspects in their decision making. This observation motivates the analysis in the next Section.

[33] 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.

[34] Since this is a between-subject study, we make no claim as to the identity of types across treatments. That is, an agent may appear as *Homo pecuniaris* in LC treatments (since competitive behavior coincides with profit maximizing) while under-contributing in HC treatments - like a *Homo behavioralis*. An opposite pattern may emerge as well.

[35] An alternative view of the evidence from the payoff-relevant measures is presented in Appendix C, where we plot the relative frequency of deviations by type and treatment. This offers more evidence that agents are able to identify the pecuniary BR.

Figure 5.1: *Difference1* versus *Difference2*



Notes: The blue circles display the average *Difference1* and *Difference2* for each Type 1 subject. The red squares display the average *Difference1* and *Difference2* for each Type 2 subject.

5.4 Quantifying altruistic and competitive motives

Given that deviations from payoff-maximizing strategies cannot be simply attributed to confusion, Type 2 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 Measuring non-pecuniary motives

Andreoni et al. (2008) define the warm-glow of giving as "the utility one gets simply from the act of giving" (p.1). Therefore an individual's utility function can be defined as $U_i = \pi(g_i, g_{-i}, \rho) + \gamma$, where γ captures the joy-of-giving motive in LC. We use observed choices by *Homo behavioralis* (Type 2) to estimate γ for each treatment. By definition, γ is the difference between the pecuniary-profit-maximizing contribution and the pecuniary-profits from the actual contribution of Type 2 subjects.

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

where $\bar{g}$ is the average contribution observed among all players and $\bar{g}_{Type2}$ is the observed average contribution of Type 2 subjects.[36] Equation (5.1) describes the choice of a *Homo behavioralis* subject: when other subjects contribute $\bar{g}$, he or she prefers to contribute $\bar{g}_{Type2}$ tokens rather than $g_i^*(\bar{g})$. We assume that the warm-glow compensates a subject for the pecuniary loss. Table 5.3 reports the estimated average magnitude of γ within each treatment; the estimates are roughly similar when comparing across treatments (between 0.75 and 0.85 tokens).[37]

[36] We assume that $g_{-i} = \bar{g}$. To eliminate early learning stages concerning the game and the environment, we concentrate on the last 10 rounds.

[37] This amounts are even lower if one convert the tokens to CAD based on the exchange rates in Table 3.1.

Table 5.3: Warm-Glow Estimates[1]

ρ	$\bar{g}$	$g_i^*(\bar{g})$	$\bar{g}_{Type2}$	γ
1	0.7	0	1.4	0.84
0.70	1.9	0.5	3.7	0.88
0.65	7.2	3.7	9.2	0.76

[1]The first column displays the degree of complementarity, $\bar{g}$ is the overall average contribution, $g_i^*(\bar{g})$ is the BR given the average contribution, $\bar{g}_{Type2}$ is the average contribution of Type 2, and γ captures the warm-glow. We only consider the last 10 rounds.

Using similar reasoning one can quantify the intensity of competitive motives in HC treatments; that is, the pecuniary payoff a subject is willing 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 5.4 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: (i) Type 2 deviations are marginally larger in $\rho = 0.54$ and (ii) 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 5.4: Competitive-Motive Estimates[1]

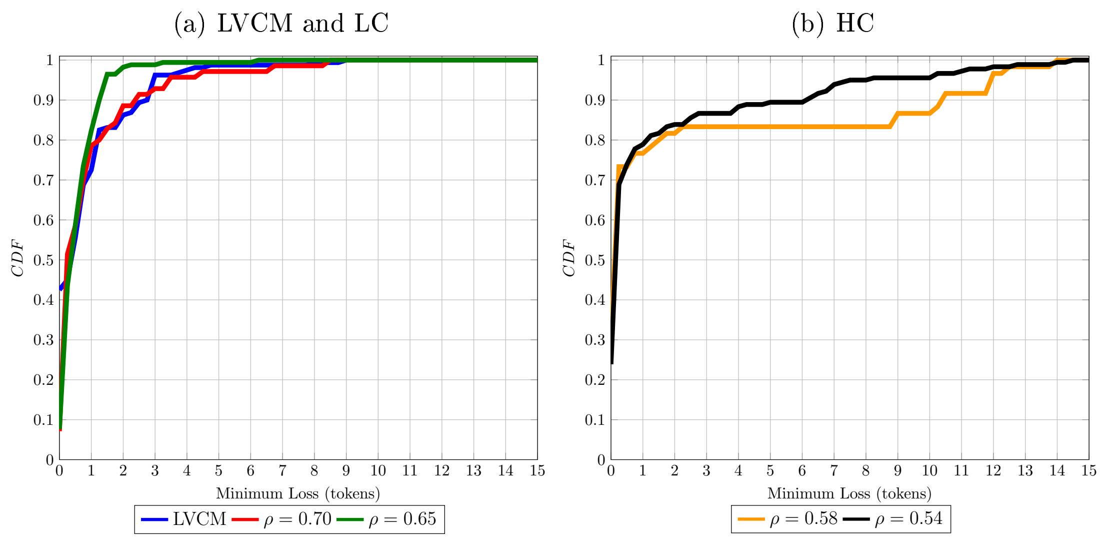
ρ	$\bar{g}$	$g_i^*(\bar{g})$	$\bar{g}_{Type2}$	κ
0.58	17.6	20	13.8	0.68
0.54	16.2	20	13.3	1.62

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

Finally, we examine the distribution of estimated γ and κ in the subjects' population. To do this, we use the *Min Loss* (defined in Section 5.1). The left panel of Figure 5.2 displays the cumulative distribution of the individual *Min Loss* values for rounds 11 to 20 in the LC and LVCM treatments. For the treatment corresponding to $\rho = 0.65$, 90% of the losses are 1.25 tokens or less. In contrast, for $\rho = 0.70$ and

LVCM, only three quarters of the losses are less than or equal to 1 token. The distributions of losses in the latter treatments treatments are characterized by a higher probability mass towards larger realization than in the case of $\rho = 0.65$, suggesting that losses tend to be less costly when $\rho = 0.65$. In a similar fashion, the right panel of Figure 5.2 plots the cumulative distribution of individual *Min Loss* values for rounds 11 to 20 in the HC treatments. In this case 80% of the losses are at most 1.5 tokens in both treatments.

Figure 5.2: Cumulative Distribution of the Individual Minimum Loss



Notes : Each line of the left panel displays the cumulative distribution of the per-round *Min Loss* for the LC and LVCM treatments. Whereas, each line of the right panel displays cumulative distribution of the per-round *Min Loss* for the HC treatments. We consider the minimum loss per subjects for rounds 11 to 20.

5.4.2 Complementarity and cost of deviations from pecuniary best-response

In the VCMC, the cost of a constant deviation from the money-maximizing strategy changes with ρ. As ρ decreases the 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 money-profit-maximizing requires a higher warm-glow value (γ) as ρ increases. This observation helps rationalize the contributions of Type 2 subjects when $\rho = 0.65$ as opposed to $\rho = 0.70$.

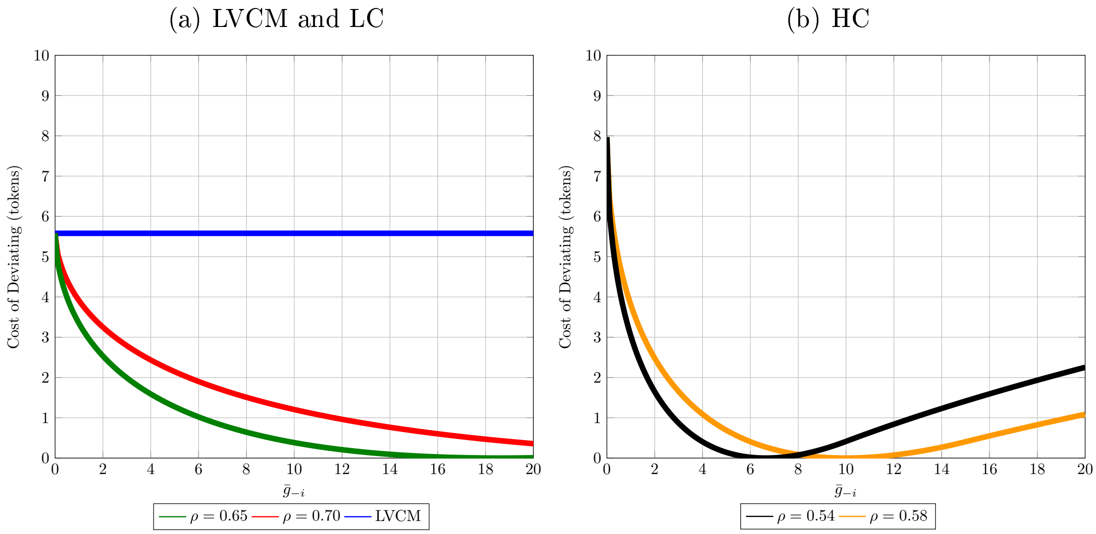
To illustrate this point we assume that subject i makes a contribution equal to the average contribution of Type 2 subjects when $\rho = 0.65$[38] and then we calculate the difference between the money earnings that subject i would make following this strategy and that obtained when monetary-best-responding to group members' contributions.[39] This difference measures the monetary cost of deviating from the profit-maximizing strategy, which is plotted on the left panel in Figure 5.3. The x-axis displays the contributions 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-contributing 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. In other words, an identical value of the "joy of giving" motive is translated into a higher over-contribution as complementarity increases (from LVCM to $\rho = 0.7$ to $\rho = 0.65$).

The right panel of Figure 5.3 displays the cost of deviating in HC treatments. Here we assume that player i makes a contribution equal to the average contribution of Type 2 subjects in HC treatments, which is 13.3 tokens. In HC the cost function does not monotonically decrease in other players' contributions, and losses start mounting if one does not best-respond to high contributions 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.

[38] Type 2 subjects contribute an average of 9.2 tokens when $\rho = 0.65$ (last 10 rounds).

[39] To facilitate the analysis we assume that other members' contributions are equal.

Figure 5.3: Cost of Deviating from the Money-Profit-Maximizing Strategy



Notes : 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 contributes 9.3 tokens (the observed average contribution 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 contributes 13.3 tokens (the observed average contribution of Type 2 in HC). The cost is equal to: $\pi(\rho, g_i^*, \bar{g}_{-i}) - \pi(\rho, g_i, \bar{g}_{-i})$.

5.5 Evidence from response times

Precise measures of subjects' response times are available for all treatments. This information provides an alternative way to peek at the mechanics of individual decision-making. Analyzing decision times in public good games has become increasingly popular following a study by Rand et al. (2012). In a one-shot LVCM experiment, they show how shorter response times positively correlate with higher contributions, and they interpret this as evidence that humans are instinctively generous. This interpretation has been challenged by, among others, Recalde et al. (2014), who point out how 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 make genuine mistakes.[40] We combine qualitative non-choice data and response-time infor-

[40] Recalde et al. (2014) design a VCM in which the dominant strategy is at the interior of the strategy space, and they replicate the finding of Rand et al. (2012) when the equilibrium contribution

mation to illustrate that some of the conclusions drawn by Rand et al. (2012) with respect to instinctive generosity are not consistent with our findings. More generally we argue that valuable information can be extracted from differences in the length of time it takes subjects to enter their contributions and from the intensity of their calculator usage over that interval.

5.5.1 Response time in the first round

First, we replicate the analysis of Rand et al. (2012). For comparability we consider only the first-round contributions in the LVCM treatment. The results confirm the findings of Rand et al. (2012): subjects who contribute zero wait 33 seconds, on average, before logging their choice. In contrast it takes only an average of 25 seconds to select a positive contribution. Our experimental design allows us to go beyond the one-shot game, and in the rest of this Section we report evidence about response times after the first round. The analysis of sequential rounds makes it feasible to assess how response times differ when observed contributions are closer, or farther, from hypothetical BRs.

5.5.2 Differences across treatments

Before proceeding, we categorize observed contributions into those that can, or cannot, be rationalized using the procedure described in Section 5.1. This distinction unveils some remarkable differences in both the quantity and quality of time use. As shown in Figure 5.4 and Table 5.5 the response time of subjects in the HC and in the LVCM treatments appear quite similar, and significantly shorter than their counterparts in the LC treatments. We can look separately at subjects who maximize their money earnings (those with low proportional loss; i.e, a loss below 0.1) and those who do not (contributions associated with proportionally higher losses).[41]

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 contributions.

[41] As before, the notion of loss is defined in Section 5.1. The threshold 0.1 corresponds to the median proportional loss for the LC treatment.

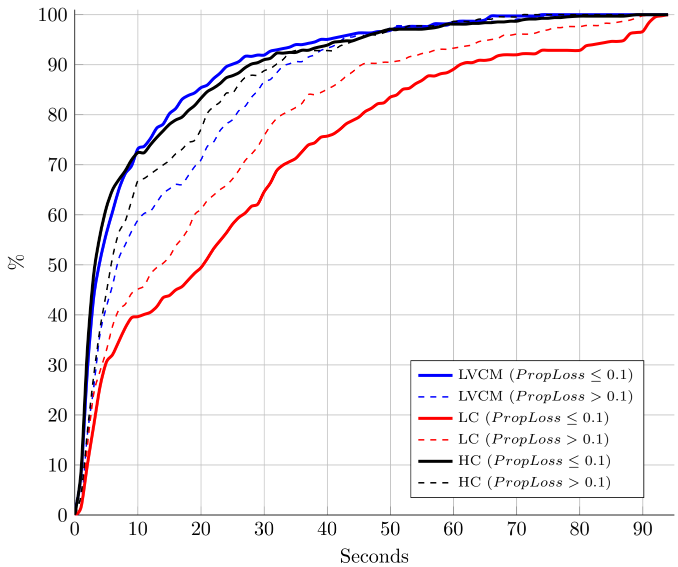
In the HC and LVCM treatments the low-loss subjects respond faster. This highlights a new and interesting discrepancy: in one set of treatments the fastest subjects are the ones who contribute little or nothing, while in another set the quickest subjects are those who get closer to a full contribution. These results suggest that both response times and the direction of deviations from BR may depend on the specific environment, and that speedy choices do not necessarily imply over-contribution.

On the other hand, in LC treatments subjects who play close to pecuniary-BR take more time before submitting their choices, possibly because calculating the (pecuniary) optimal level of contribution with precision is more difficult when complementarity is low. This interpretation is also supported by additional measurements; as we show in Appendix H, 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.

Table 5.5: Response Time

	$PropLoss \leq 0.1$			$PropLoss > 0.1$			Overall		
	Avg. seconds	(SD)	obs.	Avg. seconds	(SD)	obs.	Avg. seconds	(SD)	obs.
LVCM	10.02	(0.67)	384	14.34	(1.00)	224	11.61	(0.57)	608
LC	26.31	(1.18)	449	20.33	(0.96)	463	23.28	(0.77)	912
HC	10.54	(0.56)	689	12.65	(0.95)	223	11.06	(0.49)	912

Figure 5.4: Response-Time Frequencies



Notes: Each solid line represents the cumulative distribution function for subjects for which *PropLoss* $\leq$ 0.1 for each of the treatments. Each dashed line represents the cumulative distribution function for subjects for which *PropLoss* $>$ 0.1 for each of the treatments. The y-axis is displayed in percentage terms.

6 Related Literature

The experimental literature has focused on 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 into a public good game. Our experimental result of no-convergence to the unique Nash equilibrium in the case of $\rho = 0.65$ is in sharp contrast to experimental results in binary-action games. It testifies that the richer strategy space induces different behavioral dynamics.

Another example of a coordination game is the weakest-link game in which n agents must choose an integer from the set 1 to k. The agents' payoff depends on the minimum of all the chosen numbers. This is the extreme case of strategic complementarities. The seminal paper by Van Huyck et al. (1990) shows that subjects fail to coordinate on the efficient outcome when groups are large.

In terms of complementarity in public goods provision, there are some experiments based on Hirshleifer (1983) weakest-link mechanism. In this framework, public goods provision depends on the minimum contribution. Moreover, there are multiple Pareto-ranked equilibria because every set of symmetric choices is an equilibrium. Harrison and Hirshleifer (1989) were the first to implement this in the lab. They compare simultaneous and sequential two-player contribution games in which the provision of the public good depends on the sum of contributions, on the minimum contribution (weakest-link), or on the maximum contribution (best-shot). They find that under the weakest-link mechanism, subjects' contributions are very close to the Pareto-dominant equilibrium. Croson et al. (2005) ran a voluntary contribution experiment in which the provision of the public good depends on the lowest contributor (weakest-link). They contrast this treatment with the LVCM. They find that in most periods subjects are unable to coordinate on any of the equilibria. As in the linear case, the average contribution decreases over time. The authors suggest that imitation of the lowest contributors may explain this pattern.

In another related paper, Steiger and Zultan (2014) compare the linear case and a case in which the marginal return from the public good increases as the number of contributors increases (through increasing returns to scale, IRS). Subjects have binary choices: either contribute or not. In the IRS treatment there are two equilibria, zero contribution and full contribution. The authors implement a partner-matching protocol, and find that only groups that cooperate in early rounds are able to converge to the full contribution equilibrium. Overall, they find that contributions decrease over time, and the average contribution is not significantly different than what is observed in the linear case.

Finally, Potters and Suetens (2009) design an experiment in which there is a unique equilibrium at the interior of the choice space. They find that subjects converge faster to the equilibrium under strategic complementarity than under strategic substitutability.[42]

In terms of the analysis of non-choice data, an example is Cherry et al. (2015) who implement an output-sharing game with negative externalities. They use subjects' conjectures to analyze deviations from the theoretical predictions. They suggest that deviations are consistent with preferences for altruism and conformity.

7 Conclusions

In this paper we investigate how the introduction of complementarity among private contributions towards a public good affects human choices to contribute. Consistent with theoretical predictions we find a positive relationship between aggregate contributions and the degree of complementarity. In high-complementarity environments subjects learn to coordinate, moving towards the socially preferable equilibrium.[43] By contrast, when complementarity is very low, choices converge to the unique zero-contribution equilibrium. Subjects also seem to respond to complementarity when its intensity is sizable but not enough to introduce a second full-contribution equilibrium; in this case they persistently over-contribute and show little or no tendency towards the unique zero contribution.

Manipulating the intensity of complementarity allows us to look at the decision-making process and identify alternative motives underlying observed choices. We find that deviations from the profit-maximizing strategy cannot be attributed to confusion, but rather originate from non-pecuniary motives. Moreover, different motives are present under different degrees of complementarity.

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-

[42]The experiments implement a static game over 31 successive rounds. Between rounds there is no change in group composition.

[43]In a related study (available upon request) we investigate how convergence to the payoff-dominant (full contribution) equilibrium is affected when its basin of attraction is reduced. We do this by requiring a minimal level of public good to be produced; if this level is not attained then all contributions to the public good are lost. We show that also in such environments (and even when the threshold is high) players tend to coordinate on the full contribution equilibrium.

seekers who follow pecuniary best response strategies, others (*Homo behavioralis*) are able to calculate the payoff-maximizing strategy but deliberately deviate from it. The interaction of these 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 pecuniary rewards to deviate from BR strategies may lead to imperfect convergence to equilibrium. The presence of *Homo behavioralis* increases social welfare when complementarity is low, as it restrains group contributions from collapsing to zero, but it reduces welfare when complementarity is high and full contributions would be optimal. We also find strong evidence that *Homo pecuniarius* subjects respond to the presence of behavioral agents by adjusting their contributions - especially so in low-complementarity environments.

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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 contribution 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

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

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

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

implies concavity of π_i.

B Best-Response Range and Contributions

Figure B.1: Session 1 (LVCM)

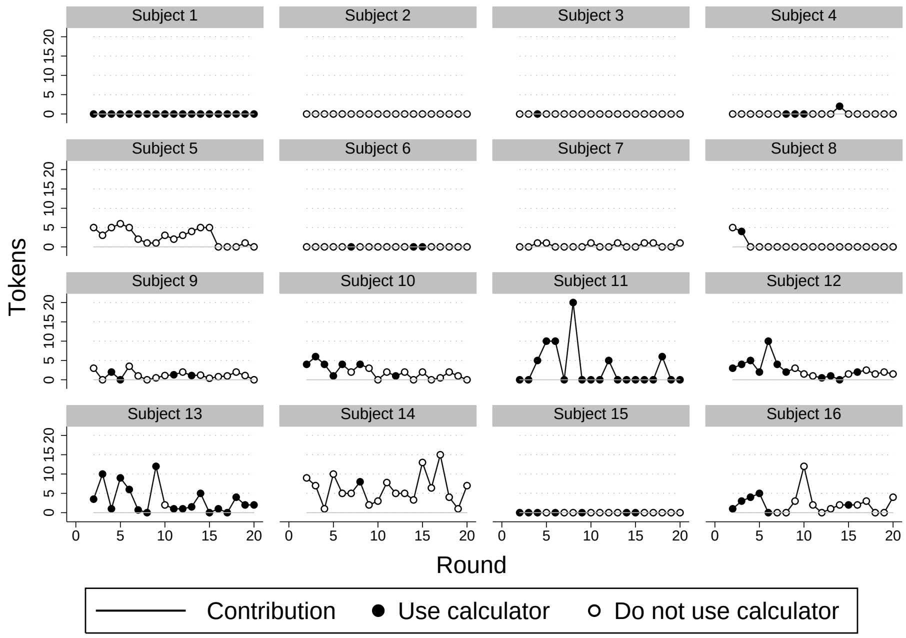


Figure B.2: Session 2 (LVCM)

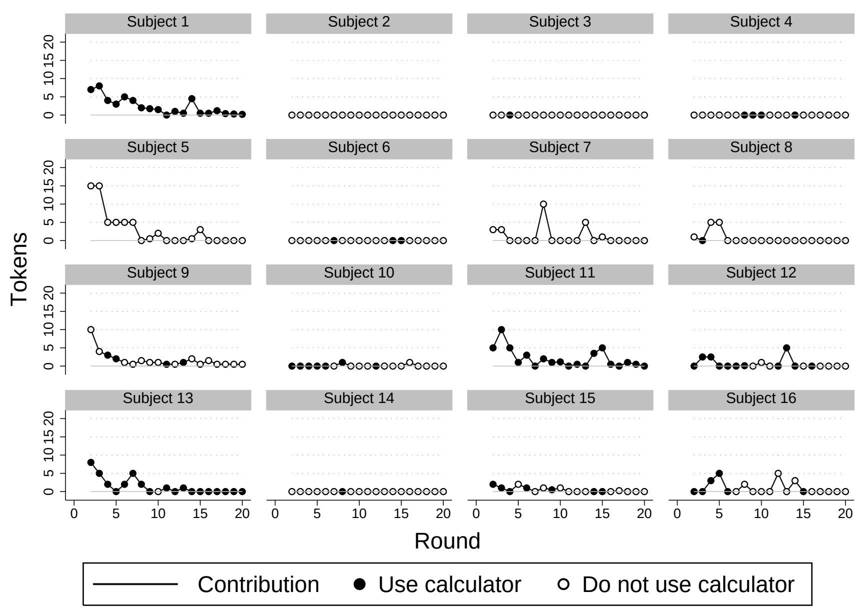


Figure B.3: Session 3 ($\rho = 0.54$)

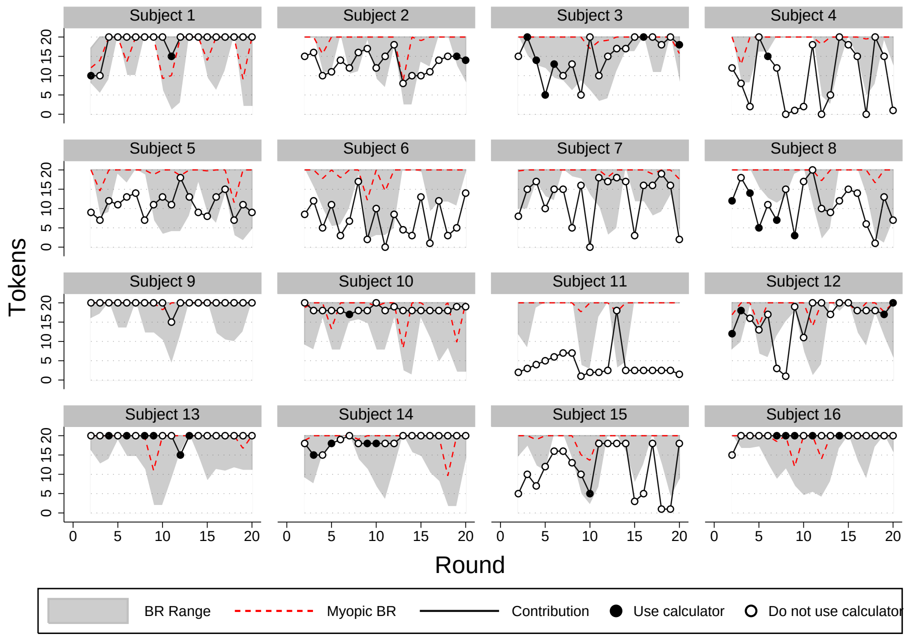


Figure B.4: Session 4 ($\rho = 0.54$)

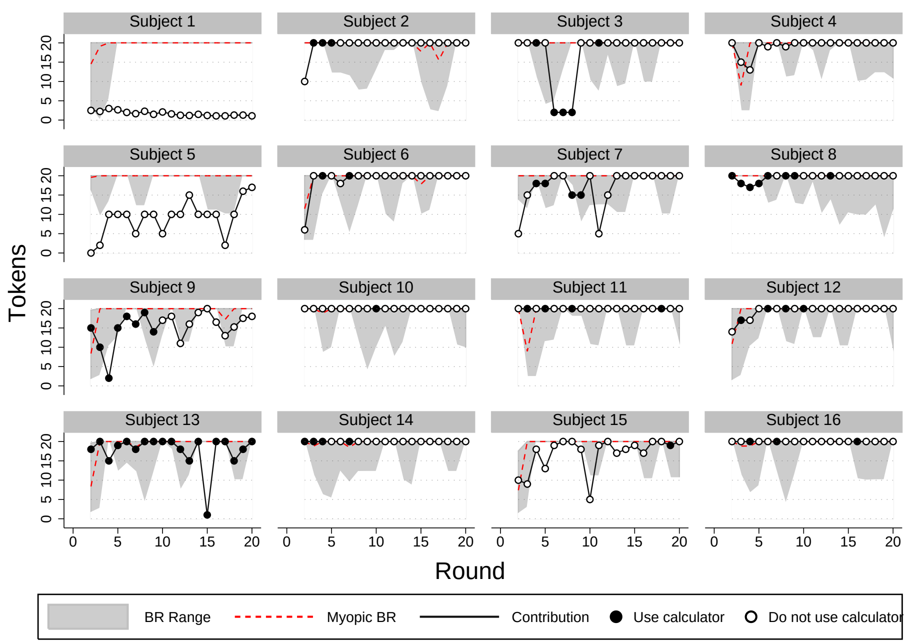


Figure B.5: Session 5 ($\rho = 0.65$)

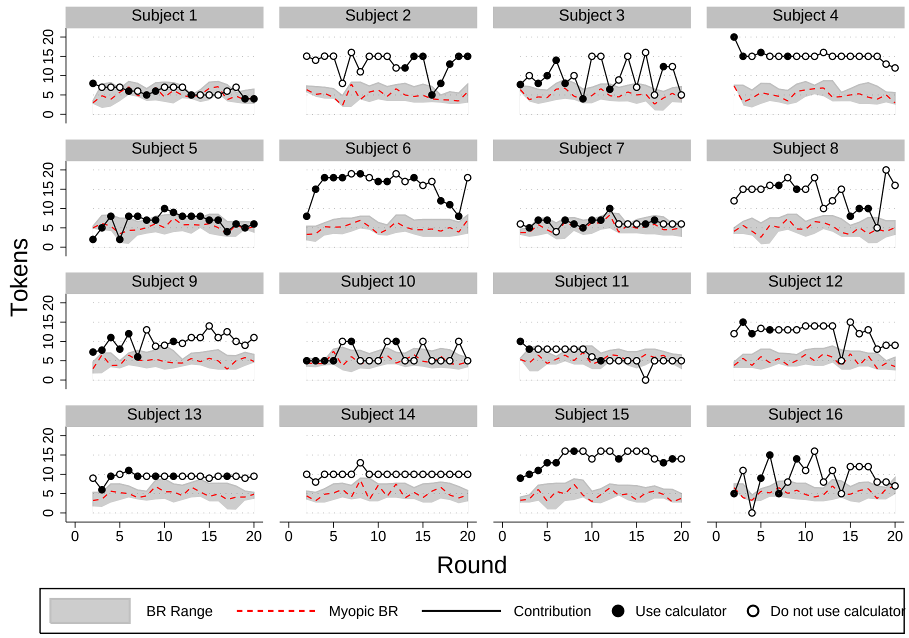


Figure B.6: Session 6 ($\rho = 0.65$)

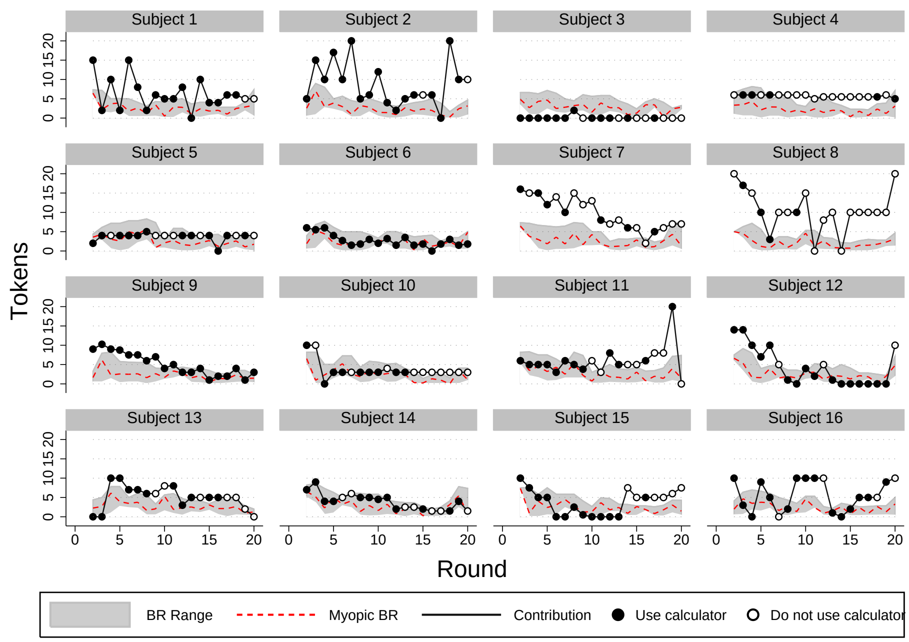


Figure B.7: Session ($\rho = 0.70$)

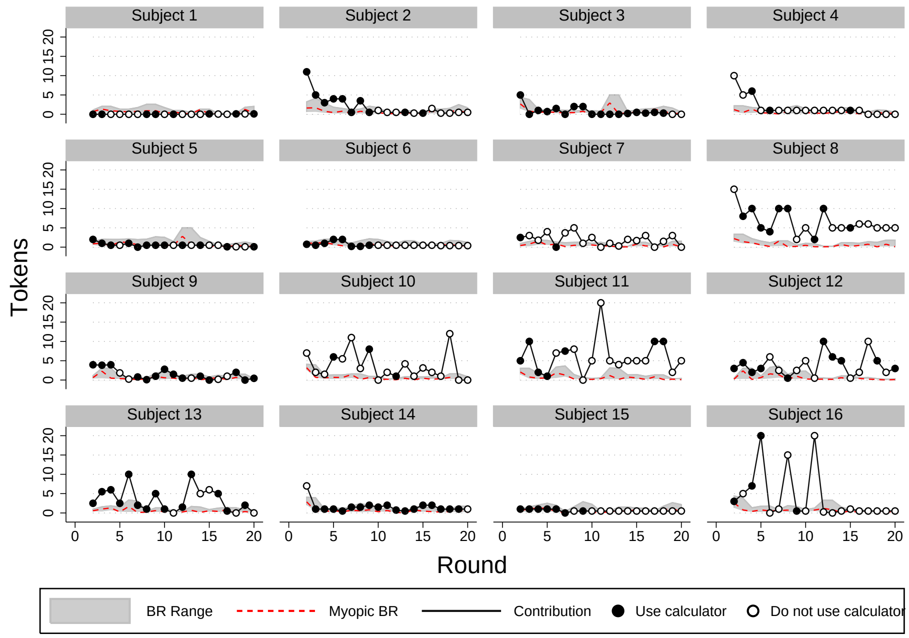
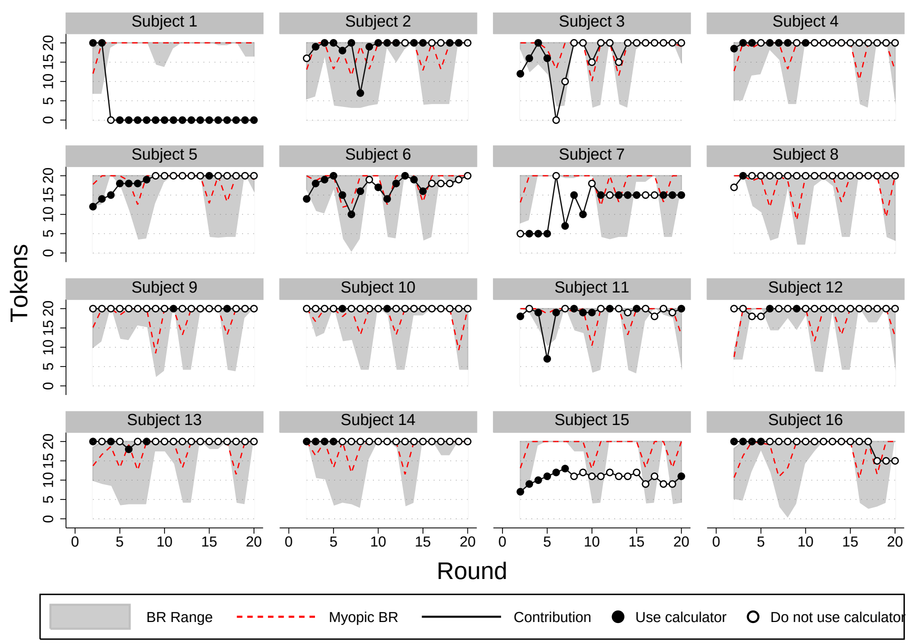


Figure B.8: Session 8 ($\rho = 0.58$)

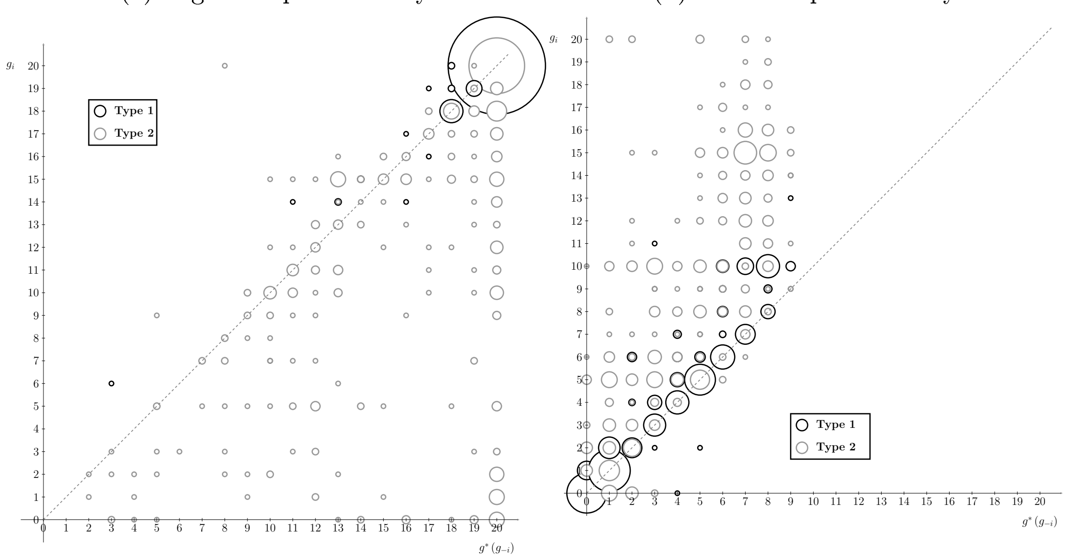


C Deviations from the Profit-Maximizing Strategies, by Type

To highlight the stark differences in behavior across types, Figure C.1 plots a scatter of actual contributions (y-axis) versus the BR associated with the lowest proportional monetary loss (x-axis). A wider circle denotes a higher frequency. Panel (a) shows this relationship in the HC group; panel (b) shows the same plot for the LC group. In both panels, Type 1 subjects are shown in black circles, while Type 2 are in gray ones. As one would expect, the average Type 1 subject makes choices that are much closer to the BR. One can simply compare the area of the circles close to the diagonal (contributions close to the BR) and the area of circles off the diagonal (contributions away from the BR). Type 2 subjects over-contribute in LC sessions and under-contribute in HC ones.

Figure C.1: Contributions versus best response (based on previous two rounds' contributions by other players)

(a) High Complementarity (b) Low Complementarity

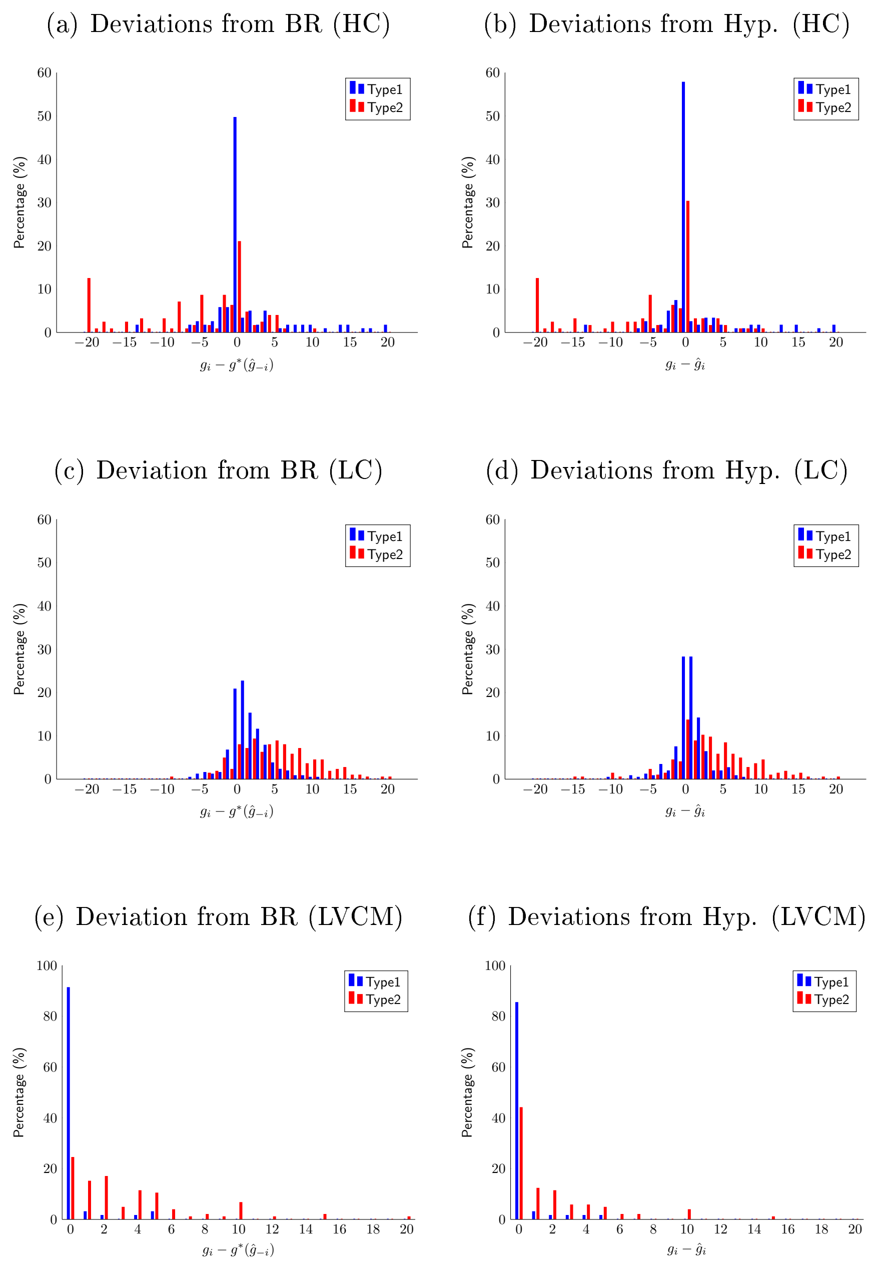


Notes : The plots displays actual contributions in the y-axis versus the BR associated with the lowest proportional loss (x-axis). In the figure a wider circle denotes a higher frequency. Type 1 subjects are shown in black circles; Type 2 are in gray ones.

An alternative way to present the differences across types is to plot the relative frequencies of deviations. The left panels in Figure C.2 display the way *Difference2* (that is, $g_i - g_i^*$) is distributed in different treatments[44]; as expected, Type 2 agents (red bars) under-contribute in HC and over contribute in LC treatments. The panels on the right side report the deviation of actual choices from the hypothetical choices (i.e., $g_i - \hat{g}_i$); these deviations can be obtained by subtracting *Difference1* from *Difference2*. They measure the extent to which deviations in actual choices are due to deviations in hypothetical ones entered in the calculator. The plots confirm that, even after controlling for the use of the calculator, Type 2 subjects under-contribute in HC and over contribute in LC and LVCM. In fact, deviations from BR occur with relative frequencies which are both qualitatively and quantitatively close to those observed for deviations from hypothetical contributions. This is evidence that participants who deviate from BR are not doing so by blindly following a misguided and erroneous optimal response. Instead, the fact that deviations from BR largely line up with deviations from hypotheticals suggests a more deliberate behavior on the part of the subjects.

[44]We plot the "per-round" average of the individual discrepancy between actual choices and BR, without controlling for use of the calculator.

Figure C.2: Deviations of actual choices from BR (*Difference2*) and from hypothetical (*Difference2 - Difference1*)



(a) Deviations from BR (HC)

(b) Deviations from Hyp. (HC)

(c) Deviation from BR (LC)

(d) Deviations from Hyp. (LC)

(e) Deviation from BR (LVCM)

(f) Deviations from Hyp. (LVCM)

Notes : The blue (red) bars of the left panel display the relative frequency (in percentage) of the deviations from the profit-maximizing strategy, $g_i - g^*(\hat{g}_{-i})$, for Type 1 (Type 2). The blue (red) bars of the right panel display the relative frequency (in percentage) of the deviations from the profit-maximizing strategy controlling for the ability to find the payoff-maximizing strategies using the calculator, $g_i - \hat{g}_i$, for Type 1 (Type 2).

D Computer Interface

Figure D.1: Main Computer Interface

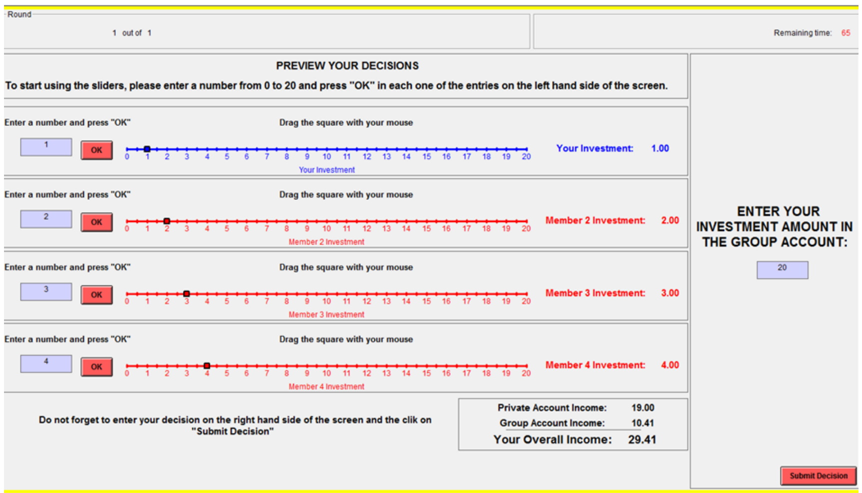
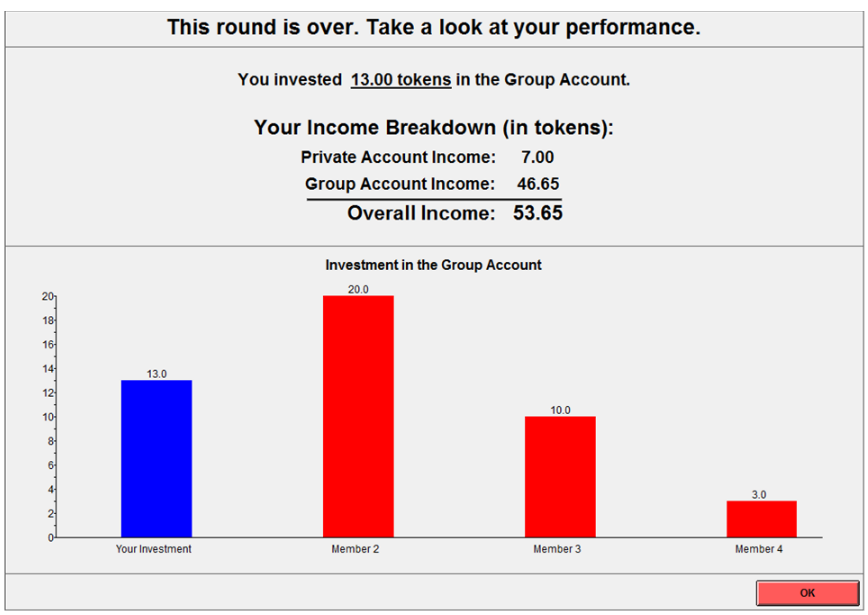


Figure D.2: Feedback



E Control Questions

Figure E.1: Control Question 1/7

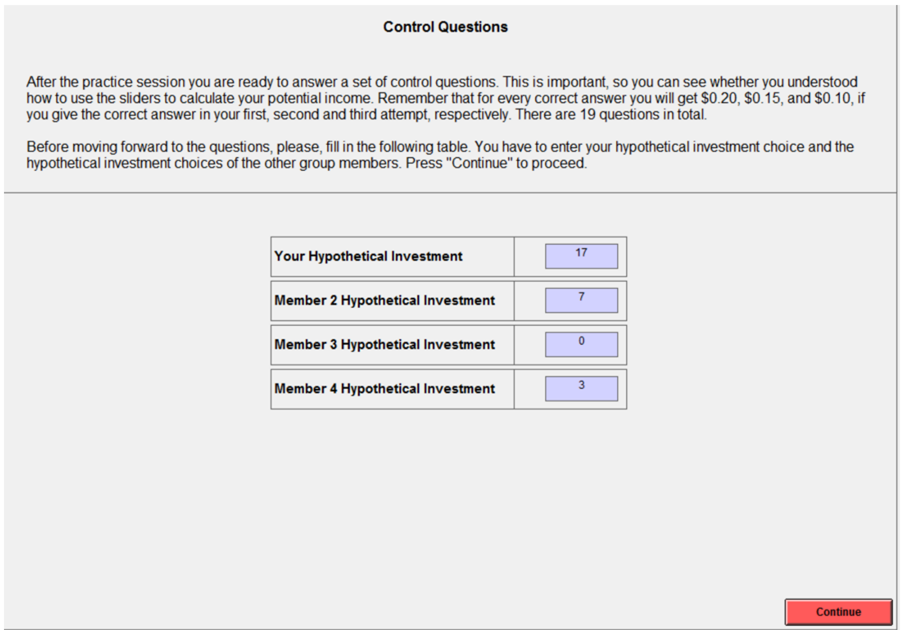


Figure E.2: Control Question 2/7

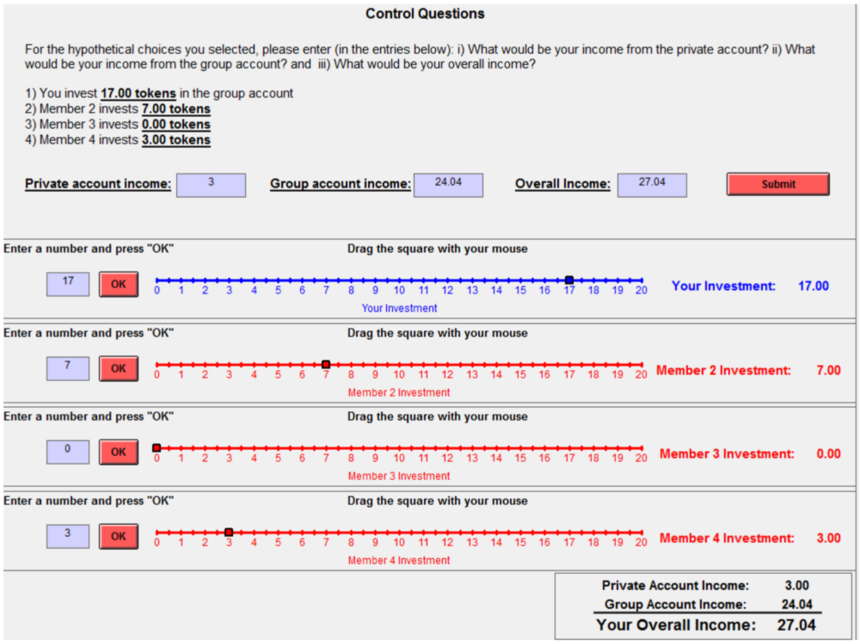


Figure E.3: Control Question 3/7

Figure E.4: Control Question 4/7

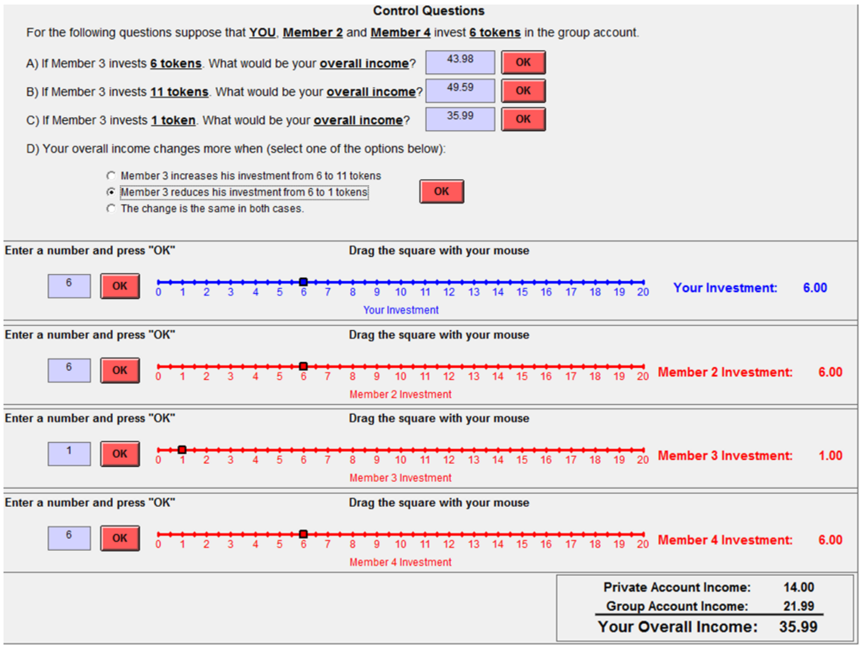


Figure E.5: Control Question 5/7

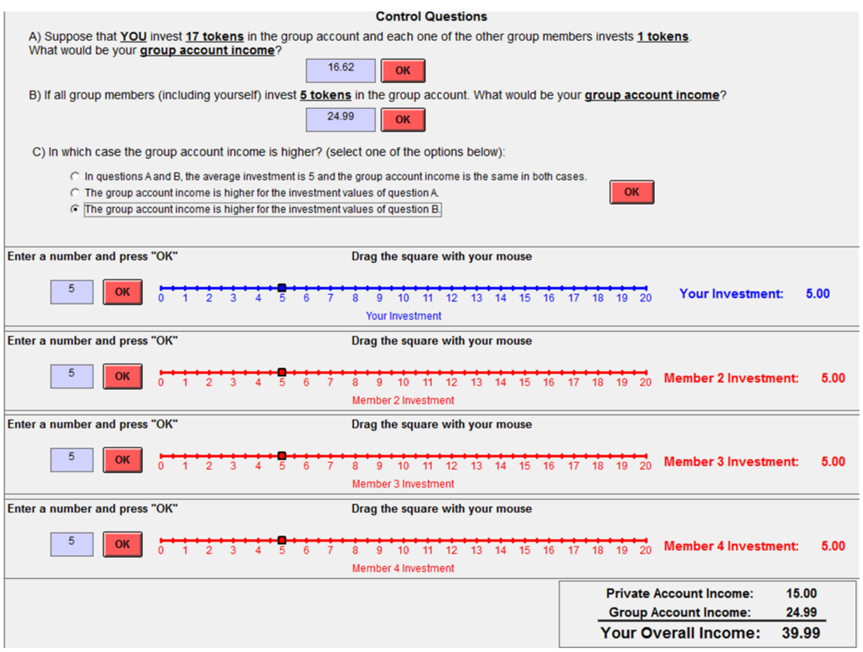


Figure E.6: Control Question 6/7

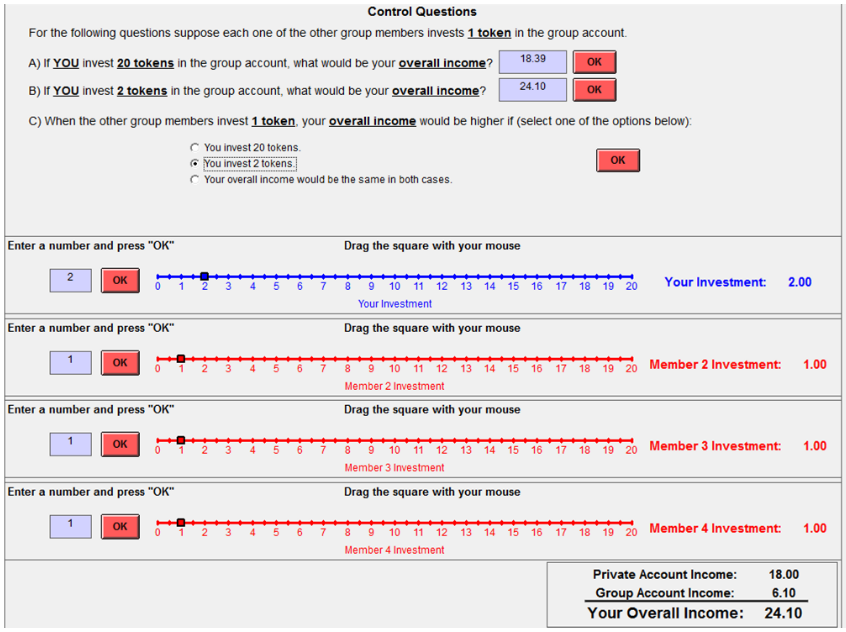
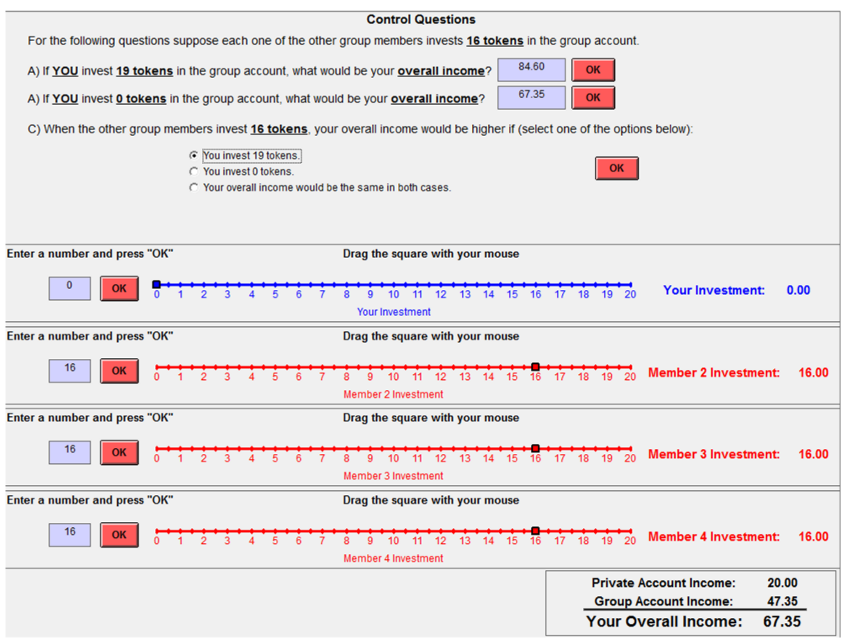


Figure E.7: Control Question 7/7



F Myopic Best Response

As a robustness check we classify subjects based on how close their contributions are from the best response given the other group members' contribution in the previous round. The procedure is analogous to the one used in Section 5.1, but in this case we consider the contributions made by other group members only in the previous round.

There are no significant differences with respect to the classification used in Section 5.1. Only 10 subjects would be re-classified as Type 1 and another 10 subjects would be re-classified as Type 2 (with respect to Section 5.1).

Table F.1 is analogous to Table 5.2.

Table F.1: Differences in Mechanical Use of the Calculator, by Subject Type within Complementarity Level (assuming myopic BR)[1]

	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	4.4	9.5	0.0	10.6	10.0	0.7	6.1	4.3	0.2
	(1.2)	(1.9)		(1.1)	(1.0)		(0.9)	(1.1)	
Hyp	12.6	13.6	0.5	14.5	14.8	0.8	9.0	9.4	0.6
	(1.3)	(1.1)		(0.9)	(0.8)		(0.6)	(0.6)	
Conj	14.1	19.7	0.2	29.8	25.1	0.2	26.7	19.1	0.1
	(2.3)	(3.3)		(3.0)	(2.2)		(3.8)	(2.8)	
Hyp Per Conj	3.2	4.1	0.1	7.0	5.8	0.1	8.6	5.9	0.0
	(0.4)	(0.4)		(0.5)	(0.4)		(1.0)	(0.8)	
Observations	16	16		24	24		24	24	

[1]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 subjects used the calculator; *Hyp.* number of hypothetical own contributions; *Conj.* No. of conjectures about others; *Hyp per Conj.* number of own hypothetical contributions entered, given a conjecture about other players' contributions. We include the practice rounds.

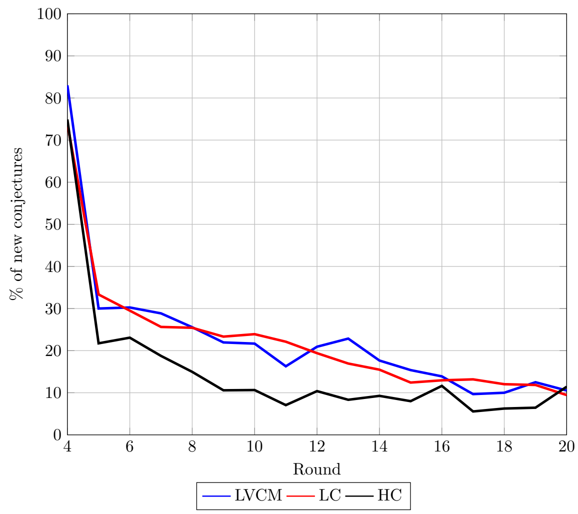
G Persistence of Conjectures

To better understand how persistent are the conjectures about other contributions, in Table G.1 we display the number of new conjectures in each round and across treatments. We also show the number of overall conjectures per round. Figure G.1 shows the five-round moving average for the new conjectures as a percentage of the overall conjectures. Note that there is a significant decrease in the percentage of innovations over time, especially in HC. This supports the hypothesis of persistence in subjects' conjectures, and suggests that some subjects form conjectures early in the experiment which do not change much. Some of them adjust only their hypothetical contributions.

Table G.1: Persistence of Conjectures

Round	LVCM		LC		HC	
	No. of New Conjectures	Overall Conjectures	No. of New Conjectures	Overall Conjectures	No. of new Conjectures	Overall Conjectures
Practice	314	314	471	471	332	332
1	11	36	42	106	12	64
2	6	23	30	66	10	33
3	9	27	20	76	8	27
4	7	18	19	69	8	38
5	6	26	17	67	2	22
6	8	25	14	61	5	23
7	0	8	12	47	1	18
8	2	13	12	47	3	26
9	2	10	8	48	0	15
10	1	4	9	27	1	12
11	2	8	5	39	1	14
12	2	8	5	40	3	10
13	1	5	4	29	0	9
14	0	9	1	20	0	9
15	1	9	4	25	0	8
16	1	5	4	25	2	7
17	0	3	4	30	0	3
18	1	4	3	33	0	5
19	0	3	1	22	0	8
20	0	4	0	17	2	12

Figure G.1: New conjectures as a percentage of overall conjectures



Notes: The solid lines of the graph display 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%.

H Intensity and Processing Speed on Calculator Usage

H.1 Intensity of calculator usage

It is not obvious that longer spells of time unambiguously imply higher effort or better information processing. Therefore we combine time measures with records of actual interactions with the interface by counting how many times the calculator was activated before a choice was recorded. Looking at monetary-low-loss responses in the LVCM and HC treatments, subjects make no use of the calculator in three quarters of the rounds. In addition, it takes an average of only 8 seconds in the LVCM and 4 seconds in the HC to submit a choice.

In the LC treatments, however, this finding is reversed, as the majority of low-loss subjects (55% of them) use the calculator. Their average time to submission is 42 seconds. Subjects who do not use the calculator spend an average of only 6 seconds before committing to a choice.[45] For the $\rho = 0.70$ treatment, in 26% of the cases in which subjects "get it wrong" and do not activate the calculator, contributions are relatively large and exceed 5 tokens. These choices cannot be rationalized under any set of conjectures and suggest some degree of guesswork on the part of agents, which may be interpreted as a combination of confusion and inability (or reluctance) to pursue a BR strategy using the calculator. In general, it appears that Type 1 subjects tend to use the calculator only in challenging environments, when identifying BR strategies is not trivial.

H.2 Processing speed

Given the evidence presented so far, it is key to distinguish between subjects who spend much of the 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 a given combination in the calculator. This is done by

[45] This value does not change if we focus on high-loss subjects who do not activate the calculator. They spend an average of only 7 seconds submitting their choices.

dividing the total time spent on the calculator by the number of combinations that are considered during that time interval. The resulting statistic is a proxy for the speed at which information is processed. Table H.1 shows that, in the LC treatments, subjects on average consider more combinations per unit of time. Moreover, subjects who play close to pecuniary-BR appear to process information significantly faster than those who don't. This is additional evidence in support of the hypothesis that in more complex environments, like the LC ones, subjects tend to exert more effort while choosing a contribution. This is especially true for a *Homo pecuniarius* subject, who not only devotes more time to the choice problem but appears to be significantly more efficient in his or her time use.

Table H.1: Processing Time

	$PropLoss \leq 0.1$			$PropLoss > 0.1$			Overall		
	Avg. seconds	(SD)	obs.	Avg. seconds	(SD)	obs.	Avg. seconds	(SD)	obs.
LVCM	11.02	(0.98)	98	15.44	(1.40)	104	13.29	(0.88)	202
LC	9.44	(0.44)	246	11.01	(0.45)	214	10.17	(0.32)	460
HC	11.11	(0.62)	163	16.55	(1.13)	53	12.45	(0.56)	216

I 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.

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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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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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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