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Toward a third-generation rational choice theory: the multiple player approach to collective action problems

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Abstract
This paper aims to contribute to the development of a "third-generation" rational choice theory by introducing a Multiple Player Approach for analysing collective action problems. Drawing on the foundational first and second generation works of Olson (The logic of collective action, Cambridge University Press, Cambridge, 1965) and Ostrom (Scand Polit Stud 23(1):3–16), we introduce five player types that we believe capture essential empirical features of many real world collective action problems: Blind Riders, Tough Riders, Hard Riders, Easy Riders, and Low Riders. We consider the complex interaction and dynamics that unfold among them. The main novelty of the analysis is to draw attention to the need for active societal support to effectively empower and reward hard riders for resolving collective action problems, particularly when facing external shocks such as the Covid-19 pandemic, Brexit, and financial crises.

Keywords Rational choice theory · Collective action problems · Game theory · Player types

1 Introduction

1.1 First and second generation rational choice theory

Since Mancur Olson's (1965) groundbreaking idea of free-riding to explain unorganized individuals' tendency to free ride instead of contributing to the provision of collective goods, the free-rider concept has been widely used in social science research (Kim and Vikander 2015; Svendsen 2020a). Free riding has broadly

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been defined as "a group who obtains benefits from group membership but does not bear a proportional share of the costs of providing the benefits" (Albanese and Van Fleet 1985: 244). Realizing that free-riding is near impossible to practice in real life, scholars have often used terms like "cheap-riding", "soft-riding" and "easy-riding", i.e., groups of players attempting to reach zero contribution but only very seldom succeeding in doing so in a group. Such a free-rider framework has mainly been applied within organizations (Verburg et al. 2018), microeconomics (prevailingly game theory and behavioral economics), rational choice, and political economy (Hillman 2019; Svendsen 2020b; Poulsen 2009, and Poulsen and Svendsen 2005).[1]Within the first-generation rational choice theory, Mancur Olson's idea of narrow self-interest as the main driver for the action of individuals and groups was dominant from the mid-1960s to about 1990. These collective action problems are even more relevant for groups when performance and welfare is under pressure due to harsh challenges such as Covid-19, Brexit, and financial crises (Table 1).

Olson's main idea was that "any group or organization, large or small, works for some collective benefit that by its very nature will benefit all of the members of the group in question" (Olson 1965: 21). However, in obtaining this collective good for the group, the free-rider problem occurs. Olson continues: "Though all of the members of the group, therefore, have a common interest in obtaining this collective benefit, they have no common interest in paying the cost of providing that collective good. Each would prefer that the others pay the entire cost, and ordinarily would get any benefit provided whether he had borne part of the cost or not" (ibid.).

During the 1990s the "second-generation" rational choice theory was developed, partly as a critique of the narrow Olsonian rational choice approach (Ostrom 1990; North 1990; Svendsen and Svendsen 2003; Ostrom and Ahn 2009). Hence, in a key article Elinor Ostrom (2000) recognizes the important legacy of Olson's collective action problem. At the same time, she criticizes the assumption of a universal *Homo Oeconomicus*. The second-generation rational choice theory should therefore attempt to offer more realistic models where social control matters (Svendsen et al. 2023a, b). Besides operating with sociological explanatory variables such as a broader typology of collective goods, group characteristics, and people's rules-in-use, "rational egoists" as the fixed players as well as other "conditional players" should be included too when solving collective action problems (Ostrom 2000: 5).

Attempting to develop Ostrom's idea of "multiple types of players" further our contribution is to suggest some elements to what one might call a 'Third Generation Rational Choice Theory' in the form of a Multiple Player Approach (MPA). MPA seeks to introduce a richer and more empirically relevant ensemble of player types; this is done by expanding the free-rider theoretical framework to include five universal types of players, which can be identified in a society (see also Svendsen et al 2023a, b): Blind Riders (BRs), Easy Riders (ERs), Hard Riders (HRs), Tough Tiders (TRs), and Low Riders (LRs). The objective of our paper is to contribute to

[1] A similar strand of research, centered on the concept of social loafing, has primarily been undertaken within organizational sociology and social psychology (Simms & Nichols 2014; Stark et al. 2007).

Table 1 Description of the five player types

Type	Attributes	Behavior	Intuition
1. Hard Rider (HR)	Non-conditional	Highest possible contribution	Hard working member of the group
2. Tough Rider (TR)	Conditional	Rewards observed good behavior and punishes observed bad behavior	Stabilizer: Long run perspective of high performing group
3. Easy Rider (ER)	Conditional	Chooses an action that maximizes the (short term) net benefit (can include a high contribution if detection risk and punishment is sufficiently high). Can employ sophisticated methods to avoid detection of low contribution	Pure myopic homo economicus—self-centred and self-serving
4. Blind Rider (BR)	Conditional	Contributes fully if the share of contributors is larger than a threshold, hereafter the contribution is reduced	Mimics overall group performance: will adapt to the behavior of the majority
5. Low Rider (LR)	Non-conditional	Contributes according to their restricted abilities	Vulnerable and/or physically/cognitively impaired individuals

the advancement of rational choice theory by studying the interaction between these new player types and to map out the key properties of the dynamic time evolution of behavior implied by it. In doing so, we draw upon the seminal works of Mancur Olson (1965) and Elinor Ostrom (2000). By incorporating a diverse range of player types and examining their interaction and resulting dynamics, we seek to enhance our understanding of how to solve collective action problems.[2]

2 The multiple player approach

Let us now describe in more detail our free rider typology. Three of the five universal players, namely Hard Riders, Tough Riders, and to some extent, Blind Riders, are high-contributing individuals to a group. Thus, Hard Riders, and Tough Riders who are capable of, and inclined to, punish and reward other players such as colleagues or managers,[3] contribute more than average to the production of collective goods. Blind Riders (roughly half of a population according to Ostrom (2000: 7)) however only continue to make a high level of contribution as long as the average contribution exceeds a certain threshold after which they reduce their contribution.[4] Among sub-average contributors are E*asy Riders* (including pure *free riders*) as well as "legitimate" easy riders, that is, *Low Riders*. While Low Riders simply cannot physically or cognitively contribute very much (they may be disabled or pensioners), Easy Riders act in bad faith (cheaters) and seek to minimize their contribution to shared group benefits (i.e., collective goods) as much as possible, striving to reach zero contribution. See the description in Table 2 below.

To avoid detection and punishment, ERs generally try to disguise their thievery of other people's (leisure) time by investing in what Bourdieu (1979: 83) terms "work of dissimulation". We term this *hiding technology*. Besides, ERs together with BRs

[2] Our work is fundamentally inspired by the seminal work of Olson (1965) that emphasises group dynamics and collective action. There is a complementary literature that examines collective action through the lens of individual rationality and "social preferences"—see for example Fehr and Schmidt (1999), Fehr and Gächter (2000), Fischbacher et al (2001), Fehr and Fischbacher (2002), and Falk, Fehr and Fischbacher (2005).

[3] Tough riders thus resemble what Hampton (1987: 256) has termed *"political entrepreneurs"*: "These are people willing to pay the cost of providing the information necessary to produce public goods because they perceive that this activity will pay off for them *individually* in a big way; e.g., it might enhance their careers or increase their power". However, in contrast to Hampton who applies a first generation public choice approach within game theory, inspired by—among others—scholars like Mancur Olson, James Buchanan, Russel Hardin and Jon Elster, we see tough riders as driven by mixed motivation. Hence, they seek to achieve both altruistic and self-interested goals, in contrast to easy riders who solely seek to take care of their own narrow interests. We do, however, not in our analysis attribute any behavioral motives for the various players, but simply describe the consequences of their actions.

[4] In a public goods experiment (P-experiment), Fischbacher and Gächter (2010: 542) find the following distribution of players: "(i) 55 percent conditional cooperators who cooperate if others cooperate, (ii) 23 percent free riders who never contribute anything, irrespective of how much others contribute, (iii) 12 percent "triangle contributors" who increase their contributions with the contribution of others up to a point and then decrease their own contributions the more others contribute, and (iv) 10 percent unclassifiable." We do not have any "triangle contributors" but base our blind riders on Ostrom's (2000) description of conditional contributors.

Table 2 The following three choices are relevant for the ER types

Options	*Resulting net benefit*	Most likely
1: $c_t^{ER} = c_t^p$ with $H_t = 0$	$NB_t^{ER}\left(c_t^p;0\right) = b_t\left(c_t^p\right) - c_t^p$	Punishment hard, hiding technologies are costly and not efficient
2: $c_t^{ER} = 0$ with $H_t = 0$	$NB_t^{ER}(0;0) = b_t(0) - p_t(0) \cdot F_t$	Punishment soft, hiding technologies are costly and not efficient
3: $c_t^{ER} = 0$ with $H_t = H_t^*$	$NB_t^{ER}\left(0;H_t^*\right) = b_t(0) - p_t\left(H_t^*\right) \cdot F_t - h_t \cdot H_t^*$	Punishment soft, hiding technologies are cheap and effective

and TRs are *conditional* players, broadly understood as people who adjust their behavior by their knowledge of other players' behavior, for example, colleagues at a workplace. In contrast, HR and LRs are *non-conditional* or fixed, players who pretty much act in the same way regardless of ideology and institutional setup. Particularly in groups with a lack of information and bad coordination (Hampton 1987), a 'pure' ER acting in bad faith will thrive. However, as mentioned, this will entail collective evils in the form of lowering the motivation of contributing among conditionally playing colleagues. The TR and ER types choose their actions based on an analysis of the potential in the group. However, the ER and the TR are motivated by opposing incentives: Whereas the TR cares about the performance of the group, the ER only cares about private short-run net benefits.

3 The MPA and the ("boxer") hard rider problem

Against this background, the purpose of this paper is to formally model the Multiple Player Approach (MPA). MPA is relevant to any organization or repeatedly interacting group in general and we argue how Hard Riders can serve as crucial agents for solving collective action problems. However, and crucially, due to what we will call a *Hard Rider Problem* the Hard Riders may not thrive and may become "extinct" over time. The Hard Rider Problem is illustrated well by the workhorse, Boxer, in George Orwell's book, *Animal Farm* (Orwell 1951). Boxer's solution to every problem is simply: "I will work harder". Consequently, Boxer worked harder and harder until one day he finally collapsed. The lazy pigs "thanked" the horse for his efforts by letting the sick Boxer be fetched by Alfred Simmonds, Horse Slaughterer and Glue Boiler (Orwell 1951: 17). We argue that it is paramount for any group to address the Hard Rider Problem. In particular, it is crucial that Hard Riders are not exploited but instead supported and rewarded.

In times of progress, the ERs have the potential to develop their hiding strategies relatively unhindered. In times of recession, however, when the "pie" shrinks, e.g. following an exogenous shock (e.g., financial crisis, covid19, Brexit, supply shortages, etc.), resources get scarce and society's needs and thus efficiency matters even more. The TRs must therefore react adequately to the ERs and such effort requires time and resources.

The needed action undertaken by TRs affects HR types in two ways. First, the HR-types will feel a personal responsibility for the group. Thus, in times of crisis they will work even harder to make the group more resilient and ride through the storm. At the same time, there is less time and fewer resources to reward the beneficial efforts of the HRs. Hence, the burden put on the HRs increases. In our analysis, we model this as a situation where an HR-type might become ill (due to stress) and consequently must leave the group. Over time, the group, therefore, holds fewer hard-working individuals, and the problem intensifies as lower average contribution also negatively affects the BRs' willingness to contribute.

Theoretically, we argue that the configurations of the Multiple Player types within specific organizational setups lead to various positive and negative economic outcomes. The outcome depends on how much the most productive types (HRs, TRs, and BRs) are exploited by the least productive types.

The *Hard Rider Problem* leads to a crowding out process where a shrinking number of individuals (HRs) contribute to an extent that makes them at risk to be worn out, prevailingly due to roving ERs in disguise combined with lack of support and/or reward.

While the classic Free Rider Problem typically arises in an institutional set-up where HRs are poorly protected (legally, morally, and management-wise), we see the Hard Rider Problem, where free riding is often carried out in a hidden and sophisticated manner by Easy Riders, as being more plausible and empirically more common. From a policy view we see ERs and TRs as the most relevant types to understand as they tend to have the deepest understanding of the game played in a group and, hence, are most receptive to incentives such as symbolic and monetary rewards or risk of punishment.

4 The multiple player approach: a model

4.1 Basics

In the following we formally describe the Multiple Player types.[5] For each type, we specify their contribution level and their net benefit from the interaction. The interaction itself is modeled as a public goods provision game where each member of the group contributes to the good, and all receive the same benefit, depending on the size of the public good in each period. The dynamics are modeled by introducing a replicator dynamics model (Taylor and Jonker 1978) where the population share of a type changes over time depending on the type's performance (in terms of net benefit) relative to other groups.

There are n different types of individuals, indexed by $i = 1, \dots, n$. In our model there are $n = 5$ player types, to be defined below. For each type i and for any period t

[5] See also Brandt and Svendsen (2010; 2019) for simpler versions of this model setup.

there are k_t^i individuals of that type. The total number of individuals in the group at time t is given by $I_t = \sum_{i=1}^{n} k_t^i$.

Each member $j = 1, \dots, k_t^i$ of the group of type i players contributes in each round c_t^{ji}, giving a total contribution level of $C_t = \sum_{i=1}^{n} \sum_{j=1}^{k_t^i} c_t^{ji}$. We assume that all individuals belonging to the same group always contribute the same in any round, such that $c_t^{ji} = c_t^i$, for each $j = 1, \dots, k_t^i$ and $i = 1, \cdots, n$. Hence,

$$C_t = \sum_{i=1}^{n} k_t^i c_t^i \tag{1}$$

The average contribution at time t is given by:

$$C_t^A = \frac{C_t}{I_t} \tag{2}$$

The share of individuals of type i at time t is given by:

$$S_t^i = \frac{k_t^i}{I_t} \tag{3}$$

Therefore, the average contribution level at time t can be written alternatively as $C_t^A = \sum_{i=1}^{n} S_t^i c_t^i$ (4)

We assume that the highest feasible individual contribution of players at time t is $c_t^{max} + a_t^i$, implying that $C_t^A \le c_t^{max} + a_t^i$. a_t^i captures the possibility that a group might contribute more under special circumstances.

We also define a certain low contribution level, c_t^P, where $c_t^{max} > c_t^P \ge 0$, such that an individual is punished if her contribution falls below c_t^P.

All individuals receive an identical benefit, b_t, from the public good produced in period t. The public goods provision technology, which converts the aggregate contribution levels to units of benefits for each individual, is assumed to be linear and defined as $b_t = \alpha_t \cdot C_t$, where$0 < \alpha_t < 1$. From $\alpha_t < 1$, it follows that one unit of contribution converts to less than one unit of benefit. The total benefit in period t is $B_t = I_t \cdot b_t$. We assume that $\frac{dB_t}{dc_t^{ji}} > 1$, which establishes the condition for the good in question to be an interesting public goods provision game.[6]

In addition to receiving benefits from the public good, individuals belonging to specific groups (displaying a behavior that is perceived by other groups to be either punishable or rewarding) can be either punished or rewarded by other individuals; this is described below. Furthermore, there are technologies to hide easy-/free-riding behavior, but, as will be made clear below, only the ERs use this hiding technology.

Let P_t^i denote the amount of punishment an individual of type i receives at time t, and denote by R_t^i the amount of rewards received. The net benefit for an individual of type i at time t is then:

[6] This follows since $\frac{dB_t}{dc_t^{ji}} = I_t \cdot \frac{\partial C_t}{\partial c_t^{ji}} = I_t \cdot \alpha_t$, which is strictly positive.

$$NB_t^i = b_t(c_t) - P_t^i + R_t^i - C_t^i \tag{5}$$

The relative performance of a group is measured by its performance relative to the average performance. A group that performs above average performance will increase its share in society in the next period, while a group performing below average will decrease its share in society in the next period. Hence, the internal growth mechanism in our model is based on an evolutionary game theoretical approach where types of players compete for resources, and those types obtaining the largest proportion of the resources will have the most offspring (see Weibull 1997).

The average performance at time t is $NB_t^A = \frac{\sum_{i=1}^n k_t^i \cdot NB_t^i}{I_t} = \sum_{i=1}^n S_t^i \cdot NB_t^i$. We use a replicator function (Taylor and Jonker 1978), as in Brandt and Svendsen (2019):

$$k_t^i = k_{t-1}^i + \rho_t \cdot \left(NB_{t-1}^i - NB_{t-1}^A\right), \rho_t > 0 \tag{6}$$

Here $\rho_t > 0$ is a parameter that measures the speed of adjustment, i.e., how responsive the composition of society is to the evolutionary pressure.

4.2 Description of player types

4.2.1 Blind riders

The Blind Riders tend to be the most numerous—typically about 40–60% due to laboratory experiments (Ostrom 2000: 7; see also Fischbacher et al 2001, and Fallucchi et al 2022). Ostrom identifies these types as conditional co-operators "willing to contribute to collective action so long as others also contribute" (Ostrom 2000: 8). Initially, they contribute with the largest amount to collective goods (e.g., through taxpaying or work performed in an organization such as a workplace), but in case the average contribution drops below a certain threshold, their contribution will decline. According to Ostrom, they differ concerning tolerance about accepting declining average contribution within a population at micro, meso, or macro levels. In case of sufficiently low average contribution, BRs might not contribute at all. Furthermore, BRs do not engage in any relationships with other individuals regarding workload/net contribution, punishment of norm-violators, or supporting individuals in need. Hence, although law- and norm-abiding themselves, BRs are unwilling to sacrifice or risk anything to see fairness and justice done.

We assume BRs differ in their sensitivity to responding to average contributions. For simplicity we assume there are two BR sub-types, namely those with a small sensitivity in terms of reciprocating a declining average contribution (type BR1) and those who are more sensitive (BR2). Formally, BR contributes fully if the average contribution (in the preceding period) is above a threshold level, with the less sensitive *BR1* type having a relatively low threshold ($\overline{C}^{BR_1}$), while the highly sensitive *BR2* type has a higher threshold level ($\overline{C}^{BR_2}$), where $\overline{C}^{BR_2} > \overline{C}^{BR_1}$. If the average contributions drop below the threshold, the individual contribution is gradually reduced as the average contribution declines and will either become zero, as the average contribution reaches a threshold value ($\underline{C}_t^{BR_i}, i = 1{,}2$), or some lowest possible contribution level $C^{Min} \geq 0$.[7]

The contribution levels of the BR_i sub-type thus becomes: $c_t^{BR_i} = \max\{\gamma_{it}^{BR} \cdot c_t^{Max}\left(BR_i\right); C_t^{Min}\}$. Here γ_{it}^{BR} is the parameter that determines the actual contribution level of BR_i, where $0 \leq \gamma_{it}^{BR} \leq 1$. γ_{it}^{BR} is defined as:

$$\gamma_{it}^{BR} = \begin{cases} 1 & for c_{t-1}^{A} \geq \overline{C}_t^{BR_i} \\ \frac{c_{t-1}^{A} - \underline{C}_t^{BR_i}}{\overline{C}_t^{BR_i} - \underline{C}_t^{BR_i}} & for \underline{C}_t^{BR_i} < C_t^A < \overline{C}_t^{BR_i} \\ 0 & for C_t^A \leq \underline{C}_t^{BR_i} \end{cases} \quad (7)$$

In this expression, if the current average contribution is above the Blind Rider's threshold, then BR contributes maximally; if, on the other hand, the current average reaches or falls below the lower threshold then the BR type decides to contribute zero; in all other cases the BR's contribution increases linearly in line with increases in the average. The net benefit for the BR types is therefore[8]: $NB_t^{BR_i}\left(c_t^{BR_i}\right) = b_t\left(c_t^{BR_i}\right) - c_t^{BR_i}$.[9]

4.2.2 Easy riders

The Easy Riders (ERs) are the most complex of all types. Their motivation is to contribute as little as possible, but they are intelligent or sly in the sense that they typically have a whole stock of strategies by which they manage to manipulate and hide their contra-productive motives and actions.

For the sake of simplicity, reduce all the potential strategies (the Easy Rider's toolbox, so to speak) to just one hiding technology which enables ER types to hide their true contribution and intention, thus allowing them to reduce the probability of being detected and subsequently punished in case they contribute below the punishment-triggering threshold contribution.

We assume that the effectiveness of the hiding technology is independent of the contribution level. However, the more resources the ERs invest into this technology, the more it reduces the probability of being detected. Let H_t measure the effort an ER type invests into the hiding technology and let $CI_t = CI_t(H_t)$ be the cost function associated with providing H_t units of effort. We assume a constant marginal costs of hiding effort, $h_t \geq 0$. $CI_t\left(H_t\right) = h_t \cdot H_t$.

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[7] In the simulation we set $C^{Min} = c_t^P$.

[8] The benefits for the individual types in this section are specified as, for a given composition of types in the organization. How the benefit will be if a specific group contributes as described is described as $b_t\left(c_t^i\right)$.

[9] We can make the BR types less responsive by, e.g., including a moving average ($\gamma_t^{w-BR_i} = \sum_{l=1}^{L} w_{t-l} \cdot \gamma_t^{BR_i}$). In the simulation described in Sect. 3 below, we set $w_{t-l} = \frac{1}{L}$ and $L = 10$).

Next, consider how the hiding technology reduces the probability of being detected. We assume that without any hiding technology contributions below c_t^P will be detected and punished with certainty. Define $p_t = p_t(H_t)$ as the probability of detection and punishment, where $p_t < 1$ for $c_t^{ER} < c_t^P$ and $p_t = 0$ for $c_t^{ER} \geq c_t^P$. The larger the hiding effort, the lower the probability of getting detected and punished, at a decreasing rate (we assume $\frac{dp_t}{dH_t} = p_{H_t}\prime < 0$, $p''_{H_t} > 0$, for $c_t^{ER} \leq c_t^P$ and $p_{H_t}\prime = 0$ for $c_t^{ER} > c_t^P$). Finally, let F_t denote the punishment in case of detection. The net benefit function for the ER type is therefore:

$$NB_t^{ER}\left(c_t^{ER};H_t\right) = b_t\left(c_t^{ER}\right) - c_t^{ER} - p_t\left(H_t\right) \cdot F_t - CI_t\left(H_t\right) \tag{8}$$

Given an assumed independence between contribution levels and effects of investments into hiding technology on the detection probability, the optimal hiding effort can be shown to be:

$$\frac{dNB_t^{ER}}{dH_t} = -p_{H_t}\prime \cdot F_t - h_t \tag{9}$$

Hence, an ER type should invest in hiding efforts until the additional benefit (the value of a smaller probability of being detected) is equal to the additional cost of this effort. We denote this optimal level of hiding effort as H_t^*, where $H_t^* = \arg\left\{-p_{H_t}\prime \cdot F_t = h_t\right\}$. If $H_t = 0$: $h_t > -p_{H_t}\prime \cdot P_t$, we are faced with a boundary solution where $H_t^* = 0$ is optimal. $H_t^* > 0$ is more likely, the smaller h_t, the larger F_t, and the larger (numerically) $p_{H_t}\prime$. Finally, for contribution levels below c_t^p, the probability of being detected is not related to the contribution level. Therefore, once the contribution level is below c_t^p, a reduction of the contribution level to zero implies no added cost, and no $c_t^{ER} \in (0, c_t^p)$ is therefore optimal. This rests on the assumption that contribution levels and effects of investments into the hiding technology on the detection probability are independent. This is shown in Table 2.

The following conditions ensure that $H_t^* > 0$ is optimal:

Condition 1:

$$NB_t^{ER}\left(0;H_t^*\right) \geq NB_t^{ER}(0;0) => h_t \cdot H_t^* \leq \left[p_t^D(0) - p_t^D\left(H_t^*\right)\right] \cdot F_t \tag{10}$$

For $c_t^{ER} = 0$, the left-hand side (LHS), which measures the cost of using the hiding technology optimally ($H_t^* > 0$), is lower than the benefit of using it, measured by the right-hand side (RHS).

Condition 2:

$$NB_t^{ER}\left(0;H_t^*\right) \geq NB_t^{ER}\left(c_t^p;0\right) => p_t^D\left(H_t^*\right) \cdot F_t + h_t \cdot H_t^* + b_t\left(c_t^p\right) - b_t(0) \leq c_t^p \tag{11}$$

Here, the LHS is the costs of using the hiding technology, while the RHS is the benefit of using hiding technology where the benefit is avoided costs of not contributing c_t^p. The LHS consists of three parts. The first part is the expected cost of being detected ($p_t^D\left(H_t^*\right) \cdot F_t$). The second part is the cost of using the hiding technology

$(h_t \cdot H_t^*)$. Finally, the third part consists of the reduced benefit from the total contribution, which reduced the public good.[10]

From Conditions 1 and 2 we can deduce that the smaller h_t and the more effective the hiding technology, the more likely the two conditions are to be satisfied. The effect of changes in F_t on the likelihood of choosing a positive H_t is ambiguous. If F_t increases, it increases the likelihood that Condition 1 is satisfied but it becomes less likely that Condition 2 is satisfied. A larger F_t makes it more likely that if $c^{ER} = 0$ is optimal, then $H_t > 0$ is optimal (gain from hiding becomes larger), but it makes it less likely that $c^{ER} = 0$ is optimal (cost from hiding increases).

In Fig. 1, we present an example of how the level of punishment F_t affects NB_t^{ER}. Then, it is possible to identify the optimal choice from Table 2. Here, we assume that the relationship between the probability of being detected and the hiding effort is given by $p_t^D(H_t) = \frac{\rho}{\rho + H_t}$ where $\rho > 0$ is a parameter measuring how effective the hiding technology is and where larger ρ means less and less effective technology. Notice that the two break-even points identify the interval of F_t where the use of hiding technology is optimal.

4.2.3 Hard riders and tough riders

4.2.3.1 Tough riders Tough riders (TRs) are willing punishers. In many groups, a formal leader is a natural candidate for undertaking a tough rider role. TR types are often the best leaders, procuring fair rules of the game including positive and negative sanctions, and, through this, securing cooperating and contributing group members (e.g., employees) rather than defecting and loafing ones.

The TR type is the most resourceful type. They are individuals with a high sense of justice, always willing to support those who work hard and punish those who do not contribute. However, the TRs have limited resources (time, energy, power, etc.) to perform these tasks, and the more they focus on identifying and punishing low contributors, i.e., "freeloaders" and/or cheaters (the ER types), the fewer resources they can use to help the more naive and less righteous-minded HRs.

The TRs have resources available that they can spend either on supporting ("rewarding") the HRs or on detecting and punishing ERs. We assume that TRs are primarily focused on detecting and punishing easy-/free-riding, and will only support HRs if there are resources left over after free riders have been detected and punished. Denote the amount of resources at the TR type's disposal by X_t^{TR}. In each period S_t^{HR} units can be used to support the HR types, while D_t units can be spent on detection and punishment efforts. The amount of resources invested into D_t depends on the observed average contribution in the preceding period. We let $D_t = D_t(c_{t-1}^A)$ denote this. The TR thus faces a budget constraint, $X_t^{TR} = S_t^{HR} + D_t(c_{t-1}^A)$, where $\frac{dD_t}{dc_{t-1}^A} \le 0$.

For simplicity, we assume a very simple relationship between the observed past average contribution and the resources allocated to detection and punishment. If the

[10] The effect is measured at the individual level.

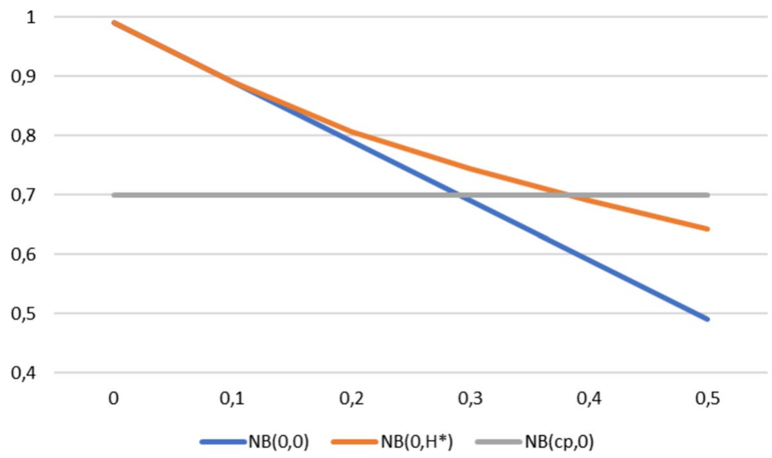


Fig. 1 The optimal strategy for the ER type as a function of the level of punishment. *Note* $c_t^{max} = 1, c_t^P = 0.3, \alpha_t = 0.1, \rho_t = 0.2, h_t = 0.1$. Breakeven points at $F_t = 0.1$, $F_t = 0.34$. X-axis measures F_t

average contribution is sufficiently large, no detection effort is undertaken by TRs; otherwise the entire budget is spent on detection and punishing. Formally,

$$If \overline{c}^D \geq c_{t-1}^A then D_t = 0$$

$$If \underline{c}^D \leq c_{t-1}^A then D_t = X_t^{TR} \tag{12}$$

$$If \overline{c}^D \geq c_{t-1}^A \geq \underline{c}^D then D_t\left(c_{t-1}^A\right) = \frac{\overline{c}^D - c_{t-1}^A}{\overline{c}^D - \underline{c}^D} \cdot X_t^{TR} \tag{13}$$

Thus, if the average contribution drops below $\overline{c}^D$, then support to the HR types diminishes. If it goes below $\underline{c}^D$, then no support for the HRs is available. Neither the support nor the punishment provides any direct net benefit for the TRs.

We assume that the population share of TRs remains constant over time. The reason is that the complex behavior of the TRs is difficult to copy. There is therefore a fixed number of these types, and we assume that they contribute a fixed amount to the public good. In the simulation described in Sect. 3, we set $c_t^{TR} = c_t^{max}$. The net benefit for the TR is therefore very simple: $NB_t^{TR} = b_t - c_t^{TR}$.

4.2.3.2 The hard rider: risk of over-riding Hard Riders always contribute with the highest possible amount, no matter the circumstances. In other words, HRs are always willing to run the extra mile for the group and undertake the lousiest and most time-consuming work tasks—and they never complain. It is therefore risky to be an HR because they will always be susceptible to exploitation (thus ending up being the "sucker", like the draught horse Boxer from Orwell's *Animal Farm*, mentioned earlier). In times with a lowering of the average contribution, they take personal responsibility and will work even harder, and the result may be stress and sickness, etc. In short, they risk *over-riding* and eventually die or become passive Low Riders. We model this by considering that for some threshold value of the average contribution, there will be a probability that the HR will have to leave the group and not return. In that case, the total amount of HR contribution will be reduced. On the other hand, HRs also receive support from the TRs. However, as already explained, this support ultimately depends on the average contribution within the group.

The behaviour of the HR type falls into four parts.

Part 1: Baseline behavior (P1).

The basic behavior is that HRs simply contribute the highest amount, disregarding the average contribution, and receive

$$b_t : c_t^{HR}(P1) = c_t^{max} \text{ and } b_t^{HR} = b_t(P1) \tag{14}$$

Part 2: Over-performance (P2).

This part adds to the behavior of the HR including the possibility that the HR types perform more than the other types, even if the others perform at their maximum. However, the HRs are not directly rewarded for their (extra) efforts. Given the overperformance, the total contribution increases for the same composition of types in the group:

$$c_t^{HR}(P2) = c_t^{max} + a_t^{HR}, a_t^{HR} > 0$$

$$b_t^{HR} = b_t(P2) > b_t(P1) \tag{15}$$

Part 3: Over-riding (P3)

This adds a probability that the HR does not contribute at all in any future period due to, e.g., stress-induced sick leave, which will make him or her leave the group for good. We assume that each HR type faces the same probability, P_t^C, of experiencing a stress-related collapse in any period t. If an HR type over-rides and consequently collapses, then this individual will no longer be in the group in future periods.

$$c_{t+1}^{HR}(P3) = 0, \text{with probability } P_t^C$$

$$c_{t+1}^{HR}(P3) = c_t^{HR}(P2), \text{with probability } 1 - P_t^C \tag{16}$$

If a HR does not collapse, the individual continues to contribute at the highest possible level.

What could influence P_t^C? We consider that since HRs exhibit a high level of conscientiousness, they must possess a high work ethic. However, being conscientious in our context implies that this player type cares most about the wellbeing of the group (rather than their own wellbeing) and takes personal responsibility for a declining total contribution. Since they cannot change the total contribution level significantly (no matter how hard they work), they are prone to collapse, driven by emotions like guilt and frustration.

We assume that when the total contribution is below a certain threshold, there is a probability, P_t^C, that an HR type no longer contributes and simply leaves the group. Assume that P_t^C is affected by c_{t-1}^A in the following way:

$$P_t^C\left(c_{t-1}^A\right) = 0 \text{ for } c_{t-1}^A \geq \bar{c}_{t-1}^C \text{ and } \frac{dP_t^C}{dc_{t-1}^A} > 0 \text{ for } c_{t-1}^A < \bar{c}_{t-1}^C \quad (17)$$

In the model we simply subtract the number of HRs that are collapsing in a group in any period from the total population of HRs. In the baseline simulation we model this so that the probability of collapse increases linearly from zero at $\bar{c}_{t-1}^C$ to one at $c_{t-1}^A = 0$:

$$P_t^C\left(c_{t-1}^A\right) = 0 \text{ for } c_{t-1}^A > \bar{c}_{t-1}^C \quad (18)$$

$$P_t^C\left(c_{t-1}^A\right) = \frac{\bar{c}_{t-1}^C - c_{t-1}^A}{\bar{c}_{t-1}^C} \text{ for } c_{t-1}^A \leq \bar{c}_{t-1}^C \quad (19)$$

Accordingly, the replicator function for an HR under P3 changes to:

$$I_t^{HR} = I_{t-1}^{HR} \cdot P_t^C + \rho_t \cdot \left(NB_{t-1}^{HR} - NB_{t-1}^A\right), \text{ where } \rho_t > 0 (20)$$

Part 4: Over-riding and reward (P4).

This part adds a reward mechanism designed by the TR types to support the HR types. Recall that the TR types have scarce resources available to support the HR types. The support reduces the probability of collapsing by reducing the threshold contribution under which the probability of collapse occurs. Hence, $\bar{c}_t^C = \bar{c}_t^C(S_t^{HR})$. The larger the support, S_t^{HR}, the lower the threshold: $\frac{d\bar{c}_t^C}{dS_t^{TR}} < 0$. In the simulation we model this in a very simple way by assuming that $\bar{c}_t^C = \frac{X_t^{TR} - S_t^{HR}}{X_t^{TR}} \cdot \bar{c}_0^C$, where $\bar{c}_0^C$ is the initial or pre-support level.

The support is modelled as a club good for the HR. All types that are identified as HR will be granted the support S_t^{HR}. The support provides two distinct benefits to the HR types. Firstly, the support acts as mental-emotional support that reduces the probability of collapsing. Secondly, it has a direct benefit-creating part. The direct benefit enhancing support is modelled by adding S_t^{HR} to the net benefit of all HR types. In total, the net benefit function for the HR types is:

$$NB_t^{HR} = b_t - c_t^{max} - a_t^{HC_1} + S_t^{HR_1} \quad (21)$$

4.2.4 Low riders

Low riders (LR) do not adjust their behavior based on any knowledge of other players' behavior. Unlike ERs they are not ill-willed exploiters but simply lack the abilities and skills to contribute to the collective good in a group above a certain level. Examples could be physically and/or mentally disabled people worn out due to a long and hard-working life. They cannot be blamed for their sub-average contribution. Hence, they can be regarded as *legitimate easy riders*.

We set the contribution of LRs to $c_i^{min} = c_t^P$, such that they are not punished. Given that the ER types could also choose c_t^P and only do so if no other action gives a higher net benefit, the LR types will never get more net benefit than the ER types, and typically less. Therefore, the description of the LRs is simple. They contribute c_t^P and receive b_t:

$$NB_t^{LR} = b_t\left(c_t^{LR}\right) - c_t^P \tag{22}$$

The simulation in the following section assumes that low riders do not grow in numbers above a certain share in a group. Moreover, and again for reasons of simplicity, we see the "low rider nature" as a life-long, innate characteristic that is not copyable or learnable. This stands in contrast to the ERs, whose strategies are highly contagious because—if being successful in a group—they will always be attractive to "weak souls" who are ready to score a quick and easy temptation pay-off.

5 Simulation results

Our model has many parameters, and it is difficult to analytically characterize the (short, medium and long run) behavior of the dynamics. We therefore employ a simulation approach. This allows us to consider the dynamics in some detail and move beyond just characterizing the steady states (rest points) of the dynamics; the well-known limitation of simulations is that we must be a content with a partial understanding of the dynamics for certain sets of parameter values and initial values.

Our simulation focuses on the Hard Rider problem: In *good times*, characterized by economic prosperity and surplus in society, the HRs are typically doing fine because they get support and thus have a low risk of over-riding. In contrast, in *bad times*, when their significant contribution paradoxically is mostly needed, the HRs will suffer and eventually break down. This is because support from TRs is reduced, and ERs become even more roving, which is why the lives of HRs become more stressful, and the probability of being caught in the Hard Rider problem, ending in eventual collapse, rapidly increases.

5.1 Domination by easy riders

There are fundamentally two types of states the system can move to: either a situation where the HRs (including TRs) dominate, or a situation where the ERs dominate.

In Fig. 2 we see an initial increase in HRs in a group. However, the average contribution is slowly reduced due to the increase in the share of low-contributing types. Once the average contribution falls below 0.9—the upper threshold for where the BRs begin adjusting their contribution—it triggers a cascade of effects that inevitably pushes the system towards the low-contribution state. BRs contribute less, and the HRs begin feeling stressed; the TRs use more resources on detecting low contribution and fewer resources to support the HRs, leading to even lower contribution, which again provides a feedback loop that reinforces lower contribution. Eventually, all HRs vanish, and only low-contributing individuals remain in the group. In bad times, e.g., the low-contribution situation described here, there is no longer sufficient surplus available to support and protect the most productive and, hence, most vulnerable HRs. Thus, we see that easy-riding becomes an increasingly serious societal and workplace-related problem, the more resources are taken away to support the high productivity types. HRs simply end up over-riding themselves and, after this transformation, contribute with close to nothing—or nothing at all. Put otherwise, this transformation reduces them to unhappy low riders—or even pure free riders.

5.2 Domination by tough and hard riders

The second generic state that the system can move to is where Tough and Hard Riders dominate the population, as shown in Fig. 3. In Fig. 3 the small increase in support provides sufficient momentum for the HR type to be the most successful. An initial phase with falling contribution could mean that HRs significantly increase in share so the contribution will reach its absolute maximum average contribution level, given by $c_t^{max} + a_t^{HR}$, given by 1.15 in the simulation.

5.3 Switching from ER to HR/TR domination

It is naturally of great interest to understand how we can cause behavior to "escape" from domination by ERs to one where HRs and TRs take over. Such a change could be due to an increase in the reward/punishment budget X_t^{TR}. If we (cf Fig. 2) increase it from 1.7 to 1.8, this results in a very different outcome, as shown in Fig. 3.

There are many other ways to generate a shift from a low- to a high-contribution state. This is described in Table 3. These results provide a "toolbox" of parameter changes that in principle can be invoked to either preserve a high-contribution state or enable a change that will move the system towards such a state.

There are three groups of effects in Table 3: Those providing more favorable conditions for the HRs, those making it harder for the ERs, and those conserving the status quo. Let us look more into the first two groups. Instead of analyzing one parameter change at a time, we focus on combining two important overarching principles, namely the effectiveness and consequences of punishing unacceptable behavior compared to rewarding preferable behavior. A society may be far away from the parameter values at which the system "shifts" from one state to another, and then more than small changes in one parameter value are needed for the shift to take place.

Initial parameter values	Generic state 1: The growth and demise of the HR types and collapse of the average contribution level

Common	
C_t^{max}	1
C^P	0,3
F_t	0,3
α_t	0,1
ρ_t	0,3

Initial group size	
BR_0^1	40
BR_0^2	40
ER_t	5
HR_0	10
TR_0	5
LR_t	5

BR types	
BR_1	
C_t^{high}	0,7
C_t^{low}	0,3
BR_2	
C_t^{high}	0,9
C_t^{low}	0,3
$C^{min}=C^P$	0,3

ER types	
H*	0,73
C_t^{ER}	0
P	0,58
ht	0,1
H*	0,73
p(H*)	0,58
rho	1

TR types	
X_t^{TR}	1,7
$C_t^{high\text{-}D}$	0,7
$C_t^{low\text{-}D}=C^P$	0,3

HR types	
a-extra	0,15
$C_t^{high\text{-}C}$	0,9
$C_t^{low\text{-}C}=C^P$	0,3
s-bar	1

LR types	
C_t^{LR}=Cp	0,3

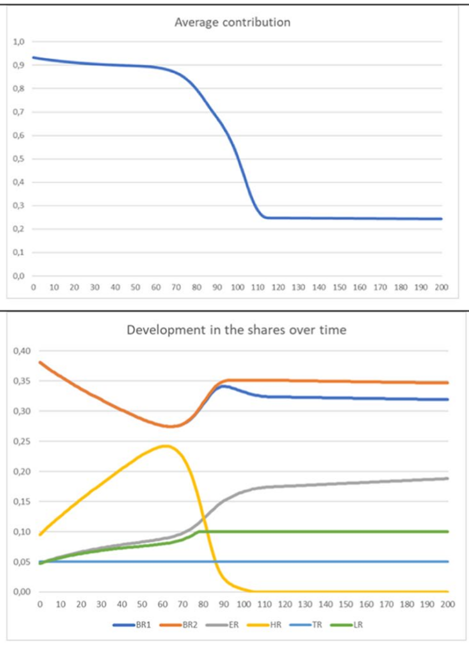


Fig. 2 Low-contribution scenario (baseline scenario)

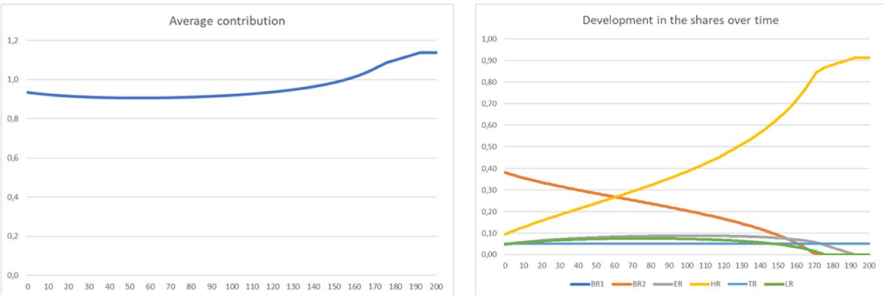


Fig. 3 High-contribution scenario (change in X_t^{TR} by 0.1 (X_t^{TR} = 1.8)) compared to baseline

We can compare three different arrangements (institutional settings): One with a low level of punishment and low support ("laissez-faire" institution); another having high punishment but low support (punish hard institution); and a third with no punishment but high support (supportive institution). For each of these arrangements we report the development in average net benefit over 200 periods together with a plot of how the shares of types develop over time.

In the situation shown in Table 4, for sufficiently low support no punishment level will push the system away from a low-contribution situation.

The required level of support is derived by initially setting $F_t = 0$ and then seeing how large X_t^{TR} needs to be for the system to move towards the high-performing scenario. In Table 5, we see that for $X_t^{TR} \geq 2.1$, no punishment is needed.

To exemplify this result from Tables 4, 5, and 6, Table 7 proceeds by calculating the development in the system compared to the original situation portrayed in Fig. 2. In case 1, we increase the punishment, F_t, by 25% while reducing X_t^{TR} by 25%. In case 2, the opposite changes are made: Reducing the punishment by 25% while increasing X_t^{TR} by 25%. The result in Table 6 is not in itself surprising due to the way we have modeled the support.

The main significance of the above analysis is a fundamental asymmetry between punishment and support: for low support, no matter how large the punishment, society ends in the low NB state (all individuals are only doing the absolute necessary). However, for sufficiently large support, no punishment is needed to get to the high net benefit state.

6 Discussion

The previous section on model simulation addressed the issue of the determinants of the size of the budget the Tough Riders have available for reward and punishment (denoted X_t^{TR}). In the model, the size of X_t^{TR} has been assumed to be exogenously determined, and its amount is therefore outside the control of the TR. Firstly, this might not be the case; secondly, we could also consider that the amount of support the Tough Riders offer to Hard Riders (S_t^{HR}) might be positively correlated with the average contribution.

The support S_t^{HR} is not necessarily monetary; it can be explicit "moral" support and recognition. In the model the responsibility for this has lied solely with the TRs. Instead of TRs using their resources on this, another strategy is to outsource that support to other groups, e.g., the Blind Riders. Building up a culture of rewarding and recognizing hard work might eventually increase S_t^{HR} to end up in a high-performing situation. This is particularly relevant since the need to support the HRs is most relevant to solve collection action problems.

A relevant question is: Are the ERs also capable of mimicking the HRs and gaining access to the S_t^{HR}? The main reason why we have included the additional contribution level of $a_t^{HR} > 0$ is to counteract these ill-intended copying strategies. This idea stems from the signaling games approach (see for example Gibbons 1992). Here, the highest-effort players need to separate from the less-effort players by overperforming to such an extent that the low-effort types no longer find it worthwhile to mimic that contribution level—even if recognized as hard-working types—but still optimal for the high-effort to make that contribution level. Although we have not modeled this formally, we can argue that the hard-working types also are willing to benefit from using additional resources to separate from the ERs, whereas the ERs

Table 3 Parameter changes that generate a shift from low to high contributions

Change in parameter	Example of change (cf Fig. 2)	Explanation for the change in state
Increasing the total resource available for support and detection	$X_t^{TR} = 1.7 \rightarrow 1.8$	Sufficient support is generated to give HRs above average net benefit
HR more stress tolerant	$\bar{c}_t^C = 0.9 \rightarrow 0.85$	The average contribution no longer triggers any stress
Larger share of BR	$BR_0^i = 40 \rightarrow 42, i = 1{,}2$	The BR in themselves conserve the status quo. (Here status quo is high average contribution)
Smaller initial share of ER	$ER_0 = 5 \rightarrow 4$	Lower initial ER → larger initial average contribution → The average contribution is no longer so low as to trigger stress for the HR + more support for HR
Increase the punishment	$F = 0.3 \rightarrow 0.35$	The ER types no longer use the hiding technology but contribute $C_t^{ER} = c_t^P$. Still, this yields below average net benefit for ER types
Increasing the punishable contribution threshold	$c_t^P = 0.3 \rightarrow 0.4$	Higher initial contribution. Therefore, the average contribution will now no longer trigger any stress
Increase cost of using hiding technology	$h_t = 0.1 \rightarrow 0.2$	Since in baseline it is optimal to use the hiding technology, this reduces ERs net benefit
Decrease the efficiency of the hiding technology	$\rho = 1 \rightarrow 1.5$	Since in baseline it is optimal to use the hiding technology, this reduces ERs net benefit

Table 4 Laissez-faire institution

Low punishment, low support: $F = 0.1$, $X_t^{TR} = 1.0$

Period (t)	Average net benefit
50	6.69
100	2.39
150	2.32
200	2.22

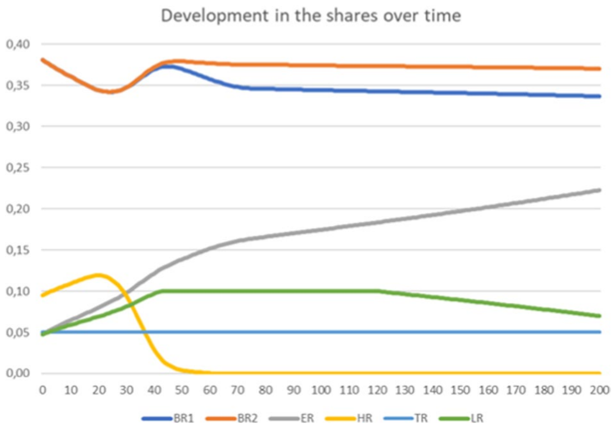
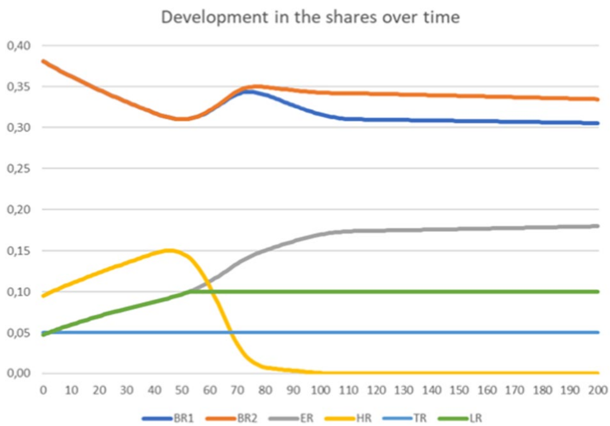


Table 5 Punish hard institution

High punishment, low support: $F \geq 0.6$, $X_t^{TR} = 1.0$

Period (t)	Average net benefit
50	8.72
100	4.57
150	2.77
200	2.77



would not be willing to do this, even if they would mistakenly be identified as HR types—the very essence of a separating equilibrium in a signaling game.

Table 6 Supportive institution

No punishment, high support: $F = 0$, $X_t^{TR} \geq 2.1$	
Period (t)	Average net benefit
50	9.27
100	9.82
150	11.60
200	13.05

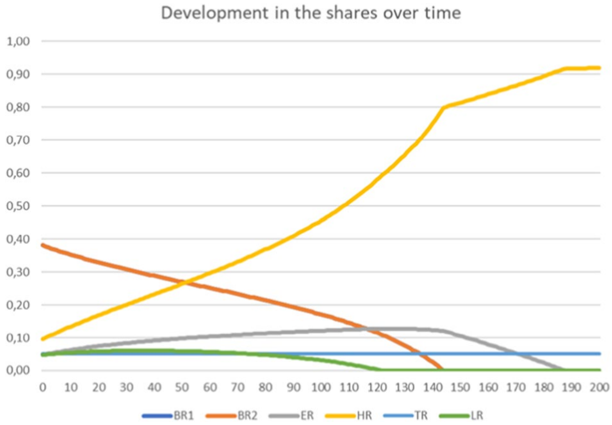


Table 7 Effect of an equal percentage change in reward and punishment

Period	Baseline	Case 1: $F = 0.38$, $X_t^{TR} = 1.28$	Case 2: $F = 0.23$,$X_t^{TR} = 2.13$
50	9.1	9.0	9.5
100	4.6	6.2	10.4
150	2.2	2.7	13.1
200	2.2	2.7	13.1

Our model is based on the static behavior of all individuals. We could consider that once the average contribution moves below a certain level, more fundamental changes need to be made. In Table 3 we describe several ways to change the system outcome. However, the longer it takes to recognize that the system is moving towards a low contribution, the harder it is to change (see Brandt and Svendsen 2019 for a more formal analysis of the effects of delays in responses to systemic issues).

Another interesting finding is shown in Fig. 2: Once the average contribution is low at a certain level, for example $C^{max}/2$, the group makes an investigation and "removes" all Easy Rider types. One may expect that such an initiative will increase the average contribution in the next stages, but instead the system moves steadily towards the low-contribution situation. The reason for this is that Blind Riders already adapted to the low contribution norm, and no mechanism in the system exists to change this situation. Change can only occur by massively increased support to the HRs and thereby helping solve collective action problems in society.

7 Conclusion

The purpose of this paper is to develop a general Multiple Player Approach (MPA) and thereby contribute toward the construction of a more holistic “third-generation” rational choice theory of how to understand and solve collective action problems. To establish a basis for our proposed “third-generation” theory, we first reviewed the first- and second-generation rational choice theories put forth by Olson (1965) and Ostrom (2000), respectively. These seminal works have laid the groundwork for our study by shedding light on the rational behavior of individuals within collective action contexts.

The game-theoretic model was based on an evolutionary model in which the proportion of player types who receive above-average returns grows in society. Similarly, the share of less successful player types will decrease over time. In our model the behavior of the successful player types will be copied through social learning. In the model we postulate five player types. *Hard Riders* (HRs) are high-contributing individuals, who are of great importance to overall society. *Easy Riders* (ERs) are low-contributing individuals, who seek to contribute as little as possible or nothing at all. *Blind Riders* (BRs) relate to the average contribution. *Tough Riders* (TRs) are players recruited among the HRs and willing to punish the ERs. Finally, *Low Riders* (LRs) cannot contribute as much as others do and hence should be supported by society.

Our simulations provide a general insight into the complex interplay between these types. Our simulations explore what parameter value changes cause the dynamics to take the population to a high rather than a low-contributing outcome. In order to be able to tackle the future challenges in any group and overall society, it is important to get to the Hard Riders’ nirvana—and not the Easy Riders’ nirvana where it is all about letting the others do the hard work for you when dealing with free riding and collective action problems.

The simulations identify several mechanisms to support a high-contribution outcome in a group. most notably the need for active societal support in empowering Hard Riders to overcome collective action problems.

Author’s contribution All three authors have contributed equally to the paper and are equally responsible for all content.

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Declarations

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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