ARTICLE



Overcoming problems of coordination and freeriding in a game with multiple public goods: dynamic contribution with information provision

Ai Takeuchi¹ · Erika Seki²

Received: 9 December 2022 / Revised: 24 April 2023 / Accepted: 27 April 2023 / Published online: 2 June 2023 © Japanese Economic Association 2023

Abstract

This study analyzes the role of information in overcoming the twin problems of freeriding and coordination failure that arise in the provision of social services with multiplicity and diminishing marginal return. We consider a model with two public goods, each of which has a threshold of effective contribution such that any costly contributions beyond the threshold generate no benefit. We analyze whether the provision of information on the threshold, which represents the need for contributions to social services, helps improve efficiency. The theoretical analyses predict that information provision enables prosocial individuals to match the thresholds, thus improving outcome efficiency. The experimental analyses confirm this prediction under a dynamic contribution system: the information on thresholds, together with the real-time update of cumulative contributions, promotes the efficient provision of multiple public goods. However, the analysis of contribution timings reveals a side effect of such information: it causes more freeriding when the need is small.

Keywords Charity · Freeriding · Coordination · Multiple public goods · Experiment · Information

Statements and declarations: none. We are thankful for the helpful comments from the anonymous reviewer and the participants of the Japanese Economic Association 2022 Autumn Meeting. This experiment was approved by the Ritsumeikan University Ethics Review Committee for Research Involving Human Participants. [Funding] This research was supported by JSPS KAKENHI [Grant Number 19K01565].

Ai Takeuchi ai-tak@fc.ritsumei.ac.jp
 Erika Seki erika_seki@econ.osaka-u.ac.jp

¹ College of Economics, Ritsumeikan University, 1-1-1 Noji-higashi, Kusatsu-shi, Shiga 525-8577, Japan

² Graduate School of Economics, Osaka University, 1-7 Machikaneyamacho, Toyonaka-shi, Osaka 560-0043, Japan

Keywords Charity · Freeriding · Coordination · Multiple public goods · Experiment · Information

JEL Classification $C72 \cdot C91 \cdot C92 \cdot H41$

1 Introduction

Many social services and individual contributions to them can be modeled as a game with multiple public goods with diminishing marginal returns. Motivating examples include volunteer service, charitable giving, and crowdfunding. When a serious natural disaster occurs, many volunteers are solicited to assist victims in different locations. Often, in such cases, too many volunteers gather at the same time in one location, hindering effective volunteer activities. Additionally, the excess supply of volunteers in one location may cause a shortage of volunteers in another location that also needs support. This example illustrates that when there are various services that require a sufficient number of contributions, it is important not only to have enough contributions in total but also to allocate them according to the needs of each service. This example also illustrates that when each service faces diminishing marginal returns from contributions there are twin problems of coordination failure and freeriding.

Coordination failure results in wasting valuable contributions, as excess volunteers may end up being redundant and inactive when they could otherwise be effective in other locations that have insufficient volunteers. This possibility and the experience of having their contributions wasted may discourage prosocial individuals from contributing in future. Thus, it is important to overcome the problem of coordination failure to make the best use of prosocial behavior in providing various services.

Hitherto, among numerous studies on public goods games (see, for example, Ledyard, 1995, Croson, 2010), only a few studies have analyzed cases of multiple public goods. Cherry and Dickinson (2008), Bernasconi et al. (2009), and Chan and Wolk (2020) considered a game with multiple linear public goods and found that individuals contribute more in total when there are multiple linear public goods than when there is only a single linear public good. In the multiple linear public goods game they studied, only freeriding problems can arise.

The closest studies to our research that examine coordination failure and freeriding are Corazzini et al. (2015; 2020). They used a multiple threshold public goods game and studied how to enhance efficiency by improving coordination. In the multiple threshold public goods game, the possibility of both freeriding and coordination failure is inherent. However, the type of coordination required is different from that in our motivating examples. In the game studied in Corazzini et al. (2015; 2020), the endowments of individuals were limited, so for the efficient provision of public goods, individuals were required to coordinate and concentrate their contribution in one public good to reach its threshold. In their study and other studies on coordination games (e.g., Van Huyck et al., 1990), coordination requires players to choose the same action to achieve social efficiency. In contrast, in the motivating examples we consider, coordination requires individuals to distribute their contributions among different public goods.¹ The coordination issue of this study resembles the choice of different routes by commuters studied in Selten et al. (2007).

The present study aims to investigate systems of information provision that will facilitate coordination and enhance contributions in multiple public goods game with diminishing marginal returns. Takeuchi and Seki (2023) considered the same problem, focusing on the fact that information about needs—what level of contribution is needed—is often not provided in motivating example cases, and analyzed whether the provision of information on needs improves efficiency. They found that providing information on needs are small. They argued that this could be due to fear of wasting one's contribution by contributing beyond what is needed. To reduce the fear of wasting one's contribution and to increase contributions, the experiment in the current study provides additional information about the contributions made by others by allowing for dynamic contributions with real-time updates.

With respect to the dynamic system of giving, inspired by Schelling (1960)'s suggestion of a dynamic system of soliciting donations,² there are a growing number of experimental studies on voluntary contribution mechanisms (VCMs) with decision making in sequential or dynamic (real-time) settings (see Vesterlund, 2015 for a comprehensive survey of the theoretical and experimental literature).

A study by Bracha et al. (2011) suggested that allowing for dynamic contributions may enhance coordination. Bracha et al. (2011) compared a single threshold public good game in sequential and simultaneous protocols, varying the size of the threshold value. In addition, they used a piecewise linear cost function that yields the interior Nash equilibrium and interior Pareto optimal outcome even when the threshold is zero (i.e., there is no threshold). When the threshold is high so that no one is willing to contribute up to the threshold alone and the contributions must be made simultaneously, coordination is required to contribute beyond the threshold. They found that in such cases, average public good provision is higher with sequential

¹ In crowdfunding, both types of coordination problems could arise. On the one hand, as studied in Corazzini et al. (2015; 2020), when the total resources that people are willing to contribute to crowd-funding are limited, it is necessary to concentrate funding in some projects so that they can reach the target amount necessary for implementation. On the other hand, on some crowdfunding sites, donations in excess of the target are possible (e.g., Kickstarter). Then, some projects may collect too much funding beyond an efficient level of operation. In this case, it is important not only to raise a sufficient sum of money but also to allocate funds optimally across multiple projects so that each project can be implemented effectively.

 $^{^2}$ Schelling (1960) examined the potential of a dynamic system in soliciting donations to the Red Cross. Since "if the contribution is divided into consecutive small contributions, each can try the other's good faith for a small price" (p.45), anticipation of the other's freeriding behavior is reduced in dynamic systems, boosting contributions.

protocols than with simultaneous protocols. They suggested that the sequential protocol reduces strategic uncertainty about whether other members will cover the rest of the threshold, thereby facilitating coordination (p. 421). Additionally, Deck and Nikiforakis (2012) found, using the minimum-effort game, that the real-time decision-making protocol in which all participants' chosen actions are monitored yields high efficiency, as it removes strategic uncertainty and enhances coordination.

Studies using public goods games with real-time decision-making protocols suggest that dynamic contribution increases cooperation. In these games, there is a given time interval in which individuals can modify their contribution while observing how the other group members are contributing. The final contribution made when the time limit is reached determines the final outcome of the game.³ Dorsey (1992) studied different forms of payoff functions and contribution-modification rules to see how these affect contribution behavior. Kurzban et al. (2001) used a single linear public goods game with a real-time decision-making protocol and found two factors that enhanced the average contribution: allowing individuals to make only upward revisions of their contributions during the time interval and providing only the lowest individual contribution in the group as real-time feedback information. Ishii and Kurzban (2008) found similar evidence using a student sample in Japan. Goren et al. (2003) studied the real-time provision of a single public good with a threshold for its provision. Based on the analysis of contribution timings in each period, they found that the timings of public good provision remained the same across periods without a tendency of delay. They concluded that the real-time protocol prevented the decaying trend of the average contribution usually observed in other studies with simultaneous protocols.

Given these findings, we adopt a dynamic contribution scheme with a real-time protocol as in Kurzban et al. (2001) and Goren et al. (2003): each player makes irrevocable contribution decisions during a given time interval and receives real-time updates on the contribution decisions made by the other group members. We study whether, under this scheme, the provision of information about needs will enhance coordination and contributions in the multiple public goods game with diminishing marginal return.

To be able to analyze the effects of providing information on needs, this study employs, with small modifications, the model of Takeuchi and Seki (2023), which introduces a threshold of effective contribution for each public good. Any contribution equal to or below the threshold is "effective", returning a constant marginal return for each unit contributed, while any contribution above the threshold is wasteful, returning a marginal return of zero. The threshold resembles the needs of the number of volunteers in the motivating example. We manipulate the information of

³ The real-time decision-making protocol is different from the continuous-time protocol studied in, for example, Friedman and Oprea (2012) and Oprea et al. (2014). The continuous-time protocol is similar to a high-frequency repeated game. The payoffs are calculated based on the chosen action for every second in the time interval. The participants can switch their actions any time, which will change the payoff stream generated. This is distinct from the real-time decision-making protocol, where the payoffs depend only on the actions chosen when the time limit is reached and not on the action modifications during the time interval.

383

the needs by making the value of the threshold unknown to the individuals (henceforth, the *partial information* condition) or known to the individuals (henceforth, the *full information* condition).⁴ To provide benchmark predictions for the experiment, we analyze the game as a static game under three assumptions regarding the preferences of the players: all players are selfish, maximizing their own payoffs; all players are prosocial, maximizing the sum of the payoffs of all the players; some members are selfish and others are prosocial, and the preference types of the members are known. When all players are selfish, the two information conditions yield the same outcome, as freeriding is a Nash equilibrium strategy. In the other two cases, the sum of contributions in the equilibrium will be equal or higher in the *partial information* condition, but the efficiency will be higher in the *full information* condition.

The summary of the experimental results is as follows. First, the prediction regarding the sum of contributions was not rejected: The average contribution rates that were unconditional on the values of the thresholds were not significantly different between the two information conditions. The prediction of efficiency was supported. Individuals in the *full information* condition increased their contribution levels with the values of the thresholds, yielding higher efficiency. However, an anomaly was observed in the *full information* treatment when the sum of the thresholds of the public goods was low.

The paper is organized as follows. Section 2 presents the model and theoretical predictions. Section 3 describes the experimental design and procedures. Section 4 analyzes the contribution rates and efficiency under the two information conditions and discusses the possible interpretations of subjects' behavior under the *full information* condition. Section 5 includes the discussion and conclusion of the paper. The Appendix includes full proofs of the propositions and additional tables.

2 The model

We model the situations of charitable giving and volunteering as a multiple public goods game with a threshold on effective contributions. In analyzing situations involving dynamic decision processes, it is important to distinguish between the analysis based on the final outcome of the game and the dynamics of the play. Here, we focus on the final outcome of the game and analyze the situation as a one-shot static game.

Let $N = \{1, ..., n\}$ be the player set. We assume for simplicity that there are only two public goods, *A* and *B*. In this game, each player *i* decides on a strategy $x_i = (x_i^A, x_i^B)$, which equals (1, 0) when *i* contributes to public good *A*, (0, 1) when *i* contributes to public good *B*, and (0, 0) when *i* does not contribute to either public

⁴ Because the threshold is a point at which the marginal return from the public goods changes, this study is also related to the literature on the public goods game with certain/uncertain marginal per capita return (MPCR) at the time the contribution is made. The effects of MPCR uncertainty in enhancing cooperation are mixed (see, for example, Dickinson, 1998, Gangadharan and Nemes, 2009, Levati et al., 2009, Stoddard, 2015, Butera et al., 2020, Cox and Stoddard, 2021).

good. Thus, the decision to contribute to a public good is binary (contribute or not contribute), and the players cannot contribute to both public goods at the same time.

For each public good, there is a threshold on effective contributions such that any contribution higher than the threshold does not increase the value of the public good. Let *k* denote a public good ($k \in \{A, B\}$) and $d^k \in \mathbb{N}$ denote *k*'s threshold on effective contributions. We assume that any contribution less than or equal to d^k benefits each member of the society by a constant value of u > 0 (we will call such contribution "effective"), but any contribution larger than d^k yields no benefits. Thus, the benefit that each player obtains from public good *k* under the strategy profile $x = (x_1, \ldots, x_n)$ is calculated as

$$u \times min\left\{\sum_{j\in\mathbb{N}} x_j^k, d^k\right\}.$$

We assume that d^k is determined randomly by nature. It takes an integer value between 1 and $\lfloor n/2 \rfloor$ with equal probability.⁵ We set the largest value to $\lfloor n/2 \rfloor$ so that it is possible to satisfy the threshold for both public goods if all members of society contribute. We also assume that d^A and d^B are independent.⁶

The payoff of a player is determined by the endowment *E*, the costs of contributing to the public good, and the benefits obtained from the public goods. We denote the cost of contribution as *c* and assume that nu > c > u. Thus, the cost of contribution is larger than the personal benefit obtained from the public good when the contribution is effective but is less than the benefit of an effective contribution to the whole society. To summarize, the payoff for player *i* under strategy profile *x* can be calculated as follows:

$$\pi_i(x) = E - c\left(x_i^A + x_i^B\right) + u \times \min\left\{\sum_{j \in N} x_j^A, d^A\right\} + u \times \min\left\{\sum_{j \in N} x_j^B, d^B\right\}.$$
 (1)

The two information conditions differ in whether the realized values of d^A and d^B are known or unknown to the players when they make their contribution decision. The values are known in the *full information* condition, and they are unknown in the *partial information* condition. To make the analysis of the *full information* condition simple and easily comparable with that of the *partial information* condition, we analyze the former conditional on the realized values of d^A and $d^{B,7}$

⁵ $\lfloor \cdot \rfloor$ and $\lceil \cdot \rceil$ represent rounding a decimal down and up to a whole number.

⁶ The independence between the thresholds is the main difference between this model and the model analyzed in Takeuchi and Seki (2023). Their model assumed that $d^k \in \mathbb{N}$ and $d^A + d^B \leq n$ and that all combinations of d^A and d^B are equally likely. This makes the values of d^A and d^B dependent and negatively correlated. However, recalling that the thresholds resemble the need for contributions to social services, their values are more likely to be independent (or positively correlated in the case of correlation). Thus, we changed the model accordingly.

⁷ Otherwise, we must treat x_i as an action profile and define a strategy profile of player *i* as a set that defines an action x_i for each possible realization of d^A and d^B .

2.1 Theoretical prediction

We analyze the game by solving the Nash equilibrium for three benchmark cases that differ in the social preferences of the players. For this analysis, we assume that the payoffs of the game are monetary payoffs, and players' preferences may depend on the monetary payoffs obtained by themselves and the other group members. The first benchmark is the case where all players are selfish, maximizing their own monetary payoffs. The second benchmark is the case where all players are prosocial, maximizing the sum of the payoffs of all group members. The third benchmark is the case where there are *m* prosocial players and n - m selfish players in the group. The full proof of the propositions is in the Appendix.

The Nash equilibrium of the first benchmark case with all selfish players follows the same logic as that of linear public goods games. For both information conditions, the dominant strategy is to not contribute to either public good. For the *full information* condition, this follows from the fact that c > u. For the *partial information* condition, to compare the marginal cost c and the marginal benefit of contribution, players must calculate the expected value of contribution because the realized values of d^A and d^B are not known. However, because the expected value of contribution includes the possibility of wasting one's contribution, it will always be less than or equal to u. Thus, in both information conditions, the cost of contribution is always greater than its benefit, so the dominant strategy is to not contribute to either public good.

The second benchmark case considers situations in which all players are prosocial and maximize the sum of the monetary payoffs of all group members. Propositions 1 and 2 state the Nash equilibria for the *full* and *partial information* conditions, respectively.⁸

Proposition 1 (Takeuchi & Seki, 2023) Let $i \in N$, and assume that all *i* are prosocial. In the full information condition, for any (d^A, d^B) , x^* is a Nash equilibrium if $\sum_{i=1}^{n} x_i^{*k} = d^k$ for $k \in \{A, B\}$.

Proposition 2 Let $i \in N$, and assume that all i are prosocial. Denote $\hat{s} = 1 + \{\lfloor n/2 \rfloor (nu-c)\}/nu$. In the partial information condition, x^* is a Nash equilibrium if $\sum_{j=1}^{n} x_j^{*k} = s^{*k}$ for $k \in \{A, B\}$, where $s^{*k} = \lfloor \hat{s} \rfloor$ when \hat{s} is not an integer and $s^{*k} \in \{\lfloor \hat{s} \rfloor, \lfloor \hat{s} \rfloor - 1\}$ otherwise.^{9,10}

⁹ When *n* is even, $\lfloor n/2 \rfloor = n/2$, so \hat{s} can be rewritten as

$$\hat{s} = \frac{-n}{2nu}c + \frac{n+2}{2},$$

and when *n* is odd, $\lfloor n/2 \rfloor = (n-1)/2$, so it can be rewritten as

$$\hat{s} = \frac{1-n}{2nu}c + \frac{n+1}{2}.$$

¹⁰ When \hat{s} is an integer, the players are indifferent between making and not making the $\lfloor \hat{s} \rfloor$ -th contribution. Thus, $\lfloor \hat{s} \rfloor$ and $\lfloor \hat{s} \rfloor - 1$ can both be s^{*k} .

⁸ Because the difference between this model and that of Takeuchi and Seki (2023) is in how the threshold values are randomized, Proposition 1 directly follows from their Proposition 3.

The intuition behind Proposition 1 is as follows. When a player is prosocial, the benefit of effective contribution nu is larger than the cost of contribution c due to the assumption that nu > c. Moreover, contributions beyond the threshold d^k are not preferred because they yield no benefit. Thus, in equilibrium, the sum of contributions to public goods k equals its threshold on effective contributions d^k .

To see the intuition behind Proposition 2, consider a player in the *partial information* condition deciding whether to be the s-th contributor to public good k. Given that s - 1 other players are contributing to public good k, the expected marginal benefit of the s-th contribution is $nu\{|n/2| - (s-1)\}/|n/2|$, which is the marginal benefit obtained if the contribution is effective (nu), multiplied by the probability of the contribution being effective. Thus, a player prefers to be the s-th contributor if

$$nu\{\lfloor n/2 \rfloor - (s-1)\} \ge c\lfloor n/2 \rfloor$$
 (2)

holds. Solving Eq. (2) for s yields $s \le 1 + \{\lfloor n/2 \rfloor (nu-c)\}/nu = \hat{s}$. Since the expected marginal benefit of the s-th contribution decreases as s increases, any strategy profile in which the sum of contributions is equal to $|\hat{s}|$, the largest integer s that satisfies this inequality, would be an equilibrium.

The third benchmark case generalizes the two previous benchmark cases. For simplicity, we assume that players are either prosocial or selfish, that there are m $(0 \le m \le n)$ prosocial players, and that each player's type is common knowledge.¹¹ We denote the set of prosocial players as $P \subseteq N$ and the set of selfish players as $N \setminus P$. This is a simple model of preference heterogeneity and uses an unrealistic assumption that players know the preference types of others. However, due to its simplicity, this model yields an insightful prediction of what would happen in the presence of preference heterogeneity and serves as a good benchmark to understand the experimental results.

First, we consider the case of the *full information* condition.

Proposition 3 Let $i \in P$ be prosocial and $j \in N \setminus P$ be selfish. Let x^* be a Nash equilibrium of the game under full information conditions with some (d^A, d^B) . Then, x^* satisfies the following:

- x_j^{*} = (0,0) for all j ∈ N\P.
 If d^A + d^B ≤ m, ∑_{i∈P} x_i^{*k} = d^k for k ∈ {A, B}.
 If d^A + d^B > m, ∑_{i∈P} x_i^{*k} ≤ d^k for k ∈ {A, B} and ∑_{i∈P}(x_i^{*A} + x_i^{*B}) = m.

The intuition behind Proposition 3 is as follows. First, the selfish players do not contribute, following the same reasoning as explained in the first benchmark case. Second, a prosocial player contributes if the contribution is effective. If the number of prosocial players is larger than the sum of the thresholds, it is possible to satisfy the thresholds of both public goods. In contrast, if the number of prosocial players

¹¹ Thus, this model is the same as the first benchmark case, where all players are selfish, when m = 0and is the same as the second benchmark case, where all players are prosocial, when m = n.

is less than the sum of the thresholds, all prosocial players will contribute to one of the public goods, but the sum of the contributions will be less than or equal to the threshold of each public good.

Let us consider a sum of contributions with respect to the sum of the thresholds of the two public goods in equilibrium $(\sum_{i=1}^{n} (x_i^{*A} + x_i^{*B})/(d^A + d^B))$. This value shows how well the group fulfilled the required level of contributions to the public goods. In the equilibrium in Proposition 3, when $d^A + d^B \le m$, this value is 1, and when $d^A + d^B > m$, it decreases as $d^A + d^B$ increases. Thus, Proposition 3 implies that given the limited number of prosocial players in the group, it is easier to satisfy the need when the threshold is lower.¹²

Next, we solve the third benchmark case for the *partial information* condition. The essence of the proof is the same as that of Propositions 2 and 3: selfish players do not contribute to either public good, and prosocial players do contribute as long as the expected marginal benefit of the contribution is larger than the marginal cost.

Proposition 4 Let $i \in P$ be prosocial and $j \in N \setminus P$ be selfish. Let x^* be a Nash equilibrium of the game under the partial information condition, and let $s^{*k} = |\hat{s}|$ when \hat{s} is not an integer and $s^{*k} \in \{|\hat{s}|, |\hat{s}| - 1\}$ otherwise for $k \in \{A, B\}$. Then, x^* satisfies the following:

- x_j^{*} = (0,0) for all j ∈ N\P.
 If s^{*A} + s^{*B} ≤ m, ∑_{i∈P} x_i^{*k} = s^{*k} for k ∈ {A, B}.
 If s^{*A} + s^{*B} > m, (∑_{i∈P} x_i^{*A}, ∑_{i∈P} x_i^{*B}) ∈ {([m/2], [m/2]), ([m/2], [m/2])}.

The second point in Proposition 4 covers the cases when there are enough prosocial players to satisfy $s^{*A} + s^{*B}$, the sum of contributions in the equilibrium of the case when all players are prosocial. Then, the sum of the contributions by the prosocial players is the same as that in Proposition 2. The third point covers the case when there are not enough prosocial players. Then, because the expected marginal benefit decreases as the number of other contributors increases, in equilibrium, the sum of contributions to each public good is approximately equal to m/2: when m is even, it is exactly equal to m/2, and when m is odd, it is equal to $\lfloor m/2 \rfloor$ and $\lfloor m/2 \rfloor$.

Finally, we compare the equilibrium outcomes across the two information conditions assuming the same distribution of preference types. If there are no prosocial players, the sum of the contributions and efficiencies obtained in the equilibrium are equal between the two information conditions. If there are some prosocial players, the expected value of the contributions is equal in the two conditions or is higher in the *partial information* condition than in the *full information* condition

¹² We can also interpret this implication from the perspective of m. Suppose that there are two groups, each with m' and m'' prosocial players (m' > m''). Then, the ratios of the contribution sum to the threshold sum both equal 1 when $d^A + d^B \le m''$, and the ratio is higher in the group with m' prosocial players when $d^A + d^B > m''$.

if $nu \ge 2(c + u)$.¹³ However, the efficiency obtained in equilibrium will be higher in the *full information* condition than in the *partial information* condition. This is because if the number of prosocial players is the same, a loss of efficiency due to freeriding is equally likely in the two information conditions, whereas a loss of efficiency due to overcontribution is possible in the *partial information* condition but will not occur in the *full information* condition.

3 Experimental design

To check the effectiveness of the provision of information about the threshold of effective contributions in increasing efficiency, we conducted a laboratory experiment. The experiment used the multiple public goods game with a threshold on effective contributions defined and analyzed in the previous section but allowed for dynamic contributions. The details of the game are explained in the next subsection. We compared the *full information* and *partial information* conditions in a between-subject design.

3.1 The implemented game

We compared the multiple public goods game with a threshold on effective contributions under the *full* and *partial information* conditions. For both information conditions, we used the following parameters: the number of group members *n* was 6, the endowment *E* and the cost of contribution *c* were 500, and the benefit of the effective contributions to the public goods *u* was 250. Thus, the MPCR was 0.5 for effective contribution. Because *n* is 6, the threshold of effective contributions d^k ($k \in \{A, B\}$) takes a value of 1, 2, or 3 with equal probability.

The differences between the game defined in Sect. 2 and the game implemented in the experiment are that in the experiment, (1) the game allowed for dynamic contributions and (2) the game was repeated for 10 rounds using the partner matching protocol. We explain each point in turn.

In the experiment, each decision round lasts 30 s. The participants can decide to contribute to public good A or to public good B at any time, and the contributions made in the group are updated and shown to all the participants in the same group in real time. Once a participant contributes, the decision cannot be changed, and when a participant does not take any action during a 30-s window, the participant is regarded as not contributing. Thus, a decision to contribute to public good A (or B) at any time during the 30 s is regarded as choosing strategy (1, 0) (or (0, 1)), and a decision to not take any action during the 30 s is regarded as choosing strategy (0, 0). Then, we use the payoff function defined in Eq. (1) to calculate the points participants obtain in the round.

¹³ If this condition holds, \hat{s} calculated in footnote 9 will be larger than the expected value of the threshold, $(\lfloor n/2 \rfloor + 1)/2$, for both even and odd *n*. Therefore, the expected value of contributions will be equal or higher in the *partial information* condition than in the *full information* condition.

389

This game was repeated for 10 rounds in the same group. In each round and for each group, the threshold value of each public good was randomly determined. This was true for both the *full* and the *partial information* conditions. Although the participants in the *partial information* condition were not able to observe the values of the thresholds, the realized values were determined before the decisions were made.

Given the parameters of the experiment, s^{*k} in Proposition 2 was 2 and 3. This is because Eq. (2) holds with equality. Thus, in the *partial information* condition, if there were enough prosocial participants, the sum of the contributions to each public good in equilibrium $(\sum_{i=1}^{6} x_i^{*A}, \sum_{i=1}^{6} x_i^{*B})$ was (2, 2), (2, 3), (3, 2), or (3, 3).

3.2 Procedures

The experiment was conducted online using Zoom, an online video communication tool. To ensure anonymity among the participants, each participant's name was changed to their participant identification number before they joined a zoom room with other participants, the video was turned off, the settings were adjusted so that the profile picture would not be displayed, and the participants were able to send chat messages to the experimenters only. Before the experiment started, the participants were asked to check their audio systems. Only those participants whose audio systems were working correctly were allowed to join the experiment. Before the experiment started, the participants were asked to fill out a questionnaire on Google Forms that asked for private information such as postal addresses and email addresses, which were required to make payments.¹⁴

Once the experiment started, the experimenter shared the PowerPoint slides in a Zoom window. Verbal instructions read aloud by the experimenter were prerecorded and included on the PowerPoint slides. First, the participants received oral explanations of the consent form and signed it by clicking through a webpage containing the consent form. Then, detailed instructions on the rules of the game and the experiment were given. The instructions used neutral terms, and all the rules of the game, including the number of repetitions and the payment method, were explained to the participants. After the instructions were given, the participants took a quiz to check their understanding. The participants who passed the quiz proceeded to the decision-making task of the experiment. First, there were 2 practice rounds so that the subjects could become familiar with the computer program and accustomed to the 30-s time limit. After the practice rounds, the groups were shuffled so that the decisions made in the practice rounds would not affect behavior in the decision-making tasks. Then, the participants made decisions for 10 rounds in these groups. When the participants finished the decision-making task, they automatically proceeded to the postexperiment questionnaire. The consent form, quiz, practice rounds, decisionmaking task, and postexperiment questionnaire were all programmed and conducted using oTree (Chen et al., 2016).

¹⁴ The file with this information was kept separate from the data file and was deleted after the payment was completed.

Each round of the decision-making task consisted of a decision-making screen and a feedback screen. An example of a decision-making screen for the *full information* condition is shown in Fig. 1. In the pull-down menu under "Your Investment Choice," the participants could choose "Invest in A" or "Invest in B." When they pressed "Confirm," the decision was finalized, the pull-down menu disappeared from their screen, and the numbers in "Current Amount of Investments" in the table were updated according to their decision.

The difference between the screen in Fig. 1 and the screen for the *partial information* condition was the lack of information on the "necessary amount of investments", which was the name used for the threshold of effective contributions in the experiment. The columns in the table were the same in both treatments, and only the numbers were missing in the *partial information* condition. This was to ensure that the participants understood that the values of the thresholds were predetermined even though they were not shown.

After 30 s, all the participants' screens switched to the feedback screen. Here, the participants received the following information: the decision the participant made, the threshold value, the total amount of contributions, and the benefits obtained for each project as well as the points the participant kept, the sum of the benefits from A and B, and the points participants gained from this round. The information provided on this page was the same in both information conditions. The participants in the *partial information* condition were able to see the threshold value of that round at this point and check their performance.

After the final round, the participants were informed of two rounds that were randomly chosen to determine their payments. The points obtained in the two randomly chosen rounds were exchanged at a rate of 1 point = 1 yen and paid together with the participation fee of 500 yen. Participants were reminded of the choices they made and the points they received in the two chosen rounds and were shown the amount of payment they would receive after the experiment.

In the postexperiment questionnaire, participants were asked about their age and gender, the college they belonged to, their subjective evaluation of their understanding of the rules of the experiment, their subjective evaluation of their willingness to take risks (Dohmen et al., 2011), and their social value orientation (SVO) using the slider measure developed by Murphy et al. (2011).¹⁵ Additionally, there were several open-ended questions on the ways they made their decisions.

¹⁵ We calculated individuals' SVO angles based on their answers to the six primary questions developed by Murphy et al. (2011). They defined an SVO angle as an arctangent of the following expression: (mean allocation for the others - 50)/(mean allocation for self - 50) (p. 773). Individuals were categorized into three SVO types (prosocial, individualistic, and competitive) according to the boundaries of SVO angles. The SVO angles of the participants in the experiment ranged between -16.26 and 46.77. 95 participants with SVO angles greater than 22.45 were categorized as prosocial individuals, 47 participants with SVO angles between -12.04 and 22.45 were categorized as individualistic individuals, and two participants with SVO angles below -12.04 were categorized as competitive individuals.

Г

Deule al 4 Januar		
Period 1 Invest	ment Choice	
Remaining Time: 0):26	
	Necessary Amount of Investments	Current Amount of Investments
Project A	1	0
Project B	3	0
Your Investment Choic	:e:	
Confirm		

Fig. 1 Sample of a decision-making screen (full information treatment)

3.3 Implementation

The experiment was conducted in September 2022 participated by undergraduate students at Ritsumeikan University.¹⁶ The participants were recruited through an advertisement posted on the university's learning management system. In total, 8 sessions were conducted, and 144 students (84 in the *full information* and 60 in the *partial information* treatment) participated in the experiment.

The characteristics of the participants in each treatment are summarized in Table 1. Although we randomly assigned the treatments to sessions, there were significantly more female participants in the *partial information* treatment. There were no statistically significant differences in the other characteristics. One point to note is that the average of the subjectively evaluated understanding of the experimental rules was high in both treatments; the participants understood the rules of the game well.

Table 2 shows the realization of threshold combinations in each treatment. Since each threshold value was randomly determined with equal probability, symmetric threshold cases were expected to occur with a probability of 1/9, whereas asymmetric threshold cases were twice as likely to occur. Most importantly, there was no

¹⁶ This experiment was approved by the Ritsumeikan University Ethics Review Committee for Research Involving Human Participants.

	Full information		Partial informati	Partial information			
	Observations	Mean	Observations	Mean	p value*		
Age (year)	84	20.69	59	20.75	0.96		
Female (proportion)	83	0.54	58	0.33	0.02		
Understanding	84	4.58	60	4.67	0.21		
Risk attitude	84	4.15	60	4.33	0.64		
SVO angle	84	25.54	60	23.71	0.74		
Prosocial (proportion)	84	0.68	60	0.63	0.60		

Table 1 Participant pool characteristics

*Female and Prosocial report the values of Fisher's exact test, The others report the values of the Wilcoxon rank-sum test, Risk attitude is on an 11-point Likert scale (0 = Completely unwilling to take risks, 10 = Very willing to take risks), Understanding is on a 5-point Likert scale (1 = Did not understand at all, 5 = Understood very well)

Table 2 Realization of thresholds	(d^A, d^B) Full info		formation	Partial informa- tion	
	(1, 1)	23	(0.164)	9	(0.09)
	(1, 2), (2, 1)	33	(0.236)	28	(0.28)
	(1, 3), (3, 1)	34	(0.243)	24	(0.24)
	(2, 2)	10	(0.071)	15	(0.15)
	(2, 3), (3, 2)	25	(0.179)	12	(0.12)
	(3, 3)	15	(0.107)	12	(0.12)

Frequency and relative frequency in parentheses are reported

significant difference in the distribution of combinations of thresholds between the treatments (p value = 0.2 using Pearson's chi-squared test).

The experiment lasted for approximately 1.5 h. The average payment was 2292 yen (approximately US\$16 at the time of the experiment), including the participation payment. This amount would allow the students to buy approximately 4 to 5 lunch boxes on campus. The payment was made using an emailed Amazon gift card and was sent on the day the experiment was conducted.

4 Results

In this section, we report the experimental results and examine the following experimental hypotheses. The hypotheses are derived from the theoretical propositions assuming that some participants in a group are prosocial and that the distribution of the number of prosocial individuals in a group is the same in the two treatments. We consider this a reasonable assumption to adopt since, according to the SVO measures, 4 out of 6 group members on average are categorized as "prosocial" in both

treatments.¹⁷ However, the caveat is that the "prosocial" participant categorized using the SVO measure of Murphy et al. (2011) does not coincide with the prosocial player assumed in the model.

We derive three hypotheses: one regarding contributions; one regarding $\sum_{j \in \mathbb{N}} (x_j^A + x_j^B) / (d^A + d^B)$, which is the extent of the group-level contribution relative to the sum of the thresholds of the two public goods (henceforth, the ratio of the contribution sum to the threshold sum); and one regarding efficiency.

- H1: The average contribution in the *full information* treatment is no greater than that in the *partial information* treatment.
- H2: In the *full information* treatment, the ratio of the contribution sum to the threshold sum is 100% up to a certain level of threshold sum and gradually decreases beyond that level. In the *partial information* treatment, the ratio will be highest when the threshold sum is lowest and decrease as the threshold sum increases.
- H3: The average efficiency in the *full information* treatment is greater than that in the *partial information* treatment.

4.1 Contribution rates

Figure 2A shows the average contribution rates of individuals in each round. The mean individual contribution rates are 0.43 in the *full information* treatment and 0.36 in the *partial information* treatment. Using each group's contribution rates averaged over 10 rounds as a unit of observation, the result of the Wilcoxon ranksum test does not reject the null hypothesis that the medians of the two treatments are equal (p value = 0.205). However, this analysis does not take into account the values of the thresholds of the two public goods. This is expected to affect the contribution level in the *full information* treatment. Figure 2B shows the average sum of contributions conditional on the threshold sum and treatment. As the figure shows, in the *full information* treatment, the average sum of contributions increases as the threshold sum increases, whereas in the *partial information* treatment, it does not vary with the threshold sum.

Table 3 reports the results of the random-effect Tobit regression using the sum of the contributions in group as a dependent variable to verify the above observations.¹⁸ The insignificant coefficient of the treatment dummy variable (Full information) in column [1] supports the abovementioned insignificant difference in mean contribution rates between the *full* and *partial information* treatments. Thus, H1 is

¹⁷ The average numbers of prosocial group members are 3.80 and 4.07 in the *full* and *partial information* treatments, respectively. There is no statistically significant difference between the two treatments in the median number of prosocial members in a group (the *p* value of the Wilcoxon rank-sum test is 0.55).

¹⁸ Tables 9 and 10 report the results of a similar regression (the multilevel mixed-effect probit model and random-effect probit model, respectively) using each individual's contribution decision in each round as a dependent variable. The results were qualitatively the same.

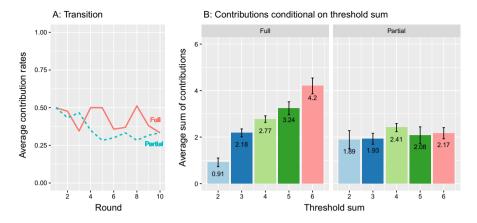


Fig. 2 Contribution rates: A the transition of the rates; B Contribution sum conditional on the threshold sum

not rejected. However, although the coefficient is insignificant, it is positive. The sign of the coefficient is not consistent with H1, which predicts that the average contribution in the *partial information* treatment will be equal to or higher than that in the *full information* treatment.

The specifications of columns [2] and [3] include the sum of the thresholds and its interaction with the information condition. In addition, the specification in column [3] controls for group characteristics such as the group average of the self-reported risk-taking attitude and the numbers of prosocial participants and female participants in each group. The insignificant coefficient of the threshold sum confirms that in the *partial information* treatment, the average group contribution does not vary with the threshold sum. The positive and significant coefficient of the threshold sum with the *full information* treatment indicates the effect of information on the thresholds in the *full information* treatment: The higher the threshold sum, the larger the average group contribution becomes. These findings match the observations of Fig. 2B. The positive and significant coefficient of the average number of prosocial participants in column [3] is consistent with the theoretical analysis that predicts an increase in contribution rates with the number of prosocial individuals in the group.

With the parameter estimates in column [3], the predicted group average contribution in the *full information* condition is smaller than that in the *partial information* condition when the threshold sum is 2. The predicted group average contribution in the *full information* condition exceeds that in the *partial information* condition when the sum of the thresholds is strictly greater than 3.¹⁹

Taking these results together, we summarize the observations on average contributions as follows:

¹⁹ Adopting the average numbers of prosocial and female participants, and the average value of risk attitude of the group reported in Table 1, when the threshold sum is 2, the predicted group contributions of the *full information* and the *partial information* conditions are 0.97 and 1.93, respectively. When the threshold sum reaches 4, the predicted value of the *full information* condition becomes 2.67, while that of the *partial information* condition is 2.09.

	[1]		[2]		[3]	
	Coefficient	p value	Coefficient	p value	Coefficient	p value
	(Std. Error)		(Std. Error)		(Std. Error)	
Full information	0.437	0.236	-2.556	0.000	-2.348	0.000
	(0.369)		(0.573)		(0.642)	
Threshold sum			0.065	0.375	0.084	0.329
			(0.073)		(0.086)	
Full information×Threshold sum			0.779	0.000	0.763	0.000
			(0.118)		(0.128)	
Risk attitude (group average)					0.202	0.260
					(0.180)	
Number of prosocial participants					0.162	0.053
					(0.084)	
Number of female participants					-0.117	0.337
					(0.122)	
Constant	2.082	0.000	1.847	0.000	0.501	0.574
	(0.280)		(0.468)		(0.890)	
Group-level variance component	0.475	0.013	0.471	0.000	0.376	0.002
	(0.191)		(0.104)		(0.123)	
Overall variance component	1.395	0.000	1.144	0.000	1.145	0.000
	(0.103)		(0.072)		(0.079)	
Observations	240		240		240	
Log likelihood	-414.514		-372.454		-369.392	

Table 3 Group level contribution by information on the threshold

Random-effect Tobit model, Dependent variable is the amount of contribution at the group level in each round to both public goods, Bootstrapped standard errors are based on 24 groups

Result 1 H1 is not rejected, as the aggregated average contributions do not differ between the treatments. Conditioned on the threshold sum, the average contribution tends to be lower in the *full* than in the *partial information* treatment when the threshold sum is low but higher when the threshold sum is high.

4.2 The ratio of the contribution sum to the threshold sum

The preceding analysis of aggregate contributions ignores the fact that groups face different threshold values in each round and the fact that it is not efficient for individuals to contribute when the other group members' contributions satisfy the threshold. To take the effects of information about the threshold values into account, we examine the ratio of the contribution sum to the threshold sum, that is, the extent to which the sum of contributions in each group satisfies the threshold sum. This ratio equals 1 if the sum of the contribution in the group exactly matches the threshold sum and equals 0 if all group members completely freeride. It is important to note that a higher ratio does not necessarily imply higher efficiency. Because we simply use the sum of the contributions and divide it by the sum of the threshold values, this ratio can take a value of 1 even when there is excessive contribution to one public good and undercontribution to the other. Section 4.3 discusses the issue of efficiency.

Figure 3A shows the time trends of the average ratio of the contribution sum to the threshold sum. The group average of the ratio of the *full information* treatment (0.66) is not significantly different than that of the *partial information* treatment (0.59) with a *p* value of 0.40 using the Wilcoxon rank-sum test. Figure 3B shows the average ratio separately according to the threshold sum. The left graph of the *full information* treatment shows that the sum of contributions satisfied approximately 70% of the sum of the thresholds except when the threshold sum was 2. The observation that the ratio dropped to a low value when the threshold sum was 2 in the *full information* treatment is not in line with the theoretical prediction. According to the prediction, the prosocial participants match the thresholds in equilibrium. Thus, the ratio of the contribution sum to the threshold sum should equal 1 as long as the threshold sum is less than or equal to the number of prosocial participants. The ratio will decrease as the threshold sum becomes greater than that number. The right-hand graph of *partial information* shows, as predicted, that the sum of the contributions increases.

We summarize the findings on the ratio of the contribution sum to the threshold sum as follows:

Result 2 The ratio does not vary with the thresholds in the *full information* treatment, whereas in the *partial information* treatment, it decreases as the thresholds increase. The observation in the *full information* treatment is not in line with H2, but the observation in the *partial information* treatment is in line with H2.

We examine the observed anomaly, i.e., the low ratio of the contribution sum to the threshold sum when the sum of the threshold is 2, in Sect. 4.4, where we investigate the timings of contribution decisions.

4.3 Efficiency

To examine whether the provision of information improves efficiency, we calculate the efficiency measured as the ratio of the difference between the actually attained and minimum attainable group payoffs and the difference between the maximum and minimum attainable group payoffs.²⁰ Figure 4A plots the average efficiency for each round. The average group efficiency across rounds of the *full information* treatment is 0.71, which is significantly higher than that of the *Partial-information* treatment

²⁰ The maximum group payoff is attained when the sum of the contributions to each public good matches its threshold. The minimum group payoff is attained in one of the two following cases: when the sum of the contributions equals zero for both public goods or when all the contributions are made to the public good with a smaller threshold. When the smaller threshold of the two public goods is sufficiently small, the latter case attains the minimum group payoff because the payoff loss of excessive contribution exceeds the payoff loss of freeriding.

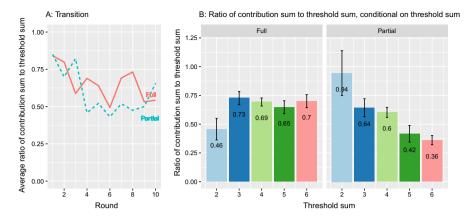


Fig. 3 Ratio of the contribution sum to the threshold sum: A the transition of the ratio; B ratios conditional on the threshold sum

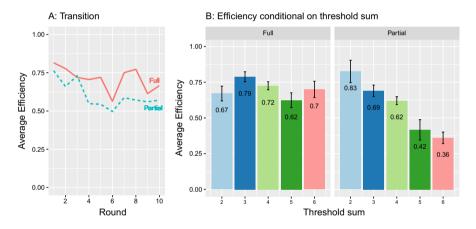


Fig. 4 Efficiency: A the transition of the efficiency; B Efficiency conditional on the threshold sum

(0.60), with a p value of 0.019 using the Wilcoxon rank-sum test. Figure 4B shows the average efficiency of the group outcomes for each treatment separately by threshold sum. In the *full information* treatment, it appears that the efficiencies are approximately the same for all threshold levels, while in the *partial information* treatment, the efficiencies tend to decline with the threshold.

Table 4 reports the results of random-effect Tobit regression using the efficiency measure as a dependent variable. The coefficients on the treatment dummy variable in column [1] are positive and significant, confirming that information on the thresholds improves average outcome efficiency. The specifications in columns [2] and [3] include the sum of the thresholds and its interaction term with the information condition to capture the differential impact of threshold sum by the informational condition on the outcome efficiencies. The negative and significant coefficient of the

threshold sum in columns [2] and [3] indicates that the average efficiencies correlate negatively with the sum of the thresholds in the *partial information* condition. The positive and significant coefficient of the interaction term implies that this negative effect of the threshold sum is offset mostly in the *full information* treatment. As a result, the average efficiencies remain relatively stable by the threshold sums in the *full information* condition. Both implications confirm the observations gained from Fig. 4B.

Using the estimated parameters in column [3], the estimated efficiency of the *full information* treatment is lower than that of *partial information* when the sum of the thresholds is 2, and it exceeds that of *partial information* when the summed threshold is 3 or greater.²¹

The next result follows from the above.

Result 3 The efficiency of the group outcome is higher in the *full information* treatment than in the *partial information* treatment. This observation supports H3.

Finally, we analyze the nature of the inefficiency, that is, whether the inefficiency is due to under- or overcontribution with respect to the thresholds. Recall that in the game analyzed, inefficiency can occur both from undercontribution (the sum of the contributions is strictly less than the threshold) and from overcontribution (the sum of the contributions is strictly more than the threshold). Freeriding increases the occurrence of undercontribution, and coordination failure increases the occurrence of overcontribution. Returning to the initial motivation of this study, we thought coordination failure was a problem worth investigating in the provision of multiple public goods with thresholds of effective contributions. This is because overcontribution to one public good may cause undercontribution to another, decreasing the overall efficiency. We then predicted that the provision of information on the thresholds together with information about others' contributions could reduce coordination failure, prevent overcontribution, and improve efficiency.

We examine whether the experimental data support this conjecture by investigating the sources of inefficiency. Table 5 lists the inefficiencies disaggregated by reasons, i.e., by whether they are due to overcontribution or undercontribution with respect to the thresholds of each public good conditional on the threshold sum. The values are calculated similarly to the efficiency measures: the reported inefficiency measure is the ratio of the foregone payoff (i.e., the difference between the actually attained payoff and the maximum attainable payoff from the good) to the difference between the maximum and minimum attainable payoffs.

By comparing the rows of undercontribution and overcontribution in Table 5, we see that efficiency losses are caused mainly by undercontribution rather than overcontribution in both treatments. Focusing on the first column, we observe that in

 $^{^{21}}$ Adopting the average numbers of prosocial and female participants, and the average value of risk attitude of the group reported in Table 1, when the threshold sum is 2, the predicted efficiencies of *full information* and *partial information* are 0.78 and 0.88, respectively. When the threshold sum reaches 3, the predicted value of the *full information* condition becomes 0.76, while that of the *partial information* condition is 0.74. When the threshold sum is 6, the predicted efficiencies of *full information* and *partial information* are 0.69 and 0.31, respectively.

	[1]		[2]		[3]		
	Coefficient (Std. Error)	p value	Coefficient (Std. Error)	p value	Coefficient (Std. Error)	p value	
Full information	0.127	0.023	-0.355	0.003	-0.328	0.025	
	(0.056)		(0.121)		(0.146)		
Threshold sum			-0.145	0.000	-0.144	0.000	
			(0.011)		(0.012)		
Full information×Threshold sum			0.122	0.000	0.120	0.000	
			(0.026)		(0.027)		
Risk attitude (group average)					0.020	0.569	
					(0.036)		
Number of prosocial participants					0.043	0.037	
					(0.020)		
Number of female participants					-0.022	0.509	
					(0.033)		
Constant	0.613	0.000	1.180	0.000	0.965	0.000	
	(0.034)		(0.069)		(0.145)		
Group-level variance component	0.087	0.000	0.100	0.000	0.081	0.000	
	(0.024)		(0.020)		(0.022)		
Overall variance component	0.254	0.000	0.228	0.000	0.227	0.000	
	(0.014)		(0.020)		(0.020)		
Observations	240		240		240		
Log likelihood	-66.222		-46.038		-43.017		

Table 4 Group efficiency by information on the threshol	Table 4	Group	efficiency	by	information	on	the	threshol	d
---	---------	-------	------------	----	-------------	----	-----	----------	---

Random-effect Tobit model, The dependent variable is group outcome efficiency in each round, Bootstrapped standard errors are based on 24 groups

the *partial information* condition, even when the threshold value is as low as 2, the inefficiency caused by overcontribution amounts to only 0.048.²² Moreover, in the *full information* treatment, when the threshold sum is 2, the inefficiency caused by undercontribution remains high (0.323). This indicates that the observed anomaly in Result 2 is caused by this high inefficiency due to undercontribution.

At this point, it is important to recall that the problem of coordination failure may account for not only the efficiency loss of overcontribution to one good but also the efficiency loss of undercontribution to another good. In such a case, the efficiency foregone due to overcontribution to one good is higher than the inefficiency

 $^{^{22}}$ The reason for this low efficiency loss caused by overcontribution in the *partial information* treatment is due to the low average contribution level. From Fig. 2B, we can see that the sum of contribution is approximately 2 or less in the *partial information* treatment. Since the minimum threshold sum is 2 in the experimental setting, a contribution of 2 or less will not cause overcontribution unless the contributions are made to the same public good. It is likely that the reduction in inefficiency due to overcontribution in the *full information* treatment is small because the inefficiency caused by overcontribution is low in the *partial information* treatment.

Table 5 Sources of inefficiency:percentage of lost payoff		Threshold sum					
		2	3	4	5	6	
	Full information						
	Efficiency loss	0.329	0.212	0.275	0.376	0.3	
	Overcontribution	0.006	0.01	0.011	0.008	0	
	Undercontribution	0.323	0.202	0.264	0.368	0.3	
	Partial information						
	Efficiency loss	0.175	0.31	0.379	0.583	0.639	
	Overcontribution	0.048	0.024	0.02	0	0	
	Undercontribution	0.127	0.286	0.36	0.583	0.639	

Table 6 Sour	ces of inefficiency	frequency of outcom	e categories
--------------	---------------------	---------------------	--------------

	7 1	2	C		
	Observations	Efficient (EF)	Freeriding (FR)	Coordination failure (CF)	FR-CF
Full information	140	30	99	4	7
(proportion)	1	0.21	0.71	0.03	0.05
Partial information	100	9	74	6	11
(proportion)	1	0.09	0.74	0.06	0.11

"Efficient (EF)" refers to the case in which the contribution sum exactly satisfies the threshold for each public good, "Freeriding (FR)" occurs when the summed contribution to each public good is less than or equal to the threshold and strictly less for at least one public good, "Coordination failure (CF)" refers to the case in which the summed contribution to at least one public good exceeds the threshold and the excess is sufficient to cover any shortage of contributions directed to another public good, "Freerid-ing and coordination failure (FR - CF)" occurs when the summed contribution to only one public good exceeds the threshold and the excess the threshold and the excess contribution to one public good is insufficient to offset the shortage of the others

of overcontribution to the good. Taking this limitation in mind, to evaluate the foregone efficiency by coordination failure, we classify the group outcomes into the efficiency categories in Table 6: "Efficient (EF)", "Freeriding (FR)", "Coordination failure (CF)" and "Freeriding and coordination failure (FR - CF)". The frequency of outcomes categorized as FR - CF was small in both treatments. Based on this, we consider that the inefficiencies due to over- and undercontribution measured in Table 5 are good approximations of the inefficiencies caused by coordination failure and freeriding, respectively. This leads us to the next result.

Result 4 In both information treatments, the efficiency loss due to coordination failure is low. The improvement in efficiency in the *full information* treatment compared to the *partial information* treatment is mainly derived from the decrease in freerid-ing, i.e., the undercontribution with respect to the threshold.

4.4 Timing of contributions

The previous analysis focused on the final outcome of each period at the group level. However, because the participants in the experiment can make dynamic contributions, analyzing the timing of contributions provides a deeper understanding of the individuals' contribution behavior.

Figure 5 plots, conditional on the threshold sum (expected threshold sum in *partial information*), the mean ratio of the contribution sum to the threshold sum at each 30-s interval.²³ Notably, under the *full information* treatment, when the threshold sum is 2, the ratio increases more slowly over the time interval and reaches a much lower level compared to the levels in cases with other threshold sums. Suppose that each prosocial individual has his or her own contribution timing and will contribute if that timing is reached and there is still room for effective contribution. Then, if we assume that the timing of the contribution is not affected by the threshold sum, the ratio should increase more quickly when the threshold sum is lower. Therefore, this observation of the curve for a threshold sum equal to 2 cannot be explained by such assumptions.

We explore the following two possible explanations for this observation.

• **BH1** Fear of simultaneous contribution by other members: A prosocial participant may be reluctant to contribute when the thresholds are nearly met because

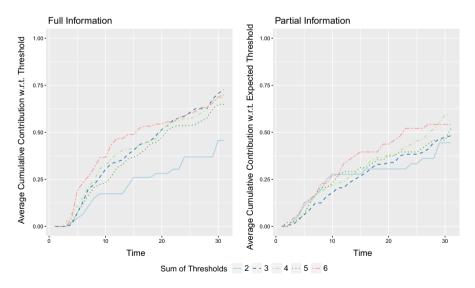


Fig. 5 Timing of contributions conditional on the treatments and the threshold sum

 $^{^{23}}$ For each second, we calculate the average of the cumulative contribution and divide it by the threshold sum.

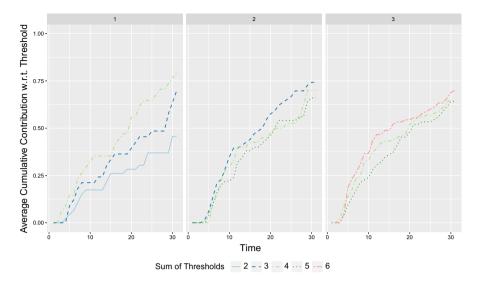


Fig. 6 Timing of contributions in the *full information* treatment conditional on the threshold and the threshold sum

his or her contribution at one point of time may be wasted if other participants contribute at exactly the same time.

• **BH2** Guilt-free freeriding: Prosocial participants prefer freeriding to contributing if the threshold can be reached without them contributing.

To explore the first possible explanation (BH1), we analyze the contribution trend of each public good. Figure 6 shows, for the *full information* treatment, the mean cumulative contributions with respect to the threshold for a public good, conditional on its threshold and the threshold sum. For example, the first graph in Fig. 6 illustrates the patterns of contribution to a public good with a threshold of 1 ($d^k = 1$) separately for each threshold sum $(d^A + d^B = 2, 3, 4)$. If the fear of simultaneous contribution by other members were the primary cause of the observation for the threshold sum of 2, we would expect the same trajectories for all threshold sum cases in the first graph, and the mean cumulative contributions with respect to the threshold would reach the same level regardless of the threshold sums. This is because in the first graph, only one more contribution will be effective, independent of the threshold sum, so the likelihood of contributing at the same time as another group member is the same. In contrast, the observed contribution trends differ depending on the threshold sums: when the threshold sum is higher, the timing of contributions is faster, and the contribution rate is higher. This observation does not support BH1 as an explanation for the anomaly.

To further verify BH1 at individual levels, Table 7 reports the results of regressing individual contribution decisions to a public good with a threshold of 1 separately for each public good (column 1 for public good A and column 2 for public

	[1] Public good A		[2] Public good B			
	Coefficient (Std. <i>p</i> value error)		Coefficient (Std. error)	p value		
Threshold of the other public good	0.157 (0.082)	0.054	0.190 (0.092)	0.039		
Prosocial	0.540 (0.244)	0.027	0.209 (0.202)	0.301		
Risk attitude	-0.002 (0.070)	0.978	-0.040 (0.039)	0.309		
Female	0.075 (0.322)	0.816	-0.023 (0.232)	0.922		
Constant	-2.298 (0.422)	0	-1.729 (0.266)	0		
Observations	354		314			
Log likelihood	-112.590		-96.384			

 Table 7 Individual contributions to a public good with a threshold of 1

Random-effect probit model, Dependent variable in column [1] is each individual's decision to contribute (= 1) or not (= 0) to public good A in rounds when the threshold of public good A is 1 (similarly for public good B in column [2]), The robust standard errors clustered at 14 group levels are reported

good B) against the threshold of the other good, controlling for the individual's risk-taking attitude, prosocial dummy and gender. The positive and significant coefficients for the threshold of the other public good for both columns confirm the insight from the first graph of Fig. 6 contradicting BH1.²⁴

We now examine the second possible explanation (BH2) and investigate whether there is supporting evidence compatible with guilt-free freeriding. When the number of potential contributors is larger than the required contribution, prosocial individuals may be more likely to withhold contributions because a decision not to contribute is justifiable to avoid excessive contribution and reduce efficiency losses. Prosocial individuals can freeride without feeling guilty about defecting from prosociality. If such guilt-free freeriding is the cause of the low contribution when the threshold is low, we can expect less contribution when the permissible number of freeriders, i.e., the difference between the number of group members (= 6) and the threshold sum, is large.

Recall that in this experiment, the group size is constant for all groups, and in all rounds, the permissible numbers of freeriders for a given sum of the thresholds are invariant. Therefore, from the final outcome of each round, we cannot distinguish the effects of the values of the thresholds from the effects of the numbers of permissible freeriders on contribution behavior. However, as the contribution timing progresses, the unsatisfied thresholds of the public goods, that is, the differences between the thresholds and the cumulative contributions already made to a public good at a particular time, become variant. Thus, by exploiting the differences among the unsatisfied thresholds, we can study the effect of the number of permitted

²⁴ However, care must be applied to interpret the results in Table 7 because these regressions do not reflect the implemented structure of individual decisions precisely. As we explained in Sect. 3.2, the participants must decide to contribute to either public good or not to contribute to either public good. This is different from making the decision to contribute or not to each public good separately.

freeriders on individual contribution decisions, controlling for the number of necessary contributions.

For analytical tractability, we cluster the 30-s contribution timings into three time periods: from the 1st to 10th seconds, from the 11th to 20th seconds, and from the 21st to 30th seconds.²⁵ The contribution decisions used for the analysis in the 11th - 20th seconds are the decisions of those who have not contributed by the 11th second regarding whether they contribute by the 20th second. Similarly, the decisions in the 21st - 30th seconds are of those who have not contributed by the 21st second regarding whether they contribute by the 30th second. We study the observations in the latter two time periods separately but do not study the first time period because the unsatisfied threshold of each public good equals its threshold, and therefore, the effect of permitted freeriders cannot be tracked.

Table 8 reports the results of analyzing the individual contribution decisions made in the two time zones separately for public good A and public good B. The dependent variables of columns [1] and [2] are the contribution decisions for public good A during the 11th - 20th s and the 21st - 30th s, respectively. The regressors include the permitted number of freeriders, the prosocial dummy and their interaction term. The control variables are the unsatisfied threshold of each public good and the individual's risk-taking attitude and gender. Columns [3] and [4] correspond to the contribution decisions for public good B.

The coefficients of interest are those related to the number of permitted freeriders. Consistently negative and significant coefficients for the prosocial type indicate that individuals with prosocial characteristics tend to withhold contributions when it is more permissible to do so. This finding is in support of BH2, guilt-free freeriding.

Result 5 The timing of the contribution is delayed when the threshold sum is low. As a result, the provision of information on the thresholds together with real-time information on the cumulative contributions reduces contribution rates when the thresholds are low.

5 Discussion and conclusion

This study examines whether the provision of information on needs together with information on the real-time updates of others' contributions help overcome the twin problems of freeriding and coordination failure prevalent in many social services. This question is motivated by examples of charitable actions and volunteering that require multiple services with different funding and human resource needs where any excessive contributions beyond these needs are wasteful. We consider a model with two public goods, each of which has a threshold of effective contribution. Any costly contributions beyond the threshold are wasted. We conduct an experiment to answer the question of whether, under a dynamic setting, the

²⁵ We thank the anonymous reviewer for suggesting this approach.

	[1] PG A, 11–20 sec.		[2] PG A, 21–30 sec.		[3] PG B, 11–20 sec.		[4] PG B, 21–30 sec.	
	Coeffi- cient (Std. error)	p value	Coeffi- cient (Std. error)	p value	Coeffi- cient (Std. error)	p value	Coeffi- cient (Std. error)	<i>p</i> value
Unsatisfied threshold A	0.149 (0.122)	0.221	0.336 (0.091)	0.000	-0.292 (0.138)	0.034	-0.249 (0.109)	0.022
Unsatisfied threshold B	-0.311 (0.152)	0.040	-0.197 (0.122)	0.107	0.232 (0.169)	0.171	0.185 (0.100)	0.063
Permitted freeriders	-0.130 (0.102)	0.202	-0.637 (0.253)	0.012	-0.507 (0.180)	0.005	0.018 (0.120)	0.881
Prosocial	0.975 (0.270)	0.000	-0.349 (0.419)	0.405	-0.178 (0.284)	0.532	0.846 (0.331)	0.011
Risk attitude	0.019 (0.040)	0.624	0.087 (0.034)	0.011	0.073 (0.048)	0.130	0.016 (0.016)	0.327
Female	-0.237 (0.149)	0.112	-0.012 (0.175)	0.945	0.295 (0.293)	0.314	-0.021 (0.149)	0.887
Prosocial × Permitted freeriders	-0.199 (0.092)	0.031	0.497 (0.289)	0.085	0.246 (0.118)	0.036	-0.283 (0.149)	0.057
Constant	-1.412 (0.549)	0.010	-1.238 (0.501)	0.013	-1.351 (0.575)	0.118	-1.684 (0.438)	0.000
Observations	674		571		674		571	
Log likelihood	-170.854		-140.936		-151.621		-142.768	

Table 8 Individual decision to contribute to each public good in two time periods

Random-effect probit model, The dependent variables of columns [1] and [2] are the contribution decisions for public good A during the 11th - 20th seconds and the 21st - 30th seconds, respectively, Similarly, the dependent variables of columns [3] and [4] are the contribution decisions for public good B, The observations used in columns [1] and [3] are the decisions of participants who have not contributed by the 11th second, while those in columns [2] and [4] are the decisions of those who have not contributed by the 21st second. The robust standard errors clustered at 14 group levels are reported

information about the thresholds improves the efficiency of providing multiple nonlinear public goods.

We find that in a dynamic setting, providing information about the thresholds of effective contribution to multiple public goods enables potential donors and prosocial individuals to meet the thresholds (Result 2). Although the provision of threshold information does not generally affect the contribution rate (Result 1), it increases the average contribution as the threshold level increases. Consequently, the provision of information promotes the overall efficiency of providing multiple public goods (Result 3).

These results lead to our conclusion: When information about others' contributions is provided, the provision of information on needs can improve outcome efficiency. This result improves upon the findings of Takeuchi and Seki (2023), which were that under a static game setting, the effects of providing information on contribution needs depend on the balance between the increase in freeriding and decrease in coordination failure. Together, the experimental results have the following policy implication: providing information on needs and dynamic information on to what extent these needs are being satisfied by others helps improve the efficiency of social services that face the twin problems of coordination failure and freeriding.

The foregoing analyses and two unexpected results in light of our initial motivating examples and theoretical analysis suggest some insights about future research. First, Result 4 implies that the reduction in freeriding, but not the reduction in coordination failure, improves the outcome efficiency in the *full information* condition. This is contrary to our expectation that the provision of information on needs reduces coordination failure, thereby improving efficiency. In fact, in our experiment, overcontributions rarely occur in the *partial information* condition, which may have obscured the expected outcome. The low contribution level in the *partial information* condition does not capture the overcontribution that occurs in the motivating examples. Thus, changing the model or the parameter setting to capture these phenomena is a topic for future research. One possibility is to change the benefits from the effective contribution so that they are larger than the cost of contribution, as studied in public goods games with an MPCR larger than 1 (e.g., Saijo and Nakamura, 1995).

Another topic for future research is the changeability/instability of prosocial behavior. The second unpredicted finding is that in the *full information* condition, the ratio of the contribution sum to the threshold sum is low, and therefore, there are high efficiency losses due to freeriding when the threshold is low. The results of the analysis on contribution timings were in line with the explanation based on guilt-free freeriding behaviors among prosocial individuals (Result 5). In other words, prosocial individuals can freeride without feeling guilty about defecting from prosociality if they think there are enough potential donors to cover the social needs. This is analogous to the concepts of the "bystander effect" in the social psychology and diminished sense of responsibility. Individuals' social preferences may be expressed differently in different social contexts and different informational environments. Studying the relationship between them will be a fruitful area of research for policy interventions aimed at promoting desirable behaviors.

A Proof

Proof of Proposition 2 Let $t^k(x_{-i}) := \sum_{j \neq i} x_j^k$ denote the sum of contributions to public good k by players other than i in strategy profile x. Suppose that $t^k(x_{-i}) = s - 1$ and $0 \le s - 1 < \lfloor n/2 \rfloor$. Then, the probability that the s-th contribution to public good k is effective is $(\lfloor n/2 \rfloor - (s - 1))/\lfloor n/2 \rfloor$. This probability is the same as the likelihood that the threshold for k is greater than s, so it takes 1 when s = 1, decreases by $1/\lfloor n/2 \rfloor$ for every s, and equals 0 when $s = \lfloor n/2 \rfloor + 1$. Given this probability, the expected payoff prosocial player i gains from contributing to public good k is

$$nE - c(t^{k}(x_{-i}) + t^{k'}(x_{-i}) + 1) + nu\left\{\sum_{j=1}^{s} (\lfloor n/2 \rfloor - (j-1))/\lfloor n/2 \rfloor + \sum_{j=1}^{t^{k'}(x_{-i})} (\lfloor n/2 \rfloor - (j-1))/\lfloor n/2 \rfloor\right\}$$

and the expected payoff from not contributing is

$$nE - c\left(t^{k}(x_{-i}) + t^{k'}(x_{-i})\right) + nu\left\{\sum_{j=1}^{s-1} (\lfloor n/2 \rfloor - (j-1))/\lfloor n/2 \rfloor + \sum_{j=1}^{t^{k'}(x_{-i})} (\lfloor n/2 \rfloor - (j-1))/\lfloor n/2 \rfloor\right\}.$$

Thus, player *i* contributes to public good *k* if

$$-c + nu \frac{\lfloor n/2 \rfloor - (s-1)}{\lfloor n/2 \rfloor} \ge 0 \tag{A.1}$$

and is indifferent between contributing and not when equality holds. Solving for *s* gives us $s \le 1 + \{\lfloor n/2 \rfloor (nu - c)\}/nu = \hat{s}$.

When \hat{s} is not an integer, Equation (A.1) holds with strict inequality, so making the \hat{s} -th contribution strictly increases the expected payoff compared to not contributing, but this is not the case for the \hat{s} + 1-th contribution. Let $s^{*k} = \lfloor \hat{s} \rfloor$, the largest integer s that satisfies Equation (A.1). x^* is a Nash equilibrium if $\sum_{j \in N} x_j^{*k} = s^{*k}$ for both $k = \{A, B\}$.

When \hat{s} is an integer, players are indifferent between making and not making the \hat{s} -th contribution. In this case, the Nash equilibrium can be defined as above, but s^{*k} can take $\lfloor \hat{s} \rfloor$ or $\lfloor \hat{s} \rfloor - 1$. Thus, there are four possible sums of contributions for the Nash equilibrium: $(\sum_{j=1}^{n} x_j^{*A}, \sum_{j=1}^{n} x_j^{*B}) \in \{(\lfloor \hat{s} \rfloor, \lfloor \hat{s} \rfloor), (\lfloor \hat{s} \rfloor - 1), (\lfloor \hat{s} \rfloor - 1, \lfloor \hat{s} \rfloor), (\lfloor \hat{s} \rfloor - 1, \lfloor \hat{s} \rfloor - 1)\}$.

Proof of Proposition 3 Let $i \in P$ be prosocial, $j \in N \setminus P$ be selfish, and the number of prosocial players be m (i.e., |P| = m), where $0 \le m \le n$. In this model, the type of each player is common knowledge. Therefore, the best response of each type does not change with the homogeneous case: it is better for the selfish player not to contribute because c > u, and it is better for the prosocial player to contribute as long as the contribution is effective because nu > c. Therefore, the sum of the contributions in equilibrium will only depend on the relative sizes of the number of prosocial players and the sum of the thresholds.

If m ≥ d^A + d^B, there are enough prosocial players to satisfy the thresholds of both public goods, so x* is a Nash equilibrium if x^{*k}_j = 0 for j ∈ N\P for both k = A, B and ∑_{i∈P} x^{*k}_i = d^k for both k = A, B.

If m < d^A + d^B, there are not enough prosocial players to satisfy the sum of the thresholds of both public goods, so all prosocial players will contribute to one of the two public goods. In this case, x^{*} is a Nash equilibrium if x_j^{*k} = 0 for j ∈ N\P for both k = A, B, ∑_{i∈P} x_i^{*k} ≤ d^k for both k = A, B, and ∑_{i∈P} (x^{*A} + x^{*B}) = m.

Proof of Proposition 4 The proof of Proposition 4 follows the same line of reasoning as the proof of Proposition 3. The selfish players will not contribute to the public goods because the cost of contribution *c* is larger than *u*, which is larger than the expected marginal benefit. The prosocial players will contribute as long as the sum of contributions *s* satisfies Equation (A.1). Denote \hat{s} and s^{*k} in the same manner as in the proof of Proposition 2. That is, $s^{*k} = \lfloor \hat{s} \rfloor$ when \hat{s} is not an integer, and $s^{*k} \in \{\lfloor \hat{s} \rfloor, \lfloor \hat{s} \rfloor - 1\}$ otherwise. Then, the sum of the contributions to each public good in the equilibrium depends on the relative sizes of s^{*k} and *m* as follows:

- If m≥ s*A + s*B, x* is a Nash equilibrium if x_j*k = 0 for j∈ N\P for both k = A, B and ∑_{i∈P} x_i*k = s*k for both k = A, B.
 If m < s*A + s*B, the sum of the contributions will be less than s*k for one or both
- If m < s^{*A} + s^{*B}, the sum of the contributions will be less than s^{*k} for one or both public goods. Because the expected marginal benefit from contribution decreases as the number of contributions increases, it is beneficial for prosocial players to contribute evenly between the two public goods. Thus, x^{*} is a Nash equilibrium if x^{*k}_j = 0 for j ∈ N\P for both k = A, B and (∑_{i∈P} x^{*A}_i, ∑_{i∈P} x^{*B}_i) ∈ {([m/2], [m/2]), ([m/2], [m/2])}.

B Additional tables

See Tables 9 and 10.

	[1]		[2]		[3]	
	Coefficient (Std. error)	p value	Coeffi- cient (Std. error)	p value	Coeffi- cient (Std. error)	p value
Full information	0.294 (0.186)	0.113	-1.580 (0.365)	0.000	-1.659 (0.366)	0.000
Threshold sum			-0.002 (0.061)	0.975	-0.002 (0.062)	0.972
Full information \times Threshold sum			0.485 (0.078)	0.000	0.483 (0.079)	0.000
Risk attitude					0.099 (0.037)	0.008
Prosocial					0.605 (0.204)	0.003
Female					0.288 (0.194)	0.138
Round	-0.054 (0.014)	0.000	-0.060 (0.014)	0.000	-0.060 (0.014)	0.000
Constant	-0.231 (0.160)	0.149	-0.210 (0.295)	0.476	-1.111 (0.358)	0.002
Variance of the random intercept at group level	$\begin{array}{c} 6.01\times 10^{-34} \\ \textbf{6}.35\times 10^{-18} \\) \end{array}$		6.25×10^{-33} 2.32 × 10 ⁻¹⁶		8.76×10^{-35} ((1.06 × 10^{-18})	
Variance of the random intercept at individual level nested in group level	0.944 (0.170)		1.110 (0.199)		0.936 (0.174)	
Observations	1440		1440		1410	
Log likelihood	-822.055		-766.712		-736.792	

Table 9 Individual contribution by information on the threshold

Multilevel mixed-effect probit model, Dependent variable is contributions at the individual level in each round to both public goods

	[1]		[2]		[3]	
	Coeffi- cient (Std. error)	p value	Coeffi- cient (Std. error)	p value	Coeffi- cient (Std. error)	p value
Full information	0.287 (0.158)	0.069	-1.514 (0.358)	0.000	-1.594 (0.384)	0.000
Threshold sum			0.010 (0.046)	0.823	0.009 (0.048)	0.847
Full information × Threshold sum			0.466 (0.077)	0.000	0.465 (0.077)	0.000
Risk attitude					0.098 (0.037)	0.009
Prosocial					0.591 (0.241)	0.014
Female					0.285 (0.221)	0.196
Constant	-0.521 (0.136)	0.000	-0.575 (0.288)	0.046	-1.460 (0.407)	0.000
Observations	1440		1440		1410	
Log likelihood	-830.199		-775.809		-745.630	

Table 10 Individual contribution by information on the threshold

Random-effect probit model, Dependent variable is contributions at the individual level in each round to both public goods, The robust standard errors clustered at 24 group levels are reported

References

- Bernasconi, Michele, Corazzini, Luca, Kube, Sebastian, & Maréchal, Michel André. (2009). Two are better than one!: Individuals' contributions to unpacked public goods. *Economics Letters*, 104(1), 31–33.
- Bracha, Anat, Menietti, Michael, & Vesterlund, Lise. (2011). Seed to succeed? Sequential giving to public projects. *Journal of Public Economics*, 93, 416–427.
- Butera, L., Philip, J. G., Daniel, H., John, A. L., & Marie-Claire, V. (2020). A New Mechanism to Alleviate the Crises of Confidence in Science-With An Application to the Public Goods Game. NBER Working Paper 26801.
- Chan, Nathan W., & Wolk, Leonard. (2020). Cost-effective giving with multiple public goods. Journal of Economic Behavior and Organization, 173, 130–145.
- Chen, Daniel L., Schonger, Martin, & Wickens, Chris. (2016). oTree-An open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, 9, 88–97.
- Cherry, T. L., & Dickinson, D. L. (2008). Voluntary Contributions with multiple public goods. In Todd L. Cherry, Stephan Kroll, & Jason Shogren (Eds.), *Environmental Economics*. Experimental Methods: Routledge.
- Corazzini, Luca, Cotton, Christopher, & Valbonesi, Paola. (2015). Donor coordination in project funding: Evidence from a threshold public goods experiment. *Journal of Public Economics*, 128, 16–29.
- Corazzini, Luca, Cotton, Christopher, & Valbonesi, Paola. (2020). Delegation and coordination with multiple threshold public goods: Experimental evidence. *Experimental Economics*, 23, 1030–1068.
- Cox, Caleb A., & Stoddard, Brock. (2021). Common-value public goods and informational social dilemmas. *American Economic Journal: Microeconomics*, 13(2), 343–69.
- Croson, R.T.A. (2010). Public goods experiments. In Durlauf, S.N., and Lawrence E. Blume eds. Behavioural and experimental economics: Macmillan Publishers.
- Deck, Cary, & Nikiforakis, Nikos. (2012). Perfect and imperfect real-time monitoring in a minimum-effort game. *Experimental Economics*, 15, 71–88.
- Dickinson, David L. (1998). The voluntary contributions mechanism with uncertain group payoffs. Journal of Economic Behavior & Organization, 35, 517–533.
- Dohmen, Thomas, Falk, Armin, Huffman, David, Sunde, Uwe, Schupp, Jürgen., & Wagner, Gert G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*, 9(3), 522–550.

- 411
- Dorsey, Robert E. (1992). The voluntary contributions mechanism with real time revisions. *Public Choice*, 73, 261–282.
- Friedman, Daniel, & Oprea, Ryan. (2012). A continuous Dilemma. American Economic Review, 102(1), 337–63.
- Gangadharan, Lata, & Nemes, Veronika. (2009). Experimental analysis of risk and unvertainty in provisioning private and public goods. *Economic Inquiry*, 47(1), 146–164.
- Goren, Harel, Kurzban, Robert, & Rapoport, Amnon. (2003). Social loafing vs. social enhancement: Public goods provisioning in real-time with irrevocable commitments. Organizational Behavior and Human Decision Process, 90, 277–290.
- Huyck, Van, John, B., Battalio, Raymond C., & Beil, Richard O. (1990). Tacit coordination games, strategic uncertainty, and coordination failure. *American Economic Review*, 80(1), 234–248.
- Ishii, Keiko, & Kurzban, Robert. (2008). Public goods games in Japan: Cultural and individual differences in reciprocity. *Human Nature*, 19, 136–156.
- Kurzban, Robert, McCabe, Kevin, Smith, Vernon L., & Wilson, Bart J. (2001). Incremental commitment and reciprocity in a real-time public goods game. *Personality and Social Psychology Bulletin*, 27(12), 1662–1673.
- Ledyard, J. O. (1995). Public goods: A survey of experimental research. In Kagel, John H. and Alvin E. Roth eds. Handbook of Experimental Economics: Princeton University Press.
- Levati, M. Vittoria., Morone, Andrea, & Fiore, Annamaria. (2009). Voluntary contributions with imperfect information: An experimental study. *Public Choice*, 138(1/2), 199–216.
- Murphy, Ryan O., Ackermann, Kurt A., & Handgraaf, Michel J. J. (2011). Measuring social value orientation. Judgement and Decision Making, 6, 771–781.
- Oprea, Ryan, Charness, Gary, & Friedman, Daniel. (2014). Continuous time and communication in a publicgoods experiment. *Journal of Economic Behavior and Organization*, 108, 212–223.
- Saijo, Tatsuyoshi, & Nakamura, Hideki. (1995). The spite dilemma in voluntary contribution mechanism experiments. *Journal of Conflict Resolution*, 39(3), 535–560.
- Schelling, T.C. (1960). The Strategy of Conflict: Harvard University Press.
- Selten, R., Chmura, T., Pitz, T., Kube, S., & Schreckenberg, M. (2007). Commuters route choice behaviour. Games and Economic Behavior, 58(2), 394–406.
- Stoddard, Brock V. (2015). Probabilistic production of a public good. Economics Bulletin, 35(1), 37–52.
- Takeuchi, Ai., & Seki, Erika. (2023). Coordination and free-riding problems in the provision of multiple public goods. Journal of Economic Behavior and Organization, 206, 95–121.
- Vesterlund, L. (2015). Using experimental methods to understand why and how we give to charity. In Kagel, John H. and Alvin E. Roth eds. Handbook of Experimental Economics Volume 2: Princeton University Press.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.