

# Exploration in Teams and the Encouragement Effect: Theory and Experimental Evidence

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This paper analyzes a two-person, two-stage model of sequential exploration, where both information and payoff externalities exist, and tests the derived hypotheses in the laboratory. We theoretically show that even when agents are self-interested and perfectly rational, the information externality induces an encouragement effect: a positive effect of first-player exploration on the optimality of the second-player exploring as well. When agents have other-regarding preferences and imperfectly optimize, the encouragement effect is strongest. The explorative nature of the game raises the expected surplus compared to a payoff equivalent public goods game. We empirically confirm our main theoretical predictions using a novel experimental paradigm. Our findings are relevant for motivating and managing groups and teams innovating not only for private but also, and especially so, for public goods. (JEL: C72, C91, D03, D83, O31),

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# 1 Introduction

Innovation plays a central role in the production of public goods, and positive payoff externalities play a central role in collaborative production of research and innovation. Today, we observe a great need for new ideas that can help us meaningfully address the problems of poor or declining educational systems, unequal access to affordable health care, imminent environmental challenges, international terrorism, social fragmentation, and the chronic offending in low-income, urban neighborhoods, to name but a few. Furthermore, in many research-intensive environments, the outcome of exploration comprises a shared or public benefit, accrued by all research team members. One promising trend in the provision of *innovations* with a public good benefit is the rise of spontaneous, voluntary, often uncoordinated, yet joint search contributions by individuals, groups, or organizations. Search is decentralized and distributed, but knowledge is freely revealed or shared. More specifically, agents privately incur costly exploration efforts in search of a solution, the benefits of which accrue to all and cannot be privately appropriated. Further, they share and update information about solutions that are potentially still feasible and about others that have been tested and abandoned during the search process. Thus, incentive design in such settings must deal with not only dynamic free-riding but also the inherent process of learning or information sharing and externalities. With very few exceptions, previous work on the voluntary provision of public goods deals with situations that are static or involve limited exogenous uncertainty<sup>1</sup> about the outcome of the contributions to public goods. This work has provided invaluable insights into the drivers of private contributions to a public good, such as the importance of other-regarding preferences or reciprocal fairness norms in sequential public good provision which generates a complementarity between the actions of early and late movers (Camerer 2003, Cappelen et al. 2015, Güth et al. 2007, Levati et al. 2007). By contrast, we specifically account for the uncertainty of a public good discovery and the complementarity driven both by the informational and other-regarding preference channel, and we thus shift focus to the dynamics of *searching* for a public good.

In this paper, we provide a model of how teams of agents (more specifically pairs of individuals) sequentially and voluntarily explore for the public good in the following

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<sup>1</sup>Exceptions include Björk et al. (2016), Dickinson (1998), Levati and Morone (2013), Vesely et al. (2017).

circumstances: when effort is privately costly but cannot be directly contracted upon, when the value of the discovery or public benefit is known (and shared), when a finite number of possible solutions exists, and when exploration is open (information is shared). For real life scenarios captured by the model we can consider two problem solvers who take turns in finding a solution to a particular problem and can find it only by pursuing one of a given number of equally promising alternatives. They can be employees who are expected to improvise in order to make their peers feel more engaged at work, research teams in search of a solution to a theoretical modeling or empirical specification problem, or industry experts, say in telecommunications, in search of a new international standard. The key contribution of our model is to deliver sharpened insight into the strategic considerations that determine individual exploration decisions. Further, our simple model lends itself not only to an analysis with self-interested and perfectly rational agents, but also to an analysis with agents who imperfectly optimize and/or hold other-regarding preferences. Using this structural model we incorporate both informational and other-regarding complementarities and exploiting an experimental design that allows disentangling the two, we test to what extent the informational channel causally effects outcomes.

Our main results, both theoretical and experimental, are as follows. In our simple exploration game, as in more complex strategic bandit models (Bolton and Harris 1999, Hörner and Skrzypacz 2016), the information externality induces an informational encouragement: a positive effect of first-player exploration on the optimality of the second-player exploring as well. The novelty here is that we show that the expected occurrence and size of the encouragement effect not only depend on the value of the public good benefits, but also on the assumptions we make about the agents' rationality. So long as we assume perfect rationality and self-interested preferences, which we do in the baseline model, the encouragement effect is only at play within a limited range of public benefit values. Intuitively, for a specific range of fairly low values of the public good benefit, only exploration by the first-player can trigger the second-player to explore as well. In the subgame perfect equilibrium of our baseline model, we thus expect (in theory) the first-player's exploration to be non-monotonic in the value of the public good. Once we allow for imperfect optimization or other-regarding preferences,<sup>2</sup> which the extensive

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<sup>2</sup>We operationalize imperfect optimization by means of the quantal response equilibrium (QRE)

empirical and laboratory literature on strategic interactions and public goods provision, respectively, suggest may matter in our setting, the existence of an encouragement effect readily extends to all possible values of the public good. Moreover, the encouragement effect in this behavioral model is largest when agents both imperfectly optimize and care about each other's payoffs, because an informational and an other-regarding encouragement effect then coexist.<sup>3</sup> Together, our first set of theoretical predictions underscore the importance of information sharing as a non-monetary channel that motivates exploration and highlight the critical role of social preferences for team exploration outcomes.

Next, to pin down the causal effect of the uncertainty of the outcome, i.e. the informational encouragement effect, on individual contributions, we theoretically compare equilibrium outcomes for the baseline as well as the behavioral model of joint exploration with those of a payoff equivalent, canonical voluntary public goods provision game (henceforth, PGG) that lacks the explorative nature. In this payoff equivalent game the total value of the public good is the same as in the exploration game (henceforth, EG), and thereby also the myopic incentives to contribute coincide in the two games. Yet, when it comes to dynamic incentives, the other-regarding encouragement appears both in the EG and the PGG, but the informational encouragement affects choices only in the EG. Comparing individual and aggregate expected outcomes in the EG with those in the PGG allows us to sharply identify the effect of the informational externality, and thus strengthen the internal validity of our main results. We establish theoretically that the expected surplus in the exploration game is weakly greater than in the payoff equivalent PGG. Uncertainty in the public goods production process thus raises expected overall contributions.

Finally, our experimental results, based on the analysis of 13,760 individual exploration decisions in a computerized laboratory environment, broadly confirm our main theoretical predictions. Observed behaviors in the laboratory are in fact best explained by the behavioral version of our exploration model, where we allow players to imper-

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(McKelvey and Palfrey 1998) and other-regarding preferences by means of the social welfare utility model (Charness and Rabin 2002). We present our rationale for these modelling choices in our theoretical section.

<sup>3</sup>There are many empirical studies evidencing the other-regarding preference channel effect (Berg et al. 1995, Clark and Sefton 2001, Falk et al. 2003, 2008) and various theories have been put forward that rationalize such patterns. The other-regarding preference channel is predicted to be active both in the public goods game and in the exploration game. Yet, the informational encouragement effect appears in the exploration game only. This effect requires the information externality channel to operate.

fectly optimize and hold other-regarding preferences. Further, we show that expected aggregate contributions in the EG consistently exceed expected aggregate contributions in the payoff equivalent PGG and we find strong empirical support for the informational encouragement effect.

The stylized PGG and EG allow us to deliver sharpened insight into interactions within teams or groups with, respectively, a certain and uncertain public benefit outcome, reliant on non-contractible, costly individual efforts with a limited set of independent alternatives. In some settings, there is a clear connection between EG and PGG, since team or group members can be organized to either follow relatively more certain but lower-return routines or to share information regarding coordinated attempts to try out new approaches with an opportunity to realize a higher return. The setting can be a research-intensive environment, or a cooperative, or a work team – say, applied econometricians at a middle-tier department which either receives funding contingent on the number of publications only, triggering the econometricians to use linear regression methods to publish high quantities in lower tier journals; or where departmental funding is contingent on publications in top-journals only, triggering the econometricians to interact, present to each other state-of-the-art identification methods, which helps each to find the best identification method for his/her respective applied research problem, and to occasionally publish in top journals. Thus, the EG can be seen as a model of high-impact, breakthrough innovation (exploration) whereas the PGG can be usefully thought of as a model of generic, incremental innovation or simply exploitation.<sup>4</sup>

To the extent that our results are externally valid, the most direct out-of-sample implications of our results relate to situations in which motivating public goods provision are important concerns. Business leaders, for instance, who value opportunities for their employees to collaboratively work on projects that can transform team productivity or job satisfaction, let alone tackle societal challenges at large, are well-advised to emphasize the inevitable uncertainty in these production processes (especially if the number of feasible solution is or can be made limited), to find ways to enhance the overall value of the public good created, promote information sharing and the dynamic nature of the discovery process. These strategies can induce more efficient outcomes.<sup>5</sup> These strategies

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<sup>4</sup>Compared to the returns from incremental innovation or exploitation, the returns to breakthrough innovation or exploration are bigger but systematically less certain (March 1991). See also (Ederer and Manso 2013).

<sup>5</sup>In their efforts to restore trust in businesses and straightforwardly build better businesses, many

can also be applied by public sector leaders. For instance, school principals who wish to encourage teachers to jointly search for approaches that effectively improve say parental engagement or community associations that wish to encourage their members to jointly search for approaches that enhance local social cohesion.

This paper is related to four strands of literature. First, our paper builds on a simple model of interactive search by Fershtman and Rubinstein (1997). We adapt this modeling framework to capture a situation where exploration is open (information is shared) and benefits in the event of discovery are public (non-rival and non-excludable). This befits our focus on voluntary and joint search for the public good and we extend the model to allow for imperfect optimization and other-regarding preferences by relaxing standard assumptions in two relevant directions as suggested by the empirical and laboratory literature. There is a vast theoretical literature on search with seminal papers by Stigler (1961) and McCall (1970) who study fixed sample and sequential search, respectively, and analyze search that is carried out by individuals in isolation from each other. We study search where team members explore sequentially one after another, and the benefits of search are public accruing to the entire team.<sup>6</sup>

Second, our paper is related to the literature on moral hazard in teams (Holmstrom 1982), especially the theoretical analyses of sequential effort provision by Strausz (1999), Winter (2006), and Winter (2009). The latter two study the strategic incentives of team members when late movers observe the effort of early movers and efforts are complementary.<sup>7</sup> Winter (2009) shows how higher exogenous rewards can lead to lower efforts (the so-called incentive reversal effect), and our result regarding the non-monotonicity of exploration in the exploration game with subgame perfect equilibrium and with self-interest motivation can really be seen as a corollary of his finding. Many of these theoretical setups have also been studied experimentally (see Part 6.1 of Plott and Smith (2008), Klor et al. (2014), and Brown et al. (2011), for instance). Relative to this literature, the

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business leaders have sharpened their focus on purpose (Hollensbe et al. 2014). Our results suggest that this could be particularly effective if the employees are pro-socially motivated and consequently feel more engaged at work (Bolino and Grant 2016)

<sup>6</sup>In the case of a sequential search for a *private* good instead of a public good (keeping the information externality), the encouragement effect no longer occurs when players are self-interested. Once we allow for other-regarding preferences, the encouragement effect kicks in, but matters less than in the public goods case.

<sup>7</sup>Sequential moves also promote contributions when efforts are not complementary, but asymmetries across parties typically erode the benefits or leadership in that case (Cappelen et al. 2015, Güth et al. 2007, Levati et al. 2007).

key contribution of our paper is twofold: First, we develop a sequential, strategic model of search in teams where the returns of costly individual search efforts are uncertain. Second, our model is simple enough to lend itself not only to an analysis of perfect rationality but also to imperfect optimization and other-regarding preferences, as well as to an experimental study in the laboratory.

Third, our model can also be recast as a model of strategic experimentation. In this literature the paper most related to ours is Bonatti and Hörner (2011). They study a strategic bandit model where each of two team members must choose between costly exploration and a safe activity, and similarly where both informational and payoff externalities coexist. They consider the so-called good news model, where exploration efforts are strategic substitutes. But in a bad news model, the exploration efforts are typically strategic complements, as pointed out by Hörner and Skrzypacz (2016) in a private goods setting.<sup>8</sup> This is more in line with our setup. Our model is a much simpler finite-alternative model. In fact, in that regard, the exploration game is reminiscent of optimal search (Weitzman 1979) and recombinant innovation (Weitzman 1998), where old ideas can be reconfigured in new ways to make new ideas, much in the spirit of the way agricultural scientists develop plant varieties by cross-pollinating existing plant varieties.<sup>9</sup> Our theoretical and experimental setup also puts far less cognitive demands on lab participants than the canonical, multi-arm bandit problems. Hence, this class of models is more amenable to laboratory testing and to the incorporation of imperfections and other-regarding preferences into the theoretical analysis of strategic exploration. By using such a model we promote the methodological ideals of Samuelson (2005) by exploiting the interplay between theory and experiments in order to advance human understanding of economic phenomena.<sup>10</sup> We further make it easier for experimental participants to understand the setting by using intuitive and visually appealing video-instructions to explain the experimental design. The video-instruction itself constitutes a methodological contribution to the experimental literature. In an independent experimental study of the bandit exploration model Halac et al. (2016), Deck and Kimbrough

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<sup>8</sup>See Hörner and Skrzypacz (2016), pp. 2-3.

<sup>9</sup>Recombinant innovation is pervasive in a wide number fields such as genomics, agriculture, drug discovery, materials science, and particle physics. Weitzman (1998) discusses the example of researchers at Menlo Park searching for a material that can be carbonized and used as a filament to produce the “electric candle.” The combinatorial-based knowledge production function is thus one type of knowledge production function that corresponds to our exploration game.

<sup>10</sup>See also Mäki (2005) and Gilboa et al. (2014).

(2017) use a similar approach. The novel exploration paradigm contributes to the experimental literature on innovation (see Ederer and Manso (2013), for instance, and Boudreau and Lakhani (2016) and Brüggemann and Bizer (2016) for two recent review articles).

Finally, our paper ties into the literature on the voluntary provision of public goods, collective action, and prosocial behaviors originally studied by Olson (1965) in a self-regarding model and by Becker (1974) with altruistic preferences.<sup>11</sup> Our paper is most closely related to the work by McBride (2006) on the discrete version of the public goods game with symmetric uncertainty about the contribution threshold. In a self-regarding model, McBride (2006) finds, like us, that uncertainties in the public good provision environment may induce non-monotonicities. However, in his model, the encouragement effect does not arise. More generally, our paper shifts attention away from uncertainty about others' degree of altruism, contribution costs, or valuations of the public good (Anderson et al. 1998, Palfrey and Rosenthal 1991) to uncertainty inherent in the production process itself and, as emphasized by Admati and Perry (1991), Compte and Jehiel (2003), and Compte and Jehiel (2004), to the sequentiality and dynamic strategic interdependency of individual contributions.

The rest of the paper is organized as follows: Section 2 presents the game-theoretic model of exploration for the public good; Section 3 explains the experimental procedure and data; Section 4 contains the experimental analysis; and Section 5 concludes.

## 2 Theory

### 2.1 Basic model of exploration with sequential moves

Consider a simple two-stage, two-player exploration game with two partners (be it two employees, two co-authors, or two industry experts). There is a finite product space (of locations) and a unique public good (i.e. treasure) in a single location within that space. The partners take turns to contribute to the exploration of the product space and each can contribute by checking in one location whether the treasure is located there. Let  $K$  denote the number of locations. Ex ante, each location is likely to hold the treasure with probability  $1/K$ , and thus without loss of generality an action of player  $i$  can be

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<sup>11</sup>Lindbeck and Weibull (1988) extend Becker's model to a dynamic setup.



denoted by a binary action  $a_i \in \{0, 1\}$  where zero indicates no contribution.

The valuation of the public good, i.e. treasure size for  $i$ ,  $\alpha_i$ , with  $i = 1, 2$ , is ex ante known, non-excludable, and obtained if and only if the public good is found (or a breakthrough is made). Without loss of generality, we can assume that  $\alpha_1 = \alpha = \alpha_2$  and let the asymmetries between the players be reflected in the contribution costs. The cost of contributing,  $c_i$ , is borne by the relevant agent. Not contributing implies zero cost. Assume that  $c_1 \geq c_2$ , which is in line with Winter (2006)'s optimal incentive mechanism.<sup>12</sup> The player in stage two can learn from the exploration of her partner in stage one. The model assumes complete and perfect information (observable effort and outcomes), though no coordination device exists. We seek for the subgame perfect equilibria of the game under different treasure size or public good value regimes.<sup>13</sup>

### 2.1.1 Subgame perfect equilibrium of the exploration game (EG)

Let us solve the subgame perfect equilibrium (SPE) of the model, by using backward induction. In stage two, if the treasure has not been found, then it is optimal for player 2 to explore iff

$$c_2 \leq \alpha/Y,$$

where  $Y \leq K$  is the number of alternatives that have a positive probability of containing a treasure in the second stage. We call this player 2's myopic incentive to explore. Since the second stage is the last, the myopic incentive is also player 2's total incentive to explore. Likewise, player 1's myopic incentive to contribute is captured by  $\alpha/K - c_1$ . The myopic incentive to contribute is all that player 1 needs to consider if player 2's choice is not affected by that of player 1. There are two such cases.

First, if  $c_2 < \alpha/K < \alpha/(K - 1)$ , then player 2's contribution cost is so low that player two finds it optimal to contribute whether player 1 contributes or not (provided the public good is not found by player 1). Second, if  $c_2 > \alpha/(K - 1) > \alpha/K$ , then player 2' cost of contribution is so high that player 2 finds it suboptimal to contribute whether player 1 contributes or not. Yet, player 1, unlike player 2, needs also to consider

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<sup>12</sup>According to Winter (2006), late movers should be given higher-powered incentives when there exist increasing returns to exploration. The basic intuition is that player 2 faces no implicit threat that his or her failure to innovate will trigger subsequent agents to shirk as well. Hence, player 2 should be provided with stronger incentives to exert effort than player 1.

<sup>13</sup>The public good could be interpreted as a project (as in Aghion and Tirole (1997)), as a mode of organization, a technological standard for an industry, or a methodological breakthrough in academic collaboration (as suggested by Bonatti and Hörner (2011)), and so forth.

dynamic effects of her choice on the contribution incentives of player 2, i.e. a potential *encouragement effect*. The encouragement effect is relevant and player 1's contribution may affect the incentives of player 2 if  $\alpha/K < c_2 < \alpha/(K-1)$ . Player 1 then prefers to contribute if

$$\frac{\alpha}{K} - c_1 + \delta\left(\frac{K-1}{K}\right)\left(\frac{\alpha}{K-1}\right) > 0, \quad (1)$$

where  $0 < \delta \leq 1$  is player 1's discount factor. The above inequality can in equivalent terms be written simply as

$$c_1 < (1 + \delta)\frac{\alpha}{K}, \quad (2)$$

capturing the simple intuition that by contributing herself, she gets another contribution for free as an optimal reaction by player 2. We summarize these conditions and their behavioral implications for perfectly rational self-interested players in Proposition 2.1.

**Proposition 2.1** *Let  $c_1 > c_2$ . Let  $\alpha_1 = \alpha_2 = \alpha$ . Conditional on the prize not having been found in the first stage, on the equilibrium path:*

- *Neither player contributes when  $\alpha < \max\{\frac{c_1 K}{1+\delta}, c_2(K-1)\}$ ;*
- *Both players contribute when  $\max\{\frac{c_1 K}{1+\delta}, c_2(K-1)\} < \alpha < Kc_2$ ;*
- *Only player 2 contributes when  $c_2 K < \alpha < c_1 K$ ;*
- *Both players contribute when  $c_1 K < \alpha$ .*

This proposition reveals that player 1's equilibrium contribution decision is non-monotonic in  $\alpha$  due to the *encouragement effect*, which is defined as the impact of player 1's contribution decision on player 2's contribution decision. Intuitively, when the value of the public good is very low, neither player finds it in his/her best interest to contribute. For somewhat higher values of the public good, neither player's myopic incentives to contribute are sufficient, but the dynamic encouragement effect triggers player 1 to explore and encourages player 2 to contribute as well if player 1 does not find the public good. Then, for even higher values of the public good, it is a dominant strategy for player 2 to contribute. Player 1 knows this and free-rides on player 2's contribution. Finally, once the value of the public good is so high that even player 1's myopic incentive dictates to contribute, then both players find it optimal to contribute. The basic intuition behind this result is precisely the same as the argument of Hörner and Skrzypacz (2016, pp. 2-3)

for why the privately optimal best response to the opponent's simple cut-off contribution strategy in a two-player bad news Poisson bandit model cannot be a simple cut-off strategy; rather it involves ranges of optimal encouragement and free-riding, corresponding to bullets two and three, respectively, in the above proposition. Thus our model allows us to test the basic encouragement intuition (Bolton and Harris 1999) of the strategic experimentation models in a considerably simpler framework which is easily understood by the participants of our experiment.

Figure 1 illustrates the core theoretical insights by using a simple numerical example. Let  $K = 4$ ,  $c_2 = 200$ ,  $c_1 = 300$  and  $\delta = 1$ . Then neither explores when  $\alpha < 600$ . Both contribute when  $600 \leq \alpha < 800$ . Only player 2 contributes when  $800 \leq \alpha < 1200$  and both players contribute when  $\alpha \geq 1200$ . Notice that the expected total contributions are 1.75 units when both contribute, since player 2 contributes only when the treasure is not found in that case, i.e. with probability 3/4.

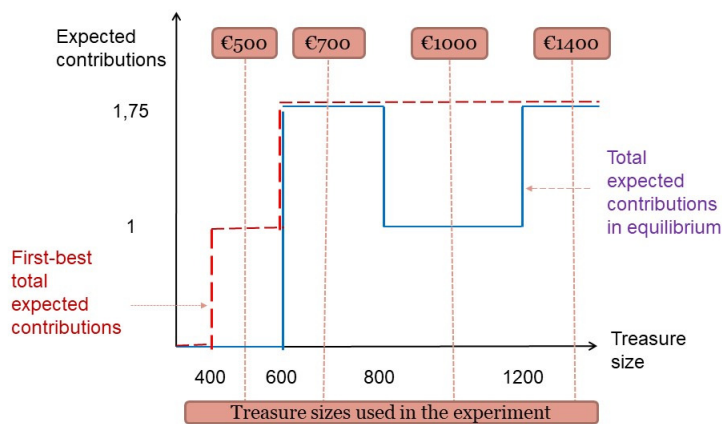


Figure 1: Theoretical predictions in the exploration game, SPE and self-interest

### 2.1.2 Subgame perfect equilibrium of the voluntary public goods game (PGG)

The standard voluntary public goods game, in its sequential two player binary choice form, is formally nested in our exploration game. To derive the standard voluntary public goods game from our exploration game, the value of the public good is distributed evenly over the entire finite product space so that in each location the value of the public good is the same and equals  $\alpha_{PGG} = \alpha/K$ . Thus, in the standard public goods version

of the game,  $1/K$ 'th of the value of the unique treasure in the exploration game is produced for each individual contribution made in the standard game, and this value is produced with certainty for each contribution that costs  $c_1$  for player 1 and  $c_2$  for player 2. Indeed, in the canonical voluntary public goods game, every individual contribution generates a public good with certainty with a marginal per capita return of  $\alpha/K$ . In our special case where only a single contribution can be made by each player and choices are sequential, the standard voluntary public goods game is in fact a sequential prisoner's dilemma. The reaction functions and SPE for the sequential prisoner's dilemma game are very well known. Let us sketch the derivation here for purposes of comparison with the exploration game. Let  $\alpha/K$  denote the public good produced for each individual contribution made. Then, player  $i$  will find it optimal to contribute to the production of a public good iff

$$c_i \leq \alpha/K. \quad (3)$$

Player 1's equilibrium contribution decision is monotonically increasing in  $\alpha/K$ . Player 1 can no longer exert an influence on player 2's decision. The *information externality*, which is a distinct characteristic of the exploration game, disappears in the voluntary public goods game and with it the *encouragement effect*. Thus, each player's myopic incentive dictates the optimal choices and each player thus (generically) has a dominant strategy independent of the other player's choice.

Intuitively, when the value of the public good is very low, neither player finds it in his/her best interest to contribute. For higher values of the public good,  $c_2 < \alpha_{PGG} < c_1$ , it is a dominant strategy for player 2 to contribute and likewise player 1 has a dominant strategy to free-ride on player 2's contribution. Finally, once the value of the public good exceeds player 1's cost, then both players have a dominant strategy to contribute.<sup>14</sup>

As illustrated in Figure 2, the equilibrium level of contributions to the production of the public good is closer to first best in the *exploration game* than in the *public goods game*. In particular, when  $\alpha/K < c_2 < \alpha/(K-1)$  and  $c_1 \leq \alpha(1+\delta)/K$  both players will contribute in the EG (if the treasure is not found by player 1), but neither will contribute in the PGG.

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<sup>14</sup>Strictly speaking, the game is a sequential prisoner's dilemma if and only if  $\alpha/K < c_i < (2\alpha)/K$  for  $i = 1, 2$ .

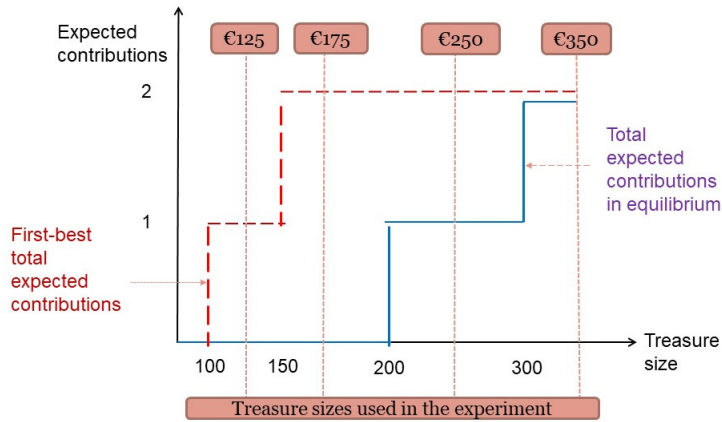


Figure 2: Theoretical predictions in the public goods game, SPE and self-interest

From a welfare perspective, it is optimal that player  $i$  contributes if  $c_i < (2\alpha)/K$ , and this is true both in the EG and the standard PGG. Thus, the welfare properties of the two games coincide. Likewise, the myopic incentives in the two games are the same. The only difference is the presence/absence of the encouragement effect, and this property in regard to the efficiency of equilibrium play drives a wedge between the two games.<sup>15</sup>

### 2.1.3 Comparison of the SPE Predictions

That the encouragement effect appears in the EG but not in the PGG yields two testable theoretical predictions.<sup>16</sup> These are the predictions that we have pre-registered on the Open Science Framework platform at <https://osf.io/> (Name: Exploration in partnership).

We summarize the main SPE hypotheses below.

<sup>15</sup>Even if both the costs and benefits of contributing in the public goods game were symmetric, then still the exploration game would yield higher welfare when parameter values satisfy:  $\alpha/K < c < \min\{\alpha/(K-1), \alpha(1+\delta)/K\}$ . In the fully symmetric parameters case though, the total amount of contributions in equilibrium is monotonically increasing in  $\alpha/K$  in both the public goods and exploration game.

<sup>16</sup>Instead of considering the subgame perfect Nash equilibria, one can compare the sets of Nash equilibria in the two games. All Nash equilibria of the public goods game are also Nash equilibria of the exploration game, but the Nash equilibrium with encouragement in the exploration game is never a Nash equilibrium in the public goods game. Thus analogs of the listed hypotheses hold for the setwise comparison as well.

1. *SPE Contribution Hypothesis*: Aggregate contributions across player types and treasure sizes will be weakly higher in the exploration game than in the public goods game. This prediction is primarily driven by first-players contributing more in the exploration game compared to the public goods game when facing the second lowest treasure size.<sup>17</sup>
2. *SPE Encouragement Effect*: Player 2 will on average contribute more than player 1 in the public goods game and, for a limited range of treasure sizes, the wedge between player 1's and player 2's exploration efforts will be smaller in the exploration game than in the public goods game.
3. *SPE Non-monotonicity Hypothesis*: In the exploration game, player 1's contributions will be non-monotonic in treasure size. In the public goods game, player 1's contributions are monotonic in treasure size.

A key intuition behind all these theoretical predictions is that there is an informational encouragement effect present in the relevant range of the value of the public benefit in the exploration game, contrary to the public goods game. Player 1 can face an implicit threat that his failure to contribute will trigger player 2 to not contribute as well. In reverse, there is also an implicit promise that his contribution will trigger player 2 to contribute as well (if the treasure is not found). Equivalently, the uncertainty in the production process of the public good invokes a complementarity between the two players' contribution decisions. As a result, aggregate equilibrium contributions or contributions to the public good are weakly higher in the exploration game than in the public goods game.

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<sup>17</sup>If the sample is balanced across treasure sizes, the predicted average number of contributions in the EG equals  $1/4 \times 0 + 1/4 \times 1.75 + 1/4 \times 1 + 1/4 \times 1.75 = 1.125$ . In the PGG, the prediction equals  $1/4 \times 0 + 1/4 \times 0 + 1/4 \times 1 + 1/4 \times 2 = 0.75$ .

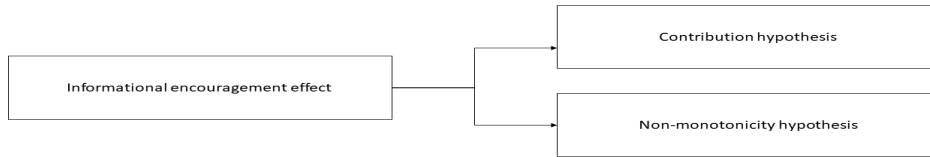


Figure 3: Logical connections between SPE hypotheses

As a final remark, we illustrate that the self-interested, risk-neutral subgame-perfect equilibrium predicts that total surplus is weakly closer to first best in the EG than in the PGG for every treasure size when assuming  $\alpha_{EG} = 4\alpha_{PGG} = 4\alpha$ , i.e. that for risk-neutral players the myopic incentive to contribute is the same in EG and PGG at each threshold treasure size (see Section 2.1.2).

Consider the following levels of treasure size VERY VERY LOW ( $\alpha_{PGG} < 100$  and  $\alpha_{EG} < 400$ ), VERY LOW ( $100 \leq \alpha_{PGG} < 150$  and  $400 \leq \alpha_{EG} < 600$ ), LOW ( $150 \leq \alpha_{PGG} < 200$  and  $600 \leq \alpha_{EG} < 800$ ), HIGH ( $200 \leq \alpha_{PGG} < 300$  and  $800 \leq \alpha_{EG} < 1200$ ) and VERY HIGH ( $\alpha_{PGG} \geq 300$  and  $\alpha_{EG} \geq 1200$ ). Notice that these treasure size levels cover the entire space of potential treasure sizes.

Looking at the predicted contributions of player 1 and the player 2 in Section 2, it is easy to calculate the expected total surplus in SPE. This latter is listed in the middle column of Table 1 for each treasure size class, and both for the PGG and for the EG. The first best contribution levels are even more straightforward to calculate: for a given number of treasures and options left, a player should contribute if two times the expected treasure size (each player receives the treasure value and thus the gross surplus equals  $2\alpha$  if the treasure is found) is greater than the private cost. Thus in the PGG, player  $i$  should contribute iff  $2\alpha_{PGG} > c_i$  (how we break the ties does not matter here). In the EG, player  $i$  should contribute if  $2\alpha_{EG}/Y - c_i$  where  $Y$  is the number of alternatives that have a positive probability of containing a treasure. Thus in the EG, player 1 should contribute if  $\alpha_{EG}/2 > 300$ . Player 2's first best contribution depends on whether player 1 contributed and whether a treasure was found. If player 1 contributed and found the treasure, then player 2 should not contribute. If player 1 contributed and did not find

a treasure, player 2 should contribute iff in addition  $2\alpha_{EG}/3 > 200$ . If player 1 did not contribute, then player 2 should contribute iff  $\alpha_{EG}/2 > 200$ . The implied first best surplus is calculated in the rightmost column of Table 1. One can immediately see that the social surplus is weakly higher in the EG than in the PGG at all levels of treasure size. Thus from the perspective of social surplus, the EG is predicted to reach a higher level of efficiency than the PGG.

Table 1: Expected total surplus

	<b>Surplus at SPE</b>	<b>Surplus at First Best</b>
<i>Very very low</i>		
PGG	0	0
EG	0	0
<i>Very low</i>		
PGG	0	$2\alpha - 200$
EG	0	$2\alpha - 200$
<i>Low</i>		
PGG	0	$4\alpha - 500$
EG	$4\alpha - 450$	$4\alpha - 450$
<i>High</i>		
PGG	$2\alpha - 200$	$4\alpha - 500$
EG	$2\alpha - 200$	$4\alpha - 450$
<i>Very high</i>		
PGG	$4\alpha - 500$	$4\alpha - 500$
EG	$4\alpha - 450$	$4\alpha - 450$



## 2.2 Behavioral Model of Sequential Exploration.

Our basic model so far assumes that each player chooses the action with the highest payoff for sure (people always perfectly optimize) and only considers his or her own payoffs (people are selfish). In this section, we relax these two assumptions. We extend our model to allow people to imperfectly optimize and have social preferences.

### 2.2.1 Imperfect Optimization

While providing a useful benchmark for understanding choice behavior in our setting, the subgame perfect Nash equilibrium also presumes strong rationality assumptions about the capacity of implementing the optimal strategy with certainty. Real behaviors, however, are typically error-prone. In our setting, players might make errors and understand that others also make erroneous choices.

This notion of bounded rationality<sup>18</sup> can be formally incorporated into our set-up by deriving the logit quantal response equilibrium (QRE) (McKelvey and Palfrey 1998) instead of the SPE.<sup>19</sup> In the logit-QRE, the choice probabilities reflect rationality in the sense that they are inversely related to the opportunity costs of the choices and the implied choice probabilities are correctly anticipated by the agents. While better strategies are more likely to be played than worse strategies, there is no guarantee that best response strategies and actions are played with certainty, and this fact is understood by all players. This relatively small departure from perfect rationality has been found to produce predictions that better fit data from laboratory experiments (Anderson et al. (1998), Goeree and Holt (2000), Goeree et al. (2010)).

In the logit quantal response model, the choice probabilities are proportional to the exponentials of the expected utilities,  $v_i$ , of the actions given the beliefs about the opponent's behavior. Let us denote the expectation of player  $i$  about the action profile  $a_j$  of the other player by  $\hat{b}_j^i(a_j)$ . In the quantal response equilibrium, player  $i$  chooses

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<sup>18</sup>See Grüne-Yanoff (2007) for an encompassing discussion of the role of the concept of bounded rationality in economics and psychology.

<sup>19</sup>We motivate our decision to study the QRE as follows: In our experimental setting, participants have ample opportunity to learn about the population behavior and to adapt their behavior accordingly. Indeed, the game is played several times in each of the different public good value specifications, altogether more than thirty times. The quantal response model, where players are assumed to have correct expectations about population behavior, thus strikes us as a more appropriate solution concept for the behavioral analysis than concepts analyzing inexperienced players (Crawford et al. 2013). On the other hand, models analyzing learning dynamics explicitly (Erev and Haruvy 2013) seem unnecessarily complicated for our main focus. The QRE-model is a simpler one-parameter model whereas non-equilibrium models of strategic thinking and learning models typically rely on a higher number of parameters.

action  $a_i$  with probability

$$b_i(a_i) = \frac{\exp\left((1/\mu) \left(\sum_{a_j} \hat{b}_j^i(a_j) v_i(a_i, a_j)\right)\right)}{\sum_a \exp\left((1/\mu) \left(\sum_{a_j} \hat{b}_j^i(a_j) v_i(a, a_j)\right)\right)}. \quad (4)$$

This formulation allows for considering both erratic decision making by self-interested agents (replace  $v_i$  with  $\pi_i$ , the pecuniary payoff of  $i$ ) and other-regarding agents (use a more general value function  $v_i$  as we do in Section 2.2.2 below).

Taking the ratio of choice probabilities of two different actions  $a'_i$  and  $a''_i$  (the odds ratio) yields

$$\frac{b_i(a'_i)}{b_i(a''_i)} = \frac{\exp\left((1/\mu) \left(\sum_{a_j} \hat{b}_j^i(a_j) v_i(a'_i, a_j)\right)\right)}{\exp\left((1/\mu) \left(\sum_{a_j} \hat{b}_j^i(a_j) v_i(a''_i, a_j)\right)\right)}, \quad (5)$$

and thus the ratio of choice probabilities is proportional to the ratio of exponentials of expected utilities. Expectations and choice probabilities must coincide in equilibrium and thus  $\hat{b}_j^i = b_j$  for  $j \neq i$ . The novel feature is noise, which increases in the noise parameter  $\mu$ . As  $\mu$  approaches infinity the choices are entirely random. As  $\mu$  tends to zero (from above), the choice probabilities converge to a Nash equilibrium of the game. Thus with  $\mu$  tending to zero and  $v_i$  replaced with  $\pi_i$ , we are back in the analysis of Section 2.1. The log of the odds ratio of choice probabilities in the QRE-model is merely

$$(1/\mu) \left( \sum_{a_j} \hat{b}_j^i(a_j) v_i(a'_i, a_j) - \sum_{a_j} \hat{b}_j^i(a_j) v_i(a''_i, a_j) \right) \quad (6)$$

and therefore it perfectly linearly reflects the expected payoff difference between choosing the two actions given the expected behavior of others.

In the sequel, we denote the probability of contributing, or the contribution rate, of player  $i$  by  $b_i$ . The probability of not contributing is thus  $1 - b_i$ . Moreover, we denote by  $b_2(e)$  the contribution rate of player two in the contingency  $e$ .

The amount of contributions  $b_1 + b_2$  (in probability mass terms) with imperfectly optimizing selfish players in the exploration game is, as in SPE, weakly greater than in the public goods game when aggregating over treasure sizes. The informational encouragement effect now appears for *all* treasure sizes (or values of the public good) in the exploration game, and yet continues to be absent in the public goods game. The intuition for this result is that now, for any given configuration of parameter values, *both*

player 2's actions (to contribute or not) occur with positive probability, and, given the information externality, contribution by player 1 always increases the payoff of contribution to player 2. Furthermore, for sufficiently large  $\mu$  the informational encouragement effect is now increasing in treasure size. Intuitively, when the stakes are higher, player 2 has more to gain following contribution by player 1. In the Appendix A, we present the formal analysis of the contribution behaviors in the QRE for the public goods and exploration games with selfish players.

### 2.2.2 Other-regarding Preferences

The behavioral and experimental economics literature on voluntary public goods provision in environments where there is no exogenous uncertainty provides a lot of evidence that other-regarding preferences must be invoked to understand the empirical contribution patterns. Although our focus is on understanding the implications of the informational encouragement effect, other-regarding preferences are likely to play a role. We thus want to understand its role in the present context and in the end be able to isolate the residual effect of the information channel when the other-regarding channel is controlled for. We therefore incorporate a more general model of preferences that embeds difference aversion and social welfare preferences as parsimonious and tractable special cases. This more general model also nests purely selfish preferences as a limiting case. We allow for people not only to be self-interested but also to care about social efficiency and inequity by integrating the goal function in a generalized version of the social welfare model by Charness and Rabin (2002).<sup>20</sup> In our setting, this goal function can be written in the following form

$$v_i(a_i, a_j) = \begin{cases} (1 - \rho) \cdot \pi_i(a_i, a_j) + \rho \cdot \pi_j(a_j, a_i) & \text{if } \pi_i(a_i, a_j) \geq \pi_j(a_j, a_i) \\ (1 - \sigma) \cdot \pi_i(a_i, a_j) + \sigma \cdot \pi_j(a_j, a_i) & \text{otherwise} \end{cases},$$

---

<sup>20</sup>Since the novelty and focus in our model and experiment is the information externality channel, and the well-documented other-regarding preference channel generates encouragement irrespective of the particular model specification, we decided to adopt a highly simplified consequentialist preference framework although it is known to abstract from some important nuances of human behavior (Falk et al. 2008). The inequity aversion model of Fehr and Schmidt (1999) the reciprocity models (Charness and Rabin 2002, Cox et al. 2007, Dufwenberg and Kirchsteiger 2004, Falk and Fischbacher 2006) and also the social esteem model of Ellingsen and Johannesson (2008) would make very similar predictions as the social welfare utility model.

for  $i = 1, 2$ , where  $\rho$  and  $\sigma$  may be negative, zero, or positive and  $\rho \geq \sigma$ .<sup>21</sup> The parameters  $\rho$  and  $\sigma$  allow for a range of different distributional preferences that rely solely on the outcomes and not on any notion of reciprocity. For instance, when  $1 \geq \rho \geq \sigma > 0$ , then these parameter values capture social welfare concerns; whereas when  $1 > \rho > 0 > \sigma$ , these parameter values correspond to inequity or difference aversion. Irrespective of the specific distributional preferences we consider,  $\rho$  is always understood to be greater than  $\sigma$  (Charness and Rabin 2002).<sup>22</sup>

### 2.2.3 Second-player Incentives and the Encouragement Effect

Let's consider first the *public goods game*. In the public goods game, every player's contribution yields a marginal per capita return of  $\alpha_{PGG} = \alpha/K$ , an ex ante fixed and certain value of public good. Suppose first that player 1 did not contribute. Then player 2's payoff equals

$$\alpha_{PGG} - (1 - \sigma)c_2 = \frac{\alpha}{K} - (1 - \sigma)c_2$$

if she contributes and 0 otherwise. Notice that the parameter  $\sigma$  indicates player 2's concern for player 1 if the payoff of player 2 is lower than that of player 1. Parameter  $\sigma$  appears here since player 1 did not contribute ( $a_1 = 0$ ) and therefore player 2's payoff falls short of that of player 1 if the player 2 contributes. In this case, the proportion of choice probabilities between contributing and not contributing equals

$$\frac{b_2(a_1 = 0)}{1 - (b_2(a_1 = 0))} = \exp\left((1/\mu) \left(\frac{\alpha}{K} - (1 - \sigma)c_2\right)\right), \quad (7)$$

and the log of the odds ratio between contributing and not contributing (7) is thus merely

$$(1/\mu) \left(\frac{\alpha}{K} - (1 - \sigma)c_2\right). \quad (8)$$

<sup>21</sup>Often, it is assumed that  $0 \leq \rho \leq 1/2$  so that weight on the other is never greater than the weight on oneself. Charness and Rabin (2002) provide very convincing evidence consistent with  $\rho > \sigma$ . For simplicity, we abstract from the reciprocity parameter of the original three-parameter model. Moreover, like Fehr and Schmidt (1999), we allow even negative values of  $\sigma$  and  $\rho$ . Notice indeed that the inequity aversion model of Fehr and Schmidt (1999) is a special case of this model with the parameter for aversion for advantageous inequality  $\rho$  and the parameter for aversion for disadvantageous inequality  $-\sigma$ . The parameters of the model of Fehr and Schmidt (1999) are further constrained by  $-\sigma \geq \rho \geq 0$ .

<sup>22</sup>Initially our pre-elicitation of other-regarding preferences using Murphy et al. (2011) aimed at making individual-specific predictions but it turned out that there is too little variation in these across individuals (see the Appendix C). According to the results of the elicitation, the average participant in our study is other-regarding thus justifying the preference model.

Suppose next that player 1 did contribute. Then player 2's payoff equals

$$2\alpha_{PGG} - (1 - \rho)c_2 - \rho c_1 = 2\frac{\alpha}{K} - (1 - \rho)c_2 - \rho c_1$$

if she also contributes and

$$\alpha_{PGG} - \rho c_1 = \frac{\alpha}{K} - \rho c_1$$

if she does not. Notice that the parameter  $\rho$  indicates player 2's concern for player 1 if the payoff of player 2 is higher than that of player 1. Parameter  $\rho$  appears here since player 1 contributed and has a higher contribution cost than player 2. Therefore player 2's payoff is higher than that of player 1 whether player 2 contributes or not. The log of the odds ratio between contribution and free-riding is thus

$$(1/\mu) \left( \frac{\alpha}{K} - (1 - \rho)c_2 \right). \quad (9)$$

In the public goods game, the only difference between expressions (8) and (9) is the behavioral other-regarding parameter terms in front of player two's contribution cost. Since  $\rho > \sigma$ , we thus establish that an *other-regarding* player two is more likely to contribute if player one also contributed. By contrast, a *selfish* player two's contribution decision (when  $\sigma = \rho = 0$ ) remains unaffected by player one's contribution choice in the standard public goods game, i.e. the public goods game. In sum, we find that an *other-regarding encouragement effect* now appears even in the public goods game, in opposition to the analysis of Section 2.1, provided that player two holds social preferences.

Consider next the *exploration game*. The analysis unfolds as in the public goods game: the other-regarding encouragement effect appears due to second-player's higher weight on first-player's welfare when first-player has contributed and thus falls behind the second-player in terms of payoff. Yet, unlike in the public goods game, first-player contribution influences second-player incentives also through an information channel. If first-player contributes and fails to find the treasure, then second-player has a higher chance of finding the treasure. Thus, the equation that describes the log-odds of second-

player contribution to no-contribution probabilities now reads

$$(1/\mu) \left( \frac{\alpha}{K-1} - (1-\rho)c_2 \right). \quad (10)$$

instead of (9). The second-player log-odds in the exploration game in the case that the first-player does not contribute coincide with those in the public goods game, i.e. (8).

Equations (8) to (10) allow us to decompose the total encouragement effect (10) – (8) into an informational effect (10) – (9), and a other-regarding effect (9) – (8). The greater are these differences, the greater are the corresponding encouragement effects. Clearly, encouragement should be stronger in the exploration game since the information channel only appears there.

#### 2.2.4 First-player and Aggregate Behavior

In the behavioral model, the other-regarding and informational encouragement effects influence second-player behavior in a more continuous manner than in SPE-theory where agents are perfectly rational and self-interested. Independently of the treasure size, the second-player will be more likely to contribute if the first-player contributes (conditional on the treasure not being found) (See Appendix A for a formal analysis). The dynamic incentive effect will thus influence first-player incentives to contribute at all treasure sizes, not just at the second-lowest treasure size. One can show that when parameters  $\mu$ ,  $\rho$ , and  $\sigma$  are sufficiently close to zero (and thus players are almost perfectly rational and self-interested), the non-monotonicity of the first-player behavior still appears.

However, when  $\mu$  is sufficiently high, the predicted first-player behavior is monotone in treasure size (see proof in the Appendix A). The horizontal lines in Figure 4 and 5 in section 3.5, depict the first-player and second-player contribution probabilities, respectively, for each treasure size in the two games for a representative agent model with parameter values  $\mu = 18$ ,  $\rho = 0$ , and  $\sigma = -1/6$ . First-mover behavior is monotone in treasure size in EG. The figures also show that contributions are, on aggregate higher in the EG than in PGG. For the case  $\mu = 18$ ,  $\rho = 0$ , and  $\sigma = -1/6$  the expected total contributions equal 0.76 and 0.94 in the PGG and EG, respectively. Moreover, one can derive a more general condition such that contribution rates in the EG are larger than in the PGG. Proposition A.4 in the Appendix A shows that quite generally, contributions

in the EG are higher than in PGG. It is natural to think that participants differ in characteristics relevant for  $\mu$ ,  $\rho$ , and  $\sigma$  and thus a model allowing for heterogeneity in this respect would be more realistic. Yet, as will be illustrated in Section 4, we lack individual level variation to empirically test such a model.

### 2.2.5 Behavioral Predictions

A straightforward comparison between the QRE for the exploration and public goods game, now allowing for a more general model of individual preferences, yields three distinct sets of testable theoretical predictions.

The following hypotheses consider the logit quantal response equilibrium for the exploration game (uncertainty) and voluntary public goods game (certainty), with players who care about their own payoff and potentially also about the payoff of their counterpart:

1. *Behavioral Contribution Hypothesis.* The aggregate contributions will be weakly higher in the exploration game than in the public goods game.<sup>23</sup>
2. *Behavioral Encouragement Effect.* In the exploration game, regardless of treasure size, the second-player is more likely to contribute if the first-player contributed but did not find a treasure compared to if the first-player did not contribute, and this difference is higher than its counterpart in the public goods game.<sup>24</sup>
3. *Behavioral Monotonicity Hypothesis.* The contribution of the first-player increases with the treasure size in the exploration game (due to stochasticity in second-mover responses to first-mover behavior).<sup>25</sup>

The behavioral analysis of Section 2.2 distinguishes the *informational* encouragement effect (compare equations (10) and (9)) and *other-regarding* encouragement effects (compare equations (9) and (8)). An *other-regarding* encouragement effect occurs in the public goods game provided player 2 holds other-regarding preferences: player 2 reacts to the contribution by player 1 by increasing the probability of contributing. The informational behavioral effect occurs in the exploration game due to the fact that first-player

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<sup>23</sup>There exists parameter values such that this happens, and proposition A.4 in the Appendix A shows that this holds quite generally.

<sup>24</sup>This latter is the theoretically predicted other-regarding encouragement effect, i.e. the difference between equations (9) and (8).

<sup>25</sup>This holds for  $\mu$  sufficiently high, see Appendix A.

contribution without finding the treasure increases the second-player's chances of finding the treasure and thus the probability of contributing. This informational effect, unlike in the SPE model, occurs for all treasure sizes in the exploration game. By subtracting the other-regarding behavioral encouragement effect from the informational behavioral encouragement effect, we can identify whether the informational effect plays a significant role or whether the encouragement is mainly driven by the other-regarding effect previously identified in the literature. The monotonicity effect merely notes that now in the behavioral model, encouragement occurs for all treasure sizes, for sufficiently high level of randomness in second-player behavior, the encouragement will increase in treasure size and even first-mover behavior will be monotone in treasure size. Notice also, that given first-player behavior and the outcome of first-player search, the probability of second-player contribution is increasing in treasure size. Yet, of course, the more likely is first mover contribution in the EG, the more likely it is that the treasure will be found in which case the second-player has fairly weak incentives to contribute. Thus, if the first-mover probability of contribution increases drastically as the treasure size increases, then the unconditional probability of second-player contribution may even fall.

Table 2 displays the testable theoretical predictions from both the SPE and Behavioral models. We use the term  $B$  to denote the contribution by the respective players 1 and 2, facing the four different treasure sizes in the two games.

Table 2: Testable theoretical predictions from the SPE and Behavioral Model

<b>Hypothesis</b>	<b>SPE</b>	<b>Behavioral</b>
Contribution Hypothesis	$B_{EG} > B_{PGG}$	$B_{EG} > B_{PGG}$
Encouragement Effect	$B_{2,EG,700}(a_1 = 1, Y = K - 1) > B_{2,EG,700}(a_1 = 0)$	<i>for all</i> $\alpha$ $B_{2,EG,\alpha}(a_1 = 1, Y = K - 1) > B_{2,EG,\alpha}(a_1 = 0)$
Non-monotonicity Hypothesis	$B_{1,EG,700} > B_{1,EG,500}$ $B_{1,EG,1000} < B_{1,EG,700}$ $B_{1,EG,1400} > B_{1,EG,1000}$	$B_{1,EG,700} > B_{1,EG,500}$ $B_{1,EG,1000} > B_{1,EG,700}$ $B_{1,EG,400} > B_{1,EG,1000}$

\* $B_{i,g,\alpha}$  refers to the contribution rate of player  $i$  in game  $g$  when the treasure size is  $\alpha$

$B_{2,g,\alpha}(e)$  specifies the (second player) contribution rate conditional on endogenous event  $e$ .

EG refers to the exploration game and PGG to the public goods game.

$B_{EG} = \sum_{i=1}^2 (1/4 \times B_{i,EG,500} + 1/4 \times B_{i,EG,700} + 1/4 \times B_{i,EG,1000} + 1/4 \times B_{i,EG,1400})$  and similarly for  $B_{PGG}$ .



### 3 Study Design and Data

To test our hypotheses we set up a lab experiment. We ran the experiment at the Cobe Lab (Aarhus University, Denmark), the Aalto Choice Tank (Aalto University, Helsinki, Finland), and the Centre for Experimental Studies and Research (BI Norwegian Business School, Oslo, Norway) during fall 2014 - spring 2016. In total 436 subjects were recruited using identical recruitment procedures.<sup>26</sup> Each subject completed a 10-minute online survey at least 5 days before participating in the laboratory experiment. The laboratory session lasted on average 70 minutes. A 6.10 USD participation fee and subsequent earnings, which averaged 7 USD, were paid in private at the end of the laboratory session.<sup>27</sup>

#### 3.1 Online Survey

After signing up to the two-part study, participants could enter the online survey directly. At the outset, participants faced five questions so as to create an anonymous personal identifier. Later, participants used this identifier to sign into the laboratory experiment. This procedure allowed us to ensure the anonymity of the participants when merging their answers from the survey with their answers from the laboratory experiment. In the online survey, we measured Social Value Orientation (SVO), risk preferences, and cognitive reasoning style. Social value orientation was measured using the SVO Slider Measure (Murphy et al. 2011), which is a six-item questionnaire where each question consists of a choice of one out of nine possible allocations of money between oneself and another anonymous participant. We used Experimental Currency Units (ECU) as currency in the online survey, and after the study was completed they were converted

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<sup>26</sup>To recruit our subjects, we used ORSEE (Greiner et al. 2004) in Norway and SONA in Denmark and Finland. The recruitment text included information about the duration, location, and incentives for both parts of the study, the online survey, and laboratory experiment. Before running the experiment we calculated a rough sample size using List et al. (2011). We assumed a power of 80% and a significance level of 5%, and to have a minimum detectable effect size of 50% we needed at least 64 observation in each group. At the time we considered a sample of around 400 participants to be large enough for the normal distribution and a good approximation for the t-distribution. In retrospect we should have done this more carefully and used the effect sizes from previous literature, when calculating the sample size. We therefore ran a post power calculation in line with Gelman and Carlin (2014) for the contribution hypothesis. When we calculated the post power analysis we used the minimum detectable effect sizes from the results with binary outcomes in Klor et al. (2014) and Steiger and Zultan (2014), i.e. 20%, and our standard error from Table 4.1., column 1. The results indicate that we have do not have a power issue, the post power is high (0.99).

<sup>27</sup>If a participant could only complete the online survey he or she was paid half the show up fee of 3.05 USD. In Norway, the average total earnings in the experiment were 42.18 USD. The higher rate was applied in order to meet the average earnings requirements of the local laboratory.

to the local currency, with an exchange rate of 30 ECU = 1.14 USD. At the start of the laboratory experiment we randomly selected in public one of the six SVO questions to be subject to payment. To measure risk aversion, we relied on two measures. The first measure was the Gneezy and Potters (1997) investment task. The participants were given 60 ECU and could invest any amount between 0 and 60 in a lottery with a 2/3 probability of getting nothing and 1/3 probability of winning two and a half times the amount invested. At the laboratory experiment we also publicly announced whether the investment task was a success or a failure in the laboratory. We publicly showed the participants three cards with letters A to C that we placed in an empty urn and shuffled. We invited one of the participants to draw one of the three cards from the urn. If the A card was drawn, each participant won two and a half times the amount he or she had invested. We complemented this risk measure with a hypothetical question asking the participant to rate his or her general risk taking on a scale from 0 to ten, with 0 being risk averse and 10 being risk loving (Dohmen et al. 2011). To measure cognitive reasoning style, we used the Cognitive Reflection Task (CRT) (Frederick 2005), which consists of three questions, without incentives. Finally, we asked the participants about their gender. The full questionnaire is in the Appendix D.

### 3.2 Laboratory Experiment

The laboratory experiment was an internet-based game programmed for the purpose of this experiment.<sup>28</sup> The participants in each session were randomly assigned a game type specific code on paper (both the exploration game and the public goods game were run in parallel in each session to ensure control for day-of-the-week or hour-of-the-day and other session effects, see Levitt and List (2011)). The software also randomly assigned each player to one of the two player types. On a few occasions, very few students signed up. Here, we randomly assigned participants to player types within sessions and randomized game type played in these sessions. We control for this in the analysis of Section 4.4. The participants played 32 rounds of either the sequential public goods or the sequential exploration game, and as either player 1 or player 2. They all encountered four levels of treasure sizes; i.e., eight rounds of each treasure size. Most participants faced the treasure sizes in ascending order. To study order effects we let a few randomly drawn

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<sup>28</sup>We thank the programmer Kristaps Dzonsons for his programming assistance

sessions face another treasure size order.

Before the laboratory experiment started, we made two random draws in public to establish the rewards tied to choices made in the online survey.<sup>29</sup> Next, we used streamed video instructions to facilitate the understanding of the laboratory game. In a simple way, the video described how the game rounds proceeded, how tournament incentives operated, and how we carried out the matching.<sup>30</sup> The participants then logged in to the game using the game type specific codes and the anonymous unique identifiers that they had created at the onset of the online survey. The participants faced written instructions and control questions (see the Appendix D). At any time of the experiment, the participants could revisit the instructions. Upon having correctly completed the control questions, the first game round could start.

At the beginning of the first game round each participant received an endowment of 12000 points. The participant's tally of points was visible and updated automatically while playing, according to the outcome of each game round. In the instructions, we informed the participants to collect as many points as possible across the game rounds. The number of rounds were however unknown to the participants. In each session the first- and the second-player with the most number of points in the public goods and exploration game respectively received a monetary prize of 13.68 USD. Each game round started with player 1 seeing four closed chests. In addition, the screen contained information of the participant's current number of points, the cost of contributing, the counterpart's cost of contributing, the size of the treasure (the treasure sizes were 500, 700, 1000, and 1400 points in the exploration game and 125, 175, 250, and 350 in the public good game), and the number of treasures left to explore. There was no information about other participants' current tally of points. The cost of contributing was kept constant throughout the session, and always higher for player 1 than for player 2 (300 versus 200 points). See Figure B.1 in the Appendix B for an image of the decision screen. Player 1 knew that player 2 will observe his or her choice before making his/her own choice. Participants playing the public goods game knew that there is a treasure of known size in each chest. In the exploration game participants knew that only one out of four chests contains a treasure. Each size of the treasure in the exploration game was

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<sup>29</sup>This did not generate uncontrolled variation since we randomized groups within each session.

<sup>30</sup>The video-instructions were 14 minutes long; visit the following link to view the video: <https://dreambroker.com/channel/1ehcya5t/77qp05es>

four times the corresponding size in the public goods game, thus keeping the expected total treasure value and the myopic incentive to contribute equal across game types.

Player 1 then had to decide whether to pay to open a chest or not. Conditioned on player 1's choice, player 2 had the same choice to make. When the second-player had made his /her choice, both players received feedback on the outcome of the game. Before each new round of the game the participant was randomly re-matched with another participant of the opposite player type within the same game type. When a participant had completed 32 rounds, the screen informed him/her of his/her total number of points. Finally, we announced the anonymous personal identifiers of the first- and the second-player winners publicly. A research assistant at each lab asked the participants for their anonymous personal identifier, found the individual specific amount of ECU they had earned in both parts of the study, converted these into EUROS, added the show up fee of 5 EURO, and noted this on a separate piece of paper. Aarhus University then transferred the money to the participants' bank accounts. At Aalto University in Helsinki and BI Norwegian Business School in Oslo, the participants then received the earnings immediately in cash.

### 3.3 The Incentive Scheme

Players 1 and 2 were by design incentivized to work as a team, but neutral language was used. Each participant in a given player role was incentivized to compete against the other participants in that role in the group with the same game type, but not against the participants in the opposing role that she was matched with. We expected such tournament incentives to (i) induce more self-interested behaviour relative to a monetary compensation that is directly proportional to the tally of collected points, (ii) afford greater control over the self-interested encouragement threshold, and thus (iii) produce a more favourable setting for the hypothesized non-monotonicity effect to arise. To see this, consider a first mover who compares herself with the other first movers in the matching group and who has other-regarding preferences of the Charness and Rabin (2002, pp.851) form with the purely Rawlsian formulation (i.e.  $\delta = 1$ ). Now if she earns the highest tally of points, she wins 13.68 USD, and her utility equals  $(1 - \lambda)13.68 + \lambda 0$ , where  $\lambda$  captures how much she cares about pursuing the social welfare versus her self-interest. On the other hand, if she is not the player with the highest tally of points,

then she earns 0 euros, and her utility equals  $(1 - \lambda)0 + \lambda 0 = 0$ . Thus, the strength of the preference for winning depends on the unobserved parameter  $\lambda$ . Independently of the value of  $\lambda$ , the winning outcome gives a higher payoff than the losing outcome, and every losing outcome gives the same payoff independently of the identity of the winner. The tournament scheme implemented is thus designed to strengthen the incentive to behave as if self-interested and to downplay other-regarding motivation. It can easily be shown that this holds for all parameterizations of the outcome-based (consequentialist) versions of the Charness and Rabin (2002) model.

To ensure that the winner-takes-it-all part of the incentive scheme does not create the differences in contribution between the EG and the PGG, we ran an extra experiment in Spring 2019. In particular, we wanted to test the contribution hypothesis in a design without the winner-takes-it-all part of the incentive scheme. In these additional sessions, the experimental design of the EG and PGG remained the same except that now participants were paid according to the total number of collected points. We introduced a conversion rate between the collected points and actual payoff that matched expectations in the main experiment so as to be able to sharply identify the effect of the incentive scheme alone. In Norway, we used a conversion rate of 0.01, where 17000 points translated into 170 NOK, and in Finland, we used a conversion rate of 0.001, where 1700 points translated into 17 EURO. Please find the written instructions for this experiment in the Appendix E.

Before running the extra experiment, we calculated the optimal sample size needed to credibly detect an effect size for the contribution hypothesis. We thus assumed that the true effect size is the effect size of the contribution hypothesis in the main study<sup>31</sup>. Moreover, we assumed a power of 0.8 and a significance level, given that we aimed to test only one hypothesis, of 0.05. In this case, the optimal sample size is 36 participants in each of the two groups (EG and PGG). We ran two sessions in Oslo, Norway, and one session in Helsinki, Finland. A total of 54 participants completed the extra experiment. We then re-estimated Table 4 using the data from the extra experiment, i.e. with no group tournament incentives. The results are similar to those in our main study, which suggests that the group tournament incentive scheme is not the cause of the found differences in contribution between the two game types. Please see Appendix Table

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<sup>31</sup>Here, we used the effect size from the experiment ran in Oslo.

B.1.<sup>32</sup>

### 3.4 Ethics and Registration of Study

Since the data from the study is never connected to identifying information, the project was not considered for full ethical review according to current legislation in Denmark, Finland, and Norway. At Aarhus University, Denmark, the project underwent an informal ethical review process by the Cobe Lab Ethical Advisory Board.<sup>33</sup> In addition, before running the analyses, but after the experimental data collection, we registered the SPE part of our study design and suggested analysis at the Open Science Foundation (Registration name: Exploration in partnership). In some cases, the analysis below deviates from the originally foreseen specification. We then report this and comment on this in the limitations section.

### 3.5 Data

A total of 430 participants completed both the online survey and the laboratory session. Each participant completed 32 game rounds of play, implying a total of 13760 observations overall. Table 3 displays a summary of the main variables from the online survey across the two game types separately. We confirm in Table B.2 that none of the variables differ significantly by type of game. About half of our sample consisted of women and participants were on average neither risk averse nor risk-loving. The average CRT score was 1.87 (sd:1.10), and 60% of the sample answered correctly all three questions of the CRT.<sup>34</sup> The average SVO angle in our sample equaled 28° (sd: 13.09). Following Murphy et al. (2011), the average participant should thus be classified as prosocial. Table B.2 in the Appendix B shows the randomization check. None of the observable variables differ by game type.

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<sup>32</sup>Since we did not fully reach the optimal sample size we conducted a post power calculation in line with Gelman and Carlin (2014) to ensure that the result is not biased by issues of low power. Here, we used the effect size from the contribution hypothesis in the main experiment and the standard error from the experiment without the group tournament incentive. The calculation shows that we do not have a power issue in this test, (0.97)

<sup>33</sup><http://bss.au.dk/en/cognition-and-behavior-lab/for-researchers/procedure-guide/>

<sup>34</sup>This percentage is higher compared to Frederick (2005), which can be due for example to learning, and the fact that the CRT has become better known over time.

Table 3: Descriptive statistics of online survey variables across game types

	n*	mean	median	sd	max	min
<i>Public goods game</i>						
Gender (1 if woman, 0 otherwise)	190	0.55	1	0.50	1	0
Risky investment choice	183	33.05	30	19.14	60	0
Risk question	186	5.90	6	2.14	10	2
CRT score	186	1.94	2	1.08	3	0
Social Value Orientation	186	26.75	31	13.39	45	-9
<i>Exploration game</i>						
Gender (1 if woman, 0 otherwise)	239	0.55	1	0.50	1	0
Risky investment choice	230	33.83	30	19.21	60	0
Risk question	231	5.70	6	2.16	10	1
CRT score	231	1.94	2	1.06	3	0
Social Value Orientation	231	28.12	33	13.09	61	-16
Observations	430					

\*Some participants did not answer all the survey questions, the number of observations therefore vary.

Figures 4 and 5 show the raw results for first and second player contributions across the four treasure sizes. The darker bars depict average contributions in the public goods game, whereas the lighter bars those in the exploration game. We find that first player contribution increases with treasure size, and hence it does not support the SPE non-monotonicity hypothesis. Rather, observed effects between game types and other qualitative patterns in our data can be better explained with a QRE model that allows for other-regarding preferences. To illustrate this, we have superimposed theoretical predictions of first- and second-player behavior on the observed frequencies for the respective players using parameter values  $\mu = 18$ ,  $\rho = 0$ , and  $\sigma = -1/6$ .<sup>35</sup>

<sup>35</sup>This model deviates from the self-interested subgame perfect equilibrium by introducing three new parameters (noise parameter and two other-regarding preference parameters) and these additional degrees of freedom increase explanatory power by construction (See Miettinen et al. (2017) for instance). In the present experiment there are also qualitative patterns in the data that are consistent with the QRE model with other-regarding motivation but not with the QRE model with self-interested individuals nor with the SPE model with self-interested individuals. For example, we find that the first-player contribution rate increases with treasure size and that in approximately 20% of the time, regardless of treasure size, the second-player contributes even when the treasure has already been found by the first-player in the exploration game. Thus, not only is the explanatory power in statistical terms higher, but also the observed qualitative treatment effects and other qualitative patterns can be better explained with a QRE model that allows for other-regarding preferences.

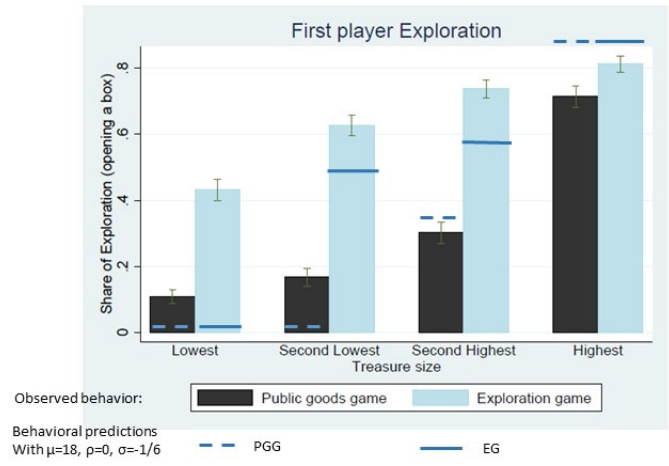


Figure 4: First-player contributions

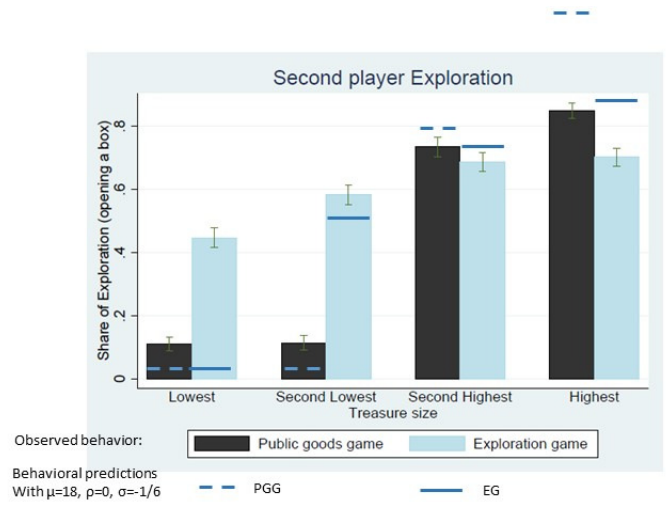


Figure 5: Second-player contributions



### 3.6 Significance Level and Multiple Comparisons

The more null hypotheses we test, the larger the probability of getting false rejections. When designing our experiment and calculating the sample size, we unfortunately did not take into account the multiple hypotheses testing. This section and the corrections were completed post-hoc, after reflecting on insightful comments from the editor and two referees. Before running the analyses, but after the collection of the data, we pre-registered three hypotheses and tests from SPE hypotheses. In post-hoc correction for multiple comparison we focused on part of these tests. The other tests we consider more exploratory, and we apply a conventional significance level of 0.05.

Simple adjustment for multiple corrections post-hoc, such as Bonferroni, might increase the probability of Type II error and reduce the power to detect an effect. We therefore used List et al. (2016) for a more sophisticated procedure of correction. This method does, however, not perfectly apply to our setting. We ran the correction code for the comparisons of the contributions between the groups we randomized (type of game and player) using average contribution for each individual. Our results still hold for such a correction, as shown in Table B.3 in the Appendix B. As a complementary method, we also used a simple post-Bonferroni correction of the 39 regression coefficient tests we present in Tables 4-7, implying an alpha of  $0.05/39=0.0012$ . Revisiting Tables 4-7 our results remain qualitatively the same. In the Figures below we now apply the corrected alpha to construct the error bars.

## 4 Results

To ease the readers' comprehension, we present our results in the order of our main testable hypotheses summarized in Table 3.1, and not in the order of pre-registered plan vs. post-hoc analysis. This makes some of our results exploratory in nature, and they should be interpreted as such. Our results are consistent with the assumption that people imperfectly optimize and care not only about their own payoffs but also about others' payoffs. Our analyses suggest the relevance of a behavioral model of sequential exploration for the public good.

## 4.1 Contribution Hypothesis

We start by analysing how individual contribution behavior varies across game type (public goods versus exploration game). As an additional step, we look at contribution differences between player types. We estimate the following basic equation:

$$b_{i,g} = \gamma_{i,g} + \beta_1 G_{i,g} + \beta_2 T_{i,g} + \beta_3 G * T_{i,g} + \varepsilon_{i,g} \quad (11)$$

where  $b_{i,g}$  denotes whether individual  $i$  contributes or not during game round  $g$  ( $b_{i,g} = 1$  if player  $i$  contributes, 0 otherwise),  $T$  denotes player type (taking the value 1 if the individual is a first-player and 0 otherwise),  $G$  denotes the game type (equaling 1 if the game is the exploration game and 0 otherwise), and  $\varepsilon$  is the error term. Table 4 reports the regression results, derived using a linear probability model (LPM) with robust standard errors clustered by individual and session.<sup>36</sup> Column (1) reports the regressions results for game type and column (2) for both game and player type. Aggregate contribution was about 24 percentage points larger ( $p < 0.001$ ) in the exploration game compared to the public goods game. These results are consistent with the *Contribution Hypothesis*, predicted by both the SPE and Behavioral models. Overall, there is no significant difference between first- and second-players' exploration behavior.

Table 4: OLS: Differences in contributions across player types

	(1)	(2)	(3)
Exploration game	0.244*** (0.022)	0.244*** (0.022)	0.155*** (0.025)
First-player		-0.030 (0.022)	-0.129*** (0.031)
First-player X Exploration game			0.178*** (0.043)
Constant	0.387*** (0.016)	0.402*** (0.017)	0.452*** (0.017)
Observations	13760	13760	13760

Robust standard errors clustered on session and individual

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

<sup>36</sup> Angrist and Pischke (2009, Ch. 3.3 and 3.4) support the choice of the linear specification rather than non-linear alternatives when a saturated model with randomized treatments is used in a panel data setting.

Column (3) of Table 4 further includes the interaction term between game type and player type. Now, the first coefficient estimate reveals that relative to the public goods game, a second-player was 15 percentage points more likely to contribute in the exploration game ( $p < 0.001$ ) than in the public goods game. The marginal effect of player type in the exploration game displays no such gap ( $\beta = -0.049$ ,  $p = 0.101$ ). The second coefficient shows that in the public goods game, the first-player was on average about 13 percentage points less likely to contribute than the second-player. This finding reflects the fact that player 1's cost of contributing is higher than that of player 2. The first-player thus has a larger myopic incentive to free ride. The interaction term suggests that the differences between player types is 18 percentage points larger in the public goods game compared to the exploration game. Taken together, these results confirm the contribution hypothesis, and the observed qualitative patterns indicate a possible encouragement effect.<sup>37</sup>

## 4.2 Encouragement Effect

To test the Encouragement hypothesis we begin by examining player 2's contribution behavior in the public goods game and exploration game separately. Figure 6 reveals that, in the PGG, the share of second-players who contributed was always greater when the first-player contributed than when she did not, except in the highest treasure size. This finding is consistent with the other-regarding encouragement effect.

Table 3 shows that the average value of the SVO angle measure equalled 27 and 28 for the respective subsamples; that is, subjects who played the public goods game and those who played the exploration game. The standard deviation was 13 in both groups. Had a subject consistently been self-regarding, the angle measure would yield a value of 8. Thus our subjects appear predominantly other-regarding. Notice that the SVO measure is a unitary measure. The other-regarding QRE predictions of our model, however, incorporate regards for the other player when there is disadvantageous versus advantageous inequality. Therefore, we developed a protocol that delivers an estimate of  $\rho$  and  $\sigma$  for each individual, using the SVO six slider questions (See Appendix C Deriving

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<sup>37</sup>Given our exogenous experimental variation and a saturated model, the linear probability model is the correct specification (Angrist and Pischke, 2009, Sections 3.3 and 3.4). Yet, even changing the specification to logit does not change our results. If we pool the data across game rounds and cluster on session the results stay the same. See Table B.4 and B.5 in the Appendix B.

$\rho$  and  $\sigma$  using the SVO sliders, for a detailed description). The results show that for the vast majority of our participants,  $\rho \geq 0.5$  and  $\sigma > 0$ . In all, 96.5 % of the participants had preferences  $\rho > \sigma$ .<sup>38</sup> This suggests that the other-regarding encouragement effect should be controlled for. However, given that we lack variation in our individual measures to estimate individual level differential effects of  $\rho$  and  $\sigma$  on contribution propensities, an other-regarding representative agent model is a good approximation.

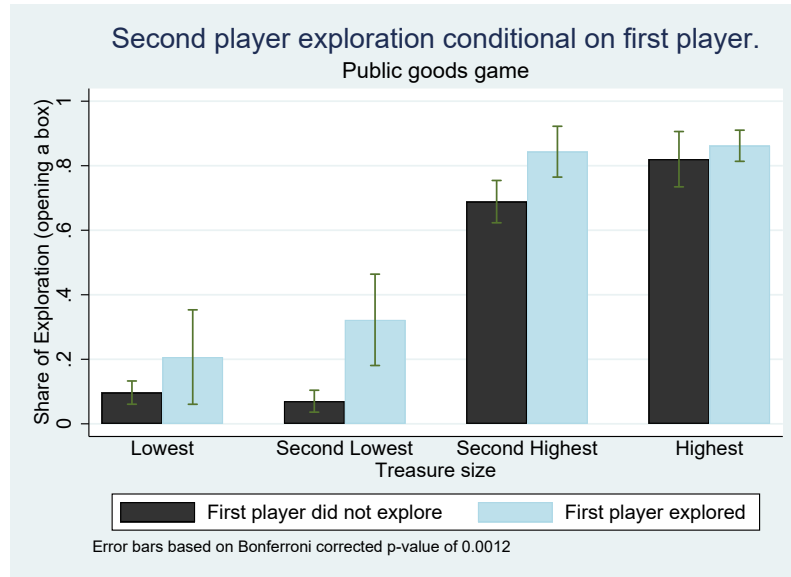


Figure 6: Public goods game: Second-player contribution conditional on first-player contribution

We next turn to the analysis of player 2's decisions in the exploration game. Figure 7 shows that when the first-player did not contribute, the second-player choice probabilities are consistent with what is optimal from a self-interest perspective in the sense that the observed contribution rate is below 50% when the contribution is suboptimal and it is above 50% when the contribution is optimal. Notice that this was true also for the patterns in Figure 6 for the public good game. However, the choices are closer to the boundaries of the private optimum in the PGG whereas they are closer to 50% in the EG. This may be due to the fact that in the EG one needs to calculate the gross expected benefit in the EG whereas it is explicitly given in the PGG. The extra cognitive effort required in the EG may increase the level of noise in behavior and reduce the responsiveness to incentives.

<sup>38</sup>Note that since the slider elicitation method does not involve interactive choices, it does not allow estimating the reciprocity parameter of the Charness and Rabin (2002) model. The second mover choices in the interactive games are likely to reflect the reciprocation preference especially if the first mover does not contribute, which thus leads to an incentive of negative reciprocation.

Figure 7 also shows that those in the role of player 2 were more likely to contribute for all treasure sizes except the highest, following a contribution by player 1 than following no contribution. This result is consistent with the informational encouragement effect, which is expected to occur in both the SPE and Behavioral model of the exploration game, i.e., the SPE informational encouragement effect (for the second-lowest treasure size) and the QRE informational encouragement effect (for all treasure sizes), respectively. That the encouragement occurs for all treasure sizes is inconsistent with the informational encouragement in SPE and consistent with the informational encouragement in the Behavioral model. However, given the prosocial character of the participants in our sample, these discrepancies in contribution decisions are possibly also driven by an other-regarding encouragement effect.

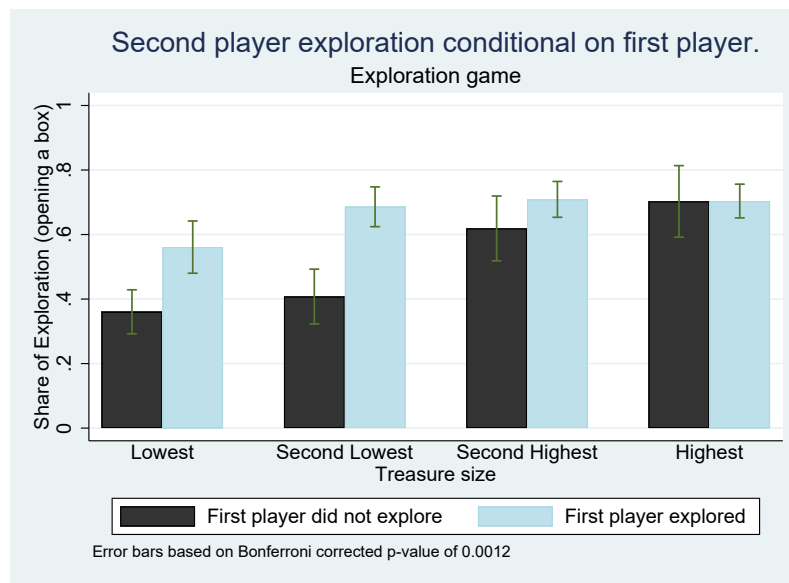


Figure 7: Exploration game: Second-player contribution conditional on first-player contribution

We then disentangle the informational encouragement effect from the other-regarding effect. To this end, we exploit the panel structure of our data and estimate an equation of a similar form as Equation 11. Now  $B_{g,i}$  corresponds to the contribution decision of second-player  $i$  during game round  $g$ . Let  $G$  again denote the game type (equalling 1 if the game is the exploration game and 0 otherwise) and  $T$  the contribution decision taken by player 1. Variable  $T$  is defined differently depending on which game type we consider. In the exploration game (EG) the variable takes on the value 1 if the first-player contributed but did not find a treasure ( $a_1 = 1, Y = 3$ ) and 0 if the first-player did not

contribute ( $a_1 = 0$ ). In the public goods game (PGG) the variable equals 1 if the first-player contributed ( $a_1 = 1, Y = 3$ ) and 0 if the first-player did not contribute ( $a_1 = 0$ ). In the exploration game the difference in second-player contribution rate when the first-player did not find a treasure versus when the first-player did not contribute reflects a combination of all encouragement effects discussed. In the public goods game, however, the difference can only capture a potential other-regarding encouragement effect. The estimated coefficient of the interaction term  $G*T$  in Equation 11 can now be interpreted as a measure of the informational encouragement effect<sup>39</sup>:

$$\begin{aligned}
 \text{Informational} = & \overbrace{(B_{EG}(a_1 = 1, Y = 3) - B_{EG}(a_1 = 0))}^{\text{total}} \\
 & - \overbrace{(B_{PGG}(a_1 = 1, Y = 3) - B_{PGG}(a_1 = 0))}^{\text{other-regarding}}
 \end{aligned} \tag{12}$$

Table 5 presents OLS regression results by treasure size. The first coefficient in each regression is an estimate of the other-regarding encouragement effect in the public goods game. This other-regarding encouragement effect is positive and significant, though it disappears for the highest treasure size. One plausible explanation for this is that for the highest treasure size, the self-interest motive to contribute outweighs any behavioral considerations. The second coefficient in each regression captures the difference between second-player contributions in the exploration game and the public goods game when the first-player did not contribute. The positive coefficients at the two lowest treasure sizes and the negative ones at the two highest ones are likely to reflect the fact that it is simply easier to grasp the privately optimal behavior in the PGG where the gross benefit is explicitly given than in the EG where each participant must calculate the expected benefit based on the treasure size and the number of alternatives to explore. Therefore behavior is closer to the private optimum in the PGG than in the EG (not to contribute for the two lowest and to contribute for the two highest when the first player did not contribute). The third coefficient estimates correspond to the value of the informational encouragement effect. We find that this effect is statistically significant and positive, lending support to the importance of the informational encouragement effect which is

<sup>39</sup>See Table 3.1 for definitions and explanations of  $B_g(e)$

not documented in the experimental literature before.<sup>40</sup>

Table 5: Second-player contributions.

	(1)	(2)	(3)	(4)
	Lowest	2nd lowest	2nd highest	Highest
First-player behavior	0.068 (0.035)	0.245*** (0.038)	0.135*** (0.038)	-0.016 (0.031)
Exploration game	0.286*** (0.026)	0.343*** (0.030)	-0.076 (0.039)	-0.172*** (0.039)
Encouragement (interaction)	0.233*** (0.048)	0.226*** (0.048)	0.188*** (0.048)	0.248*** (0.044)
Constant	0.103*** (0.012)	0.071*** (0.011)	0.695*** (0.026)	0.861*** (0.025)
Observations	3198	3006	3010	3030

OLS has robust standard errors clustered on session and individual.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

### 4.3 Non-monotonicity Hypothesis

The encouragement effect and the non-monotonicity hypotheses are closely linked. We continue to estimate the non-monotonicity by looking at player 1 behavior and player 2 behavior across the treasure sizes in the respective games.

Figures 4 and 5 present the average share of, respectively, contributions of player 1 and 2 by treasure size. These raw averages indicate that individual contribution rate was monotonically increasing in treasure size. Table B.6 and B.7 in the Appendix B show the pre-registered analysis of the contribution gap between pairwise treasure sizes across game types for the first and second-player respectively. Figures 4 and 5 as well as Table B.6 and B.7 do not fully support the *Non-monotonicity Hypothesis*. Despite there being empirical support for encouragement, greater rewards seem to invoke a higher contribution rate. These results cast doubts on the relevance of the SPE game-theoretic predictions in our setting. They lend support to a QRE model with other-regarding preferences for the exploration and public goods games.

<sup>40</sup>If we run a regular OLS regression, dropping the panel structure and cluster on session the results stay the same. See Table B.8 in the Appendix B. Notice also that the number of observations in this table is lower than in Table 8, for instance, since we have dropped the second player choices in the EG where the first player already found the treasure. Had we included those observations, we could not exploit the decomposition of the encouragement effect, but rather the informational effect would be underestimated.

In sum, our results empirically confirm the Contribution Hypothesis, aggregate contribution rate is significantly greater in the exploration than in the public goods game. Consistent with this Hypothesis, we also establish that relative to the public goods game, second-players contribute significantly more in the exploration game. Also, we find support for the Encouragement Hypothesis. We decompose the encouragement effect into two parts: the other-regarding encouragement effect which is positive and significant is already documented widely in the existing literature; the informational encouragement effect, which is also found to be positive and significant, is novel to the literature. However, we do not find indications of a non-monotonic relationship between first-player contribution rate and treasure size. This implies that we do not find an encouragement in the very narrow meaning of the definition, i.e., according to the SPE model. This SPE model would predict a non-monotonicity and incentive reversal due to the range where the first-player should contribute in order to encourage the second-player to contribute for a lower treasure size and free-ride when she knows that the second-player's incentives to contribute are sufficient.

#### 4.4 Additional analyses: Social Value Orientation, Risk Aversion and Cognitive Ability

The main results favor further exploring other-regarding preferences. We thus use the measures of preferences we elicited in the online survey before the experiment. The covariates we collected are orthogonal to the treatment status, and should not affect the results in the regressions. Including them in the regression does not change our results, see Table B.9 in the Appendix B. To examine whether there are heterogeneous effects, Table 6 shows the encouragement effect for the subsample of individualistic participants and Table 7 shows the encouragement effect for the prosocial part of the sample. In line with the theoretical prediction, the encouragement effect driven by other-regarding preferences (first coefficient) is much less pronounced among individualistic individuals compared to pro-social individuals. This lends support to a model with behavioral preferences.

In Table 8 we tried to understand whether the degree of pro-sociality mattered for contributions in the two games. We also performed a similar analysis for risk-aversion and cognitive ability but we failed to detect any difference between the risk-averse and the risk-neutral, on the one hand, and the deliberative and the intuitive thinkers, on



the other hand. Unfortunately, none of these individual characteristics help us further explain differences in contributions.

Table 6: Second player contributions - individualistic players.

	(1)	(2)	(3)	(4)
	Lowest	2nd lowest	2nd highest	Highest
First player behavior	0.015 (0.038)	0.125* (0.049)	0.119* (0.058)	-0.045 (0.051)
Exploration game	0.311*** (0.046)	0.309*** (0.055)	0.014 (0.068)	-0.156* (0.065)
Encouragement (interaction)	0.247** (0.076)	0.386*** (0.075)	0.120 (0.074)	0.297*** (0.071)
Constant	0.092*** (0.017)	0.076*** (0.019)	0.701*** (0.047)	0.853*** (0.044)
Adjusted $R^2$				
Observations	905	857	854	904

OLS has robust standard errors clustered on individual.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 7: Second player contributions - prosocial players.

	(1)	(2)	(3)	(4)
	Lowest	2nd lowest	2nd highest	Highest
First player behavior	0.099* (0.048)	0.280*** (0.047)	0.133** (0.047)	-0.005 (0.041)
Exploration game	0.291*** (0.033)	0.357*** (0.037)	-0.124* (0.049)	-0.199*** (0.050)
Encouragement (interaction)	0.239*** (0.063)	0.193** (0.059)	0.223*** (0.060)	0.241*** (0.057)
Constant	0.109*** (0.016)	0.072*** (0.014)	0.705*** (0.031)	0.872*** (0.030)
Adjusted $R^2$				
Observations	2157	2025	2034	2007

OLS has robust standard errors clustered on individual.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table 8: Contributions and SVO angle.

	(1)	(2)	(3)	(4)
	Lowest	2nd lowest	2nd highest	Highest
Exploration game	0.318*** (0.036)	0.462*** (0.033)	0.026 (0.041)	-0.105** (0.033)
First-player	0.097 (0.067)	0.073 (0.064)	-0.172* (0.083)	-0.109 (0.070)
Social Value Orientation	0.003* (0.001)	0.003* (0.001)	0.001 (0.002)	0.000 (0.001)
PlayerXSVO	-0.004 (0.002)	-0.001 (0.003)	-0.006 (0.003)	0.001 (0.003)
GametypeXPlayerXSVO	0.001 (0.002)	-0.000 (0.002)	0.011*** (0.002)	0.005** (0.002)
Constant	0.028 (0.040)	0.034 (0.035)	0.655*** (0.063)	0.820*** (0.046)
Adjusted $R^2$				
Observations	3344	3248	3328	3392

OLS has robust standard errors clustered on individual.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

#### 4.5 Robustness

To assess the robustness of our results, we conduct a number of additional tests. Firstly, we estimate equation 11 including dummy variables for each of the 32 rounds (Table B.10 in the Appendix B.) .

Secondly, in 13 out of the 36 sessions we had randomly assigned the game types between sessions instead of within sessions. To test that this does not affect our results we estimate the equation 11 again using only the sample where we randomly assigned participants to game type within the session. This sub-sample comprises 334 participants. The results are qualitatively similar, see Table B.11 in the Appendix B.

Thirdly, we tested whether the order in which we presented the treasure sizes affects contributions when shifting from one treasure size to another. On average, the first-players facing an ascending order seem to contribute between 12 % and 10 % more than first-players facing another order. However, this order effect does not change our results regarding the gap in contribution rates between the exploration and public goods game when comparing treasure sizes, i.e., our main results remain. Please see Table B.12 in the Appendix B.

Fourthly, participants played eight rounds with each treasure size. To account for possible learning, we look at contributions in the last four rounds of play for each treasure size. This implies that we cut our sample in half. Table B.13 in the Appendix B shows similar patterns as before with greater contributions as treasure size increased. Holding treasure size constant, there is a greater contribution rate in the exploration game than in the public goods game. For second-players, a large gap in contribution rates between the exploration game and public goods game prevailed for the smaller treasure sizes only.

Finally, we take a final corollary result predicted by our behavioral model to the data in an effort to further assess the relevance of this model in explaining observed behaviors. Theory predicts that with positive probability player 2 in the exploration game will contribute even after the treasure was found by player 1. Figure 8 shows that there was in fact a small share of second-players who contribute even when the treasure had been found. This share equalled about 20% of participants and was, as predicted, constant across treasure sizes.

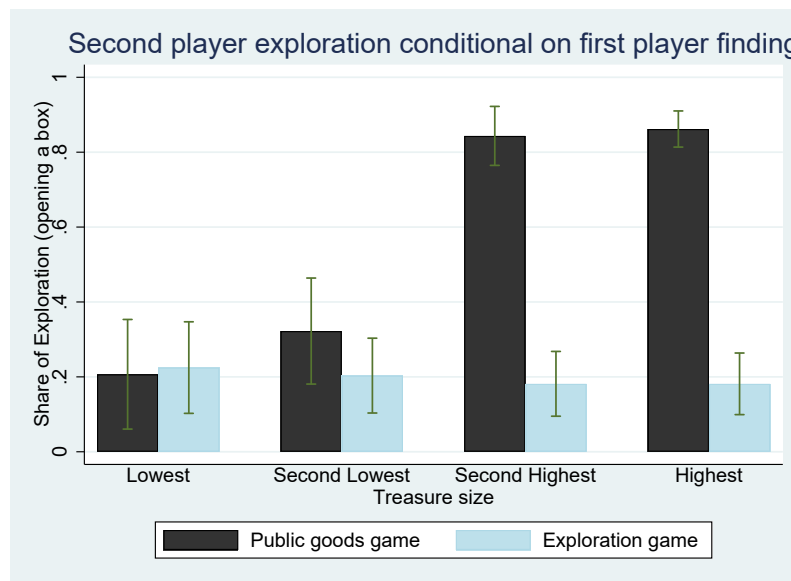


Figure 8: Second-player contribution conditional on first-player finding

#### 4.6 Limitations

Researchers' ways of conducting quantitative studies may affect the results and interpretation of findings, such as the probability of false positives leading to difficulties in interpreting research findings. This is an important discussion found across fields (Gelman and Carlin 2014, Ioannidis 2005, Maniadiis et al. 2014). We pre-registered hy-

potheses, variable coding, and some of the tests, which hopefully to some extent lessens our degree of freedom as researchers.

Maniadis et al. (2014) show that our prior beliefs about the hypothesis being true as well as the number of researchers currently exploring the question influence the probability of false positives. Using Equation 2 in Maniadis et al. (2014), we estimated the post-study probability of a true relationship being reported. When comparing the average contribution between the Exploration Game and the Public Goods Game we have an effect size of -0.5, which is considered a medium effect (Cohen 1992). Using an  $\alpha$  of 5% and our current sample size we have a power of 100. Assuming that we are the only team exploring the research question and considering the following prior probabilities; 10%, 50% and 70%, the post-study probabilities of a true relationship being reported as true is 69%, 95% and 98% respectively. These tests suggest that our results seem to be of relevance. However, as Maniadis et al. (2014) points out, future studies will decrease the probability of reporting false positives.

When interpreting our results it should be noted that we had initially taken only the SPE-predictions to the data. Ex post, as those initial predictions were only partially validated empirically, we sought to extend our basic theoretic model and augmented its realism by allowing people to imperfectly optimize and hold other-regarding preferences, not only self-regarding preferences. As it turns out, the game-theoretic predictions that derive from this fuller version of our model best predict observed behaviors in the laboratory experiment. Indeed, Anderson et al. (1998), Goeree and Holt (2000), and Goeree and Holt (2001) illustrate the power of this latter approach, and we re-express the recommendation of Goeree and Holt (1999) and Camerer et al. (2004, footnote 5) that researchers in future related theoretical and empirical work give more consideration to the QRE framework as an important theoretical benchmark.

Another limitation of our work is that our sample includes too little variation in the social value orientation (Murphy et al. 2011) that was measured a week before the actual experiment, and also too little variation in the implied social welfare utility parameters (Charness and Rabin 2002),  $\rho$  and  $\sigma$  (see the Appendix C: Deriving  $\rho$  and  $\sigma$  using the SVO sliders). There was an abundance of subjects with a tendency to share the earnings fifty-fifty, but there were few purely selfish or highly altruistic ones. This raises the importance of deriving the initial hypotheses within a framework with other-regarding

preferences (and imperfect optimization).

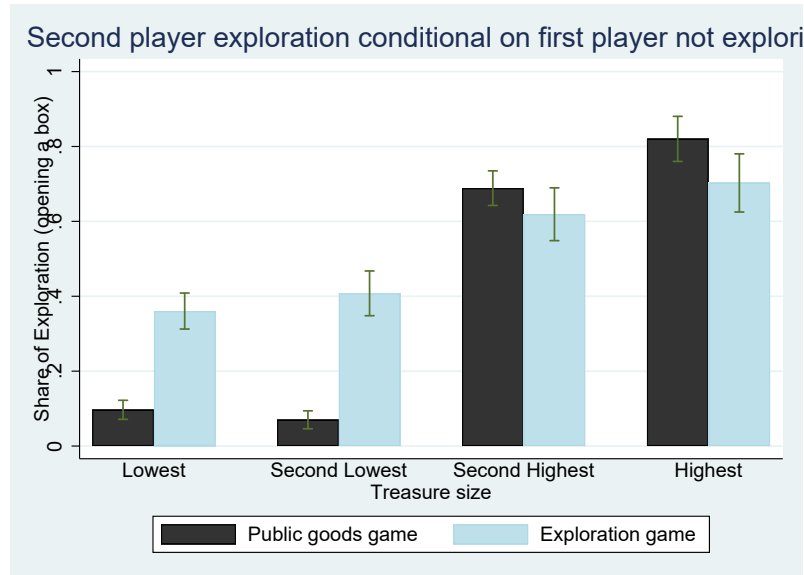


Figure 9: Second-player contributions conditional on first-player not contributing

Our exploration task is extremely simple, whereas the production function underlying innovation is admittedly anything but straightforward. With our design we are unable to separately identify the role that sensation seeking may have played in motivating exploration behaviors. That said, the simple and clear-cut model allows to decompose and carefully study the encouragement phenomenon. The experimental design served the purpose of providing clear answers for the particular hypotheses and research questions we were interested in. Our results are of course likely to be influenced by the particular context and design choices that we adopted, and further research is required to understand to what extent and when the results generalize.

## 5 Conclusion

Using a novel experimental paradigm, we explored the factors that drive an individual's decision to interactively search for the public good - in particular, how willingness to search for the public good depends on exploration payoffs and uncertainty in the public goods' production process. Our focus is on the celebrated encouragement effect (first theoretically identified by Bolton and Harris (1999)) and the closely related incentive reversal effect (first pointed out by Winter (2009)).<sup>41</sup> We also study the robustness of

<sup>41</sup>See also Hörner and Skrzypacz (2016).

these phenomena by extending it to a behavioral framework with imperfect optimization (McKelvey and Palfrey (1998) and other-regarding preferences Charness and Rabin (2002)).

We have shown that the behavioral patterns in the experimental data presented broadly conform to the theoretical predictions of our model of joint exploration under imperfect optimization and with other-regarding individuals, that contributions to exploration by player 1 motivates contributions by player 2. This encouragement effect, which we decomposed into an other-regarding and an informational part, is at play for small and large public benefits to successful exploration and in theory increases with the magnitude of the benefits. We provide evidence that not only establishes the other-regarding effect but also the entirely novel informational effect. Based on the informational effect, we theoretically derived that uncertainty in our game raises, rather than decreases, the aggregate level of exploration. Our experimental data robustly lends support to this contribution hypothesis.

Our results underscore the role of uncertainty and learning in the provision of public goods. Learning or 'open innovation' induces a synergy between individuals' contribution decisions, which brings equilibrium innovation closer to the social optimum. Future studies in less controlled field settings could potentially measure and test the social surplus directly rather than aggregate contributions. In practice, an organization's architecture (say, openness and interaction opportunities in a workspace), processes (say, whether interaction and exchange amongst peers is regularly organized) and culture (say, whether the organization strongly values openness to change versus conservation), as well as the rules and expectations set by external stakeholders (such as, rules set by external funders) can strongly affect whether agents inside the organization are more likely to exploit versus explore within a known set of independent alternatives. The insights we derive from our stylized model allow us to gain a better understanding of search in teams or groups, say by academics and scholarly output (see the example on econometricians and identification methods in the introduction) or farmers and biodiversity (say farmers in a co-op and their search for crop varieties that enhance biodiversity) to name a few examples.

Our findings are also relevant to studying sequential team innovation, when individual effort cannot be observed by the principal and agents are rewarded based on joint

output or success. As pointed out theoretically by Strausz (1999), Winter (2006), and Winter (2009), when (at least some) team members can observe other team members' effort, or the information structure can be at least partially designed, there are delicate incentive effects, i.e., encouragement and discouragement that need to be taken into account when designing how the team operates.

The experiment of Klor et al. (2014) explicitly contrasted team production with simultaneous choices versus sequential choices. They found significant non-monotonicity effects in their sequential treatments. The difference between their design and ours is that they were not interested in team search per se but rather assumed a very explicit complementarity between inputs, an increasing returns to scale technology, and asked whether sequential team production leads to incentive reversals, i.e., non-monotonicities. There was no exogenous uncertainty typical of any search process in their design. The key experimental variation in our study concerns precisely this certainty versus uncertainty (explorative nature) of returns to contribution to the public good. Yet, under subgame perfect Nash equilibrium and self-interest, the theoretical underpinnings are precisely the same. Thus, the fact that they observe a positive "incentive reversal", whereas we do not see much evidence of non-monotonicities suggests that the contextual differences influence behavior. Effects similar to ours can be observed in the experiment of Steiger and Zultan (2014) where experimental variation concerns the simultaneity vs. sequentiality of choices, on the one hand, and the complementarity of effort, on the other hand.

The paper can also be seen as contributing to the understanding of the fundamental non-monotonicity aspect in the theoretical multi-player learning and experimentation literature in strategic two-arm bandit models (Hörner and Skrzypacz (2016), pp. 2-3), which lies at the heart of the encouragement effect theoretically discovered by Bolton and Harris (1999). In our setup, no exploration broadly corresponds to the safe arm and exploration to the risky arm. The first-player can influence the second-player probability of exploring (second-player belief of high returns) by exploring. Our paper generally establishes the encouragement also empirically. Yet, the encouragement logic operates less perfectly and rationally than suggested by theory. Due to imperfect optimization, there is an encouragement effect not just around the belief threshold, but rather independently of the parameter values.

Provided that our results are externally valid, one important implication of our results is that business leaders or governments that wish to harness decentralized voluntary search for the public good are well-advised to promote (i) information-sharing, for instance, by investing in improved technological infrastructure that can speed up the sharing of information and (ii) the development of social preferences amongst its employees or citizens at large, for instance through corporate culture or educational programs.<sup>42</sup> Interestingly though, the encouragement effect in our model leads even self-interested individuals to search for the public good. Another implication is that by emphasizing the uncertainty about where the solution to a difficult public goods problem lies, one can actually elicit greater voluntary contributions. And hence, when contributions to the public good can be framed as search contributions, this will raise and not lower, as one might have thought, overall contributions and bring aggregate contributions closer to the social optimum.

Interestingly, a rapidly rising share of experimentation for the public good actually occurs outside of mainstream organizations. More citizens than ever are voluntarily stepping up and jointly (openly) searching for novel ideas and solutions in a bid to make their societies more sustainable and more inclusive (Baldwin and Von Hippel 2011, Harhoff and Lakhani 2016). Our research suggests that to enable these types of collective action it is recommended that citizens adequately appreciate in full the benefits of the public good. Also, by explicating the explorative character of these initiatives, citizens may well be more, not less, likely to contribute.

Let us finally discuss a few future related research paths that might prove particularly fruitful. The paper provides a complementary workhorse model to study some of the key questions instigated by the theoretical strategic experimentation literature in a simple setting.<sup>43</sup> Generalizations to multiplayer teams, or endogenous ordering of exploration efforts seem straightforward. A setting where players have a common value for the good but where they receive private signals about the pay-off to exploration prior to exploring opens a bridge between the literature of exploration and social learning (herding). On the other hand, if the locations contain public or private goods of variant values, the

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<sup>42</sup>See *citetAndersson2015person* for an experiment suggesting causal effects of corporate values on prosocial organizational behavior and *Kosse et al. (2018)* for an example of such a program targeted at second grade children of low socio-economic status families.

<sup>43</sup>The novel experimental framework could, for instance, be used to study experimentation in a private goods setting as well.



links to the search literature become obvious.<sup>44</sup>

The framework and methods proposed in this paper can also be used to study the effects of alternative knowledge production technologies or alternative incentive schemes on exploration behavior. For example, what if the knowledge production function is substitutional, that is, unsuccessful search lowers the probability of subsequent success, or what if there is a positive probability that none of the chests hold a treasure? Then, depending on the precise parameterization of these production functions, you could have encouragement or discouragement effects of not finding a treasure. Or what if the treasure is a lottery ticket, either at one location (EG) or in all locations (PGG), which would allow us to control away the effect of risk aversion? Given different knowledge production technologies, what is the optimal mix of private and public benefits to encourage greater exploration for the good.

It would also be of great interest to take steps away from the tightly controlled model-like laboratory settings toward more ecologically valid studies on creativity or innovativeness and to exogenously vary the uncertainty and the stakes and rewards related to the process of discovery. This class of studies encompasses both field experiments in collaboration with firms, non-profit organizations, or public sector agencies, as well as more controlled studies in the laboratory using protocols established in creativity research (Amabile et al. 1986, Erat and Gneezy 2016, Osborn 1953).

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<sup>44</sup>In fact, as opposed to the purely public good case presented in the paper, we also considered the case where rewards are purely private goods (see Appendix A.2). One can show that entirely privatizing the discovered good would have implications for the encouragement effects both through the other-regarding and through the informational channel. When  $\sigma > 0$  and  $\frac{\alpha}{K-1} - c_2 > 0$  then encouragement through both channels will be smaller and thus contributions will be reduced. The first mover's incentive to contribute is now lower since there is reason to encourage the other only to the extent that the first mover is altruistic towards the second mover. In fact, if  $\sigma \leq 0$ , the first mover has no incentive to encourage the second mover since she can only lose from the second mover's finding the treasure.

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## A Appendix: Theoretical extentions

### A.1 QRE of the public goods and exploration game

We now derive the quantal response equilibria for the exploration game and public goods game, reasoning by backward induction. For simplicity, we analyse here the case where players are self-interested. This is sufficient to break the non-monotonicity result (see Section 2).

*Exploration game:* We start by analysing player two's behavior. There are three possible cases to consider: (i) player one did not contribute, (ii) player one contributed but did not find the treasure, (iii) player one contributed and found the treasure.

In case (i) [no contribution by player one,  $a_1 = 0$ ], player two's payoff to not contributing is 0 and to contributing is

$$\frac{\alpha}{K} - c_2.$$

Thus the probability of contributing equals

$$b_2(a_1 = 0) = \frac{\exp\left((1/\mu)\left(\frac{\alpha}{K} - c_2\right)\right)}{1 + \exp\left((1/\mu)\left(\frac{\alpha}{K} - c_2\right)\right)} \quad (13)$$

and the proportion of choice probabilities between contributing and not contributing equals

$$\frac{b_2(a_1 = 0)}{1 - b_2(a_1 = 0)} = \exp\left((1/\mu)\left(\frac{\alpha}{K} - c_2\right)\right) \quad (14)$$

and the log of the odds ratio is thus merely

$$\left((1/\mu)\left(\frac{\alpha}{K} - c_2\right)\right). \quad (15)$$

It is easy to see that the probability of contributing is increasing in  $\alpha$  and decreasing in  $c_2$ . Moreover, if  $\frac{\alpha}{K} - c_2 > 0$  then  $b_2(a_1 = 0)$  is decreasing in  $\mu$ .

In case (ii) [failed exploration by player one], the payoff to not contributing still equals 0 but the payoff to contributing now equals  $\frac{\alpha}{K-1} - c_2$  which is higher than  $\frac{\alpha}{K} - c_2$ .



The implied probability of contributing now equals

$$b_2(a_1 = 1, Y = K - 1) = \frac{\exp\left((1/\mu)\left(\frac{\alpha}{K-1} - c_2\right)\right)}{1 + \exp\left((1/\mu)\left(\frac{\alpha}{K-1} - c_2\right)\right)} \quad (16)$$

which is larger than  $b_2(a_1 = 0)$ . Moreover

$$\frac{b_2(a_1 = 1, Y = K - 1)}{1 - b_2(a_1 = 1, Y = K - 1)} = \exp\left((1/\mu)\left(\frac{\alpha}{K-1} - c_2\right)\right) \quad (17)$$

and the log of the odds ratio is thus merely

$$\log\left(\frac{b_2(a_1 = 1, Y = K - 1)}{1 - b_2(a_1 = 1, Y = K - 1)}\right) = \left((1/\mu)\left(\frac{\alpha}{K-1} - c_2\right)\right). \quad (18)$$

The difference between expressions (18) and (15) reflect a positive encouragement effect

$$\frac{1}{\mu} \frac{\alpha}{K(K-1)}. \quad (19)$$

This encouragement effect is increasing in the treasure size and decreasing in  $\mu$ .

In case (iii) [successful exploration by player one i.e.  $a_1 = 1$  and  $Y = 0$ ], the payoff to not contributing equals  $\alpha$  and the payoff to contributing equals  $\alpha - c_2$ . Thus the choice probability equals

$$b_2(a_1 = 1, Y = 0) = \frac{\exp((1/\mu)(\alpha - c_2))}{\exp((1/\mu)(\alpha)) + \exp((1/\mu)(\alpha - c_2))},$$

and the proportion of choice probabilities between contributing and not contributing equals

$$\frac{b_2(a_1 = 1, Y = 0)}{1 - b_2(a_1 = 1, Y = 0)} = \frac{\exp((1/\mu)(\alpha - c_2))}{\exp((1/\mu)(\alpha))},$$

and the odds ratio between those probabilities is thus

$$\log\left(\frac{b_2(a_1 = 1, Y = 0)}{1 - b_2(a_1 = 1, Y = 0)}\right) = ((1/\mu)(\alpha - c_2)) - ((1/\mu)(\alpha)) = -(1/\mu)c_2,$$

Thus, the model predicts that even when player one did explore and found the treasure, player two contributes with a positive probability. The probability of contributing is predicted to be below 50% and if we let  $\mu$  tend to zero, the probability of mistakenly

contributing tends to zero.

Let us next consider player one's incentives to contribute. The payoff to not contributing equals

$$0 + b_2(a_1 = 0)[\alpha/K].$$

The payoff to contributing equals

$$\frac{\alpha}{K} - c_1 + \frac{K-1}{K} b_2(a_1 = 1, Y = K-1)[\alpha/(K-1)] = \frac{\alpha}{K}(1 + b_2(a_1 = 1, Y = K-1)) - c_1$$

Thus, the log of the odds ratio of choice probabilities of the first-player equals

$$\log\left(\frac{b_1}{1-b_1}\right) = (1/\mu) \left(\frac{\alpha}{K}(1 + b_2(a_1 = 1, Y = K-1) - b_2(a_1 = 0)) - c_1\right).$$

Since  $b_2(a_1 = 1, Y = K-1) - b_2(a_1 = 0) > 0$ , there is an additional dynamic incentive to contribute beyond the myopic incentive

$$\frac{\alpha}{K} - c_1 < 0.$$

Moreover, in the present model where we allow for imperfect optimization, player one can have dynamic incentives to explore even when  $\max\{\frac{c_1 K}{1+\delta}, c_2(K-1)\} < \alpha < X c_2$  [the condition for the encouragement effect to be realised in the SPE] does not hold.

Differentiating  $\log(b_1/1-b_1)$  with respect to  $\alpha$ , yields

$$\begin{aligned} & (1/\mu) \left(\frac{1}{K}(1 + b_2(a_1 = 1, Y = K-1) - b_2(a_1 = 0))\right) \\ & + (\alpha/(\mu K)) \frac{\partial(b_2(a_1 = 1, Y = K-1) - b_2(a_1 = 0))}{\partial\alpha} \end{aligned}$$

where  $\partial(b_2(a_1 = 1, Y = K-1) - b_2(a_1 = 0))/(\partial\alpha)$  has the sign of

$$\begin{aligned} & \frac{1}{\mu(K-1)} \exp\left(\frac{1}{\mu}\left(\frac{\alpha}{K-1} - c_2\right)\right) \left(1 + \exp\left(\frac{1}{\mu}\left(\frac{\alpha}{K} - c_2\right)\right)\right) \\ & - \frac{1}{\mu(K)} \exp\left(\frac{1}{\mu}\left(\frac{\alpha}{K} - c_2\right)\right) \left(1 + \exp\left(\frac{1}{\mu}\left(\frac{\alpha}{K-1} - c_2\right)\right)\right) \end{aligned} \tag{20}$$

When  $\mu$  approaches infinity, (20) approaches

$$2\left(\frac{1}{\mu(K-1)} - \frac{1}{\mu(K)}\right) \tag{21}$$

which is positive. Thus for  $\mu$  sufficiently high,  $\log(b_1/1 - b_1)$  is strictly increasing in  $\alpha$ .

*Public goods Game:* Again, reasoning by backward induction, we first consider player two's contribution decision. There now exist only two possible cases: (i) Player one does not contribute; or (ii) Player one contributes.

In case (i) [no contribution by player one,  $a_1 = 0$ ], player two's probability of contributing equals

$$b_2(a_1 = 0) = \frac{\exp\left(\left(\frac{1}{\mu}\right)\left(\frac{\alpha}{K} - c_2\right)\right)}{1 + \exp\left(\left(\frac{1}{\mu}\right)\left(\frac{\alpha}{K} - c_2\right)\right)}$$

which in log-odds terms corresponds to  $1/\mu(\alpha/K - c_2)$ . In case (ii) [player one contributes, i.e.  $a_1 = 1$ ], player two's probability of contributing equals

$$b_2(a_1 = 1) = \frac{\exp\left(\left(\frac{1}{\mu}\right)(2\alpha/K - c_2)\right)}{\exp\left(\left(\frac{1}{\mu}\right)(\alpha/K)\right) + \exp\left(\left(\frac{1}{\mu}\right)(2\alpha/K - c_2)\right)},$$

or in log-odds terms  $1/\mu(\alpha/K - c_2)$ .

There is thus no encouragement effect in the public goods game now that we abstract from other-regarding preferences in this appendix.

Let us summarize the findings.

QRE-Predictions. Second player.

**Proposition A.1** • *For a given first player action and outcome, the second player probability of contributing increases in treasure size.*

- *The second player probability of contributing is identical in the public goods game and in the exploration game if the first player did not contribute. The probability of contributing is lower in the public goods game than in the exploration game when, in the exploration game, there are unexplored alternatives left which contain a treasure with positive probability.*
- *The second player probability of contributing is positive even if there is no treasure left.*

**Proposition A.2** *Second-player probability of contributing is higher if the first-player explored an alternative that did not contain a treasure than if the first-player did not explore an alternative (compare to Second-mover bullet point two above). For  $\mu$  sufficiently high, this encouragement effect is increasing in treasure size.*

QRE-Predictions. First-player.

**Proposition A.3** *For  $\mu$  sufficiently high, the first player probability of contributing increases in treasure size.*

Denote by  $b_{1,PGG}$  and  $b_{2,PGG}$  the contribution rates (probabilities) of the first-mover and second-mover, respectively in the PGG. Denote by  $b_{2,found}$  the second-mover contribution rate conditional on first-mover having found the treasure in the EG (clearly below 1/2 and tends to 0 when  $\mu \rightarrow 0$ ). As shown in the theory Section, the behavioral model predicts that the contribution rates of the second-mover are highest in the EG when first-mover contributes but did not find the treasure. Denote this second-mover contribution rate by  $b_{2,PGG} + \Delta_{b_2}$ . Denote also the first-mover contribution rate in the EG by  $b_{1,PGG} + \Delta_{b_1}$ . Notice that  $b_{1,PGG}$ ,  $b_{2,PGG}$  as well as  $\Delta_{b_1}$  and  $\Delta_{b_2}$  are functions of the treasure size and  $\mu$ . Keep in mind that if the first-mover does not contribute, then the probability that the second-mover contributes coincides in the PGG and EG.

**Proposition A.4** *For a given treasure size, the total expected contributions are greater in the EG than in the PGG iff*

$$\frac{1}{4} (3(b_{1,PGG} + \Delta_{b_1})(b_{2,PGG} + \Delta_{b_2}) - 4(b_{1,PGG} + b_{2,PGG} - 1)) + \frac{3}{4} ((b_{1,PGG} + \Delta_{b_1})b_{2,found}) \geq 0$$

PROOF: Assume that the other-regarding preference parameters are zero. For a given treasure size, the total expected contributions in the EG can now be expressed as

$$\begin{aligned} & 0((1 - b_{1,PGG} - \Delta_{b_1})(1 - b_{2,PGG})) + ((1 - b_{1,PGG} - \Delta_{b_1})b_2) \\ & + \left( (b_{1,PGG} + \Delta_{b_1}) \left[ \frac{3}{4}(1 - b_{2,PGG} - \Delta_{b_2}) + \frac{1}{4}(1 - b_{2,found}) \right] \right) \\ & + 2 \left( (b_{1,PGG} + \Delta_{b_1}) \left[ \frac{3}{4}(b_{2,PGG} + \Delta_{b_2}) + \frac{1}{4}b_{2,found} \right] \right). \end{aligned}$$

The total contributions in the PGG equal

$$0(1 - b_{1,PGG})(1 - b_{2,PGG}) + (1 - b_{1,PGG})b_{2,PGG} + b_{1,PGG}(1 - b_{2,PGG}) + 2b_{1,PGG}b_{2,PGG},$$

and the difference between these two equals

$$\frac{1}{4} (3(b_{1,PGG} + \Delta_{b_1})(b_{2,PGG} + \Delta_{b_2}) - 4(b_{1,PGG} + b_{2,PGG} - 1)) + \frac{3}{4} ((b_{1,PGG} + \Delta_{b_{1,PGG}})b_{2,found})$$

QED

The condition merely reflects the fact that whenever the first mover contributes, the encouragement effect (first-mover does not find and thus second-mover has a higher incentive to contribute) takes place with 3/4 probability whereas choices are independent in the PGG. When  $b_{1,PGG}$  and  $b_{2,PGG}$  are sufficiently close to one and thus  $\Delta_{b_1}$  and  $\Delta_{b_2}$  must tend to zero,  $4(b_{1,PGG} + b_{2,PGG} - 1)$  is positive and the expression is negative (unless  $b_{2,found}$  is substantial). Thus in that case the total contributions must be higher in PGG than in EG. Yet, for  $b_{1,PGG}, b_{2,PGG} \leq 1/2$ ,  $4(b_{1,PGG} + b_{2,PGG} - 1)$  is negative and thus the contributions are higher in EG than in PGG. It is easy to see for instance that  $4(b_{1,PGG} + b_{2,PGG} - 1)$  is positive for the highest treasure size when  $\mu \rightarrow 0$  since then  $b_{1,PGG}, b_{2,PGG} \rightarrow 1$ . Yet, for other treasure sizes either  $b_{1,PGG}$  or  $b_{2,PGG}$  tends to 0 when  $\mu \rightarrow 0$  and thus  $4(b_{1,PGG} + b_{2,PGG} - 1)$  does not tend to exceed zero. Nevertheless  $\Delta_{b_2} > 0$  for  $\mu$  sufficiently high. Thus the encouragement effect plays a role and also  $\Delta_{b_1}$  is positive (due to strategic complementarities). Also  $b_{2,found}$  is positive. Therefore EG has higher total contributions than PGG.

## A.2 Purely private good case

It is fairly easy to understand the implications of introducing partly private benefits which accrue to the one who discovers the treasure. The model then becomes more reminiscent to that of Fershtman and Rubinstein (1997) (although important differences still exist). Let us assume for the sake of illustration that only the one who finds the treasure receives the reward (i.e., the invention yields a purely private reward). Let us begin by considering the second player. Suppose that the first player has contributed but did not find the treasure. In this case the expected utility of a second player who contributes equals

$$\left( \frac{\alpha}{K-1} - c_2 \right) (1 - \rho) - c_1 \rho \quad (22)$$

and the utility of a second mover who does not contribute equals  $-c_1\rho$ , and thus the log-odds of the choice probabilities between these two choices equal

$$(1/\mu) \left( \frac{\alpha}{K-1} - c_2 \right) (1 - \rho). \quad (23)$$

Comparing this expression to (10) in the paper shows that the other-regarding second player who puts a positive weight  $\rho$  on the first-mover's payoff has less of an incentive to contribute when the reward is purely private than when the reward is in the public domain. Formally,

$$b_{2,private}(a_1 = 1, Y = K - 1) - b_{2,public}(a_1 = 1, Y = K - 1) \quad (24)$$

$$= \frac{1}{1 + \exp\left[-\left(\frac{\alpha}{K-1} - c_2\right)(1 - \rho)\right]} - \frac{1}{1 + \exp\left[-\frac{\alpha}{K-1} + c_2(1 - \rho)\right]} \quad (25)$$

for all treasure sizes. The term within square brackets of the probability expression  $b_{2,private}(a_1 = 1, Y = K - 1)$  differs from the corresponding expression in  $b_{2,public}(a_1 = 1, Y = K - 1)$  by a factor

$$-\left(\frac{\alpha}{K-1}\right)\rho \quad (26)$$

and thus  $b_{2,private}(a_1 = 1, Y = K - 1) - b_{2,public}(a_1 = 1, Y = K - 1)$  is negative. In sum, in the case where  $a_1 = 1$  but the treasure was not found, the private nature of the reward *ceteris paribus* dampens the second player's incentive to explore. The incentives of a self-regarding second player ( $\rho = 0$ ) are unaffected.

Consider next the second player's exploration decision when the first player has not contributed. The expected utility for contributing in this case equals  $\left(\frac{\alpha}{K} - c_2\right)(1 - \sigma)$  which is also the same as the log-odds between contributing and not contributing for the second mover since the expected utility of not contributing equals zero. Thus,

$$b_{2,private}(a_1 = 0, Y = K) - b_{2,public}(a_1 = 0, Y = K) \quad (27)$$

$$= \frac{1}{1 + \exp\left\{-\left(\frac{\alpha}{K} - c_2\right)(1 - \sigma)\right\}} - \frac{1}{1 + \exp\left\{-\frac{\alpha}{K} + c_2(1 - \sigma)\right\}} \quad (28)$$

The term within square brackets of the probability expression  $b_{2,private}(a_1 = 0, Y = K)$

differs from the expression  $b_{2,public}(a_1 = 0, Y = K)$  by a factor

$$-\frac{\alpha}{K}\sigma \quad (29)$$

and thus  $b_{2,private}(a_1 = 0, Y = K) - b_{2,public}(a_1 = 0, Y = K)$  is negative if  $\sigma > 0$  and positive if  $\sigma < 0$ . The other-regarding second player who puts a positive weight  $\sigma$  on the first-mover's payoff has less of an incentive to contribute when the reward is purely private than when the reward is in the public domain. Conversely, the other-regarding second player who is inequity averse, is now more likely to explore. Notice also that if  $\sigma > 0$ , then  $b_{2,private}(a_1 = 1, Y = K - 1) - b_{2,public}(a_1 = 1, Y = K - 1)$  is smaller than  $b_{2,private}(a_1 = 0, Y = K) - b_{2,public}(a_1 = 0, Y = K)$  since  $\sigma \leq \rho$  and  $\frac{1}{K} < \frac{1}{K-1}$ . In other words, the difference between second mover's exploration in the private good versus public good case is smaller when first mover explored (but did not find the treasure) than when first mover did not explore. Nevertheless, if  $\sigma < 0$ , then in fact  $b_{2,private}(a_1 = 0, Y = K) - b_{2,public}(a_1 = 0, Y = K)$  is smaller in size than  $b_{2,private}(a_1 = 1, Y = K - 1) - b_{2,public}(a_1 = 1, Y = K - 1)$  since now  $\sigma < 0 < \rho$ .

In sum, in the case where  $a_1 = 0$ , the private nature of the reward dampens incentives to explore when the second player has social welfare concerns, but amplifies incentives to explore when the agent is inequity averse.

What happens to first mover exploration with purely private goods? The log-odds between contributing and not for the first-mover in the private goods case equal

$$\begin{aligned} & \left(\frac{\alpha}{K} - c_1\right)(1 - \rho) + \frac{K - 1}{K}b_{2,private}(a_1 = 1, Y = K - 1)\sigma\left(\frac{\alpha}{K - 1} - c_2\right) \\ & - \sigma b_{2,private}(a_1 = 0, Y = K)\left(\frac{\alpha}{K} - c_2\right) \end{aligned}$$

whereas in the public goods case they equal

$$\begin{aligned} & \rho\left(\frac{\alpha}{K}\right) + \left(\frac{\alpha}{K} - c_1\right)(1 - \rho) + \frac{K - 1}{K}b_{2,public}(a_1 = 1, Y = K - 1)\left[(1 - \sigma)\frac{\alpha}{K - 1} + \sigma\left(\frac{\alpha}{K - 1} - c_2\right)\right] \\ & - b_{2,public}(a_1 = 0)\left((1 - \sigma)\frac{\alpha}{K} + \sigma\left(\frac{\alpha}{K} - c_2\right)\right). \end{aligned}$$

Subtracting the latter from the former yields an expression that reflects the difference

in the first player contribution probability when the rewards is a pure private good versus a pure public good:

$$\begin{aligned}
& -\rho\left(\frac{\alpha}{K}\right) - \frac{K-1}{K}b_{2,public}(a_1 = 1, Y = K-1)(1-\sigma)\frac{\alpha}{K-1} + b_{2,public}(a_1 = 0, Y = K)(1-\sigma)\frac{\alpha}{K} \\
& + \sigma\left\{\frac{K-1}{K}[b_{2,private}(a_1 = 1, Y = K-1) - b_{2,public}(a_1 = 1, Y = K-1)]\left(\frac{\alpha}{K-1} - c_2\right) \right. \\
& \quad \left. - [b_{2,private}(a_1 = 0) - b_{2,public}(a_1 = 0)]\left(\frac{\alpha}{K} - \sigma c_2\right)\right\}
\end{aligned}$$

where the first row reflects the effect of privatization on first player's incentives to explore that runs through the other-regarding channel and the second term in curly brackets captures the effect that runs through the informational channel. The first term is negative since  $b_{2,public}(a_1 = 1, Y = K-1) > b_{2,public}(a_1 = 0)$ .

What about the second term? If  $\sigma > 0$ , and  $\frac{\alpha}{K} - c_2 > 0$  then the second term is negative since  $b_{2,private}(a_1 = 1, Y = K-1) - b_{2,public}(a_1 = 1, Y = K-1) < b_{2,private}(a_1 = 0) - b_{2,public}(a_1 = 0) < 0$  and  $c_2(K-1)/K < c_2$ . If  $\sigma > 0$  and  $(\frac{\alpha}{K} - c_2) < 0 < (\frac{\alpha}{K-1} - c_2)$  (this holds in the experiment if and only if  $\alpha$  equals the second-lowest treasure size), then the second term is negative. To the contrary if  $\sigma < 0$  and  $\frac{\alpha}{K} - c_2 > 0$ , then both terms inside the curly brackets are negative and since they are multiplied by a negative  $\sigma$ , the second term is positive. If  $0 > (\frac{\alpha}{K-1} - c_2) > (\frac{\alpha}{K} - c_2)$  (no private incentive to contribute under no circumstances) and  $-\sigma > \left(\frac{K}{K-1}\right)\rho$  then the latter term is positive and greater in absolute value than the former term; again since multiplied by a negative parameter  $\sigma$  the second term is negative in total. If  $0 > (\frac{\alpha}{K-1} - c_2) > (\frac{\alpha}{K} - c_2)$  and  $-\sigma < \left(\frac{K}{K-1}\right)\rho$  then the sign of the second row depends on the relative magnitudes of the various factors in the two terms of the sum.

So what can we say about the effect of privatization in total? The effects of privatization that run through the information and the other-regarding channel are both negative when  $\sigma \geq 0$  and  $0 < (\frac{\alpha}{K-1} - c_2)$ . In particular, for self-interested players, the effect of privatization on contributions is always negative since then the informational channel is all that matters and it is always negative.

The encouragement effects (both the informational and the other-regarding encouragement effects) are undermined since the first mover now gets less of both pecuniary and other-regarding benefits from second-mover finding the treasure. The incentive to



contribute is now lower for the first mover since there is reason to encourage the second-mover only to the extent that the first mover is altruistic towards the second mover. In fact if  $\sigma < 0$ , the first mover has no incentive to encourage the other since she can only lose from the second-mover finding the treasure.

## B Appendix: Additional experimental results

Table B.1: OLS: Differences in exploration. Tournament incentive removed.

	(1)	(2)	(3)
	Open	Open	Open
Game Type	0.255*** (0.064)	0.255*** (0.064)	0.071 (0.060)
First Player		-0.061 (0.064)	-0.239** (0.087)
Game Type X First Player			0.369** (0.117)
Constant	0.394*** (0.049)	0.425*** (0.049)	0.513*** (0.047)
Observations	1728	1728	1728

Robust standard errors clustered on session and individual

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

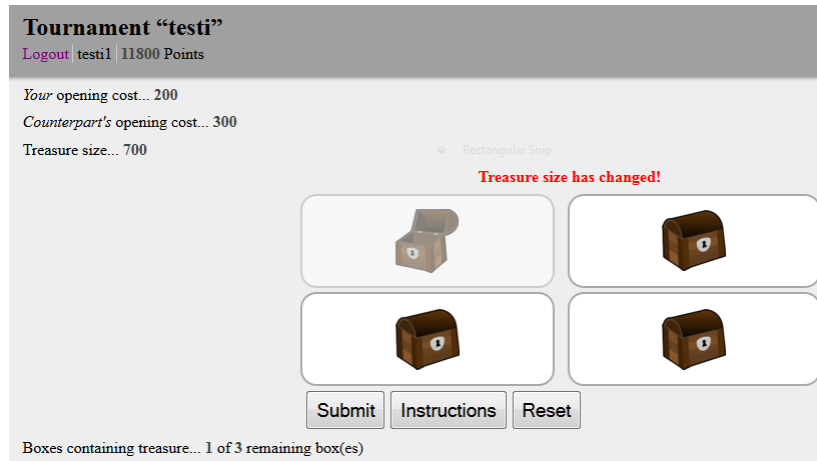


Figure B.1: Second player decision screen.

Table B.2: Differences between game types. Randomization check.

	(1) Female	(2) Risk question	(3) Cognitive reflection task	(4) Social Value Orientation
Exploration game	0.002 (0.049)	-0.154 (0.212)	-0.008 (0.048)	1.431 (1.304)
Constant	0.550*** (0.036)	5.881*** (0.158)	0.605*** (0.036)	26.654*** (0.972)
Adjusted $R^2$	-0.002	-0.001	-0.002	0.000
Observations	428	416	416	416

OLS regressions.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table B.3: MHT correction for the comparisons between player types and game types applying List et al (2016)

Treatment1	Treatment2	Difference	Remark31	Thm31	Remark37	Bonf.	Holm
PGG player 1	EG player 1	.3330	.0003	.0003	.0003	.0020	.0020
PGG player 1	PGG player 2	.1289	.0003	.0003	.0003	.0020	.0010
PGG player 1	EG player 2	.2841	.0003	.0003	.0003	.0020	.0007
EG player 1	PGG player 2	.2041	.0003	.0003	.0003	.0020	.0007
EG player 1	EG player 2	.0490	.1073	.1073	.1073	.644	.1073
PGG player 1	EG player 2	.1551	.0003	.0003	.0003	.0020	.0013

\*Using mean contributions as the outcome. We collapsed the 32 contribution decisions to 1 average per participant.

Table B.4: Logit: Differences in contributions across player types.

	(1)	(2)
	Public goods game	Exploration game
First mover	-0.135 (0.132)	-0.780*** (0.192)
Exploration game	1.319*** (0.135)	0.749*** (0.136)
First mover X Exploration game		1.156*** (0.262)
Constant	-0.549*** (0.098)	-0.233** (0.088)
Observations	13760	13760

Robust standard errors clustered on individual

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table B.5: Pooled OLS: Differences in contributions across player types

	(1)	(2)
	meanopen	meanopen
First-player	-0.030 (0.021)	-0.129*** (0.024)
Exploration game	0.244*** (0.027)	0.155*** (0.025)
First-player X Exploration game		0.178*** (0.033)
Constant	0.402*** (0.019)	0.452*** (0.018)
Adjusted $R^2$	0.219	0.247
Observations	430	430

Collapsed into one contribution decision per participant. Robust standard errors clustered on session

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table B.6: First players. Pairwise OLS comparison of sizes of treasure and game types

	(1) Lowest/2nd lowest	(2) 2nd lowest/2nd highest	(3) 2nd highest/highest
Treasure size	0.048* (0.023)	0.142*** (0.035)	0.412*** (0.044)
Exploration game	0.315*** (0.040)	0.466*** (0.045)	0.435*** (0.050)
Treasure size x Type of game	0.149*** (0.037)	-0.031 (0.044)	-0.336*** (0.050)
Constant	0.114*** (0.024)	0.161*** (0.030)	0.303*** (0.041)
Adjusted $R^2$			
Observations	3408	3400	3472

OLS has robust standard errors clustered on individual.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table B.7: Second players. Pairwise OLS comparison of sizes of treasure and game types

	(1) Lowest/2nd lowest	(2) 2nd lowest/2nd highest	(3) 2nd highest/highest
Treasure size	0.001 (0.020)	0.633*** (0.039)	0.114*** (0.028)
Exploration game	0.334*** (0.037)	0.479*** (0.034)	-0.050 (0.042)
Treasure size x Type of game	0.137*** (0.030)	-0.530*** (0.046)	-0.097** (0.035)
Constant	0.110*** (0.020)	0.103*** (0.022)	0.736*** (0.036)
Adjusted $R^2$			
Observations	3408	3400	3472

OLS has robust standard errors clustered on individual.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table B.8: Second players. Pairwise pooled OLS comparison of sizes of treasure and game types

	(1)	(2)	(3)
	Lowest/2nd lowest	2nd lowest/2nd highest	2nd highest/highest
Treasure size	0.004 (0.017)	0.623*** (0.034)	0.114*** (0.024)
Exploration game	0.338*** (0.038)	0.470*** (0.033)	-0.050 (0.039)
Treasure size x Type of game	0.131*** (0.032)	-0.520*** (0.046)	-0.096** (0.030)
Constant	0.109*** (0.018)	0.112*** (0.020)	0.736*** (0.033)
Adjusted $R^2$	0.193	0.216	0.019
Observations	3408	3400	3472

OLS has robust standard errors clustered on individual.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table B.9: Second players. Encouragement effect CG and UG.

	(1)	(2)	(3)	(4)
	Lowest	2nd lowest	2nd highest	Highest
First player behavior	0.071* (0.035)	0.241*** (0.038)	0.131*** (0.038)	-0.018 (0.032)
Exploration game	0.290*** (0.027)	0.341*** (0.030)	-0.082* (0.040)	-0.185*** (0.039)
Encouragement (interaction)	0.232*** (0.049)	0.241*** (0.049)	0.184*** (0.048)	0.256*** (0.045)
Risk question	-0.008 (0.006)	-0.001 (0.005)	-0.011 (0.006)	-0.008 (0.005)
Cognitive reflection task	0.036 (0.024)	0.021 (0.021)	0.005 (0.025)	-0.003 (0.021)
Social Value Orientation	0.001 (0.001)	0.001 (0.001)	-0.001 (0.001)	0.000 (0.001)
Constant	0.092 (0.051)	0.030 (0.042)	0.777*** (0.053)	0.912*** (0.042)
Adjusted $R^2$				
Observations	3093	2909	2911	2937

OLS has robust standard errors clustered on individual.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table B.10: First players: Pairwise comparison of size of treasure and game types.

	(1)	(2)	(3)
	Lowest/2nd lowest	2nd lowest/2nd highest	2nd highest/highest
Exploration game	0.308*** (7.91)	0.465*** (10.32)	0.434*** (8.80)
Treasure size	0.104*** (3.56)	0.144*** (3.99)	0.461*** (8.56)
Treasure size x Type of game	0.155*** (4.16)	-0.0332 (-0.75)	-0.339*** (-6.80)
Observations	3408	3400	3472
Adjusted $R^2$			

OLS has robust standard errors clustered on individual.

32 dummies for round of the game are suppressed in the Table.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table B.11: Only within assignment: Pairwise comparison of size of treasure.

	(1) Lowest/2nd lowest	(2) 2nd lowest/2nd highest	(3) 2nd highest/highest
Exploration game	0.242*** (0.062)	0.408*** (0.067)	0.398*** (0.058)
Treasure size	0.039 (0.025)	0.156*** (0.038)	0.405*** (0.048)
Treasure size x Type of game	0.169*** (0.043)	-0.037 (0.051)	-0.334*** (0.056)
Constant	0.142*** (0.037)	0.183*** (0.042)	0.324*** (0.047)
Adjusted $R^2$			
Observations	2656	2656	2656

OLS has robust standard errors clustered on individual.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

Table B.12: Controlling for order: Pairwise comparison of size of treasure.

	(1) Lowest/2nd lowest	(2) 2nd lowest/2nd highest	(3) 2nd highest/highest
Exploration game	0.285*** (0.050)	0.433*** (0.057)	0.422*** (0.050)
Treasure size	0.048* (0.023)	0.143*** (0.035)	0.413*** (0.044)
Treasure size x Type of game	0.148*** (0.037)	-0.032 (0.044)	-0.337*** (0.050)
ascendingorder	0.124*** (0.034)	0.125** (0.042)	0.104* (0.040)
Constant	0.052 (0.034)	0.098* (0.043)	0.242*** (0.043)
Adjusted $R^2$			
Observations	3392	3384	3456

OLS has robust standard errors clustered on individual.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$



Table B.13: 4 last rounds: Pairwise comparison of size of treasure.

	(1) Lowest/2nd lowest	(2) 2nd lowest/2nd highest	(3) 2nd highest/highest
Exploration game	0.315*** (0.048)	0.449*** (0.049)	0.449*** (0.052)
Treasure size	0.055* (0.026)	0.136*** (0.039)	0.452*** (0.048)
Treasure size x Type of game	0.123** (0.044)	-0.006 (0.051)	-0.387*** (0.055)
Constant	0.099*** (0.027)	0.145*** (0.032)	0.277*** (0.042)
Adjusted $R^2$			
Observations	1696	1692	1728

OLS has robust standard errors clustered on individual.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

## C Appendix: Deriving $\rho$ and $\sigma$ using the SVO sliders

What can be inferred about  $\rho$  and  $\sigma$  when looking at the choices in the six sliders tasks (see Figure C.1)? In Figure C.2, decision maker's own monetary compensation is measured along the horizontal axis, and the other's monetary compensation is measured along the vertical line. Each of the 6 tasks is presented as a line segment in Figure C.2. The marginal rate of substitution captures the individual rate at which the decision maker is indifferent between giving up a marginal amount against higher income for the other. Below the 45-degree line through the origin the decision maker's own payoff is higher than that of the other. Therefore the marginal rate of substitution between own earnings  $m$  against those of the other  $y$  equals

$$MRS(m, y) = -\frac{(1 - \rho)}{\rho},$$

and above the 45-degree line where  $y > m$ ,

$$MRS(m, y) = -\frac{(1 - \sigma)}{\sigma}.$$

Thus when estimating  $\sigma$  from the SVO choice data, we should focus on tasks 3, 4, and 5 where at least a fraction of the corresponding line segment lies above the 45-degree line in Figure C.2. If a decision maker chooses an allocation strictly above the 45 degree

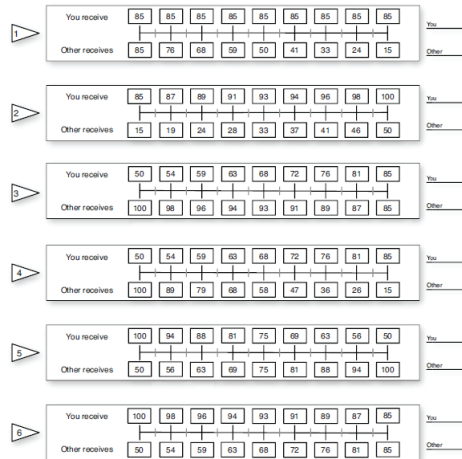


Figure C.1: SVO slider task.

line all these tasks, then the estimate satisfies  $MRS \geq -3/7$ , i.e.  $\sigma < 7/10$ . If the decision maker chooses an allocation at the 45-degree line for slider task 3, but above the 45-degree line in tasks 4 and 5, then  $\sigma \geq 1/2$ . Otherwise  $\sigma < 1/2$ .

By a similar argument, all slider tasks apart from task 3 contribute to the estimation of  $\rho$ . If choices associated with sliders 4 and 5 at extreme south-east, then  $\rho < 3/10$ , otherwise  $\rho \geq 3/10$ . In this latter case, if moreover slider 5 lies at extreme south-east, then  $1/2 > \rho \geq 3/10$ . Otherwise  $\rho \geq 1/2$ . If slider 1 is in extreme south, then  $\rho < 0$ . If moreover slider 2 is in extreme south-west, then  $\rho \leq -3/10$ .

The connection between the exploration task and the slider tasks is as follows.

- The further to the northwest from the 45-degree line are sliders 3, 4, and 5, the more willing is player two to explore when the first-player has not explored, with slider 3 to the extreme northwest indicating willingness to sacrifice and explore even for low treasure sizes and without first-player exploration.
- The further away from extreme south and east are the sliders 4, 5, and 6 below the 45-degree line, the more willing is the player to explore in reaction to first-player exploration. When sliders 1 and 2 are towards the south (and sliders 4, 5, and 6 are to the extreme south-east), a player prefers free-riding on the other's exploration effort.

Let us then consider first-player incentives to explore. The encouragement effect is defined as a positive effect of first-player exploration on second-mover probability of exploration. Keep in mind that the analysis above concludes that for a self-interested

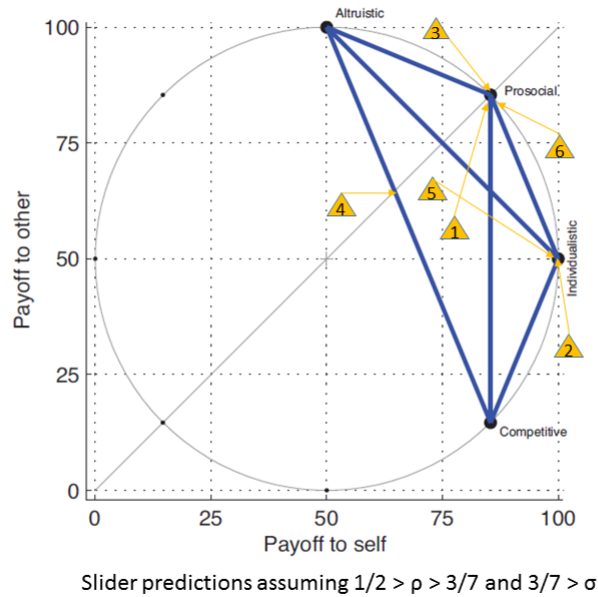


Figure C.2: SVO slider predictions.

second-mover, there is an encouragement effect in the exploration game but not in the public goods game. The encouragement effect appears in the public goods game if the second-player is other-regarding,  $1 > \rho \geq \sigma > 0$ . Moreover, the behavioral other-regarding motivation always strengthens the incentives to explore. Thus from the first-player perspective, the other-regarding motivation magnifies the strategic incentives to explore.

Let us first assume that both the first-player and the second-player are self-interested and they perfectly implement their optimal strategies and expect each other to do so (self-interest & subgame perfect equilibrium). Then there is never an encouragement effect in the public goods game but there is an encouragement effect in the exploration game if the conditions in Proposition 1 hold, that is when the treasure size is at the second-lowest level of 700 in our experiment.

Suppose then that the first-player and the second-player are self-interested and they imperfectly implement their optimal strategies and rather choose according to the QRE so that the log-odds of the choice probabilities are as displayed in Section X. Then there is again no encouragement effect in the public goods game. Yet an encouragement effect appears in the exploration game for all treasure sizes, not just the second-lowest one.

Suppose then that the first-player is self-interested but the second-player is other-

regarding and both implement their optimal strategies according to the QRE (and the first-player knows that the second-player is other-regarding). Then there is an encouragement effect both in the public goods game and in the exploration game for all treasure sizes. Yet, the encouragement effect is stronger in the exploration game.

If the first-player is other-regarding and inequity averse,  $\sigma < 0$ , then the first-player's intrinsic motivation generates a force that counteracts this indirect effect driven by the stronger encouragement effect. An inequity averse first-player knows that she has a higher cost of exploring than the second-player and the only way to reach equal payoffs or a position with advantageous inequality is by refraining from exploration. Yet, if the first-player's  $\sigma$  parameter is positive, then the first-player is efficiency concerned and more willing to contribute than a self-interested first-player for all the treasure sizes (if there is a sufficient encouragement effect).

### C.1 Estimating sigma and rho

To retrieve a crude estimate for  $\sigma$  we use slider task 3, 4, and 5. We first estimate a separate sigma for each slider task relevant for  $\sigma$ . Here the choice is coded as a share of other regarding behavior. Then we estimate an average of the estimated sigmas. For example, in task 3 there are 3 possible options lying strictly above the 45 degree line. If the individual chose the distribution in which the other gets the highest possible amount it is coded as 1, if the individual chooses the second to highest amount for the other it is coded as 2/3 and if the individual chose the third to highest amount to the other we code it as 1/3. The rest of the options lying on the 45 degree line or below are coded as 0. All options where the individual's outcome is large than the other's is relevant for rho, i.e., below the 45 degree line. We used the equivalent procedure to find an estimate for  $\rho$  as we did for estimating  $\sigma$ . Here, we use slider task 4, 5 and 6 to calculate the separate  $\rho$ .

## D Instructions and Online survey

# Welcome!

Participant

Tournament

Thank you for participating in this economic decision making tournament!

Throughout the study your choices are anonymous to other participants and all your answers will be treated confidentially.

Please read the following instructions carefully. Depending on how you and your partners decide, you can earn money in cash. Therefore, it is important that you read and follow the instructions. Should you have any questions after having read them, please raise your hand and we will come to you to answer your question. In this tournament, you are invited to make a series of decisions in a series of interactions. Each interaction has two specific roles. You will be assigned a single role which will be held constant throughout the experiment.

Throughout this study you will collect points. At the beginning of the series of interactions every participant receives an endowment. Points will be added or subtracted based on the outcome of each interaction. When you have conducted the last interaction and the tournament has come to an end two winners with highest number of points are announced, one for each role of the two-party interaction. Every participant receives 2€ in cash for participation and each winner receives an additional winning prize of 12€.

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## Tournament [tournament id]

[Logout](#)

[participant id]

Each interaction consists of two stages, where two sequential decisions are made. You are assigned to make the second decision and your counterpart the first decision. You will participate in a number of interactions throughout the study. For each new two-stage interaction you will be randomly paired with a new anonymous participant. The random draw may match you with the same counterpart more than once, but you and your counterpart will always be anonymous to each other.

### Stage 1

You and your counterpart are both presented with the same 4 boxes. Your counterpart must make the first decision and must decide whether or not to open one or more boxes. Your counterpart can open  $0$  up a maximum of  $1$  box(es).

1 of the 4 boxes (25%) contain(s) a treasure. For each treasure found by your counterpart, both you and your counterpart receive  $P$  points. This treasure size can vary across interactions, but notice that both are equally rewarded regardless of whether you or your counterpart finds a treasure.

Your counterpart's private cost of opening a box is 300 points per box. (There's no cost incurred by you when a box is opened by your counterpart.)

## Stage 2

When a decision has been made by your counterpart, you will learn which boxes, if any, were opened, and how many treasures were found. You must decide whether or not to open  $0$  or more box(es). You can open up a maximum of  $1$  box(es).

1 of the 4 boxes (25%) contain(s) a treasure. For each treasure found by you, both you and your counterpart receive  $P$  points. Recall that this treasure size can vary across interactions, but notice that both are equally rewarded whether you or your counterpart finds a treasure.

Your cost of opening a box is 200 points per box. (There's no cost incurred by your counterpart when a box is opened by you.)

When the interaction—that is, the two consecutive stages—is over, you will be given feedback about the outcome of the interaction and thereafter matched with a new randomly drawn anonymous counterpart and a new interaction starts with updated points and possibly with a new treasure size.

## Tournament

*At the start of each new interaction, you will be randomly paired with a new anonymous counterpart and a new interaction starts with updated points. Please note that the treasure size can vary across interactions, but not across participants. The private costs of opening a box varies across participants but not across interactions.*

When you have conducted the last interaction and the study has come to an end, two winners are announced: one winner is the first-mover (the participant making the first decision in each interaction) with the highest number of points, the other winner is the second-mover (the participant making the second decision in each interaction) with the highest number of points. Every participant receives 2€ in cash for participation and each winner receives an additional winning prize of 12€.

## Examples

Let, for example, the treasure size be 500 points, your box opening cost be 200, and your counterpart's opening cost be 300.  $E$  is the amount of points collected by your counterpart by

the beginning of the interaction.  $A$  is the amount of points collected by you by the beginning of the interaction. Suppose in the first stage, a box with a treasure is opened by your counterpart. In the second stage, no box is opened by you. In the end of the game:

- your counterpart will have  $E-300+500$  points
- you will have  $A+500$  points

Take another example. Suppose no box is opened by your counterpart in the first stage. A box with a treasure is opened by you in the second stage. The final points earned in this interaction will be as follows:

- your counterpart will have  $E+500$  points
- you will have  $A-200+500$  points

I have understood the instructions.  
(By disagreeing, you will be logged out.)

## Tournament [tournament id]

[Logout](#)  
[participant id]

Before entering the very first interaction we ask you to answer the following questions

### Questions

1. Tick which of the following claims is correct:

- the participants with highest and second highest number of points will win a prize
- all first- and second-movers compete for the same unique tournament prize
- the second-mover with the highest number of points wins a prize

2. Tick which of the following claims is correct:

- you will be a first-mover throughout the tournament
- you will interact with the same anonymous participant throughout the tournament
- a new second-mover participant will be randomly assigned to you for each new two-stage interaction

Suppose  $10400$  points have been collected by you by the beginning of the interaction. Your cost of opening a box is  $300$  points. Your counterpart's cost of opening a box is  $200$  points. The treasure size is  $500$  points.



If a box is opened by you in the first stage of the interaction and a treasure is found, while no box is opened by your counterpart in the second stage:

- 2. is your number of points at the end of the interaction.
- 3. is the net amount of points collected by your counterpart in the described interaction.

If no box is opened by you in the first stage and a box with a treasure is opened by your counterpart in the second stage:

- 4. is your number of points at the end of the interaction.
- 5. Your counterpart will  gain or  lose points in the described interaction.
- 6. is by how many points your counterpart's tally of points will change in the described interaction.

(If you choose to view instructions, you'll lose any answers!)

E Instructions. Experiment without group tournament incentive

# Welcome!

Participant

Tournament

Thank you for participating in this economic decision making tournament!

Throughout the study your choices are anonymous to other participants and all your answers will be treated confidentially.

Please read the following instructions carefully. Depending on how you and your partners decide, you can earn money in cash. Therefore, it is important that you read and follow the instructions. Should you have any questions after having read them, please raise your hand and we will come to you to answer your question. In this tournament, you are invited to make a series of decisions in a series of interactions. Each interaction has two specific roles. You will be assigned a single role which will be held constant throughout the experiment.

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[Privacy](#)

## Tournament [tournament id]

[Logout](#)

[participant id]

Each interaction consists of two stages, where two sequential decisions are made. You are assigned to make the second decision and your counterpart the first decision. You will participate in a number of interactions throughout the study. For each new two-stage interaction you will be randomly paired with a new anonymous participant. The random draw may match you with the same counterpart more than once, but you and your counterpart will always be anonymous to each other.

### Stage 1

You and your counterpart are both presented with the same 4 boxes. Your counterpart must make the first decision and must decide whether or not to open one or more boxes. Your counterpart can open  $0$  up a maximum of  $1$  box(es).

1 of the 4 boxes (25%) contain(s) a treasure. For each treasure found by your counterpart, both you and your counterpart receive  $P$  points. This treasure size can vary across interactions, but notice that both are equally rewarded regardless of whether you or your counterpart finds a treasure.

Your counterpart's private cost of opening a box is 300 points per box. (There's no cost incurred by you when a box is opened by your counterpart.)

## Stage 2

When a decision has been made by your counterpart, you will learn which boxes, if any, were opened, and how many treasures were found. You must decide whether or not to open 0 or more box(es). You can open up a maximum of 1 box(es).

1 of the 4 boxes (25%) contain(s) a treasure. For each treasure found by you, both you and your counterpart receive  $P$  points. Recall that this treasure size can vary across interactions, but notice that both are equally rewarded whether you or your counterpart finds a treasure.

Your cost of opening a box is 200 points per box. (There's no cost incurred by your counterpart when a box is opened by you.)

When the interaction—that is, the two consecutive stages—is over, you will be given feedback about the outcome of the interaction and thereafter matched with a new randomly drawn anonymous counterpart and a new interaction starts with updated points and possibly with a new treasure size.

## Tournament

*At the start of each new interaction, you will be randomly paired with a new anonymous counterpart and a new interaction starts with updated points. Please note that the treasure size can vary across interactions, but not across participants. The private costs of opening a box varies across participants but not across interactions.*

When you have conducted the last interaction and the study has come to an end, the points you have collected will be transformed to Norwegian Crowns (NOK) using an exchange rate announced in the laboratory.

## Examples

Let, for example, the treasure size be 500 points, your box opening cost be 200, and your counterpart's opening cost be 300.  $E$  is the amount of points collected by your counterpart by the beginning of the interaction.  $A$  is the amount of points collected by you by the beginning of the interaction. Suppose in the first stage, a box with a treasure is opened by your counterpart. In the second stage, no box is opened by you. In the end of the game:

- your counterpart will have  $E-300+500$  points
- you will have  $A+500$  points

Take another example. Suppose no box is opened by your counterpart in the first stage. A box with a treasure is opened by you in the second stage. The final points earned in this interaction will be as follows:

- your counterpart will have  $E+500$  points
- you will have  $A-200+500$  points

I have understood the instructions.  
(By disagreeing, you will be logged out.)

## Tournament [tournament id]

[Logout](#)  
[participant id]

Before entering the very first interaction we ask you to answer the following questions

### Questions

1. Tick which of the following claims is correct:

- you will be a first-mover throughout the tournament
- you will interact with the same anonymous participant throughout the tournament
- a new second-mover participant will be randomly assigned to you for each new two-stage interaction

Suppose  $10400$  points have been collected by you by the beginning of the interaction. Your cost of opening a box is  $300$  points. Your counterpart's cost of opening a box is  $200$  points. The treasure size is  $500$  points.

If a box is opened by you in the first stage of the interaction and a treasure is found, while no box is opened by your counterpart in the second stage:

- 2. is your number of points at the end of the interaction.
- 3. is the net amount of points collected by your counterpart in the described interaction.

If no box is opened by you in the first stage and a box with a treasure is opened by your counterpart in the second stage:

- 4. is your number of points at the end of the interaction.
- 5. Your counterpart will  gain or  lose points in the described interaction.

- 6. is by how many points your counterpart's tally of points will change in the described interaction.

(If you choose to view instructions, you'll lose any answers!)